Essays on Nonlinear Time-Series Modeling and Financial Markets in Emerging Economies

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To my parents…

Acknowledgments

One of the major lessons I got from my PhD experience is that–maybe this is one of those lessons you hear from several people but do not totally comprehend until you live it yourself– a doctoral study has many ups and downs, and requires hard-work, determination, concentration, and most importantly help from your colleagues, friends, and family. Certainly, this thesis would not be completed without the help and support of many people. Here, I would like to extend my sincerest gratitude for those who have particularly influenced the pace of my studies.

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Ghent, November 2016
Murat Midiliç

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Overview of the Dissertation

This PhD dissertation entitled "Essays on Nonlinear Time-Series Modeling and Financial Markets in Emerging Economies" is a collection of five essays that make empirical and theoretical contributions to the discussions on nonlinear time-series modeling and forecasting of financial series, international finance, and the role of central banks in currency markets. The ultimate motivation of the dissertation, which is embodied in the final chapter, is to explain the motivations of emerging market central banks in intervening to the currency markets. Other chapters have stemmed from the research on this topic, though first two chapters are self-contained. The third chapter gives the methodology used in the final chapter in a detailed way with an empirical application and the fourth chapter presents the literature that leads to the choice of the framework built in the final chapter of the dissertation.

The first chapter deals with a practical problem in the nonlinear time series econometrics literature. Currency interventions of central banks have been modeled with a wide range of models during the last three decades. The Smooth Transition Autoregressive Generalized Autoregressive Conditional Heteroskedasticity (STAR-GARCH) has been one of these models. The literature on the STAR-type models notes two practical issues on using the model, namely, dependency on initial values in estimating the model and high bias of the slope parameter estimator. The Iteratively Weighted Least Squares (IWLS) algorithm has been noted as a robust algorithm to the initial value selection and for a general set of nonlinear models with conditional variance. The literature shows that the maximum likelihood problem can be solved by the IWLS. The simulation study in the first chapter shows that the IWLS algorithm can deliver better estimates for the STAR-GARCH model parameters in comparison to the established maximum likelihood algorithms used in the literature. The performance of the algorithm depends on the value of the slope parameter. If the slope parameter is very high, the bias of this parameter estimator is observed to be high with all methods. The forecasting exercises with exchange rate and stock market return series add further insights about the case dependency of the performance and superiority of the IWLS algorithm. The results of the chapter on the predictability of the exchange rate returns motivate the exchange rate model used in Chapter 5.

During and in the aftermath of the recent global financial crisis, the central banks of emerging markets have mostly relied on currency interventions against the movements in the nominal exchange rates as a result of high capital flows to these markets. Excessive domestic credit growth, which is shown to be the most important signal of a financial crisis in the international finance literature, in emerging markets has been noted another important result of high capital flows. Therefore, the second chapter turns its attention to the determinants of domestic credit growth in emerging markets to motivate the context in which currency interventions will be discussed later. Using bank level data and macroeconomic indicators of Central and Eastern European countries (CEECs), it is shown that bank leverage and the real exchange rate significantly affect the domestic credit growth, and the effect is more nuanced for banks with foreign ownership status.

Chapter 3 makes an application of the Mixed Data Sampling (MIDAS) model to forecast Turkish real Gross Domestic Product (GDP) using daily financial data. Real GDP forecasts have been generated for several horizons with equity, commodity price, exchange rate, and corporate risk return series and daily factors extracted from these series. The predictive accuracy test results based on the root mean squared forecasting error values show that the MIDAS models give considerable forecasting advantage over the benchmark model and other linear models. The MIDAS model and results presented in this study are used in the final chapter of the dissertation.

Chapter 4 gives a detour of the currency intervention literature form a methodological perspective. There is an extensive literature on the currency interventions that goes back to the second half of the 1980s. The topic has been rigorously studied both for advanced and emerging market economies. The chapter fills a gap in the literature by categorizing empirical and theoretical frameworks under specific issues related to currency intervention modeling (e.g. channels of influence and endogeneity problem) in order to guide further research on the topic. The chapter draws particular attention to the lack of analyses that combine motivations of policymakers in using the currency interventions spreading different time horizons. Some empirical studies on interventions argue that isolating motivations of the policymakers would have potential benefits for the efficiency studies of currency interventions; however, since these motivations are often at different horizons, most of the studies choose to deal with one motivation and one horizon at a time. It is noted that the problem can be solved within a mixed frequency data modeling framework with methods suggested in the time-series econometrics literature such as the MIDAS or Kalman filters.

Following the literature review in the previous chapter, Chapter 5 studies two motivations of the central bank interventions to currency markets in emerging market economies. The first motivation is adjusting the exchange rate to a target level and the second motivation is accumulating foreign exchange reserves as an insurance against sudden-stops in capital inflows. The reserve accumulation motivation is incorporated to the reaction function of policymakers by extending a model of infrequent interventions that only includes exchange rate targeting. The reserve accumulation motivation is represented as the distance of actual reserve-to-GDP ratio from its optimal level. The model is estimated with the currency intervention data of Turkey during the floating exchange rate regime. As a solution to the mixed-data frequency problem, daily forecasts of reserve-to-GDP ratios are generated. The estimation results and several robustness checks show that, along with deviations from long-term exchange rate targets, the reserve accumulation has been a significant motivation in Turkey until the middle of 2013. The result has substantial implications for studies that question the effectiveness of currency interventions in Turkey, and the emerging markets in general since the interventions aimed at reserve accumulation are not expected to influence the exchange rates. If the interventions motivated only for exchange rate concerns are not isolated, the estimated effect of the interventions on the exchange rates might be biased. Therefore, studies on the effectiveness of currency interventions should be reconsidered from this perspective.

1

Estimation of STAR-GARCH Models with Iteratively Weighted Least Squares*

Abstract

This study applies the Iteratively Weighted Least Squares (IWLS) algorithm to a Smooth Transition Autoregressive (STAR) model with conditional variance. Monte Carlo simulations are performed to measure the performance of the algorithm, to compare its performance to the established methods in the literature, and to see the effect of the initial value selection method. The simulation results show that lower bias and mean squared error values are received for the slope parameter estimator from the IWLS algorithm in comparison to the other methods when the real value of the slope parameter is low. In an empirical illustration, the STAR-GARCH model is used to forecast daily US Dollar/Australian Dollar and the FTSE Small Cap index returns. 1-day ahead out-of-sample forecast results show that the forecast performance of the STAR-GARCH model improves with the IWLS algorithm and the model performs better than the benchmark model.

Keywords: STAR, GARCH, iteratively weighted least squares, Australian Dollar, FTSE
JEL classification: C15, C51, C53 C58, C87, F31

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1.1. Introduction

Nonlinear models with heteroskedastic errors have been used in analyzing financial time series data for a long time. One special type of models under this family is the Smooth Transition Autoregressive (STAR) model with conditional variance. Unlike STAR models, which are estimated by nonlinear least squares (NLS), these models are estimated by the maximum likelihood estimation (MLE), or quasi-maximum likelihood estimation (QMLE). However, in real world applications the numerical features of these models and computational aspects of the method used may lead to a complicated estimation procedure. For both NLS and MLE, the experience shows that the final estimates are highly dependent on the starting values (for STAR models, see Teräsvirta (1994), for STAR models with heteroskedastic variance, see Lundbergh et al. (1999) and van Dijk et al. (2002)), the bias of the slope parameter estimator is higher than the biases of other parameter estimators, and estimation of the slope parameter gets more difficult as the parameter value increases. This study presents a potential solution to these problems by using Iteratively Weighted Least Squares (IWLS) and compares its performance with other established algorithms.

As pointed out by Teräsvirta (1994), Lundbergh et al. (1999), van Dijk et al. (2002); one problem with the estimation of the STAR type models is to find sensible starting points for the algorithm. Due to the highly nonlinear nature of the STAR type models, estimation results are sensitive to the starting points (Chan and McAleer, 2003). Moreover, according to Teräsvirta (1994) and Chan and McAleer (2002), the degree of difficulty in estimation changes depending on the type of the transition function used in the model. A comparison of the models with logistic transition function and exponential transition function shows that the STAR models with logistic transition function proved to be more problematic than the other.

Simulation studies of Chan and Theoharakis (2011) show that the main reason for these problems seem to be the complex nature of the log-likelihoods of these functions stemmed from the slope parameter(s). For the STAR-GARCH model, Chan and Theoharakis (2011) show how the log-likelihood function behave around the optimum values of the parameters. They illustrate graphically that the log-likelihood function might be flat for exponential transition functions or lumpy for logistic transition functions around the optimum value of the slope parameter(s). These results underline the need for solution methods that are robust to local optima in estimating the STAR-type models.

One common feature of the studies that use the STAR models with conditional variance is that the models are estimated by the maximum likelihood (ML).[1] Although, in theory the ML estimation is the correct way to handle the estimation problem and gives consistent estimates; from a numerical point of view, the algorithm used in solving the ML can be sensitive to starting values and might have a poor performance in dealing with local optima issue; so the algorithm might be the reason for the problems described above. Therefore, an approach targeting robustness of the ML estimation of nonlinear models would be a potential solution to the referred problems. One such an approach is the IWLS estimation of nonlinear models with conditional variance. Mak (1993) and Mak et al. (1997) show that the maximum likelihood problems can be transformed into

[1] Other solution methods are available for STAR-type models with homoskedastic errors. Teräsvirta et al. (2010) discuss estimating the models by dividing the parameter vector into two subsets in order to reduce numerical burden. The method is first proposed by Leybourne et al. (1998). Even though it eases the numerical burden of the STAR model estimations, Maugeri (2014) show that there are cases in which the method gives "biased and inconsistent" results and the maximum likelihood algorithms should be preferred.

a problem that can be solved by the IWLS, and the performance of the algorithm is compatible with or better than the traditionally used ML algorithms in the literature for the set of models we are interested in.

The purpose of this study is to show the performance of the IWLS algorithm in estimating STAR models with conditional variance in a basic setup. For this purpose, the STAR-GARCH model is chosen to be the model used in the study. Monte Carlo (MC) simulations are carried out with a STAR-GARCH model to show the performance of the algorithm conditional on different initial values. Robustness of the algorithm to initial value selection is checked by carrying out simulations with randomly generated initial values and initial values provided by a heuristic algorithm, which has been used in the STAR model estimation literature. Brooks et al. (2001) show that there might be significant differences in the results from different software for the same problem. Therefore, the performance of the IWLS is also compared with other functions that are commonly used for the maximum likelihood and quasi-maximum likelihood estimations. These are *fmincon* function of MATLAB, and *maxLik* function of R. Special attention is paid to the slope parameters of the transition function since in practice, this parameter is found to be the most difficult to estimate in the literature. In order to account for the effect of the dynamics in the variance component of the model, simulations are carried out with several GARCH specifications. Practical implications of using the IWLS algorithm are studied with empirical applications.

The contribution of the study to the literature is twofold. First, in a basic setup, it shows that for the STAR-GARCH model, it is possible to have slope parameter estimators with smaller bias and variance with the IWLS algorithm. Second, as an empirical contribution, daily exchange rates and stock indices are forecast by the STAR-GARCH model; thus, the study contributes to the exchange rate and stock index forecasting discussions in the literature.

Simulation studies convey three key results. The first result is that when the real value of the slope parameter is low, the IWLS performs better than other methods in estimating the parameter while the IWLS does not perform worse in estimating the slope parameter when the real value of the parameter is high. The second result states that for the IWLS algorithm, bias of the slope parameter estimator from randomly generated initial values is smaller than the bias of the estimator received from the benchmark initial value selection method. According to the third result, estimation performances of the methods change as the real value of the persistency parameters in the variance equation change. In cases where performances of other methods deteriorate, the IWLS performs better in estimating these parameters.

In the empirical part of the study, daily US Dollar (USD)/Australian Dollar (AUD) exchange rate and the Financial Times Stock Exchange Small Cap (FTSE SC) returns are forecast with the STAR-GARCH model. According to the out-of-sample forecast error performance and prediction accuracy tests, the IWLS algorithm performs better than the benchmark random walk (RW) model as well as the competing algorithms. For the exchange rate forecasts, the statistical significance of the performance of the IWLS algorithm is robust to different predictive accuracy tests while robustness is not observed for the stock index forecasts, though most of the tests give significant results. Empirical exercises suggest that the traditional methods used in the literature might give misleading results in the sense that even though the smooth transition model performs better than the benchmark model; the algorithms cannot demonstrate the performance. The IWLS is shown to correct this problem in practice.

The study is organized as follows. The model and the IWLS algorithm are described in the next section. Section 1.3 presents the simulations, summarizes the results, and discusses their implications. In Section 1.4, the STAR-GARCH model is used in empirical illustrations to forecast daily exchange rate and stock index returns. The final section summarizes and concludes.

1.2. STAR-GARCH Model and IWLS Estimation

To the best of my knowledge, STAR-type models have never been estimated by the IWLS algorithm in the literature; so the aim of the study is to first show its performance in a basic setup. The STAR-GARCH model has been selected because of its simplicity within the available extensions of the STAR-type models in the literature and it has a wide range of empirical applications that include estimation of daily and intra-daily S&P 500 index (Chan and McAleer, 2002, 2003), daily major exchange rates (Westerhoff and Reitz, 2003), and monthly commodity prices (Reitz and Westerhoff, 2007). The IWLS algorithm can be extended to other STAR-type models with conditional variance based on the potential success of the algorithm in this basic setup.

This section first describes the STAR-GARCH model and gives the non-trivial stationary conditions both for the mean and variance equations. Then, the IWLS algorithm is described.

1.2.1. STAR-GARCH Model

Consider a STAR(p) model with a GARCH(q_1,q_2) component and $t = 1-p, 1-(p-1), ..., T-1, T$ as the following:

$$y_t = x_t\phi^{(1)} + x_t\phi^{(2)}G_t(.) + \varepsilon_t, \tag{1.1}$$

$$\varepsilon_t = v_t\sqrt{h_t},\ v_t \sim N(0,1), \tag{1.2}$$

$$h_t = \omega + \sum_{i=1}^{q_1}\alpha_i\varepsilon_{t-i}^2 + \sum_{j=1}^{q_2}\beta_j h_{t-j}, \tag{1.3}$$

where $x_t = (1, y_{t-1}, y_{t-2}, ..., y_{t-p})$ is a $1\times(p+1)$ vector; $\phi^{(1)} = (\phi_0^{(1)}, \phi_1^{(1)}, \phi_2^{(1)}, \ldots, \phi_p^{(1)})'$, and $\phi^{(2)} = (\phi_0^{(2)}, \phi_1^{(2)}, \phi_2^{(2)}, \ldots, \phi_p^{(2)})'$ are $(p+1)\times 1$ vectors of coefficients; $G_t(.)$ is the transition function; ω is the constant of the variance process; α_i is the ARCH coefficient for $i = 1,..,q1$; β_j is the GARCH coefficient for $j = 1,..,q2$, and h_t is the conditional variance. The errors in the mean equation, ε_t, are assumed to be orthogonal to x_t. The logistic transition function, $G_t(.)$, is given by:

$$G_t(y_{t-d}; e^{\eta}, c) = \frac{1}{1+e^{-e^{\eta}(y_{t-d}-c)}}, \tag{1.4}$$

where y_{t-d}, $d > 0$, is the transition variable, e^{η} is the slope parameter, and c is the location parameter. The slope parameter is expressed as an exponential function. In contrast to the traditional literature which gives the slope parameter as $\gamma > 0$; following Goodwin et al. (2011) and Hurn et al. (2015), the parameter is written as a monotonic transformation of γ. By doing so, the interval for the parameter of interest, η, can take values in the interval $(-\infty, \infty)$. In this way, one eliminates the non-negativity restriction on the parameter and the search for the slope parameter focuses on a smaller range of values because of the exponential mapping of η to γ (Hurn et al., 2015). The interval for $G_t(.)$ stays the same with the transformation: as $\eta \to -\infty$, $G_t(.) \to 0.5$ and the model approaches to a linear AR(p)-GARCH(q_1,q_2) model. As $\eta \to \infty$, $G_t(.) \to 1$ and the model approaches to a threshold AR (TAR(p))-GARCH(q_1,q_2) model. The corresponding log-likelihood function for observation t of the model is

$$l_t = -\frac{1}{2}lnh_t - \frac{\varepsilon_t^2}{2h_t}. \tag{1.5}$$

The model is assumed to be weakly stationary. For nonlinear models with heteroskedastic conditional errors, Meitz and Saikkonen (2008) give the stationary conditions and conclude the stationary conditions for the mean and the variance can be checked separately. According to Meitz and Saikkonen (2008), one of the following two conditions is sufficient for the mean to be stationary:

$$\sum_{i=1}^{p} max\left\{\left|\phi_i^{(1)}\right|,\left|\phi_i^{(1)}+\phi_i^{(2)}\right|\right\} < 1, \tag{1.6a}$$

$$\rho(\{\mathbf{A}_1,\mathbf{A}_2\}) < 1. \tag{1.6b}$$

In condition (1.6b), $\rho(\{\mathbf{A}_1,\mathbf{A}_2\})$ is the joint spectral radius of $\mathbf{A}_1 = \bar{\mathbf{A}}_p([\phi_1^{(1)}...\phi_p^{(1)}]')$ and $\mathbf{A}_2 = \bar{\mathbf{A}}_p([\phi_1^{(1)}+\phi_1^{(2)}...\phi_p^{(1)}+\phi_p^{(2)}]')$ where $\bar{\mathbf{A}}_p$ is defined as the following:

$$\bar{\mathbf{A}}_p(a) = \begin{bmatrix} a_1 & a_2 & ... & a_{p-1} & a_p \\ 1 & 0 & ... & 0 & 0 \\ 0 & 1 & ... & 0 & 0 \\ . & . & ... & . & . \\ . & . & ... & . & . \\ . & . & ... & . & . \\ 0 & 0 & ... & 1 & 0 \end{bmatrix}.$$

In the simulations, both stationarity conditions are checked. In practice, it is most convenient to use the condition (1.6a) since computation of the joint spectral density can be burdensome as p increases.

In the MC simulations, the conditional variance is assumed to follow a GARCH(1,1) model. The weak stationarity condition of the conditional variance is thus $\alpha_1+\beta_1 < 1$. Non-negativity of the conditional variance requires $\omega > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$. Finally, the conditional variance is assumed to be fourth moment stationary which, when the errors are normal, implies the condition $3\alpha_1^2+2\alpha_1\beta_1+\beta_1^2 < 1$ (for the fourth moment conditions of a GARCH processes see He and Teräsvirta (1999a) and He and Teräsvirta (1999b)).

1.2.2. IWLS Estimation of the STAR-GARCH Model

The IWLS is a robust regression algorithm that goes back to Beaton and Tukey (1974) and was first used for robust polynomial fitting. In order to illustrate the basic setup for the IWLS assume that y is a $T\times 1$ vector of observations, $\mathbf{X}$ is a $T\times n$ matrix of regressors, β is an $n\times 1$ vector of parameters, and $\mathbf{W}$ is an $n\times n$ diagonal weight matrix. Then, parameter estimates at the r^{th} IWLS iteration at can be written as follows:

$$\hat{\beta}_r = \hat{\beta}_{r-1} + (\mathbf{X}'\mathbf{W}_r\mathbf{X})^{-1}(\mathbf{X}'\mathbf{W}_r(y-\mathbf{X}\hat{\beta}_{r-1})). \tag{1.7}$$

where the weight matrix $\mathbf{W}_r$ is a function of the residuals from the previous step. This is why the IWLS is sometimes referred to as "iteratively *re*weighted least squares". It is possible to assign a functional structure to the weight matrix by using weight factors (see Beaton and Tukey (1974) for an example with bi-weight regression). A simple example of the weights is one in which the elements of $(y-\mathbf{X}\hat{\beta}_{r-1})/k$, where k is a scale parameter, form the main diagonal of $\mathbf{W}_r$ which itself is a diagonal matrix. The scale parameter k can be chosen beforehand depending on the data and the purposes of the analysis or can be determined in step $r-1$ to be used in step r. At the initial step, the sum of the weights can be equal to one or a unit weight can be assigned to each element. The IWLS can be used with numerical algorithms such as Gauss-Newton and Levenberg-Marquardt, and it has a wide range of application areas besides econometrics such as sparse recovery, face recognition, and magnetic resonance imaging (see Holland and Welsch (1977), Chartrand and Yin (2008), Daubechies et al. (2010)).

Mak et al. (1997) show the superiority of the IWLS over the BHHH algorithm in the estimation of an ARCH model. Li and Li (1996) estimate their DTARCH model with the IWLS and show that it is faster than the BHHH algorithm. Biases of some parameter estimators are comparable with those of the BHHH estimators, whereas for some other parameters the IWLS estimators are less biased of the two. Besides being faster, the IWLS is less sensitive to the choice of starting values. Green (1984) notes that "General experience seems to be that choice of starting values for the parameter estimates is not particularly critical". These features of the IWLS make it useful in the estimation of STAR models with conditional variance.

Based on the results of Mak (1993), Mak et al. (1997) derive an IWLS algorithm for a very general class of nonlinear models with heteroskedastic errors. For the clarity of the subsequent application of the algorithm to the STAR-GARCH model, the main results of Mak (1993) and Mak et al. (1997) are restated here.

Let y be a vector of observations with size T, θ be a q-dimensional vector of parameters, and $p(y,\theta)$ be the density function of y under θ. Let θ_0 be the true parameter vector and assume that θ_0 lies in an open parameter space $\Omega=\{\theta\}\subseteq\mathbb{R}^q$. Ω is assumed to contain an estimator of θ_0, $\hat{\theta}$, as a root of

$$f(y,\theta)=0. \tag{1.8}$$

The core assumption of the setup is that an estimator of Equation (1.8) is unbiased, i.e. $E\left\{f(y,\theta)|\theta\right\}=0$ where $E\left\{.|\theta\right\}$ denotes the expectation operator. The scale of $f(y,\theta)$ is assumed to be the order of $O_p(T^{-1/2})$. Mak (1993) defines the function $g(.)$ for any θ, $\tilde{\theta}$ as follows:

$$g(\tilde{\theta},\theta)=E\left\{f(y,\theta)|\tilde{\theta}\right\}=0. \tag{1.9}$$

An inductive sequence $\left\{\theta_{(r)}\right\}_0^\infty$ is defined as follows. Assume $\theta_{(r)}$ is given. For large T, where $f(y,\theta)\simeq E\left\{f(y,\theta_{(r)})|\theta_0\right\}$, θ_0 can be approximated by a θ which equates the observed value of f with the expected value under θ such that

$$f(y,\theta_{(r)})=E\left\{f(y,\theta_{(r)})|\theta_{(r+1)}\right\}=g(\theta_{(r+1)},\theta_{(r)}). \tag{1.10}$$

If we take $r\to\infty$ and use the condition of unbiasedness, we see that if $\left\{\theta_{(r)}\right\}_0^\infty$ converges, it will converge to a root of Equation (1.8).

Using this result, Mak (1993) reaches the following main results:

$$\left.\frac{\partial g(\tilde{\theta},\theta)}{\partial\tilde{\theta}}\right|_{\theta} = -E\left\{\left.\frac{\partial f(y,\theta)}{\partial\theta}\right|_{\theta}\right\}, \tag{1.11}$$

$$\left.\frac{\partial\psi}{\partial\theta}\right|_{\hat{\theta}} \rightarrow 0 \qquad as \qquad T\rightarrow\infty, \tag{1.12}$$

$$Pr(S_n)\rightarrow 1 \qquad as \qquad T\rightarrow\infty, \tag{1.13}$$

and

$$\theta_{(2)} - \hat{\theta} = o_p(T^{-1/2}), \tag{1.14}$$

where S_n is the event that $\left\{\theta_{(r)}\right\}_0^\infty$ converges, and $\psi:\mathbb{R}^q\rightarrow\mathbb{R}^q$ is an implicit function so that

$$f(y,\theta) = g\left\{\psi(\theta),\theta\right\}. \tag{1.15}$$

ψ relates $\theta_{(r)}$ to $\theta_{(r+1)}$ as $\psi(\theta_{(r)}) = \theta_{(r+1)}$. For maximum likelihood estimations in which $f(y,\theta)$ is a vector of partial derivatives and might be complicated for further differentiation, the result given by Equation (1.11) (*Lemma 1* in Mak (1993)) suggests an alternative method. According to Equation (1.12) (*Lemma 2* in Mak (1993)), as T gets larger; when evaluated at the real value of θ, change in the implicit function ψ with respect to θ will converge to zero. Result (1.13) (*Theorem 1* in Mak (1993)) denotes the convergence probability of the sequence $\left\{\theta_{(r)}\right\}_0^\infty$ will approach to 1 as T gets larger. Finally, result (1.14) (*Theorem 2* in Mak (1993)) shows that the proposed algorithm converges very fast just in 2 steps.

If Equation (1.15) does not have an explicit solution, Mak (1993) suggests using the following linearization:

$$g(\tilde{\theta},\theta) + \left[\left.\frac{\partial g(\tilde{\theta},\theta)}{\partial\tilde{\theta}}\right|_{\tilde{\theta}=\theta}\right]'(\tilde{\theta}-\theta) = \left[\left.\frac{\partial g(\tilde{\theta},\theta)}{\partial\tilde{\theta}}\right|_{\tilde{\theta}=\theta}\right]'(\tilde{\theta}-\theta) = f(y,\theta). \tag{1.16}$$

Based on these results, Mak et al. (1997) start building an IWLS algorithm for nonlinear models with heteroskedastic errors first by defining $f(y,\theta)$ as follows:

$$f(y,\theta) = \frac{\partial lnp(y,\theta)}{\partial\theta} \tag{1.17}$$

where $lnp(y,\theta)$ is the density of y. The nonlinear model that is used for deriving the results is given as the following:

$$y_t = \mu(z_t, y_{t-1}, y_{t-2}, \ldots, y_{t-p}, \theta) + \varepsilon_t, \tag{1.18}$$

where z_t is a vector of regressors and ε_t is conditionally normally distributed with mean 0, $E(\varepsilon_t) = 0$, and variance given by

$$h_t = h(z_t, y_{t-1}, y_{t-2}, \ldots, y_{t-p}, \theta). \tag{1.19}$$

It has to be noted that the model specification is very general and for derivation of the further results the model is assumed to satisfy some regularity conditions. Even though such a general specification is feasible, there might be some practical concerns while implementing the method for estimating a specific nonlinear model.

Set $y = (y_T, y_{T-1}, y_{T-2}, ...)$, then we have $f(y,\theta)$ after differentiating the log-likelihood function as the following:

$$f(y,\theta) = -\frac{1}{2}\sum \frac{\partial h_t}{\partial \theta}\left\{\frac{1}{h_t} - \frac{(y_t-\mu_t)^2}{h_t^2}\right\} + \sum \frac{\partial \mu_t}{\partial \theta}\frac{(y_t-\mu_t)}{h_t}. \tag{1.20}$$

From Equation (1.15), we have:

$$g(\tilde{\theta},\theta) = -\frac{1}{2}\sum \frac{\partial h_t}{\partial \theta}\left\{\frac{1}{h_t} - \frac{\tilde{h}_t + (\tilde{\mu}_t-\mu_t)^2}{h_t^2}\right\} + \sum \frac{\partial \mu_t}{\partial \theta}\frac{(\tilde{\mu}_t-\mu_t)}{h_t}, \tag{1.21}$$

where $\tilde{\mu}_t = \mu(z_t, y_{t-1}, y_{t-2}, ..., y_{t-p}, \tilde{\theta})$ and $\tilde{h}_t = h(z_t, y_{t-1}, y_{t-2}, ..., y_{t-p}, \tilde{\theta})$. According to (1.11), Fisher's information matrix can be derived first by differentiating $g(\tilde{\theta},\theta)$ with respect to $\tilde{\theta}$, which gives

$$\begin{aligned}\frac{\partial g(\tilde{\theta},\theta)}{\partial \tilde{\theta}} = -\frac{1}{2}\sum\left\{-\frac{1}{h_t^2}\left(\frac{\partial \tilde{h}_t}{\partial \tilde{\theta}}\right) - \frac{2(\tilde{\mu}_t-\mu_t)}{h_t^2}\left(\frac{\partial \tilde{\mu}_t}{\partial \tilde{\theta}}\right)\right\}\left(\frac{\partial h_t}{\partial \theta}\right)' +\\ \sum\frac{1}{h_t}\left(\frac{\partial \tilde{\mu}_t}{\partial \tilde{\theta}}\right)\left(\frac{\partial \mu_t}{\partial \theta}\right)'.\end{aligned} \tag{1.22}$$

Therefore, at $\tilde{\theta} = \theta$, the Fisher's information matrix can be written as

$$\mathbf{I}(\theta) = \frac{1}{2}\sum\frac{1}{h_t^2}\left(\frac{\partial h_t}{\partial \theta}\right)\left(\frac{\partial h_t}{\partial \theta}\right)' + \sum\frac{1}{h_t}\left(\frac{\partial \mu_t}{\partial \theta}\right)\left(\frac{\partial \mu_t}{\partial \theta}\right)'. \tag{1.23}$$

The IWLS algorithm is derived by using the Equations (1.20)-(1.22) and (1.16). Inserting Equations (1.20)-(1.22) in (1.16), we have

$$\begin{aligned}\sum\frac{1}{2}\frac{1}{h_t^2}\frac{\partial h_t}{\partial \theta}\left\{\left(\frac{\partial h_t}{\partial \theta}\right)'(\tilde{\theta}-\theta) + h_t - (y_t-\mu_t)^2\right\} +\\ \sum\frac{1}{h_t}\frac{\partial \mu_t}{\partial \theta}\left\{\left(\frac{\partial \mu_t}{\partial \theta}\right)'(\tilde{\theta}-\theta) - (y_t-\mu_t)\right\} = 0.\end{aligned} \tag{1.24}$$

The terms of (1.24) can be rearranged in order to have:

$$\sum W_{1t} z_{1t}\{y_{1t} - z_{1t}'\tilde{\theta}\} + \sum W_{2t} z_{2t}\{y_{2t} - z_{2t}'\tilde{\theta}\} = 0, \tag{1.25}$$

where

$$\begin{aligned}W_{1t} &= \frac{1}{h_t}, \quad z_{1t} = \frac{\partial \mu_t}{\partial \theta}, \quad y_{1t} = \left(\frac{\partial \mu_t}{\partial \theta}\right)'\theta + (y_t-\mu_t),\\ W_{2t} &= \frac{1}{h_t^2}, \quad z_{2t} = \frac{\partial h_t}{\partial \theta}, \quad y_{2t} = \left(\frac{\partial h_t}{\partial \theta}\right)'\theta - h_t + (y_t-\mu_t)^2.\end{aligned}$$

The weights W_{1t} and W_{2t} are based on the conditional variance h_t. The h_t is in the denominator so as the variance at a certain point in time increases, the weight assigned to that certain point will decrease.

At the $(r+1)$th step, $\theta_{(r+1)}$ is computed as the weighted least squares estimate:

$$\theta_{(r+1)} = \left\{ \sum_{m=1}^{2} \sum_{t} W_{mt} z_{mt} z'_{mt} \right\}^{-1} \left\{ \sum_{m=1}^{2} \sum_{t} W_{mt} z_{mt} y_{mt} \right\}, \tag{1.26}$$

where $m = 1,2$ represent the mean and variance equations respectively, and θ in the definitions of W_{mt}, z_{mt}, and y_{mt} are replaced with $\theta_{(r)}$.

There are some advantages of the algorithm. It only uses the first derivatives of the log-likelihood function and this gives a computational advantage over the algorithms that also need second order derivatives. Second, see (1.14), the algorithm promises a fast convergence. Third, it is a robust algorithm. In this context, this feature of the algorithm is reflected on the weights that would be low for possible large shocks (i.e. possible outliers in the sample). Fourth, Green (1984) notes that initial values are not very critical. For the examples given in Mak (1993), initial values are found to be independent of the starting values. However, Green (1984) also notes cases in which the final IWLS estimates may depend on the starting values.

On the other hand, the behavior of the algorithm is not tractable except for simple cases. According to Green (1984), the algorithm can be seen as a fixed point problem and if the algorithm converges, the results will be a solution to the likelihood equations.

1.3. Simulation Study

The aim of the simulations is to evaluate the performance of the IWLS algorithm in estimating the STAR-GARCH model, compare the performance of the algorithm with other functions/algorithms used in the literature, and define circumstances in which it performs better or worse, if any.

1.3.1. Simulation Design

The IWLS algorithm is compared with the *fmincon* function of MATLAB, and *maxLik* function of R. The estimation methods are compared in terms of mean, standard deviation, median, bias and mean squared error (MSE). The distributional properties of the estimates are also compared with several distribution comparison tests as robustness checks.

Before going further in describing the simulation setup and results, it is worth noting the similarities and differences between these methods to better comment on the results. *fmincon* is a minimization function of MATLAB that can handle linear and nonlinear constraints, equality and inequality constraints, and parameter boundaries.[2] In the ML estimations, one should insert the negative of the log likelihood function as the objective function. Interior-point, trust-region-reflective, sequential quadratic programming, and active-set algorithms are optional in the function. In the simulations, interior-point algorithm has been used with *fmincon* since active-set algorithm requires a user-supplied gradient, and trust-region-reflective and sequential quadratic programming algorithms are not large scale algorithms, which would create problems for long time series. *maxLik* function is the maximisation function of the maxLik package of R that is designed for the ML applications.[3] Newton Raphson, BHHH, BHGS, Simulated ANNealing,

[2] For a detailed description of the function and its features, please see http://www.mathworks.com/help/optim/ug/fmincon.html

[3] For a detailed description of the function and its features, please see http://www.http://cran.r-project.org/web/packages/maxLik/maxLik.pdf

Conjugate Gradients, and Nelder-Mead algorithms are available as optional within the function. *maxLik* can also handle linear constraints and parameter boundaries. Inequality constraints are only allowed for the Nelder-Mead algorithm; so this algorithm has been used with *maxLik* during the study.

The IWLS algorithm cannot handle constraints or boundaries. Instead, following the recommendation of Mak et al. (1997), if a parameter value at step r happens to be out of bounds, it is replaced with a value that is close to the boundary.[4] This is done by using the smallest distance between two numbers that is defined by the software. For MATLAB, the smallest distance is identified as 2.2204×10^{-16} and when, for instance, a parameter value is above the boundary at a specific step r, then the value if replace by the boundary value minus 2.2204×10^{-16} to be used in the next step.[5]

Parameters of the simulated series are specified as the following:

$$\begin{aligned} y_t &= 0 - 0.35y_{t-1} + 0.55y_{t-2} + (0.02 + 0.20y_{t-1} - 0.25y_{t-2})G(y_{t-1}; e^{\eta}, 0.02), \\ h_t &= 0.001 + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}. \end{aligned}$$

The parameter values for the $\phi^{(1)}$ and $\phi^{(2)}$ are selected to ensure the stationary conditions for the models are satisfied. These model parameters are used with two η specifications in order to observe the effect of the slope parameter on estimation performances. The selected η values are $ln5$ and $ln100$, which correspond to the slope parameter values of 5 and 100 in the traditional notation in the literature and these are commonly used values to show behaviors of the STAR models for different slope parameters.

This parameterization is used with 9 different GARCH parameters starting with $(\alpha, \beta) = (0.09, 0.90)$ and increase (decrease) β (α) by 0.01 until $(\alpha, \beta) = (0.01, 0.98)$ for each η values used. The purpose of this exercise is to compare the estimation performances of the methods for low values of α since as it is pointed out by Zivot (2009) for GARCH estimations, when some parameters are close to be unidentified[6], maximum likelihood estimations may not be reliable.

Figure 1.1 depicts selected representative series from the simulated data. The figure includes the plots for y_t and h_t against time, and G_t against the transition variable y_{t-1}. As it can be seen on the plots of the transition variables, when the value of the slope parameter is low, transition from one state to another state is smoother. In addition to that, these figures show the effect of different GARCH specifications. For higher values of α, the volatility clusters in the data are more apparent.

A crucial part of estimating the STAR-GARCH (or STAR type) models is the sensitivity of the final estimates to the starting points. For IWLS algorithm; Green (1984), Mak et al. (1997), and Li and Li (1996) state that initial points are not found to be important. The relevance of this claim for the STAR-GARCH model is tested by comparing estimates from two different sets of initial values: estimates of the Simulated Annealing (SA) algorithm and randomly generated initial

[4] For their problem, Mak et al. (1997) replace with 0; but for the problem at hand, replacing with a value that is close to the boundary is seen to work better since value of 0 for some parameters might lead the function to be undefined. Handling the constraints and boundaries can be seen as the major disadvantage of the IWLS against other algorithms.

[5] This procedure implies that the boundaries are defined as real boundary value $\pm 2.2204 \times 10^{-16}$ in practice; therefore, if a parameter estimate is found to be exactly at this value, then that estimation is discarded from the simulations.

[6] In the case of GARCH, β is unidentified when $\alpha = 0$.

values. In addition to its features noted below, the SA algorithm is chosen for the comparison instead of the widely used "grid search" method following the simulation results by Schleer (2015), who show that the SA algorithm delivers better results than the grid search method.

The SA algorithm is a heuristic algorithm that can be used for optimization when traditional algorithms fail to converge or to get values close to the global maximum when there is local maxima problem in the function of interest. Given the initial temperature, maximum temperature, temperature reduction function, acceptance criteria, and stopping criterion[7](Goffe et al., 1994; Brooks and Morgan, 1995); the SA algorithm can be sketched in five steps: (i) generate a random point calculate the loss function for this point (e.g. log-likelihood function), (ii) select another point and decide if this point stays or not based on an acceptance criterion, (iii) decrease the temperature based on the temperature reduction function, (iv) reanneal, and (v) end the algorithm when the stopping criterion is satisfied. The acceptance and temperature reduction functions used in the study can be given as follows:

$$\text{acceptance} = e^{\frac{Loss_{new}-Loss_{old}}{\text{Temp}}}, \tag{1.27}$$

$$\text{Temp} = \text{Temp}_0 * 0.95^{n_{SA}}, \tag{1.28}$$

where acceptance is the acceptance probability, $Loss_{new}$ and $Loss_{old}$ denote loss function values for the old and new points to be decided on, $n_{SA} = 1, \ldots, N_{SA}$ is the number of annealing, Temp_0 is the starting temperature, Temp is the new temperature at the annealing number n_{SA}.

Goffe et al. (1994) compare the SA algorithm with a simplex algorithm, a conjugate gradient algorithm, and a quasi-Newton algorithm and show that the SA algorithm performs better than the others. The performance of the algorithm is supported by Brooks and Morgan (1995), who measure the performance of the algorithm with a problem in which maximum likelihood estimations fail to converge. It is also noted that the SA algorithm might fail to find the global optimum when the problem at hand is very complex (Goffe et al., 1994).[8,9] In the simulations of this study, the SA algorithm is started by the randomly generated initial values which are then also used to estimate the model.

A second set of initial values randomly generated with respect to the stationary conditions given for the mean and variance of the STAR-GARCH model. For the slope parameter, initial values are chosen randomly in the interval $[1,4]$, and for the location parameter, initial values are chosen to be the mean of the series that are estimated.

The number of replications for each study is 1000. The parameter bias and MSE of the estimations are calculated as follows:

$$\text{bias} = (\sum_{n=1}^{1000} (\hat{\theta}_n - \theta))/1000,$$

$$\text{MSE} = (\sum_{n=1}^{1000} (\hat{\theta}_n - \theta)^2)/1000,$$

[7] The terminology of the SA algorithm comes from the physics and material sciences literature. In this context, we can consider temperature only as a parameter of acceptance. High temperature leads to high acceptance probability. Temperature is systematically decreased with the temperature reduction function; so that the probability of accepting a point as the optimum gets lower.

[8] For an application of the algorithm and other heuristic algorithms for STAR type models, please see Schleer (2015). For other applications of the SA algorithm, please see Nakatsuma (2000) and Bernard et al. (2012)

[9] Despite the desirable features of the SA, it is not chosen to be the estimation algorithm because as the parameter number increases, the algorithm gets slower.

where $\hat{\theta}_n$ is the parameter estimates from the n^{th} estimation.

1.3.2. Simulation Results

Tables 1.1-1.4 give mean, median, standard deviation, bias, and MSE for the parameter estimates for simulations with GARCH specifications $(\alpha, \beta) = \{(0.09, 0.90), (0.01, 0.98)\}$ of both low and high values of the slope parameter. Results from the simulations with other GARCH specifications are similar to the ones reported here.[10] The tables also include average iteration numbers, which show that on average the IWLS algorithm has lower number of iterations than the other methods. Figure 1.2 shows the fast convergence of the IWLS algorithm at the first two steps which justifies the theory of Mak (1993).

A number of observations on the simulations results can be listed. First, *maxLik* performs poorly compared to other methods. The bias and MSE of mean and variance parameters are larger than others with the *maxLik* function for all GARCH and slope parameter specifications. This function performs well only in the estimation of the slope and location parameters, and in one case is the best of all three methods.

Second; in the estimation of the mean parameters except the slope and location parameters, the IWLS algorithm and *fmincon* perform similarly. None of the methods systematically outperforms the other with respect to the bias and the MSE.

The performance of the methods in estimating the slope parameter gets worse when the value of the parameter is increased. The IWLS algorithm performs best in estimating the slope parameter when the real value of the parameter is low. The performance of the algorithm is better with randomly generated initial values and the bias drops to 0.003 with the $(\alpha, \beta) = (0.09, 0.90)$ specification. This performance of the algorithm is beaten by the *maxLik* function only for two GARCH specifications with the SA initial values and sometimes this function performs close to the IWLS; but the performance of the *maxLik* is shadowed by its comparatively lower performance in estimating other mean parameters. On the contrary; when the slope parameter is high, none of the methods shows significantly better performance in estimating the slope parameter. In this case, *fmincon* performs best and the IWLS algorithm is the second best. Figures 1.3 and 1.4 plot kernel distribution of the slope parameter estimates. As these plots show, the IWLS estimates are clustered around the real value of the parameter when $\eta = ln5$, while the distribution of *fmincon* estimates has a fatter right tail. When $\eta = ln100$, the differences between the distributions become more pronounced. The estimates from *fmincon* are clustered closer to $ln100$; but still all methods give high estimator bias.

The significance of the differences between slope parameter estimates are further scrutinized by nonparametric distribution comparison tests. The differences are analysed with two-sample Kolmogorov-Smirnov (KS) (Kolmogorov, 1933; Smirnov, 1948), Ansari-Bradley (AB) (Ansari et al., 1960), Wilcoxon rank sum (RS) (Wilcoxon, 1945), and Aslan-Zech (AS) (Aslan and Zech, 2005) tests. The null hypothesis of KS and AZ tests is that the two same samples come from the same continuous distribution and the alternative is that they do not. In the AB test, the null hypothesis is that the samples come from the same distribution against the alternative that they have the same mean but different variances. When medians of two samples considered are not equal, Ansari et al. (1960) suggest subtracting the medians before the test. The null hypothesis of the RS test is that the samples are from distributions with equal medians and the alternative is that

[10] These results are available upon request.

they are not. The tests are used to compare IWLS estimates with estimates from other methods both for the SA and random initial values, and for comparing estimates from the SA initial values and the random initial values for each method.

For the cases reported in the study, results for the distribution comparison tests are given in Tables 1.5-1.8. The tables first list the results for the comparisons of the IWLS estimates with the estimates from the other methods and then the results for the comparison of the estimates with the SA initial values and randomly generated initial values. According to the p-values of the tests, the null hypotheses can be rejected consistently for the comparison of the IWLS with *fmincon* when the slope parameter is low. In this case, difference of IWLS estimates from *maxLik* estimates cannot be significantly rejected only with the RS test for the $(\alpha,\beta) = (0.01, 0.98)$ specification and the SA initial values. When the slope parameter is high, the null hypotheses of the test are significantly rejected most of the time but the evidence against the difference between the distributional properties of the slope parameter estimators from the IWLS and other methods is not robust. Results for the comparison of the SA and randomly generated initial values are function specific. For the IWLS, the null hypotheses are consistently rejected only for the case $(\alpha,\beta) = (0.09, 0.90)$ and the slope parameter is high. For *fmincon*, they are consistently rejected when the slope parameter is low; and finally for *maxLik*, they are consistently rejected for all cases. Therefore, for the comparison of SA and random initial values, the results suggest that there is not significant evidence supporting the argument that they give significantly different results with the IWLS; but with *maxLik* the difference is significant while for *fmincon*, the method for generating initial values matter only when the slope parameter is low.

For both low and high value specifications of the slope parameter, location parameter of the IWLS algorithm with the randomly generated initial values always has the smallest bias and MSE. Overall, the IWLS gives better estimates for this parameter.

Some differences can be observed in the GARCH persistency parameter estimations. As the β parameter increases, the bias of this parameter estimator increases with all methods. For the $(\alpha,\beta) = (0.01, 0.98)$ specification, the bias of β estimator is around -0.25 from *fmincon* for both slope parameter specifications and initial value generation processes. Nevertheless, the bias from the IWLS algorithm gets to 0.055 at most and the MSE is the smallest with the IWLS algorithm.

Overall, the better performance of the IWLS algorithm in estimating the slope parameter, location parameter, and the β parameter suggest that this algorithm might provide better estimation results when the real slope parameter is low, and in all cases it should not do worse than other methods. On the method of initial value selection, results of distribution comparison tests suggest that estimates from the random initial values and SA initial values are not significantly different from each other for the slope parameter, which is the parameter that is shown to be the most different within estimation methods. However, there are some caveats to be noted on these results. First, the results are derived under the assumption of stationarity for both the mean and the variance equations. If there is significant evidence against stationarity, the comparison results given here may not be reliable and since the IWLS algorithm is based on these regularity conditions, the algorithm should not be preferred. Second, the STAR component studied here is a basic model with only one slope and location parameter that corresponds to a two-state model. The performance of the IWLS algorithm should also be investigated when the number of states increased. Third, the current model does not assume any nonlinearities in the variance component; but there are models such as STAR-STGARCH of Lundbergh et al. (1999) who assume that there is a smooth transition component in the variance and the transition variable is the errors of the mean equation.

In order to clarify the implications of the simulation results in practice, the next section includes forecasting exercises with daily exchange rate and stock index returns. Since *maxLik* has a poor performance in the simulations, the empirical exercise does not use this function.

1.4. Empirical Application

In this part of the study, two daily series are used for forecasting. The section first describes the series used, then the model specification is given. Finally, results of the forecasting exercises and predictive accuracy tests are reported.

USD/AUD, where AUD is the unit currency, is the first series used in the forecasting exercises. According to the most recent survey of the Bank for International settlements, USD and AUD is the fourth most traded currency pair globally with a share of 6.8% of the total $5.3 trillion volume per day (BIS, 2013). The top panel of Figure 1.5 shows the evolution of the exchange rate during the period under consideration, 26/12/2007-26/08/2015. USD appreciates against AUD during the global financial crisis and returns back to its pre-crisis level after 2010. It drops to a lower level than the pre-crisis USD/AUD exchange rate. This depreciation period is common for many currencies against USD until 2013 due to the Quantitative Easing (QE) policy of the US Federal Reserve (FED). USD starts to appreciate again in 2013 after by the announcement of end of the QE policy of FED. The middle panel of the same figure gives the returns of the exchange rates, e_t, which is calculated as the following:

$$e_t = log(\frac{E_t}{E_{t-1}}), \tag{1.29}$$

where E_t denotes the level of the exchange rate at time t.

Exchange rate modeling has been one of the most controversial topics in the international economics and finance literature since the seminal work of Meese and Rogoff (1983) empirically showed that exchange rate models are outperformed by the RW model. Both univariate time series models and models with macroeconomic fundamentals have been the subject of the discussion. Most of the studies focus on the prediction of exchange rate levels and at the monthly frequency or lower.[11] Discussing the modeling of exchange rates in general is beyond the scope of this study. The purpose of the exercise is merely to see the forecasting performance of the IWLS algorithm with respect to other estimation methods and a benchmark model.

The second series to be forecast by the STAR-GARCH model is the FTSE SC index daily returns. The FTSE SC index consists of companies starting from the 351st to the 619th largest listed in the FTSE and these companies make around 2% of the market capitalization. The motivation in using the index stems from the discussions on the relation between company size and expected returns of investments. Since the work of Banz (1981) who show small companies have higher returns than large ones, role of the size have been discussed in the literature and have been relevant for portfolio selection. Recently, Fama and French (2015, 2016) argue the topic in the context of factor models and underline the role of size in asset pricing. An interesting stylized fact about the FTSE SC index is volatility of the series that justifies the discussions in the literature. During the

[11] Recently, in a detailed literature review, Rossi (2013) shows that the performance of in-sample and out-of-sample predictive power of exchange rate models depend on the selection of the benchmark model, exchange rate model considered, selected variables, forecast horizon, and forecast accuracy test used.

first years of the global financial crisis yearly return jumps to 40% in 2009–which was the highest yearly return in the last decade within the FTSE 100, 250, and SC indices–from -61% in 2008. The top panel of Figure 1.6 shows the evolution of the stock index for the period between 26/12/2007 and 26/08/2015. The noted drop in the index in 2008 and rebound in 2009 can be observed in this panel. The daily return is calculated by Equation (1.29) and is plotted in the middle panel of Figure 1.6.

The descriptive statistics of both return series are given in Table 1.9. The normality hypothesis of the series is tested by the Jarque-Bera normality test, and the null of normal distribution is rejected at 1% significance level for both series.

The STAR-GARCH model specification procedure includes several steps and follows Lundbergh et al. (1999) and Li and Li (1996) who use similar models. The modeling cycle starts with the lag selection. In the second step, a linear model with the selected lag is fitted and the errors are tested for remaining autocorrelation with the ARCH-LM test. In the final step, STAR-type nonlinearity is tested and appropriate transition variable is selected, if there is any.

Typical financial data series include many data points and for these series, traditional lag selection criteria tend to give either high or no lag value at all.[12] Rech et al. (2001) propose a lag selection procedure to solve this problem for series that might have nonlinearities. The method calculates the traditional information criteria after running regressions with the interactions of the considered variables for a selected polynomial degree. It is shown that as the degree of the polynomial increases, the reliability of the selection procedure increases. Rech et al. (2001) recommend running the regressions for several lag values, calculate Schwarz Bayesian Information Criterion (SBIC) or Akaike Information Criterion (AIC), which are the standard information criteria in the literature to determine the number of variables to be used in a linear model, and then select the appropriate lag. For the lag selection of return series, the maximum lag length and maximum polynomial level are set to 10 and 4 respectively. Here, the SBIC is used for the lag selection. For the USD/AUD series, with polynomial levels 1 to 3, the lag is selected to be 3, but at the highest polynomial level, the optimum lag length is selected to be 2. Based on the theoretical results given in Rech et al. (2001), lag length of 2 is used in the study. The same selection procedure gives a lag length of 2 for the FTSE SC index return series.

In the next step, an AR(2) model is fitted to the series and error terms from both regressions are tested for autocorrelation with the ARCH-LM test. The maximum lag number for the test is set to 8. According to the results given in Table 1.10, the null hypothesis of no autocorrelation is rejected at 1% significance level at any given lag for both error terms.

Then, the STAR-type nonlinearity test of Teräsvirta (1994) is used to decide on the nonlinearity in the data and corresponding delay variable. The results of the tests are given at the bottom of Table 1.9 for lag values 1 and 2. Similar results are received from tests with both series. The p-values show that linearity is rejected for both lags and it is more significant for lag 2; so the second lag is chosen to be the transition variable for both USD/AUD and FTSE SC returns.

[12] Initially, 182 daily financial series (i.e. 36 exchange rate, 49 commodity price, and 97 stock index return series) are considered for the STAR-GARCH model. Most of these series are eliminated at the lag selection step of the modeling cycle and for some series that pass the lag selection procedure, the smooth-transition type of nonlinearity test do not provide significant evidence for sake of a nonlinear model. A complete list of the series considered are given in Table 1.31 in Appendix 1.5. There are series that have passed both steps but do not perform well in the forecasting exercises. The list of these 10 series and the forecasts statistics for the 1-day ahead forecasts are given in Appendix (1.5) on Tables 1.32 and 1.33 respectively. It is interesting to see that four other pairs of AUD exchange rates proceed to the last stage of the exercise. The might be taken as an evidence supporting the non-linearity in the AUD exchange rate.

Considering the specification test results, a STAR-GARCH(2;1,1) model with $d = 2$ is fitted to the series. The estimation results with the full samples are given in Table 1.11 for USD/AUD and in Table 1.12 for the FTSE SC index. According to the full sample estimation results, the estimate for the slope parameter is the highest with the IWLS algorithm that is started with the SA initial values for both series. Another observation on the results is the estimated ARCH effect coefficient is larger in the FTSE SC index series.

For the forecasting exercise, the length of the initial sample is chosen to be 1500 and 500 1-day ahead forecasts are calculated initially. The mean forecasting error (MFE), mean square forecasting error (MSFE), mean absolute forecasting error (MAFE), *Theil's U* and Pesaran and Timmermann (1992) (PT) test of directional forecasting for all models and methods used in the exercise are given in Tables 1.13 and 1.14 for USD/AUD and the FTSE SC index respectively. The RW with a drift is used as the benchmark model for the comparisons and the results of the models for MFE, MSFE, and MAFE are given with respect to the performance of the RW. *Theil's U* is calculated as follows:

$$\textit{Theil's } U = \frac{\sqrt{\frac{1}{K}\sum_{k=1}^{K}(e_{L+k}-\hat{e}_{L+k})^2}}{\sqrt{\frac{1}{K}\sum_{k=1}^{K}(e_{L+k})^2}+\sqrt{\frac{1}{K}\sum_{k=1}^{K}(\hat{e}_{L+k})^2}} \tag{1.30}$$

where L is the size of the initial sample, $k = 1,..,K$ denotes the number of forecasts and K is the total number of forecasts (i.e. $K + L = T$), $\hat{e}_{L+k}$ is the forecast value of e_{L+k} at time $L+k$. The statistic gives a measure of the forecast performance corrected by the real values. The statistic takes values between 0 and 1 and as the performance of a model gets better, the statistic approaches to 0. Finally, PT is a nonparametric test statistic that measures the directional forecasting ability of a model. The null hypothesis of the PT test is that the model at hand is not able to forecast the direction of changes and the test statistic has a standard normal distribution.

The forecasts statistics for the conditional mean of USD/AUD show that the best performing method is the IWLS algorithm with random initial values. *Theil's U* statistics show that the non-linear STAR-GARCH model performs better than the linear models irrespective of the method and initial value. The best performance is from *fmincon* function with the SA initial values. However, the IWLS algorithm with random initial values is the only method that beats the RW model with every metric. The MSFE and MAFE of the method are slightly below the values from the RW while every other method does worse than the benchmark model. For the PT, the IWLS with random initial values has the highest value but it is not significantly able to predict the direction of changes in the data.

In case of the FTSE SC index conditional mean forecasts, the IWLS algorithm with random initial values again gives the best performance based on MSFE; but the AR(2)-GARCH model also outperforms the RW model. Based on the *Theil's U*, IWLS with random initial values performs better than the AR(2)-GARCH model. For the directional forecasting, the models cannot give statistically significant results in this case either.

The significance of the difference between the RW and other models are further tested with the predictive ability tests. The first test to be used in the analysis is the Diebold et al. (1995) (DM) test of equal predictive accuracy. The test statistic of the DM test has a standard normal distribution. However, in cases where two nested models are compared with the test, it is shown that asymptotically the test statistic does not have a standard normal distribution and rejects null too often (McCracken, 2007). For comparison of forecasts from nested models, Clark and West (2007) (CW) propose a test that uses and "adjusted" MSFE term which is the sample average of the squares of the differences between two model forecasts. CW is the second test to compare predictive ability of forecasts.

As shown by Rossi (2013) for the case of exchange rates, results on the forecast performance of models might change depending the predictive ability tests used. In order to see the robustness of the DM and CW test results, predictive ability of the models are tested by the encompassing and mean squared error based test statistics.[13] These tests are ENC_t (Harvey et al., 1998), ENC_F (Clark and McCracken, 2001), MSE_t, and MSE_F (McCracken, 2007). Let $\hat{\varepsilon}_{0,t+1}$ denote the 1-day ahead forecast error from the benchmark model (i.e. RW) and $\hat{\varepsilon}_{1,t+1}$ denote the forecast error from the model to be compared. Define $\hat{d}_{t+1} = \hat{\varepsilon}^2_{0,t+1} - \hat{\varepsilon}^2_{1,t+1}$, $\hat{c}_{t+h} = \hat{\varepsilon}_{0,t+1}(\hat{\varepsilon}_{0,t+1} - \hat{\varepsilon}_{1,t+h})$, and $\hat{\sigma}^2_1 = (K-1+1)\sum_{t=L}^{T-1} \hat{\varepsilon}^2_{1,t+1}$. Then the test statistics can be written as the following:

$$\text{ENC\_t} = \frac{K^{-1/2}\sum_{t=L}^{T-1} \hat{c}_{t+1}}{\hat{S}_{cc}^{1/2}}, \tag{1.31}$$

$$\text{ENC\_F} = \frac{\sum_{t=L}^{T-1} \hat{c}_{t+1}}{\hat{\sigma}^2_1}, \tag{1.32}$$

$$\text{MSE\_t} = \frac{K^{-1/2}\sum_{t=L}^{T-1} \hat{d}_{t+1}}{\hat{S}_{dd}^{1/2}}, \tag{1.33}$$

$$\text{MSE\_F} = \frac{\sum_{t=L}^{T-1} \hat{d}_{t+1}}{\hat{\sigma}^2_1}, \tag{1.34}$$

where $\hat{S}_{cc}$ and $\hat{S}_{dd}$ denote Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) variance for $\hat{c}_{t+h}$ and $\hat{d}_{t+h}$ respectively. In cases where the assumptions of the test statistics are violated, Clark and McCracken (2010) propose to use a bootstrapping method in which "artificial" samples are used to calculate the test statistics. In order to create the artificial samples, first the benchmark model is estimated and the estimates are stored, then the forecast errors of the bigger model is fitted with an moving average model and the estimates of the moving average model is used to create artificial forecast errors by changing the moving average model with draws form standard normal distribution. Finally, the artificial forecast errors are added to the fitted values of the benchmark model to create the artificial samples. In this study, this procedure is repeated for 10,000 times to calculate the test statistics and the p-values for each is calculated.

The test statistics for the predictive ability test are given in Tables 1.15 and 1.16; and accompanying bootstrapped p-values for ENC_t, ENC_F, MSE_t, and MSE_F test statistics are given in Tables 1.20 and 1.21. For the case of the exchange rate series, the DM test statistics suggest that *fmincon* forecasts with the SA initial values are significantly different from the RW forecasts. The negative values of these test statistics imply that the performance of the RW model is better than the performance of these models. On the other hand, the DM test statistic is also negative for the IWLS with SA initial values but not significant; and even though the DM test is not significant for the IWLS with random initial values, other test statistics suggest that the IWLS forecasts with random initial values are significantly better than the RW forecasts. The significance level is lower with the ENC_F test which is, according to Busetti and Marcucci (2013), the most powerful of the

[13] Corradi and Swanson (2002) propose a nonparametric test for comparison of from nonlinear models and linear models. The test is also recommended by Teräsvirta (2006) for STAR-type models. This test could also be used in checking the predictive accuracy of the models

tests used here.

For the case of stock index series; according to the CW test, AR(2)-GARCH and the IWLS with random initial values perform significantly better than the RW. However, in this case neither of the performances is robust to different tests. Performance of the IWLS with random initial values is significantly better according to the MSE_t and MSE_F tests while the performance of the AR(2)-GARCH is significantly better according to ENC_t and MSE_t test statistics. ENC_F test does not report any significant result in this case.

The forecasts tests statistics for the variance component of the models are given in Tables 1.17 and 1.18 and the predictive accuracy test statistics are given in Table 1.19. We do not have a nested model issue for the volatility forecasts; so only DM test is used for comparison of accuracy. In both cases, STAR-GARCH models cannot outperform the benchmark model based on the MSFE statistic and on the contrary to the conditional mean forecasts, results for the *Theil's U* statistics are mixed. The DM test statistics suggest that in the case of USD/AUD, the IWLS with the SA initial values is the only method that does not significantly perform worse than the benchmark model; and in the case of the FTSE SC index, the only method that does not significantly perform worse than the benchmark is the IWLS with random initial values. *fmincon* with both SA and random initial values perform significantly worse than the benchmark in both cases. Differences in the IWLS and *fmincon* suggest that, as shown in the simulation studies, estimation method has practical implications also for the conditional variance component.

As a further analysis, the 5-day ahead forecasts for both of the series are also calculated for both of the series in order to check the performance of the STAR-GARCH model and the algorithms at longer horizons. The forecast statistics and predictive accuracy test statistics are given in Tables 1.22-1.30. The results indicate that the nonlinear models do not perform better than the RW at this horizon. In fact, for the conditional mean of the FTSE SC returns, the AR(2)-GARCH is the model has a statistically significant forecasting performance than the RW.

The empirical studies show that the IWLS algorithm with random initial values give better forecasts than the benchmark model and as a more relevant point to the argumentation of this study, it gives better forecast results than the *fmincon* function. It has to be noted, however, the performance is only observed at the 1-day ahead forecasts.

1.5. Conclusions

This study considers the application of the IWLS algorithm to the STAR-GARCH models in order to find a solution to initial value selection and slope parameter estimation in STAR-type models. The performance of the algorithm is compared with other methods in a simulation study for different values of the slope parameter, GARCH persistency parameters, and the initial value selection procedure. Real data application of the algorithm is shown in an empirical exercise with USD/AUD daily exchange rate and the FTSE SC stock index returns.

The simulation studies show the cases when the IWLS algorithm performs better than considered maximum likelihood estimation functions based on bias and MSE of the parameter estimators. The MSE and bias of the slope parameter estimator are shown to be the lowest with the IWLS algorithm with randomly generated initial values when the real value of the slope parameter is low. When the real value of the slope parameter is high, the MSE and bias of the slope parameter turns out to be high with all methods; thus, the IWLS algorithm does not deliver desired results in this case. In addition to that, for the GARCH parameter estimators, the IWLS algorithm give better results compared to other methods as the real value of the ARCH parameter decreases. The practical implications of these results are shown with two empirical cases in which the IWLS algorithm significantly performs better than the benchmark model and *fmincon* function for the 1-day ahead forecasts.

Another result received from the simulation study is that for the slope parameter estimator, the initial value selection method delivers significantly different results for *fmincon* and *maxLik* but not for the IWLS algorithm. However, in the forecasting exercises, it is observed that the IWLS algorithm with randomly generated initial values outperforms the IWLS with SA initial values, which might be taken as evidence for the use of random initial values with the IWLS as it is argued in the literature.

The model used in this study is a basic one and there are some regularity conditions. Further research is needed to see the performance of the algorithm with more complex models such as a STAR model with more than one location parameters or models that also include nonlinearities in the conditional variance. The algorithm can easily be extended to estimate such kind of models as long as their first order derivatives are provided.

In conclusion, the simulation study and empirical applications show that the IWLS algorithm can be chosen as an estimation method for STAR-type models with conditional variance by concerning less about the initial value selection.

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Tables

Table 1.1: Monte Carlo simulation results, $(\alpha, \beta) = (0.09, 0.90)$ and $\eta = ln5$

		SA			random		
		IWLS	fmincon	maxLik	IWLS	fmincon	maxLik
$\phi_0^{(1)}$	mean	0.030	0.025	0.150	0.022	0.025	0.130
	std.	0.085	0.064	0.192	0.074	0.066	0.271
	median	0.007	0.009	0.081	0.005	0.010	0.034
	bias	0.030	0.025	0.150	0.022	0.025	0.130
	MSE	0.008	0.005	0.059	0.006	0.005	0.090
$\phi_1^{(1)}$	mean	-0.305	-0.311	-0.159	-0.318	-0.311	-0.153
	std.	0.121	0.098	0.233	0.104	0.095	0.241
	median	-0.331	-0.327	-0.208	-0.337	-0.324	-0.221
	bias	0.045	0.039	0.191	0.032	0.039	0.197
	MSE	0.017	0.011	0.091	0.012	0.011	0.097
$\phi_2^{(1)}$	mean	0.533	0.525	0.503	0.530	0.518	0.391
	std.	0.071	0.061	0.183	0.066	0.064	0.266
	median	0.522	0.519	0.489	0.519	0.514	0.429
	bias	-0.017	-0.025	-0.047	-0.020	-0.032	-0.159
	MSE	0.005	0.004	0.036	0.005	0.005	0.096
$\phi_0^{(2)}$	mean	-0.015	-0.003	-0.199	-0.008	-0.001	-0.135
	std.	0.139	0.117	0.290	0.120	0.122	0.401
	median	0.002	0.002	-0.143	0.002	0.004	-0.105
	bias	-0.035	-0.023	-0.219	-0.028	-0.021	-0.155
	MSE	0.020	0.014	0.132	0.015	0.015	0.185
$\phi_1^{(2)}$	mean	0.162	0.159	0.093	0.172	0.156	0.032
	std.	0.113	0.101	0.277	0.100	0.101	0.351
	median	0.176	0.171	0.101	0.185	0.170	0.032
	bias	-0.038	-0.041	-0.107	-0.028	-0.044	-0.168
	MSE	0.014	0.012	0.088	0.011	0.012	0.152
$\phi_2^{(2)}$	mean	-0.228	-0.219	-0.181	-0.222	-0.214	-0.116
	std.	0.110	0.094	0.275	0.104	0.101	0.395
	median	-0.213	-0.207	-0.174	-0.209	-0.202	-0.140
	bias	0.022	0.031	0.069	0.028	0.036	0.134
	MSE	0.013	0.010	0.081	0.012	0.012	0.174
η	mean	1.527	1.863	1.397	1.613	2.038	2.546
	std.	1.415	1.377	1.405	1.355	1.435	1.198
	median	1.163	1.401	1.049	1.268	1.617	2.532
	bias	-0.082	0.254	-0.213	0.003	0.428	0.937
	MSE	2.008	1.958	2.016	1.835	2.242	2.310
c	mean	0.030	0.039	-0.019	0.029	0.067	0.118
	std.	0.197	0.216	0.439	0.177	0.270	0.717
	median	0.015	0.033	-0.071	0.027	0.052	0.125
	bias	0.010	0.019	-0.039	0.009	0.047	0.098
	MSE	0.039	0.047	0.194	0.031	0.075	0.523
ω	mean	0.002	0.001	0.005	0.002	0.001	0.015
	std.	0.008	0.001	0.011	0.005	0.001	0.039
	median	0.001	0.001	0.002	0.001	0.001	0.003
	bias	0.001	0.000	0.004	0.001	0.000	0.014
	MSE	0.000	0.000	0.000	0.000	0.000	0.002
α	mean	0.096	0.095	0.133	0.096	0.095	0.174
	std.	0.033	0.012	0.071	0.029	0.012	0.121
	median	0.092	0.095	0.111	0.092	0.095	0.132
	bias	0.006	0.005	0.043	0.006	0.005	0.084
	MSE	0.001	0.000	0.007	0.001	0.000	0.022
β	mean	0.892	0.888	0.806	0.892	0.888	0.678
	std.	0.036	0.015	0.179	0.029	0.015	0.288
	median	0.896	0.888	0.874	0.896	0.889	0.825
	bias	-0.008	-0.012	-0.094	-0.008	-0.012	-0.222
	MSE	0.001	0.000	0.041	0.001	0.000	0.132
midrule	Aver. iterations	15.763	57.056	325.347	16.887	67.076	513.803

The Monte Carlo simulation results for the STAR-GARCH model with $(\alpha, \beta) = (0.09, 0.90)$ and $\eta = ln5$. For each parameter; the mean, standard deviation, median, bias and MSE of the estimates are given. The sample size is 2000 and the number of replications is 1000.

Table 1.2: Monte Carlo simulation results, $(\alpha, \beta) = (0.01, 0.98)$ and $\eta = ln5$

		SA			random		
		IWLS	fmincon	maxLik	IWLS	fmincon	maxLik
$\phi_0^{(1)}$	mean	0.032	0.024	0.133	0.025	0.022	0.143
	std.	0.097	0.064	0.177	0.083	0.061	0.269
	median	0.007	0.009	0.060	0.003	0.009	0.045
	bias	0.032	0.024	0.133	0.025	0.022	0.143
	MSE	0.010	0.005	0.049	0.007	0.004	0.093
$\phi_1^{(1)}$	mean	-0.311	-0.319	-0.191	-0.320	-0.322	-0.162
	std.	0.115	0.094	0.211	0.111	0.092	0.241
	median	-0.337	-0.336	-0.244	-0.341	-0.336	-0.239
	bias	0.039	0.031	0.159	0.030	0.028	0.188
	MSE	0.015	0.010	0.070	0.013	0.009	0.093
$\phi_2^{(1)}$	mean	0.536	0.524	0.503	0.533	0.520	0.402
	std.	0.068	0.057	0.148	0.066	0.058	0.240
	median	0.525	0.517	0.488	0.522	0.513	0.434
	bias	-0.014	-0.026	-0.047	-0.017	-0.030	-0.148
	MSE	0.005	0.004	0.024	0.005	0.004	0.079
$\phi_0^{(2)}$	mean	-0.018	-0.003	-0.176	-0.011	-0.001	-0.133
	std.	0.148	0.116	0.267	0.132	0.110	0.378
	median	0.001	0.002	-0.138	0.004	0.001	-0.114
	bias	-0.038	-0.023	-0.196	-0.031	-0.021	-0.153
	MSE	0.023	0.014	0.109	0.018	0.013	0.166
$\phi_1^{(2)}$	mean	0.169	0.169	0.122	0.178	0.173	0.050
	std.	0.109	0.098	0.261	0.104	0.098	0.342
	median	0.183	0.180	0.139	0.184	0.185	0.068
	bias	-0.031	-0.031	-0.078	-0.022	-0.027	-0.150
	MSE	0.013	0.010	0.074	0.011	0.010	0.139
$\phi_2^{(2)}$	mean	-0.233	-0.220	-0.184	-0.228	-0.213	-0.078
	std.	0.099	0.086	0.218	0.095	0.088	0.341
	median	-0.219	-0.207	-0.173	-0.215	-0.198	-0.100
	bias	0.017	0.030	0.066	0.022	0.037	0.172
	MSE	0.010	0.008	0.052	0.010	0.009	0.146
η	mean	1.478	1.951	1.574	1.591	2.191	2.624
	std.	1.332	1.371	1.390	1.367	1.415	1.155
	median	1.117	1.516	1.324	1.213	1.947	2.586
	bias	-0.131	0.342	-0.036	-0.018	0.581	1.015
	MSE	1.790	1.995	1.931	1.866	2.338	2.363
c	mean	0.030	0.059	0.043	0.031	0.065	0.097
	std.	0.204	0.207	0.428	0.185	0.221	0.662
	median	0.025	0.048	0.046	0.029	0.056	0.106
	bias	0.010	0.039	0.023	0.011	0.045	0.077
	MSE	0.042	0.044	0.184	0.034	0.051	0.443
ω	mean	0.006	0.027	0.053	0.005	0.027	0.050
	std.	0.016	0.032	0.034	0.015	0.032	0.034
	median	0.001	0.004	0.058	0.001	0.003	0.052
	bias	0.005	0.026	0.052	0.004	0.026	0.049
	MSE	0.000	0.002	0.004	0.000	0.002	0.004
α	mean	0.023	0.034	0.061	0.024	0.033	0.140
	std.	0.021	0.013	0.061	0.033	0.013	0.145
	median	0.021	0.032	0.046	0.021	0.032	0.091
	bias	0.013	0.024	0.051	0.014	0.023	0.130
	MSE	0.001	0.001	0.006	0.001	0.001	0.038
β	mean	0.925	0.702	0.457	0.936	0.704	0.451
	std.	0.143	0.313	0.314	0.117	0.315	0.318
	median	0.965	0.931	0.407	0.965	0.932	0.416
	bias	-0.055	-0.278	-0.523	-0.044	-0.276	-0.529
	MSE	0.024	0.175	0.372	0.016	0.175	0.380
	Aver. iterations	24.642	58.851	250.351	27.381	71.213	418.890

The Monte Carlo simulation results for the STAR-GARCH model with $(\alpha, \beta) = (0.01, 0.98)$ and $\eta = ln5$. For each parameter; the mean, standard deviation, median, bias and MSE of the estimates are given. The sample size is 2000 and the number of replications is 1000.

Table 1.3: Monte Carlo simulation results, $(\alpha,\beta) = (0.09, 0.90)$ and $\eta = ln100$

		SA			random		
		IWLS	fmincon	maxLik	IWLS	fmincon	maxLik
$\phi_0^{(1)}$	mean	0.007	0.005	0.145	0.006	0.008	0.119
	std.	0.037	0.022	0.173	0.030	0.034	0.278
	median	0.003	0.002	0.079	0.003	0.003	0.044
	bias	0.007	0.005	0.145	0.006	0.008	0.119
	MSE	0.001	0.001	0.051	0.001	0.001	0.091
$\phi_1^{(1)}$	mean	-0.333	-0.337	-0.161	-0.335	-0.334	-0.163
	std.	0.074	0.061	0.233	0.070	0.063	0.239
	median	-0.343	-0.342	-0.212	-0.343	-0.339	-0.223
	bias	0.017	0.013	0.189	0.015	0.016	0.187
	MSE	0.006	0.004	0.090	0.005	0.004	0.092
$\phi_2^{(1)}$	mean	0.552	0.550	0.538	0.553	0.544	0.409
	std.	0.048	0.038	0.176	0.043	0.050	0.274
	median	0.553	0.551	0.527	0.553	0.549	0.436
	bias	0.002	0.000	-0.012	0.003	-0.006	-0.141
	MSE	0.002	0.001	0.031	0.002	0.003	0.095
$\phi_0^{(2)}$	mean	0.016	0.020	-0.183	0.017	0.019	-0.099
	std.	0.060	0.039	0.278	0.047	0.055	0.412
	median	0.019	0.020	-0.131	0.019	0.020	-0.072
	bias	-0.004	0.000	-0.203	-0.003	-0.001	-0.119
	MSE	0.004	0.001	0.118	0.002	0.003	0.184
$\phi_1^{(2)}$	mean	0.174	0.177	0.085	0.178	0.172	0.023
	std.	0.082	0.070	0.274	0.073	0.078	0.339
	median	0.177	0.180	0.092	0.178	0.177	0.017
	bias	-0.026	-0.023	-0.115	-0.022	-0.028	-0.177
	MSE	0.007	0.005	0.088	0.006	0.007	0.146
$\phi_2^{(2)}$	mean	-0.265	-0.260	-0.253	-0.265	-0.254	-0.141
	std.	0.073	0.054	0.258	0.061	0.067	0.395
	median	-0.261	-0.259	-0.248	-0.261	-0.256	-0.167
	bias	-0.015	-0.010	-0.003	-0.015	-0.004	0.109
	MSE	0.006	0.003	0.067	0.004	0.005	0.168
η	mean	2.581	3.431	1.360	2.785	3.430	2.550
	std.	1.363	1.075	1.425	1.198	1.053	1.133
	median	2.526	3.572	0.975	2.720	3.553	2.561
	bias	-2.024	-1.174	-3.245	-1.820	-1.175	-2.055
	MSE	5.954	2.534	12.559	4.747	2.488	5.505
c	mean	0.026	0.028	0.012	0.023	0.055	0.094
	std.	0.098	0.085	0.422	0.061	0.209	0.711
	median	0.021	0.022	-0.019	0.024	0.023	0.084
	bias	0.006	0.008	-0.008	0.003	0.035	0.074
	MSE	0.010	0.007	0.178	0.004	0.045	0.511
ω	mean	0.001	0.001	0.005	0.001	0.001	0.014
	std.	0.005	0.001	0.011	0.004	0.001	0.037
	median	0.001	0.001	0.002	0.001	0.001	0.003
	bias	0.000	0.000	0.004	0.000	0.000	0.013
	MSE	0.000	0.000	0.000	0.000	0.000	0.002
α	mean	0.092	0.096	0.132	0.092	0.096	0.174
	std.	0.022	0.012	0.063	0.015	0.012	0.120
	median	0.091	0.095	0.110	0.091	0.095	0.134
	bias	0.002	0.006	0.042	0.002	0.006	0.084
	MSE	0.001	0.000	0.006	0.000	0.000	0.021
β	mean	0.895	0.887	0.806	0.895	0.888	0.684
	std.	0.024	0.015	0.176	0.016	0.015	0.281
	median	0.897	0.888	0.873	0.896	0.888	0.828
	bias	-0.005	-0.013	-0.094	-0.005	-0.012	-0.216
	MSE	0.001	0.000	0.040	0.000	0.000	0.125
	Aver. iterations	13.077	52.991	331.108	10.040	62.154	517.008

The Monte Carlo simulation results for the STAR-GARCH model with $(\alpha,\beta) = (0.09, 0.90)$ and $\eta = ln100$. For each parameter; the mean, standard deviation, median, bias and MSE of the estimates are given. The sample size is 2000 and the number of replications is 1000.

Table 1.4: Monte Carlo simulation results, $(\alpha, \beta) = (0.01, 0.98)$ and $\eta = ln100$

		SA			random		
		IWLS	fmincon	maxLik	IWLS	fmincon	maxLik
$\phi_0^{(1)}$	mean	0.010	0.009	0.148	0.008	0.009	0.138
	std.	0.036	0.027	0.172	0.033	0.029	0.259
	median	0.006	0.006	0.076	0.004	0.005	0.055
	bias	0.010	0.009	0.148	0.008	0.009	0.138
	MSE	0.001	0.001	0.051	0.001	0.001	0.086
$\phi_1^{(1)}$	mean	-0.330	-0.331	-0.167	-0.333	-0.332	-0.167
	std.	0.066	0.058	0.217	0.064	0.057	0.252
	median	-0.337	-0.336	-0.229	-0.339	-0.336	-0.240
	bias	0.020	0.019	0.183	0.017	0.018	0.183
	MSE	0.005	0.004	0.080	0.004	0.004	0.097
$\phi_2^{(1)}$	mean	0.553	0.551	0.540	0.554	0.550	0.417
	std.	0.043	0.038	0.143	0.041	0.039	0.242
	median	0.552	0.552	0.540	0.554	0.552	0.446
	bias	0.003	0.001	-0.010	0.004	-0.000	-0.133
	MSE	0.002	0.001	0.021	0.002	0.002	0.076
$\phi_0^{(2)}$	mean	0.012	0.013	-0.180	0.013	0.014	-0.119
	std.	0.058	0.041	0.271	0.055	0.044	0.366
	median	0.015	0.015	-0.134	0.016	0.015	-0.084
	bias	-0.008	-0.007	-0.200	-0.007	-0.006	-0.139
	MSE	0.003	0.002	0.114	0.003	0.002	0.153
$\phi_1^{(2)}$	mean	0.176	0.176	0.087	0.179	0.176	0.033
	std.	0.075	0.070	0.238	0.074	0.071	0.332
	median	0.175	0.176	0.104	0.180	0.177	0.050
	bias	-0.024	-0.024	-0.113	-0.021	-0.024	-0.167
	MSE	0.006	0.005	0.069	0.006	0.006	0.138
$\phi_2^{(2)}$	mean	-0.265	-0.262	-0.247	-0.264	-0.259	-0.118
	std.	0.066	0.055	0.217	0.062	0.055	0.345
	median	-0.261	-0.260	-0.251	-0.263	-0.259	-0.160
	bias	-0.015	-0.012	0.003	-0.014	-0.009	0.132
	MSE	0.005	0.003	0.047	0.004	0.003	0.137
η	mean	2.623	3.305	1.472	2.674	3.353	2.659
	std.	1.383	1.144	1.330	1.312	1.124	1.158
	median	2.568	3.457	1.165	2.593	3.495	2.649
	bias	-1.983	-1.300	-3.134	-1.931	-1.253	-1.946
	MSE	5.841	2.998	11.587	5.451	2.831	5.126
c	mean	0.024	0.029	0.032	0.021	0.032	0.109
	std.	0.094	0.094	0.419	0.092	0.126	0.646
	median	0.021	0.022	0.003	0.022	0.022	0.066
	bias	0.004	0.009	0.012	0.001	0.012	0.089
	MSE	0.009	0.009	0.176	0.008	0.016	0.425
ω	mean	0.005	0.027	0.053	0.004	0.026	0.053
	std.	0.014	0.032	0.034	0.014	0.032	0.039
	median	0.001	0.004	0.057	0.001	0.004	0.053
	bias	0.004	0.026	0.052	0.003	0.025	0.052
	MSE	0.000	0.002	0.004	0.000	0.002	0.004
α	mean	0.022	0.034	0.058	0.022	0.033	0.141
	std.	0.013	0.013	0.051	0.014	0.013	0.148
	median	0.021	0.032	0.045	0.020	0.032	0.089
	bias	0.012	0.024	0.048	0.012	0.023	0.131
	MSE	0.000	0.001	0.005	0.000	0.001	0.039
β	mean	0.928	0.705	0.459	0.941	0.710	0.440
	std.	0.140	0.313	0.307	0.108	0.312	0.324
	median	0.965	0.931	0.416	0.965	0.932	0.385
	bias	-0.052	-0.275	-0.521	-0.039	-0.270	-0.540
	MSE	0.022	0.173	0.366	0.013	0.170	0.397
	Aver. iterations	23.220	55.510	265.642	21.220	67.647	416.994

The Monte Carlo simulation results for the STAR-GARCH model with $(\alpha, \beta) = (0.01, 0.98)$ and $\eta = ln100$. For each parameter; the mean, standard deviation, median, bias and MSE of the estimates are given. The sample size is 2000 and the number of replications is 1000.

Table 1.5: Distribution comparisons, $(\alpha, \beta) = (0.09, 0.90)$ and $\eta = ln5$

	KS	AB	RS	AZ
IWLS random vs.				
fmincon	0.000	0.000	0.000	0.000
maxLik	0.000	0.000	0.000	0.000
IWLS SA vs.				
fmincon	0.000	0.000	0.000	0.000
maxLik	0.000	0.000	0.002	0.000
random vs. SA				
IWLS	0.075	0.360	0.023	0.077
fmincon	0.012	0.000	0.010	0.107
maxLik	0.000	0.002	0.000	0.000

P-values of the distribution comparison tests for the STAR-GARCH model with $(\alpha, \beta) = (0.09, 0.90)$ and $\eta = ln5$. The columns give results for two-sample Kolmogorov-Smirnov test (KS), Ansari-Bradley test (AB), Wilcoxon rank sum test (RS), and Aslan-Zech test (AZ). The null hypotheses of the tests are given in the text.

Table 1.6: Distribution comparisons, $(\alpha, \beta) = (0.01, 0.98)$ and $\eta = ln5$

	KS	AB	RS	AZ
IWLS random vs.				
fmincon	0.000	0.000	0.000	0.000
maxLik	0.000	0.000	0.000	0.000
IWLS SA vs.				
fmincon	0.000	0.000	0.000	0.000
maxLik	0.000	0.000	0.491	0.000
random vs. SA				
IWLS	0.075	0.455	0.026	0.512
fmincon	0.001	0.000	0.000	0.001
maxLik	0.000	0.000	0.000	0.000

P-values of the distribution comparison tests for the STAR-GARCH model with $(\alpha, \beta) = (0.01, 0.98)$ and $\eta = ln5$. The columns give results for two-sample Kolmogorov-Smirnov test (KS), Ansari-Bradley test (AB), Wilcoxon rank sum test (RS), and Aslan-Zech test (AZ). The null hypotheses of the tests are given in the text.

Table 1.7: Distribution comparisons, $(\alpha,\beta) = (0.09, 0.90)$ and $\eta = ln100$

	KS	AB	RS	AZ
IWLS random vs.				
fmincon	0.000	0.247	0.000	0.000
maxLik	0.014	0.686	0.000	0.004
IWLS SA vs.				
fmincon	0.000	0.018	0.000	0.000
maxLik	0.000	0.116	0.000	0.000
random vs. SA				
IWLS	0.001	0.090	0.000	0.001
fmincon	0.999	0.771	0.850	1.000
maxLik	0.000	0.000	0.000	0.000

P-values of the distribution comparison tests for the STAR-GARCH model with $(\alpha,\beta) = (0.09, 0.90)$ and $\eta = ln100$. The columns give results for two-sample Kolmogorov-Smirnov test (KS), Ansari-Bradley test (AB), Wilcoxon rank sum test (RS), and Aslan-Zech test (AZ). The null hypotheses of the tests are given in the text.

Table 1.8: Distribution comparisons, $(\alpha,\beta) = (0.01, 0.98)$ and $\eta = ln100$

	KS	AB	RS	AZ
IWLS random vs.				
fmincon	0.000	0.311	0.000	0.000
maxLik	0.105	0.284	0.897	0.015
IWLS SA vs.				
fmincon	0.000	0.017	0.000	0.000
maxLik	0.000	0.760	0.000	0.000
random vs. SA				
IWLS	0.459	0.148	0.405	0.478
fmincon	0.855	0.954	0.403	1.000
maxLik	0.000	0.010	0.000	0.000

P-values of the distribution comparison tests for the STAR-GARCH model with $(\alpha,\beta) = (0.01, 0.98)$ and $\eta = ln100$. The columns give results for two-sample Kolmogorov-Smirnov test (KS), Ansari-Bradley test (AB), Wilcoxon rank sum test (RS), and Aslan-Zech test (AZ) respectively. The null hypotheses of the tests are given in the text.

Table 1.9: Descriptive statistics

	Min.	Max.	Mean	Var.	Skewness	Kurtosis	Normality
USD/AUD	-0.0670	0.0883	0.0001	0.0001	0.8623	15.5294	0.0001
FTSE SC	-0.0615	0.0377	0.0001	0.0001	-0.8860	9.1194	0.0001
	LM-test for nonlinearity of STAR type						
	d=1	d=2					
USD/AUD	1.62×10^{-7}	$9.78\times10^{-13*}$					
FTSE SC	0.097	$8.23\times10^{-6*}$					

The descriptive statistics for the daily USD/AUD returns. The column "Normality" gives the p-value for the Jarque-Bera normality test.

Table 1.10: ARCH-LM test

USD/AUD		FTSE SP	
statistic	p-value	statistic	p-value
53.05	3.24×10^{-13}	114.58	0
358.01	0	151.59	0
443.75	0	203.43	0
473.27	0	285.53	0
478.87	0	305.25	0
479.16	0	331.36	0
480.12	0	345.79	0
484.00	0	356.31	0

ARCH-LM test results for the AR(2) model errors.

Table 1.11: Estimation results-USD/AUD

	RW	AR(2)	IWLS (SA)	fmincon (SA)	IWLS (R)	fmincon (R)
$\phi_0^{(1)}$	4.83×10^{-5}	4.99×10^{-5}	0.0001	0.0001	0.0005	4.79×10^{-5}
	(0.0001)	(0.0012)	(7.82×10^{-6})	(4.51×10^{-5})	(1.07×10^{-5})	(4.93×10^{-6})
$\phi_1^{(1)}$		-0.0224	-0.0103	0.0708	-0.0122	-0.0196
		(0.6679)	(0.0007)	(0.0015)	(0.0006)	(0.0005)
$\phi_2^{(1)}$		0.0001	-0.0281	0.0091	-0.0022	0.0089
		(0.7879)	(0.0009)	(0.0021)	(0.0011)	(0.0006)
$\phi_0^{(2)}$			-6.88×10^{-5}	-6.83×10^{-5}	-0.0014	-0.0315
			(1.33×10^{-5})	(4.78×10^{-5})	(2.58×10^{-5})	(0.0002)
$\phi_1^{(2)}$			-0.0329	-0.1027	-0.0117	-0.1576
			(0.001)	(0.0018)	(0.0011)	(0.003)
$\phi_2^{(2)}$			0.1017	-0.0062	0.0947	0.5421
			(0.0013)	(0.0021)	(0.0016)	(0.004)
η			5.936	1.3532	2.042	1.7535
			(1.5383)	(0.067)	(0.057)	(0.0275)
c			0.0016	-0.0107	0.0041	0.0304
			(4.64×10^{-5})	(0.0002)	(9.24×10^{-5})	(6.50×10^{-5})
ω	3.91×10^{-7}	3.60×10^{-7}	3.81×10^{-7}	1.10×10^{-6}	3.78×10^{-7}	1.02×10^{-6}
	(1.24×10^{-5})	(1.91×10^{-5})	(1.05×10^{-7})	(1.57×10^{-7})	(1.04×10^{-7})	(1.53×10^{-7})
α	0.0768	0.0766	0.0756	0.0877	0.0741	0.0854
	(0.3889)	(0.5447)	(0.0012)	(0.0016)	(0.0012)	(0.0018)
β	0.9214	0.9221	0.9224	0.8982	0.9234	0.9018
	(0.0272)	(0.7891)	(0.0013)	(0.0021)	(0.0013)	(0.0022)
N. Ite.	17	24	7	28	10	57

The estimation results for the full sample of USD/AUD returns. Standard deviations are in the parentheses.

Table 1.12: Estimation results-FTSE SC

	RW	AR(2)	IWLS (SA)	fmincon (SA)	IWLS (R)	fmincon (R)
$\phi_0^{(1)}$	0.0005	0.0004	1.39×10^{-4}	-7.69×10^{-4}	-1.67×10^{-3}	-0.009
	(0.0001)	(0.0001)	(9.95×10^{-6})	(3.07×10^{-5})	(4.44×10^{-5})	(0.0001)
$\phi_1^{(1)}$		0.097	0.1469	0.1995	0.1987	0.3807
		(0.0253)	(0.0007)	(0.0011)	(1.13×10^{-3})	(0.0018)
$\phi_2^{(1)}$		0.0642	0.0945	-4.59×10^{-5}	-2.85×10^{-2}	-0.2884
		(0.0267)	(0.001)	(0.0017)	(0.0021)	(0.0034)
$\phi_0^{(2)}$			5.05×10^{-4}	1.67×10^{-3}	2.50×10^{-3}	0.0098
			(1.44×10^{-5})	(3.89×10^{-5})	(5.74×10^{-5})	(0.0001)
$\phi_1^{(2)}$			-0.0341	-0.1496	-0.102	-0.2895
			(0.0011)	(0.0016)	(0.0016)	(0.0019)
$\phi_2^{(2)}$			-0.1137	-0.0121	-0.0008	0.3485
			(0.0016)	(0.0019)	(0.0023)	(0.0034)
η			3.2368	1.2127	0.9956	2.2101
			(0.1262)	(0.025)	(0.025)	(0.0292)
c			1.09×10^{-4}	-3.89×10^{-3}	-4.39×10^{-3}	-1.81×10^{-2}
			(3.97×10^{-5})	(7.53×10^{-5})	(9.67×10^{-5})	(3.56×10^{-5})
ω	1.22×10^{-6}	1.24×10^{-6}	1.26×10^{-6}	1.54×10^{-6}	1.25×10^{-6}	1.53×10^{-6}
	(3.97×10^{-7})	(3.54×10^{-7})	(1.88×10^{-7})	(2.07×10^{-7})	(1.88×10^{-7})	(2.07×10^{-7})
α	0.1302	0.1309	0.1327	0.1388	0.1318	0.1369
	(0.0198)	(0.0199)	(0.0035)	(0.0038)	(0.0036)	(0.0038)
β	0.8556	0.8541	0.8518	0.8395	0.8529	0.8414
	(0.0224)	(0.0217)	(0.0043)	(0.0048)	(0.0043)	(0.0048)
N. Ite.	14	18	23	41	87	72

The estimation results for the full sample of the FTSE Small Cap index returns. Standard deviations are in the parentheses.

Table 1.13: Forecasts statistics-USD/AUD (conditional mean), 1-day ahead

	MFE	MSFE	MAFE	*Theil's U*	PT
RW	0.0006	3.72×10^{-5}	0.0045	0.9839	-0.4866
AR(2)	1.0002	1.0000	1.0002	0.9844	-0.2145
IWLS (SA)	1.1344	1.0259	1.0302	0.8618	-0.6627
fmincon (SA)	1.6050	1.6258	1.1239	0.7289	0.0819
IWLS (R)	0.8637	0.9911	0.9964	0.9025	1.2945
fmincon (R)	1.0419	1.0206	1.0076	0.9171	-1.2478

The forecasts statistics for the 500 1-day ahead forecasts with the daily USD/AUD returns. The columns respectively give mean forecasting error (MFE), mean square forecasting error (MSFE), mean absolute forecasting error (MAFE), *Theil's U* and Pesaran and Timmermann (1992) (PT) test statistic of directional forecasting.

Table 1.14: Forecasts statistics-the FTSE SC (conditional mean), 1-day ahead

	MFE	MSFE	MAFE	*Theil's U*	PT
RW	-0.0005	2.58×10^{-5}	0.0035	0.9027	0.0000
AR(2)	0.9100	0.9965	1.0001	0.9066	1.1168
IWLS (SA)	0.9358	1.0431	1.0357	0.8403	-0.6893
fmincon (SA)	1.0111	1.8748	1.1609	0.7151	-1.1157
IWLS (R)	0.8113	0.9902	1.0127	0.8177	0.8206
fmincon (R)	0.9500	1.0415	1.0180	0.8021	0.3126

The forecasts statistics for the 500 1-day ahead forecasts with the daily FTSE Small Cap returns. The columns respectively give mean forecasting error (MFE), mean square forecasting error (MSFE), mean absolute forecasting error (MAFE), *Theil's U* and Pesaran and Timmermann (1992) (PT) test statistic of directional forecasting.

Table 1.15: Predictive accuracy tests-USD/AUD (conditional mean), 1-day ahead

	DM	CW	ENC_t	MSE_t	ENC_F	MSE_F
AR(2)	-0.04	0.06	0.06	-0.04	0.00	-0.01
IWLS (SA)	-1.43	0.33	0.26	-1.44	1.16	-12.64
fmincon (SA)	-1.84*	-0.99	-0.99	-1.84	-9.94	-192.45
IWLS (R)	0.84	1.97**	1.95***	0.84***	4.95**	4.50***
fmincon (R)	-1.74*	-1.00	-1.00	-1.75	-2.59	-10.07

The predictive accuracy test statistics for the daily USD/AUD return forecasts. The columns respectively give statistics for Diebold-Mariano (DM), Clark-West (CW), ENC_t, MSE_t, ENC_F, and MSE_F tests. P-values for the ENC_t, MSE_t, ENC_F, and MSE_F tests are calculated by bootstrapping. * p<0.10, ** p<0.05, *** p<0.01

Table 1.16: Predictive accuracy tests-FTSE SC (conditional mean), 1-day ahead

	DM	CW	ENC_t	MSE_t	ENC_F	MSE_F
AR(2)	1.37	1.81*	1.50***	1.37***	0.96	1.75
IWLS (SA)	-1.73	-0.37	-0.26	-1.73	-1.50	-20.66
fmincon (SA)	-1.66	-0.42	-0.42	-1.66	-6.09	-233.30
IWLS (R)	0.43	1.63*	2.06	0.43**	12.67	4.96**
fmincon (R)	-0.73	0.60	0.60	-0.73	5.54	-19.90

The predictive accuracy test statistics for the daily FTSE Small Cap return forecasts. The columns respectively give statistics for Diebold-Mariano (DM), Clark-West (CW), ENC_t, MSE_t, ENC_F, and MSE_F tests. P-values for the ENC_t, MSE_t, ENC_F, and MSE_F tests are calculated by bootstrapping. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 1.17: Forecasts statistics-USD/AUD (conditional variance), 1-day ahead

	MFE	MSFE	MAFE	*Theil's U*
RW	-3.79×10^{-6}	4.52×10^{-9}	4.19×10^{-5}	0.5402
AR(2)	0.969	0.9987	0.9979	0.5407
IWLS (SA)	1.3332	1.0281	1.0236	0.5380
fmincon (SA)	4.4476	2.2516	1.2720	0.5959
IWLS (R)	1.2064	1.0298	1.0193	0.5422
fmincon (R)	3.9215	2.2363	1.1998	0.5714

The forecasts statistics for the 500 1-day ahead forecasts with the daily USD/AUD return realized variance. The columns respectively give mean forecasting error (MFE), mean square forecasting error (MSFE), mean absolute forecasting error (MAFE), and *Theil's U*.

Table 1.18: Forecasts statistics-FTSE SC (conditional variance), 1-day ahead

	MFE	MSFE	MAFE	*Theil's U*
RW	-2.24×10^{-6}	9.11×10^{-9}	2.96×10^{-5}	0.6957
AR(2)	0.8736	1.0125	0.9993	0.702
IWLS (SA)	1.0795	1.0243	1.0148	0.7017
fmincon (SA)	4.3977	1.2421	1.2139	0.6551
IWLS (R)	1.6562	1.0971	1.0554	0.6796
fmincon (R)	5.8406	1.6196	1.3314	0.6471

The forecasts statistics for the 500 1-day ahead forecasts with the daily FTSE SC return realized variance. The columns respectively give mean forecasting error (MFE), mean square forecasting error (MSFE), mean absolute forecasting error (MAFE), and *Theil's U*.

Table 1.19: Predictive accuracy test- DM (conditional variance), 1-day ahead

	USD/AUD	FTSE SC
AR(2)	1.33	-1.62
IWLS (SA)	-1.03	-1.96**
fmincon (SA)	-2.35**	-1.84*
IWLS (R)	-1.74*	-1.38
fmincon (R)	-1.73*	-1.84*

The DM test statistics for the daily USD/AUD and FTSE SC returns conditional variance forecasts. * p<0.10, ** p<0.05, *** p<0.01

Table 1.20: Predictive accuracy tests p-values-USD/AUD, 1-day ahead

		ENC_t	MSE_t	ENC_F	MSE_F
AR(2)	90^{th}	0.15	0.05	0.03	0.01
	95^{th}	0.18	0.07	0.08	0.01
	99^{th}	0.47	0.08	0.60	0.01
IWLS (SA)	90^{th}	2.99	1.92	33.81	12.58
	95^{th}	3.08	2.16	41.90	13.37
	99^{th}	3.35	2.39	53.43	14.47
fmincon (SA)	90^{th}	1.88	1.86	369.10	287.38
	95^{th}	1.89	1.87	391.28	303.53
	99^{th}	1.94	1.87	404.23	310.51
IWLS (R)	90^{th}	0.23	-0.55	1.54	-1.87
	95^{th}	0.33	-0.43	3.34	-1.26
	99^{th}	0.82	-0.26	9.82	-0.61
fmincon (R)	90^{th}	2.27	1.89	23.17	11.10
	95^{th}	2.32	1.98	30.85	11.64
	99^{th}	2.52	2.07	40.22	12.18

The bootstrapped percentile values for ENC_t, MSE_t, ENC_F, and MSE_F test statistics. The number of bootstrap is 10,000.

Table 1.21: Predictive accuracy tests p-values-FTSE SC, 1-day ahead

		ENC_t	MSE_t	ENC_F	MSE_F
AR(2)	90^{th}	1.23	1.04	2.57	2.33
	95^{th}	1.32	1.07	4.59	2.95
	99^{th}	1.48	1.12	13.38	4.43
IWLS (SA)	90^{th}	3.16	1.56	48.62	16.95
	95^{th}	3.77	1.97	100.48	30.44
	99^{th}	4.78	2.77	281.12	119.21
fmincon (SA)	90^{th}	1.68	1.65	472.91	389.80
	95^{th}	1.69	1.66	502.61	410.99
	99^{th}	1.80	1.67	527.83	428.04
IWLS (R)	90^{th}	2.09	-0.49	34.16	-3.79
	95^{th}	2.78	-0.09	72.96	-0.72
	99^{th}	4.01	0.81	196.32	21.28
fmincon (R)	90^{th}	1.35	0.79	47.07	17.42
	95^{th}	1.56	0.91	61.87	19.62
	99^{th}	2.63	1.03	95.78	23.81

The bootstrapped percentile values for ENC_t, MSE_t, ENC_F, and MSE_F test statistics. The number of bootstrap is 10,000.

Table 1.22: Forecasts statistics-USD/AUD (conditional mean), 5-day ahead

	MFE	MSFE	MAFE	*Theil's U*	PT
RW	0.0006	3.72×10^{-5}	0.0044	0.9840	-0.7971
AR (2)	1.0013	0.9999	1.0002	0.9844	-0.5211
IWLS (SA)	1.0005	0.9998	1.0002	0.9844	-0.5211
fmincon (SA)	1.2266	1.0107	1.0114	0.9182	-0.7264
IWLS (R)	1.0212	0.9999	1.0003	0.9329	-0.8792
fmincon (R)	1.4947	1.0273	1.0160	0.8589	-0.0984

The forecasts statistics for the 500 5-day ahead forecasts with the daily USD/AUD returns. The columns respectively give mean forecasting error (MFE), mean square forecasting error (MSFE), mean absolute forecasting error (MAFE), *Theil's U* and Pesaran and Timmermann (1992) (PT) test statistic of directional forecasting.

Table 1.23: Forecasts statistics-FTSE SC (conditional mean), 5-day ahead

	MFE	MSFE	MAFE	*Theil's U*	PT
RW	-0.0004	2.63×10^{-5}	0.0035	0.9027	0.0000
AR (2)	0.9244	0.9991	1.0001	0.9072	0.0000
IWLS (SA)	1.6987	1.0147	1.0020	0.8550	-0.0845
fmincon (SA)	0.9535	1.0011	1.0001	0.9053	-0.8954
IWLS (R)	1.6753	1.0207	1.0065	0.8539	1.4548
fmincon (R)	0.3622	1.1654	1.0874	0.8054	-1.1799

The forecasts statistics for the 500 5-day ahead forecasts with the daily FTSE Small Cap returns. The columns respectively give mean forecasting error (MFE), mean square forecasting error (MSFE), mean absolute forecasting error (MAFE), *Theil's U* and Pesaran and Timmermann (1992) (PT) test statistic of directional forecasting.

Table 1.24: Predictive accuracy tests-USD/AUD (conditional mean), 5-day ahead

	DM	CW	ENC_t	MSE_t	ENC_F	MSE_F
AR(2)	0.93	1.17	1.33***	0.05	1.08***	0.08**
IWLS (SA)	-2.25**	-0.36	-0.37	-0.56	-1.72	-5.29
fmincon (SA)	-1.57	0.88	0.88	1.29	0.02	0.05
IWLS (R)	-1.61	0.37	0.34	1.15	-1.74	-13.28
fmincon (R)	0.02	-1.04	-1.02	-26.85	-1.54	-257.24

The predictive accuracy test statistics for the daily USD/AUD return 5-day ahead forecasts. The columns respectively give statistics for Diebold-Mariano (DM), Clark-West (CW), ENC_t, MSE_t, ENC_F, and MSE_F tests. P-values for the ENC_t, MSE_t, ENC_F, and MSE_F tests are calculated by bootstrapping. * p<0.10, ** p<0.05, *** p<0.01

Table 1.25: Predictive accuracy tests-FTSE SC (conditional mean), 5-day ahead

	DM	CW	ENC_t	MSE_t	ENC_F	MSE_F
AR(2)	1.48	1.55*	1.63***	0.23	1.56**	0.43
IWLS (SA)	-2.40**	-0.89	-0.84	-1.60	-1.88	-7.22
fmincon (SA)	-3.79***	-0.48	-0.50	-0.20	-0.67	-0.55
IWLS (R)	-2.09**	-1.27	-1.29	-2.56	-2.44	-10.16
fmincon (R)	-0.66	-1.92	-1.90	-10.57	-3.48	-70.95

The predictive accuracy test statistics for the daily FTSE Small Cap return 5-day ahead forecasts. The columns respectively give statistics for Diebold-Mariano (DM), Clark-West (CW), ENC_t, MSE_t, ENC_F, and MSE_F tests. P-values for the ENC_t, MSE_t, ENC_F, and MSE_F tests are calculated by bootstrapping. * p<0.10, ** p<0.05, *** p<0.01

Table 1.26: Forecasts statistics-USD/AUD (conditional variance), 5-day ahead

	MFE	MSFE	MAFE	*Theil's U*
RW	-3.67×10^{-6}	4.53×10^{-9}	4.20×10^{-5}	0.54
AR(2)	0.97	1.00	1.00	0.54
IWLS (SA)	1.22	1.03	1.02	0.54
fmincon (SA)	4.03	2.54	1.23	0.61
IWLS (R)	1.43	1.02	1.02	0.53
fmincon (R)	6.37	3.58	1.37	0.60

The forecasts statistics for the 500 5-day ahead forecasts with the daily USD/AUD return realized variance. The columns respectively give mean forecasting error (MFE), mean square forecasting error (MSFE), mean absolute forecasting error (MAFE), and *Theil's U*.

Table 1.27: Forecasts statistics-FTSE SC (conditional variance), 5-day ahead

	MFE	MSFE	MAFE	*Theil's U*
RW	-3.05×10^{-6}	9.39×10^{-9}	3.06×10^{-5}	0.68
AR(2)	0.94	1.00	1.00	0.68
IWLS (SA)	1.19	0.95	1.01	0.66
fmincon (SA)	3.09	1.50	1.17	0.65
IWLS (R)	1.26	1.01	1.03	0.68
fmincon (R)	4.63	1.50	1.32	0.64

The forecasts statistics for the 500 5-day ahead forecasts with the daily FTSE SC return realized variance. The columns respectively give mean forecasting error (MFE), mean square forecasting error (MSFE), mean absolute forecasting error (MAFE), and *Theil's U*.

Table 1.28: Predictive accuracy test-DM (conditional variance), 5-day ahead

	USD/AUD	FTSE SC
AR(2)	0.59	0.97
IWLS (SA)	-2.25^{**}	0.89
fmincon (SA)	-1.77^{*}	-1.11
IWLS (R)	-1.76^{*}	-1.22
fmincon (R)	-2.21^{**}	-2.03^{**}

The DM test statistics for the daily USD/AUD and FTSE SC returns conditional variance 5-day ahead forecasts. * p<0.10, ** p<0.05, *** p<0.01

Table 1.29: Predictive accuracy tests p-values-USD/AUD, 5-day ahead

		ENC_t	MSE_t	ENC_F	MSE_F
AR(2)	90^{th}	0.88	0.68	0.13	0.08
	95^{th}	0.90	0.71	0.25	0.08
	99^{th}	1.01	0.76	0.68	0.09
IWLS (SA)	90^{th}	2.96	1.94	31.02	11.49
	95^{th}	3.05	2.21	39.48	12.39
	99^{th}	3.32	2.41	53.78	13.75
fmincon (SA)	90^{th}	1.61	1.57	567.53	476.06
	95^{th}	1.61	1.58	605.97	511.80
	99^{th}	1.65	1.59	632.88	533.92
IWLS (R)	90^{th}	2.86	2.06	14.45	5.42
	95^{th}	2.88	2.26	19.87	5.67
	99^{th}	2.93	2.45	26.75	5.92
fmincon (R)	90^{th}	0.83	0.18	3.56	0.37
	95^{th}	0.86	0.33	5.24	0.55
	99^{th}	0.97	0.48	9.93	0.62

The bootstrapped percentile values for ENC_t, MSE_t, ENC_F, and MSE_F test statistics for 5-day ahead forecasts. The number of bootstrap is 10,000.

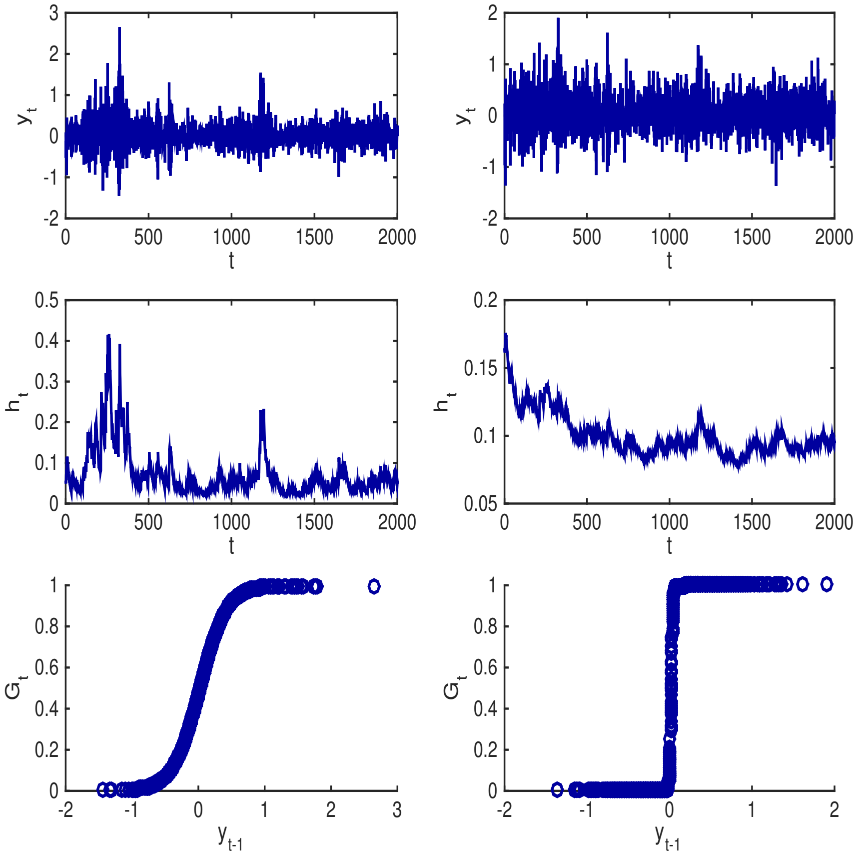
Table 1.30: Predictive accuracy tests p-values-FTSE SC, 5-day ahead

		ENC_t	MSE_t	ENC_F	MSE_F
AR(2)	90^{th}	1.45	1.34	0.69	0.93
	95^{th}	1.51	1.36	1.20	1.33
	99^{th}	1.64	1.40	3.17	2.23
IWLS (SA)	90^{th}	2.99	1.63	12.44	5.34
	95^{th}	3.42	1.93	21.69	7.46
	99^{th}	4.13	2.33	46.78	15.55
fmincon (SA)	90^{th}	3.68	3.44	119.88	76.33
	95^{th}	3.72	3.51	132.97	80.70
	99^{th}	3.84	3.57	147.11	84.99
IWLS (R)	90^{th}	2.44	1.51	10.69	4.68
	95^{th}	2.57	1.69	14.62	5.24
	99^{th}	2.88	1.89	24.55	6.26
fmincon (R)	90^{th}	3.36	3.07	4.90	7.81
	95^{th}	4.38	4.11	11.94	20.02
	99^{th}	5.73	5.45	34.20	59.42

The bootstrapped percentile values for ENC_t, MSE_t, ENC_F, and MSE_F test statistics for 5-day ahead forecasts. The number of bootstrap is 10,000.

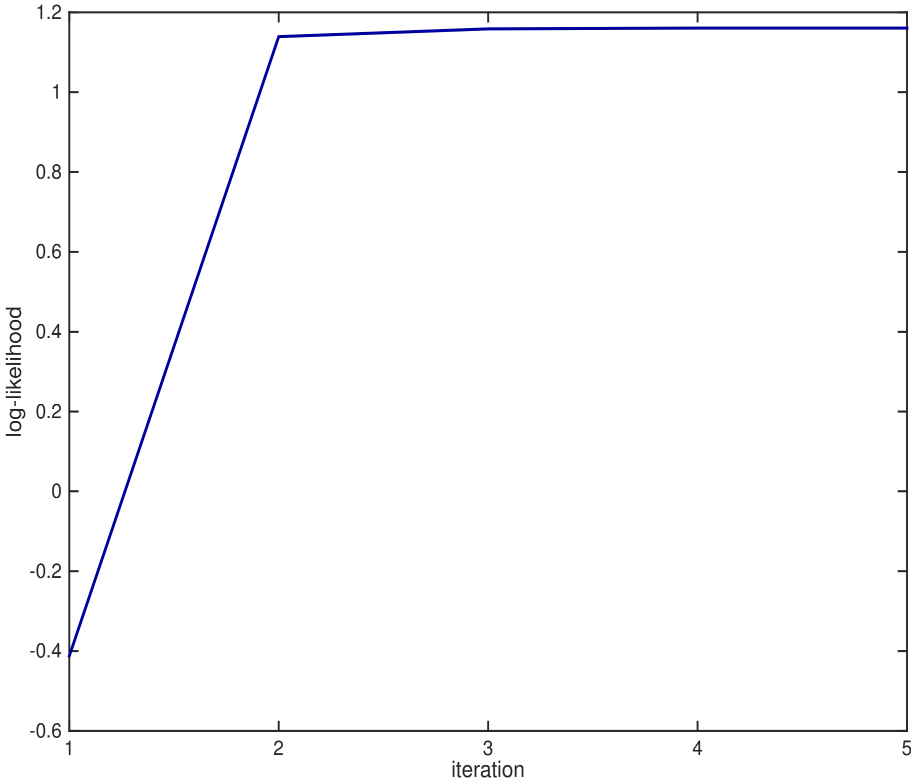
Figures

Figure 1.1: Simulated data



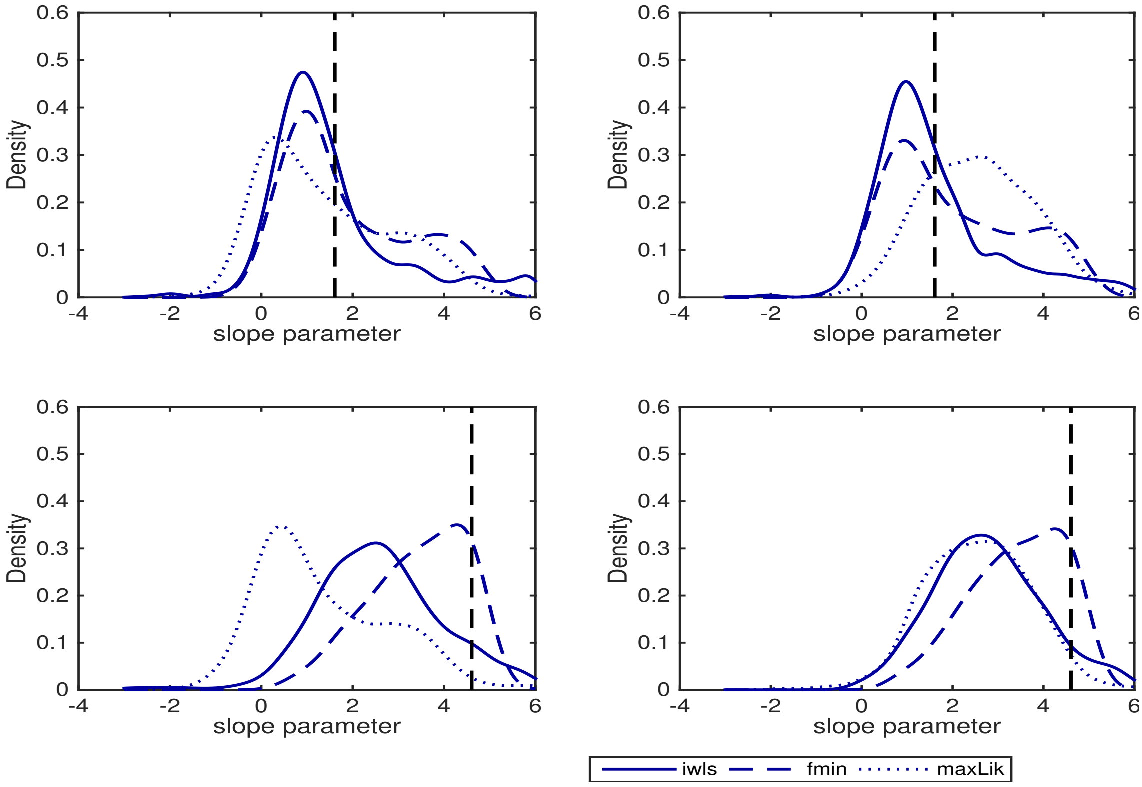
Representative plots of the simulated data with $(\alpha, \beta) = (0.09, 0.90)$ with $\eta_{re} = ln5$ (on the left) and $(\alpha, \beta) = (0.01, 0.98)$ specifications with $\eta_{re} = ln100$ (on the right) . Top panels: y_t against t, middle panels: h_t against t, bottom panels: G_t against y_{t-1}. The sample size is 2000.

Figure 1.2: IWLS log-likelihood function



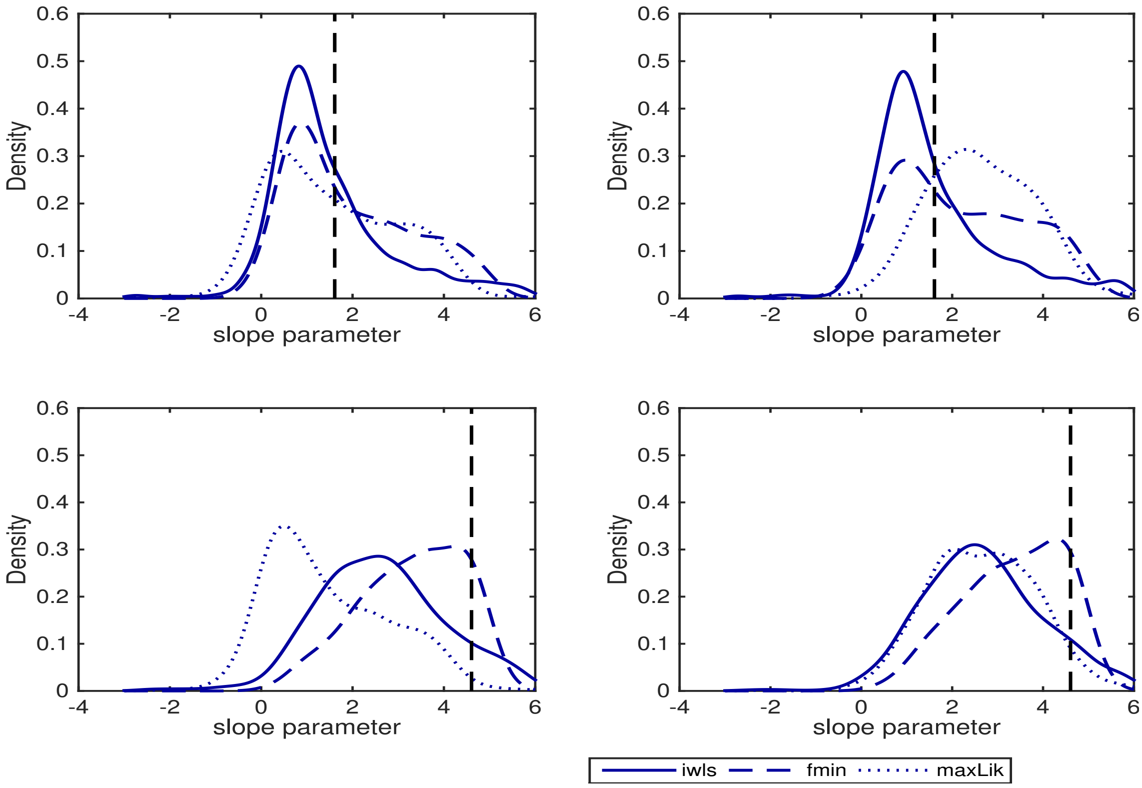
The evaluation of the log-likelihood function values during the IWLS estimation. This is a representative plot from the simulations with $(\alpha, \beta) = (0.09, 0.90)$ specification and $\eta_{re} = ln5$.

Figure 1.3: Estimated η, $(\alpha, \beta) = (0.09, 0.90)$



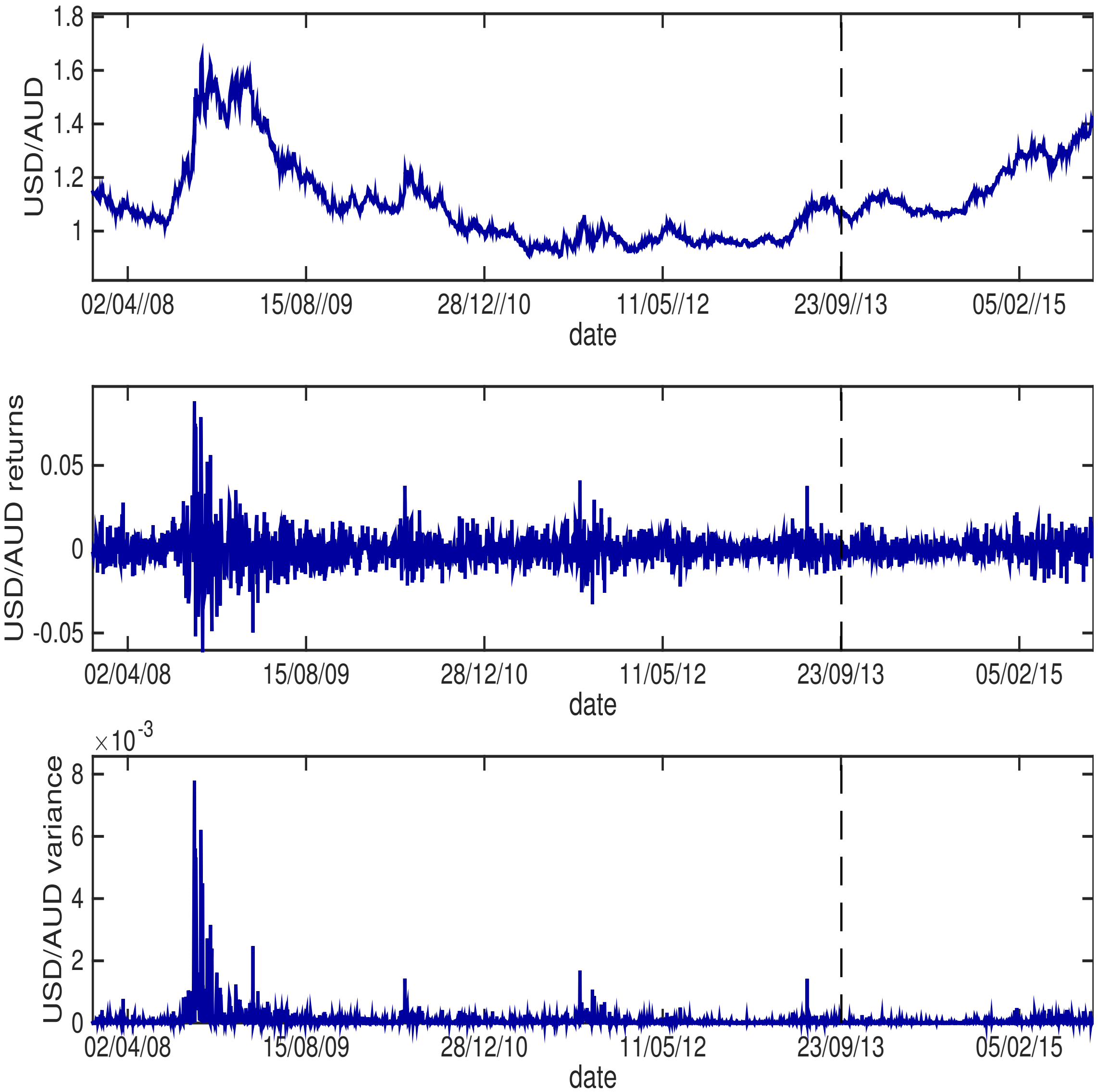
The Kernel density plots of the slope parameter estimations for the $(\alpha, \beta) = (0.09, 0.90)$ specification. Top left panel: real slope parameter value is $ln5$, with SA initial values, top right panel: real slope parameter values is $ln5$, random initial values; bottom left panel: real slope parameter value is $ln100$, with SA initial values, bottom right panel: real slope parameter value is $ln100$, with random initial values. The vertical dashed line represents the real value of the slope parameter.

Figure 1.4: Estimated η, $(\alpha,\beta) = (0.01, 0.98)$



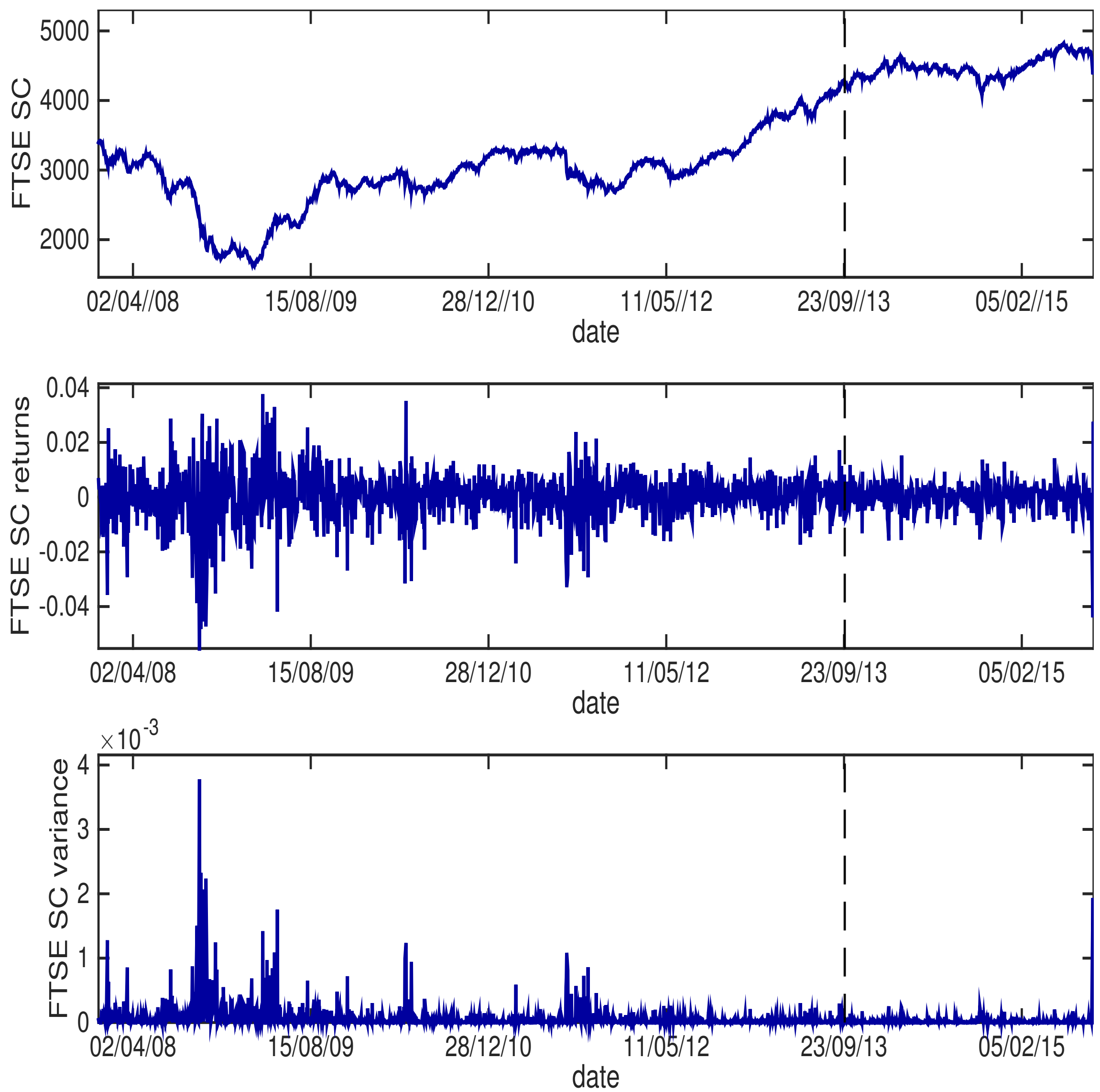
The Kernel density plots of the slope parameter estimations for the $(\alpha,\beta) = (0.01, 0.98)$ specification. Top left panel: real slope parameter value is $ln5$, with SA initial values, top right panel: real slope parameter values is $ln5$, random initial values; bottom left panel: real slope parameter value is $ln100$, with SA initial values, bottom right panel: real slope parameter value is $ln100$, with random initial values. The vertical dashed line represents the real value of the slope parameter.

Figure 1.5: USD/AUD data



The plots for the daily USD/AUD exchange rates. Top panel: daily exchange rate levels, middle panel: daily exchange rate returns, bottom panel: realized variance of the daily exchange rate returns. The dashed vertical line marks the start of the forecasting period. *Source: Datastream*

Figure 1.6: FTSE SC data



The plots for the daily FTSE Small Cap stock index. Top panel: daily index levels, middle panel: daily index returns, bottom panel: realized variance of the daily index returns. The dashed vertical line marks the start of the forecasting period. *Source: Datastream*

Appendix

A. The names of the daily series considered for the empirical application

Table 1.31: The list of daily financial series, all

Exchange Rates	Stock Indices (1)	Stock Indices (2)	Commodity Prices
US $ TO UK £(WMR) - EXCHANGE RATE	NYSE COMPOSITE - PRICE INDEX	FTSE WORLD $ - PRICE INDEX	Crude Oil-Brent Cur. Month FOB U$/BBL
AUSTRALIAN $ TO UK £(WMR) - EXCHANGE RATE	NYSE ENERGY INDEX - PRICE INDEX	FTSE USA OIL & GAS - PRICE INDEX	Crude Oil-WTI Spot Cushing U$/BBL - DS MID PRICE
JAPANESE YEN TO UK £(WMR) - EXCHANGE RATE	NYSE FINANCIAL INDEX - PRICE INDEX	FTSE USA OIL & GAS PROD - PRICE INDEX	Gold Bullion LBM U$/Troy Ounce
SWISS FRANC TO UK £(WMR) - EXCHANGE RATE	NYSE HEALTH CARE INDEX - PRICE INDEX	FTSE USA OIL/EQ SVS/DST $ - PRICE INDEX	LME-Copper Grade A Cash U$/MT
CANADIAN $ TO UK £(WMR) - EXCHANGE RATE	NYSE INTERNATIONAL 100 INDEX - PRICE INDEX	FTSE MULTINATIONALS ($) - PRICE INDEX	Crude Oil-Brent Dated FOB U$/BBL
SINGAPORE $ TO UK £(WMR) - EXCHANGE RATE	NYSE TMT INDEX - PRICE INDEX	FTSE 100 - PRICE INDEX	S&P GSCI Commodity Total Return - RETURN IND. (OFCL)
EURO TO UK £(ECU HISTORY WMR) - EXCHANGE RATE	NYSE US 100 INDEX - PRICE INDEX	FTSE ALL SHARE - PRICE INDEX	CRB BLS Spot Index (1967=100) - PRICE INDEX
NEW ZEALAND $ TO UK £(WMR) - EXCHANGE RATE	NYSE ARCA AIRLINE - PRICE INDEX	FTSE SMALL CAP - PRICE INDEX	Bloomberg- Commodity TR - RETURN IND. (OFCL)
HONG KONG $ TO UK £(WMR) - EXCHANGE RATE	NYSE ARCA BASIC INDUSTRIES - PRICE INDEX	FTSE UK BANKS - PRICE INDEX	LME-Aluminium 99.7% Cash U$/MT
SOUTH AFRICA RAND TO UK £(WMR) - EXCHANGE RATE	NYSE ARCA BIOTECHNOLOGY - PRICE INDEX	FTSE UK FINANCIALS - PRICE INDEX	Crude Oil WTI Cushing U$/BBL
RUSSIAN ROUBLE TO UK £(WMR) - EXCHANGE RATE	NYSE ARCA BROKER DEALER - PRICE INDEX	FTSE UK INDUSTRIALS - PRICE INDEX	Natural Gas, Henry Hub U$/MMBTU
BRAZILIAN REAL TO UK £(WMR) - EXCHANGE RATE	NYSE ARCA COMPOSITE - PRICE INDEX	S&P 500 COMPOSITE - PRICE INDEX	Baltic Exchange Dry Index (BDI) - PRICE INDEX
INDIAN RUPEE TO UK £(WMR) - EXCHANGE RATE	NYSE ARCA COMPOSITE FINANCIAL - PRICE INDEX	S&P500 ES ENERGY - PRICE INDEX	LME-Nickel Cash U$/MT
NORWEGIAN KRONE TO UK £(WMR) - EXCHANGE RATE	NYSE ARCA COMPOSITE HEALTHCARE - PRICE INDEX	S&P500 ES FINANCIALS - PRICE INDEX	LME-SHG Zinc 99.995% Cash U$/MT
US $ TO EURO (WMR&DS) - EXCHANGE RATE	NYSE ARCA COMPOSITE INDUSTRIALS - PRICE INDEX	S&P500 ES INDUSTRIALS - PRICE INDEX	London Platinum Free Market $/Troy oz
UK £TO EURO (WMR&DS) - EXCHANGE RATE	NYSE ARCA COMPOSITE NATURAL RESC. - PRICE INDEX	S&P RETAIL COMPOSITE - PRICE INDEX	TR/CC CRB Index TR - RETURN IND. (OFCL)
SWISS FRANC TO EURO (WMR) - EXCHANGE RATE	NYSE ARCA COMPOSITE TECHNOLOGIES - PRICE INDEX	S&P SMALLCAP 600/ CITIGROUP GRTH - PRICE INDEX	LME-Copper, Grade A 3 Months U$/MT
JAPANESE YEN TO EURO (WMR) - EXCHANGE RATE	NYSE ARCA COMPUTER HARDWARE - PRICE INDEX	S&P500 BANKS - PRICE INDEX	Wheat No.2,Soft Red Cts/Bu
RUSSIAN ROUBLE TO EURO (WMR) - EXCHANGE RATE	NYSE ARCA COMPUTER TECH. - PRICE INDEX	S&P500 ES MATERIALS - PRICE INDEX	Crude Oil WTI FOB Cushing U$/BBL
NORWEGIAN KRONE TO EURO (WMR) - EXCHANGE RATE	NYSE ARCA CONSUMER SERVICES - PRICE INDEX	S&P GLOBAL INFRA $ - PRICE INDEX	Raw Sugar-ISA Daily Price c/lb
AUSTRALIAN $ TO EURO (WMR) - EXCHANGE RATE	NYSE ARCA CONSUMER STAPLES - PRICE INDEX	S&P GLOBAL 100 - PRICE INDEX	Silver, Handy&Harman (NY) cts/Troy OZ
BRAZILIAN REAL TO EURO (WMR) - EXCHANGE RATE	NYSE ARCA GOLD BUGS - PRICE INDEX	DAX 30 PERFORMANCE - PRICE INDEX	Gold, Handy & Harman Base $/Troy Oz
CANADIAN $ TO EURO (WMR) - EXCHANGE RATE	NYSE ARCA GOLD MINERS - PRICE INDEX	MSCI WORLD U$ - PRICE INDEX	LME-LMEX Index - PRICE INDEX
SOUTH AFRICA RAND TO EURO (WMR) - EXCHANGE RATE	NYSE ARCA MAJOR MARKET - PRICE INDEX	EURO STOXX 50 - PRICE INDEX	LME-Steel Billet 3 Mth U$/MT
INDIAN RUPEE TO EURO (WMR) - EXCHANGE RATE	NYSE ARCA OIL - PRICE INDEX	STOXX EUROPE 600 E - PRICE INDEX	Cocoa-ICCO Daily Price US$/MT
HONG KONG $ TO EURO (WMR) - EXCHANGE RATE	NYSE ARCA SEMICONDUCTOR - PRICE INDEX	FRANCE CAC 40 - PRICE INDEX	LME-Lead Cash U$/MT
AUSTRALIAN $ TO JAPAN YEN - EXCHANGE RATE	NYSE ARCA TECHNOLOGY - PRICE INDEX	MSCI EM U$ - PRICE INDEX	LME-Nickel 3 Months U$/MT
US $ TO JAP. YEN FX SPOT RATE - EXCHANGE RATE	NYSE ARCA TECHNOLOGY 100 - PRICE INDEX	TOPIX - PRICE INDEX	Coffee-Brazilian (NY) Cents/lb
SWISS FRANC TO 100 JAPAN.YEN (SNB) - EXCHANGE RATE	NYSE ARCA TELECOM - PRICE INDEX	SHANGHAI SE A SHARE - PRICE INDEX	Corn No.2 Yellow Cents/Bushel
CANADIAN $ TO JPY FX CROSS RATES - EXCHANGE RATE	NYSE ARCA TOBACCO - PRICE INDEX	HANG SENG - PRICE INDEX	Palladium U$/Troy Ounce
GBP TO JAP. YEN FX CROSS RATE - EXCHANGE RATE	NYSE ARCA UTILITIES - PRICE INDEX	FTSE MIB INDEX - PRICE INDEX	S&P GSCI Energy Total Return - RETURN IND. (OFCL)
EURO TO AUSTRALIAN $ - EXCHANGE RATE	NYSE TOTAL BREADTH - BREADTH INDEX	KOREA SE COMPOSITE (KOSPI) - PRICE INDEX	LME-Aluminium 99.7% 3 Months U$/MT
JAPANESE YEN TO AUSTRALIAN $ - EXCHANGE RATE	DOW JONES COMPOSITE 65 STOCK AVE - PRICE INDEX	IBEX 35 - PRICE INDEX	Soyabeans, No.1 Yellow C/Bushel
UK POUND TO AUSTRALIAN $ - EXCHANGE RATE	DJ US BROAD STOCK MARKET - PRICE INDEX	S&P/ASX 200 - PRICE INDEX	Aluminium-Stocks LME In Warehouses-MT - INVENTORY VOLUME
CANADIAN TO AUSTRALIAN $ SPOT (TP) - EXCHANGE RATE	DJ US TOTAL STOCK MKT - PRICE INDEX	SWISS MARKET (SMI) - PRICE INDEX	Cotton,1 1/16Str Low -Midl,Memph C/Lb
SWISS FRANC TO AUSTRALIAN $ - EXCHANGE RATE	DJ US COMPLETION TOTAL STOCK MKT - PRICE INDEX	MSCI EUROPE U$ - PRICE INDEX	S&P GSCI Gold Total Return - RETURN IND. (OFCL)
AUSTRALIAN $ TO US $ - EXCHANGE RATE	DJ US LARGE CAP GR TOTAL STOCK MKT. - PRICE INDEX	EURO STOXX - PRICE INDEX	S&P GSCI Precious Metal Tot. Ret. - RETURN IND. (OFCL)
	DJ US LARGE CAP TOTAL STOCK MKT - PRICE INDEX	AEX INDEX (AEX) - PRICE INDEX	Wheat US HRS 14% Del Mineapolis/Dulut
	DJ US LARGE CAP VAL TOTAL STOCK MKT - PRICE INDEX	S&P/TSX COMPOSITE INDEX - PRICE INDEX	Ammonia,Europe CFR NWE $/MT
	DJ US MICRO CAP TOTAL STOCK MKT - PRICE INDEX	BANGKOK S.E.T. - PRICE INDEX	Jet Kerosene FOB Singapore U$/BBL
	DJ US MID CAP GR TOTAL STOCK MKT - PRICE INDEX	IDX COMPOSITE - PRICE INDEX	Jet Kerosene-Cargos CIF NWE U$/MT
	DJ US MID CAP TOTAL STOCK MKT - PRICE INDEX	OMX STOCKHOLM 30 (OMXS30) - PRICE INDEX	LME-Aluminium Alloy Cash U$/MT
	DJ US MID CAP VAL TOTAL STOCK MKT - PRICE INDEX	STRAITS TIMES INDEX L - PRICE INDEX	S&P GSCI Silver Total Return - RETURN IND. (OFCL)
	DJ US SMALL CAP GR TOTAL STOCK MKT - PRICE INDEX	BEL 20 - PRICE INDEX	APX Power UK Spot Base Load Index
	DJ US SMALL CAP TOTAL STOCK MKT - PRICE INDEX	STOXX EUROPE 50 - PRICE INDEX	Aluminium Alloy-LME Warehouse Stocks - INVENTORY VOLUME
	DJ US SMALL CAP VAL TOTAL STOCK MKT - PRICE INDEX	TAIWAN SE WEIGHED TAIEX - PRICE INDEX	Butane Mont Belvieu Del. Pipe UC/GAL
	FTSE ALL WORLD $ - PRICE INDEX	MDAX FRANKFURT - PRICE INDEX	Copper-Stocks In LME Warehouses-MT - INVENTORY VOLUME
	FTSE GLOBAL 100 ($) - PRICE INDEX	MSCI AC WORLD U$ - PRICE INDEX	Corn US No.2 South Central IL $/BSH
	FTSE USA BANKS - PRICE INDEX		Crude Oil, Tapis FOB Malaysia U$/BBL

The list of the daily financial series considered for the empirical application. The list contains the names 37 exchange rate, 97 stock index, and 49 commodity prices series.

B. Series considered for the forecasting exercise and the forecast statistics

Table 1.32: The list of daily financial series, forecasting step

Names
AUSTRALIAN $ TO UK £(WMR) - EXCHANGE RATE
AUSTRALIAN $ TO EURO (WMR) - EXCHANGE RATE
JAPANESE YEN TO AUSTRALIAN $ - EXCHANGE RATE
CANADIAN TO AUSTRALIAN $ SPOT (TP) - EXCHANGE RATE
FTSE WORLD $ - PRICE INDEX
NYSE COMPOSITE - PRICE INDEX
NYSE HEALTH CARE INDEX - PRICE INDEX
NYSE INTERNATIONAL 100 INDEX - PRICE INDEX
NYSE US 100 INDEX - PRICE INDEX
NYSE ARCA TELECOM - PRICE INDEX

The list of daily financial series that passed the lag selection procedure; but do not deliver improvements over the RW model in the forecasting exercise.

Table 1.33: The forecast statistics, other series, 1-day ahead

		MFE	MSFE	MAFE	Theil's U	PT			MFE	MSFE	MAFE	Theil's U	PT
AUD/GBP	RW	0.0006	3.54×10^{-5}	0.0044	0.97	-7.20×10^{13}	NYSE Comp.	RW	-0.0004	5.54×10^{-5}	0.0053	0.94	0
	AR (2)	0.91	1.00	1.00	0.99	-5.65		AR (2)	1.01	1.00	1.00	0.94	0.00
	IWLS (SA)	0.81	1.00	1.00	0.95	0.08		IWLS (SA)	0.33	1.01	1.00	0.89	0.03
	fmincon (SA)	0.90	1.04	1.02	0.87	-1.13		fmincon (SA)	1.26	1.12	1.02	0.77	0.33
	IWLS (R)	0.81	1.02	1.01	0.88	-0.21		IWLS (R)	0.23	1.04	1.02	0.91	0.12
	fmincon (R)	0.74	3.10	1.25	0.72	-0.16		fmincon (R)	1.24	1.15	1.07	0.78	-0.69
AUD/EURO	RW	0.0003	4.04×10^{-5}	0.004	0.97	-7.20576×10^{13}	NYSE Health C.	RW	-7.16×10^{-5}	6.13×10^{-5}	0.0056	0.92	0
	AR (2)	0.92	1.01	1.01	0.92	-0.55		AR (2)	1.19	1.00	1.00	0.92	0.00
	IWLS (SA)	0.74	1.02	1.01	0.92	-0.10		IWLS (SA)	-1.80	1.01	1.00	0.91	0.34
	fmincon (SA)	0.96	1.09	1.03	0.85	-0.46		fmincon (SA)	-0.31	1.11	1.03	0.81	-0.46
	IWLS (R)	0.93	1.02	1.01	0.84	0.50		IWLS (R)	-2.06	1.02	1.01	0.90	-0.70
	fmincon (R)	2.12	2.36	1.21	0.72	-0.71		fmincon (R)	-0.15	1.49	1.13	0.71	-0.40
JPY/AUD	RW	-0.0004	4.11×10^{-5}	0.0046	0.95	0	NYSE Int. 100	RW	-4.05×10^{-4}	6.77×10^{-5}	0.006	0.97	0
	AR (2)	1.00	1.00	1.00	0.96	0.00		AR (2)	0.98	1.00	1.00	0.98	-2.11
	IWLS (SA)	0.27	1.01	1.01	0.93	-3.13		IWLS (SA)	0.81	1.01	1.01	0.88	-1.90
	fmincon (SA)	0.64	1.16	1.03	0.74	-1.79		fmincon (SA)	1.66	1.30	1.10	0.75	-1.80
	IWLS (R)	0.26	1.02	1.01	0.89	-1.35		IWLS (R)	1.03	1.07	1.04	0.85	-2.17
	fmincon (R)	2.35	4.37	1.26	0.73	-0.49		fmincon (R)	3.05	2.74	1.43	0.71	-0.31
CAD/USD	RW	-0.0001	2.68×10^{-5}	0.003	0.98	0	NYSE US 100	RW	-4.18×10^{-4}	5.61×10^{-5}	0.0053	0.93	0
	AR (2)	0.73	1.03	1.01	0.90	-0.50		AR (2)	1.01	1.00	1.00	0.93	0.00
	IWLS (SA)	0.56	1.01	1.01	0.88	0.26		IWLS (SA)	0.21	1.02	1.01	0.91	-1.00
	fmincon (SA)	1.39	1.04	1.03	0.89	-2.05		fmincon (SA)	0.97	1.01	1.00	0.89	-1.32
	IWLS (R)	0.84	1.06	1.02	0.79	-0.55		IWLS (R)	0.04	1.03	1.01	0.92	0.02
	fmincon (R)	0.46	5.17	1.44	0.76	-0.81		fmincon (R)	0.69	1.12	1.05	0.79	0.03
FTSW World	RW	-0.0004	3.93×10^{-5}	0.0045	0.93	0	NYSE ARCA Tel.	RW	-7.72×10^{-4}	1.02×10^{-4}	0.007	0.95	0
	AR (2)	0.97	1.00	1.00	0.93	0.10		AR (2)	1.00	1.00	1.00	0.95	0.00
	IWLS (SA)	1.41	1.11	1.06	0.78	1.09		IWLS (SA)	1.00	1.02	1.02	0.86	-0.99
	fmincon (SA)	1.08	1.01	1.01	0.83	-0.07		fmincon (SA)	1.33	1.10	1.03	0.77	0.93
	IWLS (R)	0.89	1.01	1.02	0.79	1.23		IWLS (R)	0.61	1.02	1.02	0.86	-0.77
	fmincon (R)	1.74	1.22	1.10	0.76	0.57		fmincon (R)	1.42	1.19	1.07	0.77	-1.21

The forecasts statistics for the 500 1-day ahead forecasts with the daily financial series deliver improvements over the RW model. The columns respectively give mean forecasting error (MFE), mean square forecasting error (MSFE), mean absolute forecasting error (MAFE), *Theil's U* and Pesaran and Timmermann (1992) (PT) test statistic of directional forecasting.

2

The Role of the Real Exchange Rate for Credit Growth in Central and Eastern European Countries: A Bank-level Analysis*

Abstract

This study analyzes the effects of macroeconomic and bank-level variables on the loan growth of banks in Central and Eastern European countries (CEECs) for the period between 1999 and 2010. Differences between private, state, domestic and foreign banks are analyzed by using the ownership structures of banks. We show that, unlike macroeconomic factors and other bank-level variables, leverage growth and equity growth have consistently significant effects on the loans of both domestic and foreign banks. The real exchange rate turns out to be a significant factor only for foreign banks. The latter result is important in understanding the transmission of global shocks to domestic credit. The results are robust to different specifications.

Keywords: credit growth, emerging markets, real exchange rate, leverage
JEL code: G21, F31

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2.1. Introduction

Domestic credit growth has been noted as one of the most important signals of a financial crisis in the international finance literature. It is therefore crucial for policymakers to know the determinants of credit growth in order to proactively protect their economies. Based on the findings in the international finance literature on the relationship between credit growth and cross-border capital flows, this study tries to identify the effects of bank-specific and macroeconomic supply-side factors on credit growth in Central and Eastern European countries (CEECs). Special attention is given to the effects of the real effective exchange rate and bank leverage.

CEECs have witnessed an economic transformation during the last two decades as a result of the transition to market economies, which accelerated during the EU membership process of these countries. Some key features of the transformation include financial liberalization, rapid credit growth and privatization of commercial banks, as well as a general increase in the number of foreign banks operating in these countries. CEECs have gradually liberalized foreign direct investment (FDI) flows before portfolio flows, capital inflows before capital outflows and long-term flows before short-term flows (Von Hagen and Siedschlag, 2010). The advantages and disadvantages of liberalization of financial markets have been debated in the literature. Kaminsky and Schmukler (2008) empirically show that short-term disadvantages of financial market liberalization such as increased volatility of financial markets are compensated, in the long-term, by regulations and reforms that would improve financial institutions. The short-term disadvantages of liberalization are given as risky behavior of banks (Schneider and Tornell, 2004) and lending boom-bust cycles in imperfect financial markets (Tornell et al., 2003).To illustrate, for instance, during 2001-2010 domestic credit reached 38% of gross domestic product (GDP) in Bulgaria, while it was 30% in Romania and 23% in Hungary. On the bank ownership side of the story, the number of foreign banks operating in these countries increased to 262 in 2011 from 118 in 1997, while the number of domestic banks decreased to 123 in 2011 from 241 in 1997. This transformation of the financial markets and the banking sector in particular has raised questions about both the domestic lending of banks and their ownership statuses. Concerning domestic credit, it is the question of sustainable credit growth and the consequences of economic shocks. On the ownership side, the focus is on the added value of foreign banks to the efficiency of the banking sector and their role as a transmission channel of shocks in their parent countries. It is argued that a foreign-owned bank might carry shocks in the parent company's economy to the domestic economy, thereby making a country exposed to shocks in other countries. Therefore, policymakers would be interested in the determinants of credit growth in order to keep track of it as an indicator of a financial crisis and the role of foreign banks in the stability of their respective economies. Accordingly, the banking sector can be regulated to mitigate possible negative effects of credit growth and bank ownership structures.

The aim of this study is to investigate supply-side factors, namely banks' balance sheet elements and macroeconomic indicators, on the growth rate of commercial bank loans. The study first refers to the recent findings in the literature on the link between capital flows and domestic credit growth. Based on this link, focus is placed on the real exchange rate, leverage, leverage growth and equity growth, which are the crucial elements of the recent model by Bruno and Shin (2015) that tries to explain the relationship between cross-border capital flows and liquidity. Appreciation of the real exchange rate is empirically found to be one of the two most consistent predictors of a financial crisis by Gourinchas and Obstfeld (2012)), who find the most important one to be the credit growth. Therefore, this study tries to gauge the relationship between two important variables at the bank level. Regarding the previous results in the literature on the differences between domestic and foreign banks, we further analyze whether the ownership of banks makes a difference on the sign and size of the effect. Subsamples of domestic and foreign banks, namely government-owned and private domestic banks and greenfield and takeover foreign banks, are considered in order to identify the effects of the features of each ownership status.

Our findings underline the importance of the variables under consideration and point to the difference of foreign banks. Leverage growth and equity growth are the only variables that are consistently significant in all subsamples and under all robustness checks. None of the other bank-level or macroeconomic variables is found to be significant in all specifications and subsamples. Another robust result is that the real exchange rate is significant with the expected sign for the pooled sample and for the foreign bank subsample. When foreign banks are divided into further sub-samples, the effect of the real exchange rate has a consistently significant effect only for the greenfield banks.

The study is organized as follows. Section (2.2) provides a review of the literature on the linkages of capital flows and credit growth, describes key variables and their theoretical roles in the linkages, and summarizes the literature on the effects of bank ownership on domestic credit growth. Section (2.3) describes the dataset and variables used in the regressions, while (2.4) introduces the econometric methodology used in the study. Section (2.5) reports the main findings and robustness checks. Section (2.6) concludes the paper.

2.2. Literature Review

The empirical analysis of the study relies on models and empirical findings provided in the literature on the relationship between capital flows and domestic credit growth, the effect of bank ownership on bank lending, and the influence of the real and the nominal exchange rates on lending behavior.

First of all, the empirical literature provides evidence on a significant relation-ship between the cross-border capital flows and domestic credit growth. The evidence implies that there is a positive correlation between domestic growth and capital flows. Magud et al. (2014) find that capital flows have a significantly positive effect on domestic credit growth in emerging European countries for the period between 1999 and 2008, to which the authors refer as the "credit boom" period. Similarly, for 27 European countries between 2003 and 2008, Lane and McQuade (2014) find that increasing capital inflows as a result of financial integration, especially debt flows, significantly increase credit growth. Intuitively, the link can be explained by the increasing financial potential of the banking sector (Lane and McQuade, 2014). With financial integration, banks now add foreign depositors, borrowing on the inter-bank money market, international bonds and foreign portfolio investors to their funding sources.

Bruno and Shin (2015) built a model to explain changes in cross-border credit movements by focusing on equity, leverage and the real exchange rate. In this model, a bank tries to maximize the market value of its equity based on the balance sheet equation and the leverage constraint. In this context, the level of leverage refers to the rate a bank can transform a dollar increase in capital into lending. The model of Bruno and Shin (2015) implies that if the real effective exchange rate increases (e.g. because of local currency appreciation or US dollar depreciation), borrowing by local banks from global banks will increase at the aggregate level and cross-border flows will increase. It will have a similar effect as a decrease in credit risk. The model also implies that the real effective exchange rate is directly linked to the leverage decisions of banks and that both leverage and leverage growth are positively correlated with cross-border loans. The real exchange rate, however, is the only variable that is shown to be consistently significant and to have the theoretically correct sign in their empirical exercise.

Even though the model does not explain the domestic lending behavior of commercial banks *per se*, its implications can be used to explain changes in the domestic lending behavior of banks by the link between cross-border flows and credit growth. Variables that affect cross-border banking movements are expected to have effects similar to those of domestic credit growth since the cross-border borrowings of banks can be used as a source for financing domestic lending. In the case of real effective exchange rate appreciation, a decline in credit risk or a decline in leverage or leverage growth, banks would borrow more from international markets and lend in domestic markets, thus playing an intermediary role between international markets and domestic residents. The intuition for leverage is in line with Adrian and Shin (2010)), who show that if a bank's leverage decreases, it will try to increase its balance sheet by either borrowing from abroad, lending domestically or using both channels.

Empirical evidence for the effect of leverage in credit growth is presented in Adrian and Shin (2014)), who point out the link between the balance sheets of financial intermediaries and their lending activities. If a financial intermediary has a strong balance sheet, *ceteris paribus*, it will find much easier to lend. According to Adrian and Shin (2014), the leverage of banks is procyclical and linked to their decisions on new assets, loans and securities purchases.

A similar argument regarding the effect of the real exchange rate on credit growth is based on the Fisherian channel of the transmission of capital flows (Von Hagen and Siedschlag, 2010), which can be summarized as follows:[1] In countries with fixed exchange rate regimes, the relative prices of non-tradable goods will increase after an appreciation of the real exchange rate and the central banks will try to stabilize the nominal value of the exchange rate. Therefore, producers of non-tradables will face a lower real interest rate and larger cash flows. This, in turn, will increase the value of their assets that can be used as collateral for bank loans. Thus, demand for credit will increase.

The explanation above holds for economies with fixed exchange rates. The effect of deviations from the fixed exchange rate regime has also been questioned in the literature. Magud et al. (2014) empirically show that the flexibility of exchange rates has a negative impact on credit growth during credit boom periods. Their study is carried out using the *de facto* exchange rate regime classification of Reinhart and Rogoff. The results suggest that countries with less flexible exchange rates will have more credit growth and it is argued that this relationship might be explained by the absorption of capital inflows due to the appreciation of exchange rates in a purely floating exchange rate regime, while in a fixed exchange rate regime the effect will not be totally sterilized and the non-sterilized part of the inflows will lead to greater credit expansion than would be the case in a floating exchange rate regime (Magud et al., 2014). Another argument given by Montiel and Reinhart (2001) is that in a fixed exchange rate regime, banks might consider the fixed level of the

[1] The line of arguments in Von Hagen and Siedschlag (2010) is based on Calvo and Reinhart (2000), Calvo (2002) and Calvo et al. (2004).

exchange rate as a guarantee on foreign claims and look for more foreign funding. Finally, it is argued that incentives to borrow in foreign currencies might be higher in credible fixed exchange rate regimes (Magud et al., 2014). The role of exchange rate regimes in lending behavior at the bank level is tested by dropping the real exchange rate from the regressions and adding the regime variable.

Lane and McQuade (2014) assume that the effect of financial integration works through its impact on domestic banks (i.e. financial integration increases the financing opportunities for domestic banks). However, the composition of bank ownership has undergone another transformation that has been argued to affect credit growth in European emerging markets. For instance, Aydin (2008) analyzes the reasons for the rapid credit growth in CEECs and the role of bank ownership. The study shows that economic growth and deepening of financial markets in these countries during their transition to market economies were important for credit growth during the 1990s. It is pointed out that foreign banks facilitated credit growth in these economies and loans by foreign banks were higher on average than the loans provided by domestic banks. An interesting result of the study is that the funding of bank loans has changed over time. During the 1990s, foreign banks behaved like domestic banks and used customer deposits as a source of loans; later, however, they started to borrow more from their parent banks or other major banks (Aydin, 2008) to finance loans.

Cull and Martinez Peria (2010) study the consequences of foreign bank participation in developing countries. According to their findings, the efficiency of the banking sector increases after the market entry of foreign banks and the sector becomes more stable. This increase in the efficiency of the banking sector is also confirmed in a previous study by Claessens et al. (2001). The result relating to stability justifies the implications of Crystal et al. (2002), who find that foreign bank participation leads to less volatile credit growth. Cull and Martinez Peria (2010) also argue that foreign bank participation increases access to financing.

Bruno and Hauswald (2014) find three real effects of the increase of foreign bank participation. First, the existence of foreign banks relaxes financial constraints in the market, which means that domestic residents have greater access to financing through the international links of the foreign banks (i.e. multinational banks and parent banks). Second, they overcome informational barriers to lending. Third, they mitigate the legal obstacles of debt contracting. Finally, Brown et al. (2011) show that foreign owned banks are more likely to reject loan applications than domestic banks, especially loan applications from small and government-owned firms. The authors argue that foreign owned banks "cherry pick" (i.e. are more selective) firms in host countries; therefore, only applications from big and transparent firms are approved.

2.3. Data

This study uses bank-level micro variables, foreign exchange regime specification and macroeconomic indicators. The dataset covers the years 1999 to 2010 and includes 14 Central and Eastern European emerging market economies, namely Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, the Russian Federation, Slovakia, Slovenia, Turkey and Ukraine.

The banking data comes form an unbalanced yearly dataset that has been used by De Haas et al. (2012). The dataset uses the Bankscope database of *Bureau van Dijk* for the bank specific data. The initial dataset contains information on 1,777 different banks. However, the availability of data for each bank changes throughout the years. The first reason for this is the addition of new banks to the dataset and deletion of existing ones, which might be due to several reasons such bankruptcy, acquisition or merger. The second reason is that not all variables in the dataset are consistently reported by each bank.

The dataset reports changes in the ownership structure of banks. This feature of the dataset allows us to analyze the impact of bank ownership on domestic credit growth. Table (2.1) reports the number of domestic and foreign banks in each country for the years 1999 and 2010. The first observation in the table is the increasing number of foreign banks and a drop in the number of banks in each country. The only exceptions are the Russian Federation and Ukraine. Even though the number of foreign banks is higher in these countries in 2010 compared to 1999, the number of domestic banks also increased in the same period, especially in Russia, where the number of domestic banks increased by a factor of eight. At the same time, the number of foreign banks in Russia grew from 17 to 66.

A crucial aspect of the dataset is its compatibility with the aggregate values of domestic credit in CEECs, as other financial institutions can also provide credits to customers. The World Development Indicators (WDI) database published by the World Bank reports both domestic credit provided to the private sector in general and domestic credit provided to the private sector by banks both as a ratio to GDP. According to these series, as shown in Figures (2.1) and (2.2), the banking sector provides most of the credit to the private sector and, in some cases almost, all of the domestic credit. Therefore, the results of the study are expected to have implications not only on the lending behavior of the banking sector, also on the total domestic credit growth in CEECs.

At the bank level, domestic credit is provided by the *gross loans* variable in the dataset (De Haas et al., 2012). Within the loan variables that give different loans categories of banks, *gross loans* are selected for two reasons. unlike the sub-categories of loans, there are fewer missing values in this variable. Second, *gross loans* successfully summaries the domestic credit provided by banks. Table (2.2) reports the correlation of the ratio of the aggregated gross loans provided by the banks in the dataset to GDP with the domestic credit provided by banks as a share of GDP. There is a strong positive correlation between the real value of domestic credit and the proxy variable in most of the countries. For Estonia, the correlation coefficient is 0.22; for other countries, it goes up to 0.97. These correlations also support the use of the dataset as a proxy for the aggregate banking sector data.

Values for credit growth, leverage, and equity growth for certain years are given in Table (2.3). The table also distinguishes the values for the foreign and domestic bank subsamples. As displayed in the table, foreign banks are characterized by higher credit growth, leverage and equity growth even though the pattern changes for some years and is more apparent for leverage. Domestic banks and the whole sample suffer from negative credit growth in 2009, while foreign banks experience shrinkage in credit in 2010.

Changes in the foreign exchange regimes are collected from the annual reports on *Exchange Arrangements and Exchange Restrictions* of the International Monetary Fund (IMF). The IMF classifies exchange rate regimes under four broad categories, which are hard pegs, soft pegs, floating regimes (market determined exchange rates) and residual. There are nine separate subcategories under the first three categories, which can be listed from the least flexible to the most flexible as no legal tender, currency board, conventional peg, stabilized arrangement, crawling peg, crawl-like arrangement, pegged exchange rate arrangements, floating and free floating. Exchange rate regimes that do not fit in any of these categories are grouped under "residual".

Macro variables and other financial indicators are retrieved from two sources. The annual GDP growth, consumer price index (CPI) and domestic debt as a share of GDP data are from the World Bank WDI database, and the national currency per US Dollar data are from the International Financial Statistics database of the IMF.

The definitions of the variables used in the study are as follows:

- *Baseline bank-specific variables*
  - Leverage is defined by the logarithm of ratio of assets to assets minus liabilities of a bank.
  - Leverage growth is the first difference of the Leverage variable.
  - Equity growth is generated by taking the difference of the logarithm of equities of a bank.
- *Macro variables*
  - ΔRER is the change in the real effective exchange rate of a country. RER follows the definition used in Bruno and Shin (2015), which is logarithm of nominal exchange rate times the ratio of US inflation and domestic inflation.
  - ΔGDP is the year-on-year GDP growth in a country.
  - ΔDebt/GDP is the growth of the ratio of gross debts to the GDP.
  - ΔM2 is the growth of money stock (M2) in an economy.
  - Inflation is the inflation rate in a country.
  - VIX is the Chicago Board Options Exchange Market Volatility Index (VIX).
- *Other bank-specific variables*
  - Deposits growth is generated by taking the difference of the deposits of a bank.
  - Profitability is the return on equity in percentage.
  - Loan quality is the ratio of loan loss reserves to gross loans.
  - Loan/deposit ratio is the ratio of net loans to short term funding in percentage.
  - Efficiency is the ratio of cost to income in percentage.
  - Liquidity is the ratio of liquid assets to the sum of deposits and short term funding.

In order to avoid the effects of possible mergers and acquisitions, the credit growth variable is trimmed if the value of the variable exceeds the 99^{th} percentile. Descriptive statistics of the variables are given in Table (2.4). Table (2.5) reports the correlation of the credit growth variable with bank level variables and macroeconomic indicators. Credit growth has a negative correlation with ΔRER and a positive correlation with leverage, leverage growth and equity growth; however, the correlation with the leverage variable is small compared to other correlation values.

2.4. Econometric Methodology

The panel data regression equation used in the study can be given as follows:

$$\Delta GL_{it} = c + \sum_{k=1}^{m} \alpha_k macrolevel_{i,t}^{k} + \sum_{j=1}^{n} \beta_j banklevel_{i,t}^{j} + \varepsilon_{i,t}, \tag{2.1}$$

where ΔGL_{it} is the growth of gross loans for bank i at time t, m is the number of macro level variables, n is the number of bank level variables, and $\varepsilon_{it} \sim IID(0, \sigma_{\varepsilon}^{2})$ is the error term. ΔRER, GDP, Debt/GDP, and ΔM2 are included as *macrolevel* variables. The macro level variables are included in all regressions except the one with the VIX variable. For the *banklevel* variables, different permutations of the bank level variables are used. Baseline bank-specific variables are first used one-by-one, then all together, and with other bank-specific variables in order to see their robustness to inclusion of other variables.

The regressions use a fixed effects model with year dummies and clustering of countries. The year dummies are added to the regressions for two reasons. The first reason is that empirical evidence suggests that banking behavior in lending might be different between normal times and financial crisis years (Peek and Rosengren, 2000; Goldberg, 2002; Peria et al., 2002; Everaert et al., 2015). By using year dummies, the effect of the crisis is assumed to be grasped by allowing the intercept to change every year. The second reason is that, as pointed out by Roodman (2006), inclusion of time dummies makes correlation across individuals (i.e. banks in our case) less likely after an idiosyncratic shock. The variance estimator is clustered at the country level to handle the possibility of correlation in the error term

Before estimation of the fixed effect model, the Hausman test (Hausman, 1978) is used to decide on fixed effects versus random effects models. According to the test statistics, the random effects model is significantly rejected.[2]

The expected signs of the variables and differences between domestic and foreign banks can be given as follows: The leverage variable measures a bank's capability of turning extra capital into lending while the difference variable shows the capability based on the existing capital stock. Both variables are expected to have a positive effect on credit growth. For foreign banks, which are assumed to have better international financial borrowing conditions, the effects of these variables are expected to be higher.

The impact of country-specific economic conditions is measured by the macro control variables. A high economic growth rate is expected to have a positive impact on credit growth, while an increase in debt-to-GDP growth is expected to have a negative impact since accumulating debt might increase financial risk in a country. The money stock growth variable measures the effect of currency restrictions. In order to hedge itself against currency risk or benefit from changes in the foreign exchange markets, a bank should be able to borrow domestically, buy foreign exchange and deposit it or vice versa. A currency mismatch would mitigate this option. Therefore, ΔM2 is expected to have a positive sign and the effect is expected to be more significant for foreign banks.

The expected sign of inflation is ambiguous. Although inflation increases nominal credit, at the same time it is associated with a drop in credit growth (see e.g. Égert et al. (2006)) because

[2] Results are available upon request. It has to be noted that the random effects model is not significantly rejected for small model specifications of state owned banks. However, for the largest model this is not the case, and insignificance of the fixed effects model for these cases does not effect the main conclusions derived from the regressions.

of its negative impact on growth, creation of uncertainty due to the increased volatility of high inflation rates and the unwillingness of banks to lend when they experience high inflation rates.

In addition to the macro control variables, separate regressions will be carried out using the VIX index. This variable is used to analyze the impact of global risk on domestic loans. As global risk increases, domestic credit is expected to decrease. For foreign banks, which are more likely to be influenced by global conditions due to their relations with their parent banks, the magnitude of the impact is expected to be higher.

Deposits growth measures the effect of the funding conditions of an individual bank on credit growth (De Haas and Lelyveld, 2014). A bank with better funding conditions is expected to have a higher rate of credit growth. The effects of other bank-level variables are ambiguous and they are added to the regressions as control variables.

2.5. Empirical Results

2.5.1. Baseline Results

Table (2.6) displays the estimation results for various specifications for the pooled sample. The exact specification does not substantially change the results, though GDP growth becomes insignificant in the richest specification (5) and leverage in specification (4) when leverage growth is also included. Note that the number of banks in the sample changes slightly due to data availability in the range from 1,198 to 1,396 depending on the specification. The R^2 substantially increases from 0.205 to 0.519: adding bank-specific variables therefore significantly adds to the explanatory power of the model. The sample regressions therefore corroborates with the findings by Bruno and Shin (2015) at the bank level.

The results show that credit growth shows a close link with both macroeconomic and bank-specific variables. While the former certainly model credit demand, the latter can to some extent be interpreted as capturing supply-side factors. According to our analysis and for the full sample, the change in the debt/GDP ratio is negatively linked to credit growth, whereas inflation is positively linked to credit growth. As nominal credit growth will in general be affected by inflation, this also gives insights on whether inflation is detrimental to real private credit growth. With a coefficient of less than 1, inflation in fact dampens credit growth (Guo and Stepanyan, 2011). The positive coefficient of GDP growth as a standard explanatory variable for credit growth becomes insignificant when the full set of micro variables is added, meaning that its role is captured by one of those measures.

In the pooled sample, changes in the real exchange rate show a significantly negative sign, meaning that a depreciation of the domestic currency goes along with an increase of the credit volume.

Finally, a broad set of bank-specific variables turn out to be relevant. All coefficients except the one for profitability are significant. Both leverage and leverage growth show the expected positive relation with credit growth; the same applies to equity and deposit growth and the loan/deposit ratio, indicating a link between the ability to lend and credit growth. These coefficients therefore reflect the supply side of the credit market. The coefficient for loan quality is found to be significantly negative, indicating that a rapid credit expansion may happen at the cost of lower credit quality or that picking high-quality loans limits credit expansion.

Furthermore we find that efficiency and liquidity are negatively linked with credit growth. As

De Haas and Van Lelyveld (2010) point out, the expected sign for these variables is indeterminate. This is because on the one hand liquidity ratios may reflect risk aversion and accordingly a moderate expansion of credit and *vice versa*, or on the other hand, because high excess liquidity may enable banks to rapidly expand their credit portfolio.

The analysis for the subsamples in Tables (2.7)-(2.11) shows some remarkable differences between the groups. Concerning the macro variables, the link between GDP and credit growth breaks is particularly pronounced for state-owned banks. While there are no consistent differences between the subsamples in the coefficients of money growth, the debt/GDP ratio and inflation, the macroeconomic variables turn out to differ between subsamples but do not show a consistent pattern.

Leverage growth and equity growth all have the expected signs and are consistently significant at the 1% level in every specification. They seem to be the main drivers of credit growth in all bank categories. Similar to Bruno and Shin (2015)), however, we do not see the same consistency in the leverage variable, with the coefficient also being quite small. Other variables except loan quality and loan-to-deposits ratio do not give consistently significant results. Inflation is only significant for the greenfield banks subsample. These results provide empirical evidence for the model developed in Bruno and Shin (2015) with micro data.

The sign of the real exchange rate variable is still intuitively correct, but it is significant throughout only for the subsample of foreign banks. In contrast, for domestic private banks, the coefficient in absolute terms is larger than the one for foreign banks, but it loses its significance in the specification with all bank-level variables. The picture for (domestic) state-owned banks is similar. In summary, we do find some evidence that the real exchange rate channel is typical for foreign banks, but we cannot conclude that it exclusively works through these banks. It also seems to affect private domestic banks to some extent and, to an even lesser extent, state-owned banks.

2.5.2. Effect of Flexible Exchange Rate Regimes

The previous subsection analyzed the impact of real exchange rate changes on the growth rate of loans and found that–for the full sample–a depreciation of domestic currencies goes along with increased credit growth. A related question deals with the impact of the exchange rate regime on credit growth. One would expect credit growth to be higher under a pegged exchange rate regime for a couple of reasons. First, Magud et al. (2014) describe how capital inflows create a link between the exchange rate regime and credit expansion. While under a floating exchange rate capital inflows appreciate the domestic currency, there will be no further effects on monetary aggregates. This only partly holds under a fixed regime, when the central bank is forced to intervene. The reason for this is that sterilization of the intervention is costly and therefore in most cases incomplete and the monetary base is expanded. As a consequence, more rigid exchange rate regimes are likely to be accompanied by stronger credit growth when capital flows in. Second, as Montiel and Reinhart (2001) point out, deposit insurance for claims acquired by foreign depositors on domestic banks coupled with a pegged (e.g. guaranteed) exchange rate reduces the banks' cost of attracting external funds. Accordingly, they increase their lending capacity. At the same time, a pegged exchange rate creates incentives for taking on debt in a foreign currency.

Therefore, we drop the changes in the real exchange rate and replace them with a dummy variable, which takes the value of one if the regime is flexible and zero if it is rigid. Instead of the nine regimes defined by the IMF, floating exchange rate regimes are taken to represent the positive value in the dummy variable in order to avoid further fragmentation of the data in the subsample regressions. Other regimes are taken to be the rigid regimes. The results are displayed in (2.12). For the pooled sample, we find a highly significant relation between the flexibility of the exchange rate regime and credit growth, corroborating the findings by Magud et al. (2014): If the exchange rate regime moves towards a more flexible one, credit growth increases. This relation, however, no longer remains significant when we turn to the subgroups of banks. Although the sign of the coefficient remains positive for all bank groups, it is no longer significant.

2.5.3. Effect of VIX

Finally, we follow the approach Bruno and Shin (2015) and use the VIX index as a proxy for global leverage. The rationale is that when global risk increases capital inflows to emerging markets will decrease (Forbes and Warnock, 2012). Therefore an increase in the VIX should go along with a decrease in bank loans due to a reduction in capital flows.

Regressions results with the VIX index as an additional variable are displayed in Table (2.13). The sign for the real exchange rate remains negative when the VIX is added. The coefficient for the VIX itself, however, shows the expected sign only for domestic banks. For the other bank groups, the coefficient is insignificant and positively signed. This means that for all groups other than domestic banks, credit growth increases in line with global uncertainty.

2.5.4. Robustness Checks

GMM estimation

A robustness check with generalized method of moments (GMM) is carried for two reasons. The first reason is that previous studies such as De Haas and Lelyveld (2014) show that, at the bank level, there is a statistically significant relation between credit growth and its first lag. Therefore, a lagged credit growth variable is included in the regressions and the problems that such inclusion entails are solved by estimating the equation using a GMM estimator as suggested in the literature. The second reason is the possibility of endogenous relations of the bank-level variables.

The GMM model is estimated by the system GMM estimator for panel data developed by Holtz-Eakin et al. (1988) and Arellano and Bond (1991) (AB). The two-step GMM estimator is used to account for the possibility of heteroskedasticity in the data. The two-step GMM estimator is reported to give downward biased standard errors; so the finite sample correction of Windmeijer (2005) is employed. In the estimation of the models, lags of credit growth, leverage, leverage growth, equity growth, loan quality, loan-to-deposit ratio, and liquidity from the bank-level variables are assumed to be endogenous, while the macroeconomic variables are treated as strictly exogenous variables.

Regressions are carried out with the longest specification that used both macroeconomic variables and bank-level variables. The results for the GMM estimations are given in Table (2.14).[3] The results for leverage growth and equity growth are robust to the GMM estimation. The results show that for the pooled sample and foreign banks, the real exchange rate variable is still significant. The real exchange rate is also significant for the domestic private banks and takeover banks

[3] The AB GMM estimations are sensitive to changes in the number of instruments and a Hansen p-value that is close to 1 indicates that there might be a problem with the number of instruments used (Roodman, 2006). The number of lags of the endogenous variables is constrained to get the best possible results from the regressions.

but, as reported below, the results are not robust to other specifications.

Net loans

As mentioned earlier, there are different definitions of loans provided by banks in the dataset and we choose to use gross loans, which are defined as net loans plus loan loss reserves. In order to check the robustness of the baseline results with a different definition of loans, regressions are carried out by defining credit growth as the change in net loans.

The regression results with the net loans credit growth variable are given in Table (2.15). The results for leverage growth and equity growth are robust to the new credit growth specification, while the exchange rate variable is only significant in the pooled sample and foreign bank regressions.

Small sample

The baseline regressions use the banking data regardless of the survival time of banks during the study period. One criticism of this approach would be that the results might be driven by the banks that have only a few observations in the dataset. This point is taken into account by repeating regressions with banks that have more than seven years of data.

Table (2.16) gives the results with the smaller dataset. As can be seen in the table, the number of banks in the pooled regressions drops to 1,198 from 1,338. The main points of the baseline regressions are confirmed with the smaller dataset.

2.6. Conclusions

This study analyzes the link between credit growth with supply-side bank-level and macroeconomic variables. It turns out leverage growth and equity growth are the dominating determinants. Furthermore, the real exchange rate has a significant impact through local banks. The variables we find to be relevant play a role in cross-border capital flows in the Bruno and Shin (2015) model.

We do not find that other macroeconomic variables play a prominent role; the same applies to bank-specific variables. The results are robust to a couple of modifications. Furthermore, we investigate whether credit growth is affected by the flexibility of the exchange rate regime. We do find that credit growth differs depending on the aggregate level. The coefficient of the exchange rate regime dummy has a negative sign, but the link becomes insignificant for all bank groups in the sample. Therefore, we conclude that the exchange rate regime plays a marginal role compared with the impact of the (real) exchange rate itself. Our results therefore are in conflict with those of Magud et al. (2014), who conclude that flexibility of exchange rate regimes has a negative influence of domestic credit growth.

Our analysis therefore revisits some previous findings from the literature, but adds to it by testing the role of the real exchange rate in the determination of loans at the bank level. This aspect is particularly interesting in the course and aftermath of the recent financial crisis, during which the US dollar appreciated against most emerging market currencies. Our results might also provide guidance in policymaking as the US dollar returns to its pre-crisis value.

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Tables

Table 2.1: Number of foreign and domestic banks

	Number of Banks			
	Domestic		Foreign	
	1999	2010	1999	2010
Bulgaria	21	11	9	21
Croatia	44	21	9	28
Czech Republic	17	12	18	32
Estonia	7	4	7	8
Hungary	9	11	26	39
Latvia	20	14	6	11
Lithuania	9	4	5	7
Poland	26	16	32	58
Romania	19	9	11	25
Russia	184	945	17	66
Slovakia	15	4	10	19
Slovenia	21	16	7	11
Turkey	47	30	10	25
Ukraine	32	43	7	35
Total	471	1140	174	385

Number of foreign and domestic banks for each country used in the dataset. The table gives the number of banks that exist in the dataset.

Table 2.2: Correlation of gross loans and domestic credit

	correlation
Bulgaria	0.95
Croatia	0.95
Czech Republic	
Estonia	0.22
Hungary	0.87
Latvia	0.97
Lithuania	0.95
Poland	0.68
Romania	0.96
Russia	0.93
Slovakia	0.75
Slovenia	0.97
Turkey	0.94
Ukraine	0.84

Correlation of aggregated gross loans as a share of GDP with domestic credit provided by banks as a share of GDP for each country in the sample.

Table 2.3: Key variable values

		2001	2005	2008	2009	2010	All
Credit growth	All	0.19	0.22	0.27	-0.003	0.03	0.22
	Foreign	0.24	0.21	0.16	0.02	-0.06	0.25
	Domestic	0.16	0.23	0.3	-0.01	0.03	0.21
Leverage	All	8.1	7.3	7.6	7	5.9	7.4
	Foreign	9	9.6	9.7	9.1	5.9	9.3
	Domestic	7.7	6.5	7.2	6.6	5.9	6.8
Equity growth	All	0.16	0.14	0.23	0.03	0.17	0.2
	Foreign	0.19	0.1	0.12	0.08	0.1	0.21
	Domestic	0.14	0.17	0.26	0.02	0.17	0.2

Values of key variables over time for pooled sample, foreign banks, and domestic banks

Table 2.4: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Credit growth	0.217	0.331	-1.115	1.102	6974
Leverage	8.446	22.353	-100.385	1589.499	5720
Leverage growth	0	0.357	-2.12	4.868	5357
Equity growth	0.206	0.348	-5.403	3.915	6957
RER	-0.059	0.097	-0.269	0.267	6959
ΔM2	0.208	0.126	-0.63	0.945	6946
ΔGDP	0.036	0.055	-0.18	0.122	6974
ΔDebt/GDP	-0.012	0.051	-0.391	0.162	6830
Inflation	0.792	0.166	0.193	1.011	6974
Deposits growth	0.146	0.857	-10.092	10.878	6324
Profitability	10.051	27.297	-611.584	917.951	6960
Loan quality	6.586	7.662	-2.392	100	6366
Loan/deposit ratio	100.497	76.647	0	991.39	6891
Efficiency	72.011	25.629	0.159	475.303	6940
Liquidity	55.292	58.213	0	967.981	6902
VIX	0.223	0.118	0.107	0.461	6974

Table 2.5: Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Credit growth	(1)	1															
Leverage	(2)	.024	1														
Leverage growth	(3)	.26	.22	1													
Equity growth	(4)	.38	-.21	-.54	1												
ΔRER	(5)	-.34	-.02	-.12	-.27	1											
ΔM2	(6)	.14	-.051	.078	.084	-.2	1										
ΔGDP	(7)	.39	-.0097	.13	.28	-.76	.39	1									
ΔDebt/GDP	(8)	-.27	.048	-.11	-.17	.39	-.45	-.6	1								
Inflation	(9)	-.3	.022	-.15	-.13	.27	-.48	-.49	.71	1							
Deposits growth	(10)	.27	.012	.22	.1	-.11	.026	.11	-.081	-.09	1						
Profitability	(11)	.11	.034	-.099	.25	-.083	.041	.11	-.1	-.072	.043	1					
Loan quality	(12)	-.29	-.044	-.073	-.15	.086	-.0088	-.1	.061	.09	-.1	-.12	1				
Loan/deposit ratio	(13)	-.029	-.063	-.069	-.041	.058	.01	-.1	.078	.17	-.1	-.037	-.0022	1			
Efficiency	(14)	-.22	-.015	-.017	-.17	.18	-.068	-.23	.15	.25	-.078	-.25	.12	.04	1		
Liquidity	(15)	-.12	-.049	-.088	.066	-.011	.016	-.018	.00084	.092	-.083	-.012	.14	.17	.067	1	
VIX	(16)	-.32	.012	-.12	-.24	.73	-.41	-.88	.48	.36	-.095	-.074	.071	.086	.18	.014	1
Observations		6974															

Correlation matrix of the variables used in the study. The correlation values are for the whole sample.

Table 2.6: Pooled sample

	1	2	3	4	5
Leverage	0.0057**			0.0013	0.0029**
	(2.38)			(1.03)	(2.42)
Leverage growth		0.16***		0.47***	0.51***
		(19.72)		(20.60)	(26.20)
Equity growth			0.22***	0.54***	0.61***
			(14.91)	(29.25)	(31.11)
ΔRER	-0.68***	-0.67***	-0.58***	-0.28**	-0.23***
	(-4.79)	(-4.68)	(-5.32)	(-3.01)	(-3.78)
ΔM2	-0.082	-0.11	-0.054	-0.0026	0.0028
	(-0.75)	(-0.84)	(-0.73)	(-0.04)	(0.05)
ΔGDP	2.39***	2.26**	1.72**	0.92**	0.63
	(3.26)	(2.95)	(2.76)	(2.47)	(1.60)
ΔDebt/GDP	-1.18**	-1.35***	-0.45	-1.07***	-0.72***
	(-2.17)	(-3.12)	(-1.28)	(-4.44)	(-4.12)
Inflation	0.77***	0.59**	0.53***	0.40***	0.41**
	(3.05)	(2.54)	(3.19)	(3.07)	(2.44)
Deposits growth					0.017***
					(10.77)
Profitability					-0.00060
					(-1.63)
Loan quality					-0.011***
					(-22.73)
Loan/deposit ratio					0.0014***
					(21.25)
Efficiency					-0.00052*
					(-1.88)
Liquidity					-0.0014**
					(-2.85)
Constant	-0.49**	-0.20	-0.24**	-0.18*	-0.078
	(-2.84)	(-1.27)	(-2.20)	(-2.10)	(-0.81)
N	5624	5289	6771	5289	4675
R^2 overall	0.205	0.261	0.276	0.488	0.519
R^2 between	0.094	0.162	0.192	0.447	0.430
R^2 within	0.274	0.312	0.306	0.472	0.575
N. Banks	1338	1318	1396	1318	1198

Regression results for the pooled sample. Fixed effects regression with time fixed effects and country is chosen to be the group variable for the variance estimator. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: Private domestic banks

	1	2	3	4	5
Leverage	0.0096***			-0.0017*	0.0025
	(14.20)			(-1.98)	(1.49)
Leverage growth		0.15***		0.45***	0.49***
		(14.51)		(18.55)	(25.21)
Equity growth			0.23***	0.51***	0.61***
			(12.17)	(21.04)	(41.92)
ΔRER	-0.55**	-0.81***	-0.56***	-0.38**	-0.24
	(-2.35)	(-3.86)	(-4.03)	(-2.51)	(-1.57)
ΔM2	-0.047	-0.00077	-0.048	0.11*	0.092*
	(-0.46)	(-0.01)	(-0.57)	(1.88)	(2.09)
ΔGDP	2.02*	1.97*	1.63*	0.75	0.35
	(2.02)	(1.96)	(1.88)	(1.37)	(0.75)
ΔDebt/GDP	-1.55	-1.81**	-0.39	-1.48***	-1.29***
	(-1.71)	(-2.47)	(-1.00)	(-3.34)	(-3.22)
Inflation	0.49*	0.32	0.27	0.31**	0.24
	(2.03)	(1.74)	(1.22)	(2.26)	(1.32)
Deposits growth					0.016***
					(21.50)
Profitability					-0.00021
					(-1.09)
Loan quality					-0.010***
					(-39.32)
Loan/deposit ratio					0.0015***
					(39.94)
Efficiency					-0.00081***
					(-3.23)
Liquidity					-0.0019***
					(-22.80)
Constant	-0.24	-0.15	-0.13	-0.18*	0.0092
	(-1.57)	(-1.12)	(-0.90)	(-1.95)	(0.08)
N	3978	3810	4589	3810	3541
R^2 overall	0.245	0.272	0.304	0.482	0.508
R^2 between	0.150	0.187	0.265	0.529	0.428
R^2 within	0.286	0.313	0.310	0.458	0.575
N. Banks	1021	1009	1071	1009	939

Regression results for the domestic private banks sub-sample. Fixed effects regression with time fixed effects and country is chosen to be the group variable for the variance estimator. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: State banks

	1	2	3	4	5
Leverage	0.0044			-0.00066	0.0058
	(0.55)			(-0.10)	(0.56)
Leverage growth		0.16***		0.49**	0.40*
		(5.08)		(2.90)	(2.07)
Equity growth			0.16***	0.54**	0.47**
			(3.42)	(3.04)	(2.44)
ΔRER	-0.77***	-0.69**	-0.57**	-0.15	-0.10
	(-3.44)	(-2.57)	(-2.36)	(-0.50)	(-0.34)
ΔM2	0.14	0.084	0.11	0.20**	0.054
	(0.82)	(0.45)	(0.73)	(2.69)	(0.66)
ΔGDP	3.96***	3.59***	3.12**	2.08**	1.63*
	(3.41)	(3.81)	(2.81)	(2.49)	(2.02)
ΔDebt/GDP	-0.76	-0.57	-0.25	-0.31	0.28
	(-1.38)	(-0.97)	(-0.71)	(-0.55)	(0.45)
Inflation	1.71***	1.12***	1.36**	0.59*	0.56
	(3.68)	(3.33)	(2.73)	(1.81)	(1.67)
Deposits growth					0.034
					(1.12)
Profitability					-0.0015
					(-0.79)
Loan quality					-0.022***
					(-4.56)
Loan/deposit ratio					0.0014*
					(1.98)
Efficiency					-0.0014
					(-1.29)
Liquidity					-0.00015
					(-1.08)
Constant	-1.02***	-0.95***	-0.80**	-0.58*	-0.080
	(-3.22)	(-3.40)	(-2.27)	(-2.13)	(-0.44)
N	368	338	441	338	268
R^2 overall	0.110	0.177	0.115	0.474	0.413
R^2 between	0.003	0.026	0.028	0.412	0.420
R^2 within	0.275	0.312	0.259	0.473	0.532
N. Banks	76	74	79	74	62

Regression results for the state banks sub-sample. Fixed effects regression with time fixed effects and country is chosen to be the group variable for the variance estimator. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: Foreign banks

	1	2	3	4	5
Leverage	0.0027**			0.0019	0.0023***
	(2.19)			(1.61)	(3.09)
Leverage growth		0.20***		0.54***	0.63***
		(3.97)		(5.29)	(10.30)
Equity growth			0.19***	0.59***	0.70***
			(6.57)	(6.84)	(11.31)
ΔRER	-0.62***	-0.52***	-0.63***	-0.21**	-0.19**
	(-3.96)	(-3.70)	(-4.91)	(-2.89)	(-2.54)
ΔM2	-0.015	-0.061	-0.026	-0.064*	-0.050*
	(-0.25)	(-1.03)	(-0.44)	(-2.13)	(-1.82)
ΔGDP	1.31**	1.43**	1.21**	0.57**	0.55*
	(2.53)	(2.33)	(2.62)	(2.42)	(1.88)
ΔDebt/GDP	-1.72***	-1.70***	-1.03*	-1.10***	-0.39
	(-3.82)	(-4.11)	(-2.09)	(-3.94)	(-1.39)
Inflation	0.87***	0.77***	0.59**	0.34**	0.23
	(3.06)	(3.47)	(2.73)	(2.72)	(1.70)
Deposits growth					0.0052
					(0.89)
Profitability					-0.00014
					(-0.31)
Loan quality					-0.0029
					(-0.81)
Loan/deposit ratio					0.0012***
					(4.13)
Efficiency					0.0016***
					(3.16)
Liquidity					-0.0014*
					(-2.03)
Constant	-0.45**	-1.13***	-0.23	-0.61***	-0.67***
	(-2.30)	(-4.70)	(-1.52)	(-4.78)	(-5.29)
N	1278	1141	1741	1141	866
R^2 overall	0.190	0.274	0.251	0.497	0.613
R^2 between	0.120	0.148	0.129	0.254	0.417
R^2 within	0.307	0.396	0.334	0.552	0.679
N. Banks	286	276	311	276	230

Regression results for the foreign banks sub-sample. Fixed effects regression with time fixed effects and country is chosen to be the group variable for the variance estimator. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: Greenfield banks

	1	2	3	4	5
Leverage	0.0041			0.0011	0.0027***
	(1.63)			(0.80)	(3.05)
Leverage growth		0.25***		0.59***	0.62***
		(9.90)		(8.46)	(9.54)
Equity growth			0.19***	0.65***	0.73***
			(4.33)	(7.93)	(8.61)
ΔRER	-0.68***	-0.68***	-0.56***	-0.23***	-0.18*
	(-3.63)	(-4.84)	(-3.26)	(-3.04)	(-1.88)
ΔM2	-0.015	-0.052	-0.062	-0.068	-0.019
	(-0.20)	(-0.78)	(-0.86)	(-1.64)	(-0.52)
ΔGDP	1.39**	1.63**	1.17**	0.56**	0.35
	(2.18)	(2.53)	(2.70)	(2.89)	(1.09)
ΔDebt/GDP	-1.38***	-1.57***	-0.79	-1.03***	-0.63*
	(-3.09)	(-3.61)	(-1.50)	(-3.59)	(-1.80)
Inflation	0.78**	0.82***	0.56**	0.36**	0.40*
	(2.53)	(3.63)	(2.56)	(2.37)	(1.80)
Deposits growth					-0.013
					(-1.48)
Profitability					-0.00071
					(-1.26)
Loan quality					-0.0072**
					(-2.67)
Loan/deposit ratio					0.0013***
					(3.76)
Efficiency					0.0015*
					(2.10)
Liquidity					-0.0012*
					(-1.82)
Constant	-0.41*	-1.17***	-0.15	-0.61***	-0.23*
	(-2.05)	(-4.69)	(-1.03)	(-3.52)	(-2.00)
N	823	738	1079	738	539
R^2 overall	0.139	0.236	0.214	0.528	0.632
R^2 between	0.063	0.061	0.093	0.408	0.592
R^2 within	0.258	0.374	0.284	0.547	0.665
N. Banks	164	157	178	157	127

Regression results for greenfield (foreign) banks sub-sample. Fixed effects regression with time fixed effects and country is chosen to be the group variable for the variance estimator. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.11: Takeover banks

	1	2	3	4	5
Leverage	0.0015**			0.0025**	-0.0013
	(2.43)			(2.43)	(-0.45)
Leverage growth		0.11		0.42*	0.71***
		(1.03)		(1.92)	(8.95)
Equity growth			0.17***	0.46***	0.71***
			(3.47)	(3.12)	(12.16)
ΔRER	-0.50***	-0.25	-0.72***	-0.073	-0.17
	(-3.42)	(-1.44)	(-5.12)	(-0.49)	(-1.50)
ΔM2	-0.055	-0.16**	0.056	-0.15**	-0.14
	(-0.78)	(-2.54)	(0.79)	(-2.67)	(-1.58)
ΔGDP	1.34***	1.32**	1.17*	0.72**	1.16***
	(3.52)	(2.73)	(1.90)	(2.51)	(3.34)
ΔDebt/GDP	-2.39***	-1.60***	-1.74**	-1.00*	0.33
	(-3.43)	(-3.27)	(-2.27)	(-1.94)	(1.01)
Inflation	1.08**	0.52	0.77**	0.063	-0.37
	(2.90)	(1.66)	(2.90)	(0.20)	(-1.05)
Deposits growth					0.012**
					(2.34)
Profitability					0.00034
					(0.50)
Loan quality					0.011**
					(2.65)
Loan/deposit ratio					0.00090***
					(3.08)
Efficiency					0.0018
					(1.50)
Liquidity					-0.0041***
					(-4.73)
Constant	-0.57**	-0.060	-1.11***	0.14	0.35
	(-2.33)	(-0.27)	(-4.08)	(0.70)	(1.31)
N	455	403	662	403	327
R^2 overall	0.302	0.400	0.317	0.514	0.587
R^2 between	0.182	0.273	0.160	0.232	0.327
R^2 within	0.461	0.506	0.453	0.608	0.769
N. Banks	122	119	133	119	103

Regression results for takeover (foreign) banks sub-sample. Fixed effects regression with time fixed effects and country is chosen to be the group variable for the variance estimator. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.12: Exchange rate regime

	1	2	3	4	5	6
Leverage	0.00056***	0.00041***	0.0025	0.0057	0.00056**	-0.0019
	(5.12)	(3.42)	(1.43)	(0.58)	(2.50)	(-0.73)
Leverage growth	0.52***	0.65***	0.49***	0.40*	0.64***	0.73***
	(29.09)	(11.09)	(24.56)	(2.07)	(9.97)	(9.87)
Equity growth	0.62***	0.70***	0.61***	0.47**	0.73***	0.72***
	(33.23)	(11.44)	(43.86)	(2.46)	(8.96)	(12.62)
ER Regime	0.035***	0.014	0.020	0.050	0.013	0.0076
	(3.24)	(1.13)	(1.07)	(1.11)	(1.19)	(0.28)
ΔM2	0.015	-0.053	0.094*	0.053	-0.017	-0.16
	(0.31)	(-1.59)	(2.05)	(0.81)	(-0.49)	(-1.67)
ΔGDP	0.69*	0.51*	0.36	1.72**	0.28	1.14***
	(1.92)	(1.88)	(0.79)	(2.35)	(0.85)	(3.50)
ΔDebt/GDP	-0.62**	-0.23	-1.24**	0.42	-0.54	0.52
	(-2.38)	(-0.84)	(-2.52)	(0.87)	(-1.64)	(1.64)
Inflation	0.61***	0.20	0.37	0.91	0.43*	-0.46
	(3.38)	(1.45)	(1.15)	(1.69)	(1.80)	(-1.37)
Deposits growth	0.016***	0.0043	0.015***	0.032	-0.014	0.011**
	(10.73)	(0.71)	(20.23)	(1.06)	(-1.66)	(2.35)
Profitability	-0.00052	-0.00026	-0.00019	-0.00099	-0.00089	0.00029
	(-1.60)	(-0.59)	(-1.20)	(-0.55)	(-1.63)	(0.43)
Loan quality	-0.011***	-0.0040	-0.010***	-0.022***	-0.0081***	0.0093**
	(-19.22)	(-1.42)	(-38.58)	(-4.37)	(-3.77)	(2.40)
Loan/deposit ratio	0.0014***	0.0011***	0.0015***	0.0015*	0.0012***	0.00087**
	(20.78)	(4.02)	(39.51)	(1.97)	(3.68)	(2.86)
Efficiency	-0.00039	0.0016***	-0.00078***	-0.0011	0.0014*	0.0019
	(-1.55)	(3.21)	(-3.32)	(-1.06)	(2.07)	(1.49)
Liquidity	-0.0014**	-0.0014*	-0.0019***	-0.00018	-0.0011*	-0.0042***
	(-2.90)	(-1.99)	(-24.08)	(-1.19)	(-1.79)	(-5.37)
Constant	-0.39**	-0.66***	-0.18	-0.69	-0.29	0.39
	(-2.55)	(-3.75)	(-0.60)	(-1.19)	(-1.51)	(1.33)
N	4685	876	3541	268	543	333
R^2 overall	0.487	0.594	0.500	0.358	0.622	0.564
R^2 between	0.385	0.392	0.419	0.375	0.588	0.303
R^2 within	0.574	0.676	0.575	0.535	0.664	0.769
N. Banks	1199	231	939	62	127	104

Results for regressions with exchange rate regime variable. The columns report results for (1) pooled sample, (2) domestic private banks, (3) state banks, (4) foreign banks, (5) greenfield banks, (6) takeover banks respectively. Fixed effects regression with time fixed effects and country is chosen to be the group variable for the variance estimator. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.13: VIX

	1	2	3	4	5	6
Leverage	0.0054**	0.0093***	0.0041	0.0027*	0.0013	0.0041
	(2.21)	(14.50)	(0.58)	(1.97)	(1.48)	(1.54)
ΔRER	-0.46**	-0.29	-0.35	-0.46**	-0.38*	-0.49*
	(-2.18)	(-1.04)	(-1.25)	(-2.27)	(-1.84)	(-2.08)
VIX	0.16	-0.074	0.54**	1.18***	1.57***	1.04***
	(0.95)	(-0.31)	(2.69)	(5.88)	(13.75)	(4.12)
Constant	-0.097*	-0.046	-0.17**	-0.52***	-0.69***	-0.48***
	(-2.04)	(-0.70)	(-2.63)	(-6.29)	(-12.95)	(-4.77)
N	5709	4030	375	1304	463	841
R^2 overall	0.221	0.244	0.181	0.216	0.355	0.155
R^2 between	0.132	0.150	0.127	0.163	0.229	0.094
R^2 within	0.260	0.279	0.220	0.285	0.417	0.243
N. Banks	1344	1027	76	287	122	165

Results for regressions with VIX index. The columns report results for (1) pooled sample, (2) domestic private banks, (3) state banks, (4) foreign banks, (5) greenfield banks, (6) takeover banks respectively. Fixed effects regression with time fixed effects and country is chosen to be the group variable for the variance estimator. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.14: Robustness, GMM estimation

	1	2	3	4	5	6
Leverage	0.0082***	0.0076*	0.0029	-0.00015	-0.000011	-0.00016
	(2.83)	(1.82)	(0.29)	(-0.19)	(-0.01)	(-0.05)
Leverage growth	0.44***	0.36***	0.33*	0.64***	0.83***	0.81***
	(6.10)	(4.90)	(1.92)	(11.36)	(7.34)	(4.92)
Equity growth	0.58***	0.53***	0.46***	0.65***	0.85***	0.91***
	(9.71)	(7.06)	(3.31)	(11.73)	(6.16)	(4.88)
ΔRER	-0.29***	-0.48**	-0.20	-0.14*	0.0084	-0.064
	(-3.07)	(-2.49)	(-0.66)	(-1.68)	(0.06)	(-0.43)
ΔM2	0.033	0.066	0.058	-0.075	-0.027	-0.11
	(0.57)	(0.94)	(0.35)	(-0.90)	(-0.16)	(-1.19)
ΔGDP	0.25	0.46	1.55	0.57**	-0.072	-0.081
	(0.97)	(1.29)	(0.88)	(2.34)	(-0.18)	(-0.14)
ΔDebt/GDP	-0.49**	-0.86***	-0.79	-0.34	-1.50	-0.84
	(-2.29)	(-3.18)	(-0.54)	(-1.27)	(-1.59)	(-1.15)
Inflation	-0.11	0.058	-0.080	-0.052	0.14	-0.12
	(-1.05)	(0.47)	(-0.20)	(-0.50)	(0.45)	(-0.39)
Deposits growth	0.019	0.053*	-0.0011	0.0096	-0.063	-0.018
	(0.66)	(1.90)	(-0.01)	(0.46)	(-1.27)	(-0.20)
Profitability	0.0017*	0.0012	-0.0024	-0.00014	-0.0013	-0.00015
	(1.72)	(0.83)	(-0.76)	(-0.19)	(-0.84)	(-0.13)
Loan quality	-0.0087***	-0.0082***	-0.0070	-0.0061	-0.0091	-0.012
	(-3.17)	(-2.89)	(-1.14)	(-1.64)	(-0.94)	(-1.37)
Loan/deposit ratio	0.00056**	0.00083***	0.0020**	0.00068**	0.0015***	0.00086
	(2.03)	(3.09)	(2.29)	(2.22)	(2.87)	(1.32)
Efficiency	0.00083	-0.000095	0.00016	0.0029***	0.0014	0.00093
	(1.49)	(-0.13)	(0.07)	(4.54)	(0.75)	(1.04)
Liquidity	0.00019	-0.00051	-0.00043**	-0.00016	-0.00078	-0.0018*
	(0.92)	(-1.28)	(-2.05)	(-0.18)	(-0.42)	(-1.87)
Credit growth(-1)	-0.19***	-0.21***	-0.24*	-0.14***	-0.075	-0.21***
	(-3.57)	(-3.73)	(-1.95)	(-2.93)	(-1.48)	(-2.94)
Constant	0.023	0.023	-0.0046	-0.011	-0.45	0.29
	(0.20)	(0.20)	(-0.01)	(-0.10)	(-1.23)	(0.98)
N	3718	2705	230	783	488	295
Hansen P-val	0.126	0.878	0.972	0.901	0.817	0.393
AR(1) P-val	0.000	0.000	0.085	0.000	0.000	0.020
AR(2) P-val	0.981	0.923	0.624	0.769	0.607	0.590
N.insts	296	296	75	236	76	74

Results for GMM estimations with two-step Bond (2002) estimator with Windmeijer (2005) correction of standard errors. Leverage, leverage growth, and equity growth variables are assumed to be endogenous, macroeconomic variables are assumed to be exogenous. Year dummies are included. The columns report results for (1) pooled sample, (2) domestic private banks, (3) state banks, (4) foreign banks, (5) greenfield banks, (6) takeover banks respectively. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.15: Robustness, net loans

	1	2	3	4	5	6
Leverage	0.0029**	0.0025	0.015	0.0018	0.0022**	-0.0015
	(2.31)	(1.51)	(1.70)	(1.66)	(2.35)	(-0.47)
Leverage growth	0.49***	0.46***	0.32	0.65***	0.64***	0.65***
	(18.79)	(19.32)	(1.80)	(7.79)	(7.43)	(6.64)
Equity growth	0.58***	0.59***	0.39*	0.69***	0.68***	0.69***
	(25.92)	(31.64)	(2.23)	(10.93)	(8.64)	(8.22)
ΔRER	-0.32***	-0.47*	-0.100	-0.21*	-0.22	-0.22
	(-4.94)	(-2.11)	(-0.35)	(-2.04)	(-1.74)	(-1.76)
ΔM2	-0.058	-0.012	0.071	-0.089*	-0.059	-0.18**
	(-1.21)	(-0.25)	(0.93)	(-1.94)	(-1.17)	(-2.30)
ΔGDP	0.72	0.49	1.61	0.66*	0.58	1.08**
	(1.58)	(1.10)	(1.64)	(2.04)	(1.42)	(2.40)
ΔDebt/GDP	-0.69***	-1.16***	0.29	-0.60*	-0.78*	0.12
	(-3.87)	(-3.41)	(0.50)	(-1.99)	(-2.04)	(0.28)
Inflation	0.39**	0.27	0.27	0.28	0.44	-0.35
	(2.59)	(1.20)	(0.71)	(1.26)	(1.53)	(-0.82)
Deposits growth	0.022***	0.021***	0.056	-0.0077	-0.019*	0.061
	(11.09)	(25.66)	(1.60)	(-0.65)	(-1.90)	(0.89)
Profitability	-0.00047	-0.000050	-0.0013	0.00016	-0.00016	-0.00023
	(-1.22)	(-0.19)	(-0.50)	(0.36)	(-0.31)	(-0.39)
Loan quality	-0.020***	-0.020***	-0.017***	-0.0083**	-0.0098***	-0.0028
	(-33.92)	(-28.65)	(-4.56)	(-2.78)	(-4.34)	(-0.51)
Loan/deposit ratio	0.0016***	0.0017***	0.0022**	0.00062*	0.00071*	0.00065
	(18.99)	(39.44)	(2.62)	(1.97)	(1.81)	(1.26)
Efficiency	-0.00031	-0.00047	-0.00080	0.0016**	0.0017*	0.0012
	(-0.98)	(-1.62)	(-0.90)	(2.60)	(2.11)	(1.00)
Liquidity	-0.0013**	-0.0021***	-0.00016	-0.0013*	-0.0011	-0.0034**
	(-2.32)	(-38.23)	(-1.68)	(-1.80)	(-1.46)	(-2.40)
Constant	-0.15	-0.039	-0.027	-0.65***	-0.24	0.45
	(-1.31)	(-0.20)	(-0.11)	(-3.04)	(-1.26)	(1.55)
N	3718	2705	230	783	488	295
R^2 overall	0.511	0.484	0.464	0.677	0.643	0.713
R^2 between	0.442	0.386	0.501	0.684	0.618	0.666
R^2 within	0.600	0.606	0.559	0.709	0.690	0.785
N. Banks	1109	860	61	214	119	95

Results with net loans growth instead of gross loans growth. The columns report results for (1) pooled sample, (2) domestic private banks, (3) state banks, (4) foreign banks, (5) greenfield banks, (6) takeover banks respectively. Fixed effects regression with time fixed effects and country is chosen to be the group variable for the variance estimator. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

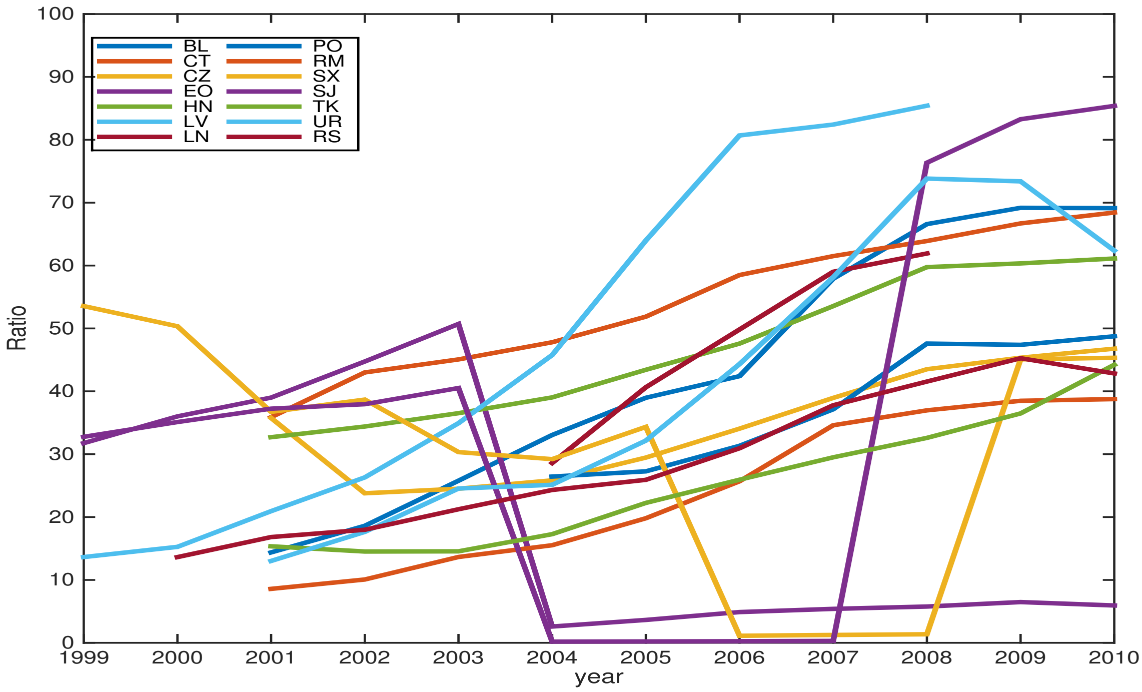
Table 2.16: Robustness, small sample

	1	2	3	4	5	6
Leverage	0.0029**	0.0025	0.0058	0.0023***	0.0027***	-0.0013
	(2.42)	(1.49)	(0.56)	(3.09)	(3.05)	(-0.45)
Leverage growth	0.51***	0.49***	0.40*	0.63***	0.62***	0.71***
	(26.20)	(25.21)	(2.07)	(10.30)	(9.54)	(8.95)
Equity growth	0.61***	0.61***	0.47**	0.70***	0.73***	0.71***
	(31.11)	(41.92)	(2.44)	(11.31)	(8.61)	(12.16)
ΔRER	-0.23***	-0.24	-0.10	-0.19**	-0.18*	-0.17
	(-3.78)	(-1.57)	(-0.34)	(-2.54)	(-1.88)	(-1.50)
ΔM2	0.0028	0.092*	0.054	-0.050*	-0.019	-0.14
	(0.05)	(2.09)	(0.66)	(-1.82)	(-0.52)	(-1.58)
ΔGDP	0.63	0.35	1.63*	0.55*	0.35	1.16***
	(1.60)	(0.75)	(2.02)	(1.88)	(1.09)	(3.34)
ΔDebt/GDP	-0.72***	-1.29***	0.28	-0.39	-0.63*	0.33
	(-4.12)	(-3.22)	(0.45)	(-1.39)	(-1.80)	(1.01)
Inflation	0.41**	0.24	0.56	0.23	0.40*	-0.37
	(2.44)	(1.32)	(1.67)	(1.70)	(1.80)	(-1.05)
Deposits growth	0.017***	0.016***	0.034	0.0052	-0.013	0.012**
	(10.77)	(21.50)	(1.12)	(0.89)	(-1.48)	(2.34)
Profitability	-0.00060	-0.00021	-0.0015	-0.00014	-0.00071	0.00034
	(-1.63)	(-1.09)	(-0.79)	(-0.31)	(-1.26)	(0.50)
Loan quality	-0.011***	-0.010***	-0.022***	-0.0029	-0.0072**	0.011**
	(-22.73)	(-39.32)	(-4.56)	(-0.81)	(-2.67)	(2.65)
Loan/deposit ratio	0.0014***	0.0015***	0.0014*	0.0012***	0.0013***	0.00090***
	(21.25)	(39.94)	(1.98)	(4.13)	(3.76)	(3.08)
Efficiency	-0.00052*	-0.00081***	-0.0014	0.0016***	0.0015*	0.0018
	(-1.88)	(-3.23)	(-1.29)	(3.16)	(2.10)	(1.50)
Liquidity	-0.0014**	-0.0019***	-0.00015	-0.0014*	-0.0012*	-0.0041***
	(-2.85)	(-22.80)	(-1.08)	(-2.03)	(-1.82)	(-4.73)
Constant	-0.078	0.0092	-0.080	-0.67***	-0.23*	0.35
	(-0.81)	(0.08)	(-0.44)	(-5.29)	(-2.00)	(1.31)
N	4675	3541	268	866	539	327
R^2 overall	0.519	0.508	0.413	0.613	0.632	0.587
R^2 between	0.430	0.428	0.420	0.417	0.592	0.327
R^2 within	0.575	0.575	0.532	0.679	0.665	0.769
N. Banks	1198	939	62	230	127	103

Results with banks that have at least 7 consecutive years of observations. The columns report results for (1) pooled sample, (2) domestic private banks, (3) state banks, (4) foreign banks, (5) greenfield banks, (6) takeover banks respectively. Fixed effects regression with time fixed effects and country is chosen to be the group variable for the variance estimator. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

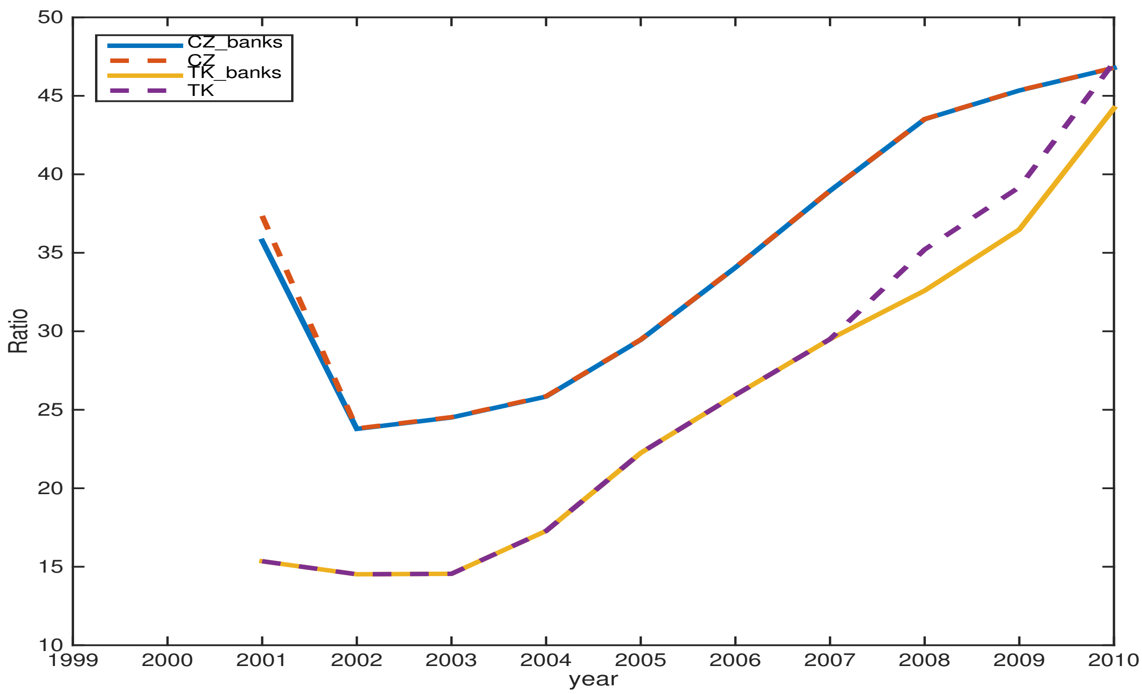
Figures

Figure 2.1: Domestic credit by banks



Domestic credit to the private sector provided by banks as a share of GDP for all countries in the sample. *Source: World Bank, WDI*

Figure 2.2: Domestic credit comparison



Comparison of domestic credit and domestic credit provided by banks as shares of country GDPs for the Czech Republic and Turkey. Dashed lines represent overall domestic credit as a share of GDP. *Source: World Bank, WDI*

3

Forecasting Turkish Real GDP Growth in a Data Rich Environment*

Abstract

This study generates nowcasts and forecasts for the growth rate of the Gross Domestic Product (GDP) in Turkey using 204 daily financial series with Mixed Data Sampling (MIDAS) framework over the period 2010Q2-2016Q2. Daily financial series include commodity prices, equity indices, exchange rates, and global and domestic corporate risk series. Forecasting exercises are also carried out with the daily factors extracted from separate financial data classes and from the whole dataset. The findings suggest that MIDAS regression models and forecast combinations provide advantage in exploiting information from daily financial data compared to the models using simple aggregation schemes. In addition, incorporating daily financial data into the analysis improves the forecasts substantially. The best forecasting performance is obtained by daily factors from separate asset classes. These results indicate that both the information content of the financial data and the flexible data-driven weighting scheme of MIDAS regressions play an essential role in forecasting the future state of the Turkish economy.

Keywords: Real GDP Growth, Forecasting, MIDAS
JEL classification: C22, C53, G10

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3.1. Introduction

Gross Domestic Product (GDP) is one of the most important indicators which summarize economic activity. However, it is unavailable at frequencies higher than quarterly and released with a significant lag. Considering the importance of timely assessment of current and future economic developments, forecasting GDP is an important task for policymakers. To forecast GDP data, analysts usually track timelier and high-frequency indicators, including monthly, weekly or daily data. In the literature, leading property of financial market variables about the future state of the economy has been pointed out (Stock and Watson, 2003). In this study, we generate nowcasts and forecasts for Turkish quarterly GDP growth by employing high frequency financial data with the Mixed Data Sampling (MIDAS) models and evaluate forward-looking nature of financial variables for the Turkish economy starting from the second quarter of 2010 until the second quarter of 2016.

Regarding use of high frequency data in forecasting GDP, mapping movements in these indicators into real GDP growth is not an easy task because there is mixed frequency in the data. For example, GDP data are sampled quarterly, employment and inflation data are sampled monthly, and asset price data are sampled daily. The simplest approach is to aggregate the high frequency data to obtain a balanced data set at the same low frequency. Explicitly, a forecaster may time aggregate three monthly samples of employment data into a single observation for each quarterly sample of GDP data by taking an average of the monthly data. However it is simple, in general, temporal aggregation entails a loss of information (Marcellino, 1999). Moreover, it also changes the data generating mechanism, which may lead to considerable difference between the dynamics of the aggregate and high or mixed frequency model. This indicates that key econometric features can be spuriously modified when employing the aggregated data (Marcellino, 1999). In this paper, we follow MIDAS approach developed by Ghysels et al. (2004). MIDAS models are one of alternative approaches to model the mixed-frequency data to avoid the mentioned problems related to temporal aggregation. They have parsimonious specifications based on distributed lag polynomials, which flexibly deal with data sampled at different frequencies and provide a direct forecast of the low-frequency variable (Ghysels et al., 2004; Clements and Galvão, 2008).

The advantages of using MIDAS regressions in terms of improving quarterly macro forecasts with monthly data, or improving quarterly and monthly macroeconomic predictions with a small set of daily financial data have been investigated in the literature (Kuzin et al., 2011; Armesto et al., 2009; Clements and Galvão, 2008, 2009; Galvão, 2013; Tay, 2007; Schumacher and Breitung, 2008; Ghysels and Wright, 2009; Hamilton, 2008; Monteforte and Moretti, 2013). However, these studies limit the number of variables in the regression and do not incorporate large set of data into their analysis. Apart from previous works, Andreou et al. (2013) use large cross-section of around one thousand financial time series to forecast quarterly US GDP growth rate. They extract a small set of daily factors from these large dataset and apply forecast combination methods. Their application shows that MIDAS model forecasts are able to outperform naive models substantially.

Most of the existing studies employing MIDAS regression models focus on the US or the euro area economy to forecast quarterly series (Tay, 2007; Clements and Galvão, 2009), but few on the developing economies. In this study, we take Turkey as our laboratory. The reason is that it is a small open economy and exhibits similar macroeconomic dynamics to other emerging economies. Assessing the ability of financial market variables to anticipate Turkish output growth may provide valuable information about the forward-looking nature of financial variables in peer countries.

The literature related to forecasting Turkish GDP is quite limited. In one of the rare studies, Akkoyun and Günay (2012) employ small scale dynamic factor model. They forecast quarterly GDP growth with monthly data by following Kalman filter approach. They find that some combination of hard indicators such as industrial production, export and import quantity indices and soft indicators such as Purchasing Managers Index (PMI) and PMI new orders have predictive power for the output growth. Sacakli-Sacildi (2015) tests forecasting performance of Bayesian vector autoregression (BVAR) methodology for Turkish GDP growth rate. However, to our best knowledge, MIDAS regression modeling has not been used for forecasting Turkish GDP growth and this paper is the first attempt in exploring forecasting ability of financial data using MIDAS regression models for Turkish output growth. In this study, we follow the forecasting strategy introduced by Andreou et al. (2013) and generate nowcasts and forecasts of Turkish GDP growth using 204 daily financial series. We analyze whether financial data provide information about the future state of the economy and improve forecasting ability.

Our results suggest that there are statistically significant gains in using daily financial data and MIDAS models. MIDAS models with daily series and quarterly factors perform better than the benchmark model and other linear models at every horizon in consideration. The robustness of the results is proven by different predictive ability tests. Another implication of the results is that daily factors extracted from commodities, forex, and foreign corporate risk series give the best forecasts at certain horizons and in others, their results are competitive with other financial data classes. The results also reveal that combination of small set of daily factors received from separate asset classes provides substantial forecasting gains. This implies that small set of series can be employed in following the Turkish economy.

The article is organized as follows. Section 2 describes the MIDAS models and the forecasting methodology. Section 3 describes the dataset and Section 4 presents the empirical results. Finally, Section 5 concludes.

3.2. Forecasting Methodology

This section describes the MIDAS models and forecast combination methods that are used in the study. The aim of the section is to give the intuition and details of MIDAS models and how they are implemented in macroeconomic forecasting. The model is compared and contrasted with other methods in the literature to give a clear picture of its flexibility as well as its limitations. To improve forecast performance, the study uses forecast combination methods. The second part of the section explains the forecast combination methods and how they are used.

3.2.1. MIDAS Models

In order to understand innovations brought by MIDAS to single equation estimation of mixed frequency data, first consider a bridge equation (Baffigi et al., 2004; Diron, 2008), which is one of the early methods in the literature. In this linear regression methods, low frequency variable is projected on aggregated values of high frequency observations for a specified lag of low frequency time period in the form:

$$Y_t = \beta_0 + \sum_{j=1}^{q_x} \beta_j Z_{(t-q_x)} + \varepsilon_t, \tag{3.1}$$

where Y_t is the low frequency variable of interest; q_x is the number of low frequency lags; β_j is the corresponding coefficient for the aggregated high frequency variable at low frequency lag j; $Z_t = \sum_{i=0}^{m-1} \omega_i X_{(m-i,t)}$ is the aggregated high frequency variable to the lower frequency with m is the fixed number of high frequency periods in one single low frequency period, (i,t) is the i^{th} lagged high frequency period in the low frequency period t, $X_{(i,t)}$ is the high frequency variable, ω_i is the weight of high frequency observation for lag i; and $\varepsilon_t \sim N(0,1)$ is the error term. The high frequency weights can be flat (i.e. $\omega_i = 1/m$) or in another pre-determined form (Schumacher, 2016). In this setup, reliable estimations of the low frequency variable necessitates the correct form of aggregation of the high frequency variable into low frequency. Therefore, a crucial drawback of the model is that the imposed aggregation schemes might lead to severe aggregation bias.

A potential solution to the aggregation bias in terms of a bridge equation is to quit the aggregation and project Y_t on, for instance, every observation of the high frequency variable for each lag of the low frequency. This approach might work well when m is small (e.g. $m = 3$ such as in the case of estimation of a quarterly variable with monthly data). However; for instance, in a quarterly low frequency and daily high frequency setting, even only one lag of the quarterly data is used, there are more than 60 parameters to estimate corresponding each day in the lagged quarter. Thus, parameter proliferation is another potential problem with the single equation models like the bridge equations.

Novelty of the MIDAS models lies in its solution to handling high frequency data. In its simplest form, the novelty can be described as aggregating data parsimoniously and allowing data to decide on the aggregation weights. MIDAS does these by using polynomial distributed lag functions to weigh the high frequency data. Consider the basic MIDAS model[1]:

$$Y_t = \beta_0 + \beta_1 \sum_{j=0}^{(q_X-1)} \sum_{i=0}^{(m-1)} \omega(\theta, i + j * m) X_{(m-i,t-j)} + \varepsilon_{(t)}, \tag{3.2}$$

where $\omega(\theta, i + j * m)$ is the polynomial distributed lag function that depends on hyper parameter θ.

Specification of weights is central to the MIDAS models since it gives the parsimony of the model over models such as bridge equations and Autoregressive Distributed Lags (ADL). There is a number of polynomial functions suggested in the literature some of which are Beta function, exponential Almon lag function, step function, and Almon distributed lag polynomial. This study is using Almon distributed lag polynomial[2] in which the weights can be written as

$$\omega(\theta, i) = \sum_{p=0}^{n_p} \theta_p i^p, \tag{3.3}$$

and assumes that the weight of the i^{th} lag can be calculated with underlying $(n_p + 1)$ hyper parameters $\theta = (\theta_0, \ldots, \theta_p)$. Now, assume that one wants to estimate quarterly data with daily data and a quarter consists of 66 working days. Instead of assigning weights separately to each lag and estimating 66 coefficients, with two or three hyper parameters the Almon lag polynomial solves the parameter proliferation problem. Furthermore, weights are data driven which prevents aggregation

[1] For a detailed overview of MIDAS models, please see Ghysels et al. (2004), Wohlrabe (2009), and Foroni and Marcellino (2013).

[2] Almon distributed lag polynomial has delivered the best results for the Turkish economy. Results with other polynomial functions are available upon request.

bias.

Compared to other methods, MIDAS has several advantages in dealing with mixed frequency data (Ghysels et al., 2004). First, if the number of lags is high, which is usually the case when the frequency difference of the low and high frequency variables gets higher, MIDAS presents a solution to parameter proliferation problem as stated above. Second, on the contrary to the methods that impose fixed structural relations for aggregation such as taking the mean of the data or using the first or last point in a given period, MIDAS lets the data decide for the weight of each point in a given period. Ghysels et al. (2004) show that MIDAS is always more efficient than simple data aggregation.

Third, MIDAS gives a reduced form method which does not require complexity of other alternative methods in the literature such as Kalman filters. The performance of MIDAS models against state-space models has been discussed by Andreou et al. (2011) and Bai et al. (2013). These studies show that in simple frameworks Kalman filters are found to be more efficient. However, comparisons with more complex problems imply that MIDAS models are less "prone" to specification errors and are easier to implement with a few parameters. This is why in a data-rich environment, such as in the empirical study of Andreou et al. (2013) with over 900 daily financial series, MIDAS can be preferred as the forecasting model.

3.2.2. Forecasting with MIDAS

This study deals with the problem of forecasting GDP growth in a data-rich environment and follows the methodology sketched in detail by Andreou et al. (2013). MIDAS forecast equation corresponding to the Equation 3.2 can be written as follows:

$$Y_{t+h} = \beta_0^h + \beta_1^h \sum_{j=0}^{(q_X-1)} \sum_{i=0}^{(m-1)} \omega(\theta^h, i + j * m) X_{(m-i,t-j)} + \varepsilon_{(t+h)}^h, \tag{3.4}$$

where β_0^h is the constant coefficient, β_1^h is the common slope, $\omega(\theta^h, i + j * m)$ is the weight for the lagged high frequency values, and $\varepsilon_{(t+h)}^h$ is the error term.

As it can be seen in Equation 3.4, MIDAS forecasts depend on the forecast horizon; thus, it has to be re-estimated for each horizon of interest and it gives direct forecasts for each of these horizons. This property of MIDAS makes it more robust in comparison to methods that use iterated forecasting since this forecasting method might cumulate possible model misspecification errors and cause inferior forecasts (Marcellino et al., 2006; Andreou et al., 2011).

Equation 3.4 is not directly used in forecasting Turkish quarterly GDP growth. First, considering the persistence of growth in an economy, lags of GDP growth are included. Assume that the variable of interest, Y_t, is the quarterly GDP growth, then 3.4 can be modified as follows:

$$Y_{t+h} = \beta_0^h + \sum_{k=0}^{(q_Y-1)} \rho_k^h Y_{(t-k)} + \beta_1^h \sum_{j=0}^{(q_X-1)} \sum_{i=0}^{(m-1)} \omega(\theta^h, i + j * m) X_{(m-i,t-j)} + \varepsilon_{(t+h)}^h, \tag{3.5}$$

where q_y is the number autoregressive lags and ρ_k^h are the corresponding coefficients to these lags.

Second deviation from the basic MIDAS model is the inclusion of factors extracted by Principal Component Analysis (PCA). As noted by Stock and Watson (2002) and Andreou et al. (2013), quarterly factors (i) reduce the dimensionality of variables at hand, and (ii) might improve the performance of macroeconomic forecasts. PCA is elected as the method of factor extraction following Andreou et al. (2013). The results of Marcellino and Schumacher (2010) show that the extraction method does not effect the forecasting results.

Two types of factors are included in the regressions. The first type of factors is extracted from quarterly macroeconomic series and included in the regressions as the following:

$$Y_{t+h} = \beta_0^h + \sum_{k=0}^{(q_Y-1)} \rho_k^h Y_{(t-k)} + \sum_{k=0}^{(q_F-1)} \alpha_k^h F_{(t-k)} + \beta_1^h \sum_{j=0}^{(q_X-1)} \sum_{i=0}^{(m-1)} \omega(\theta^h, i+j*m) X_{(m-i,t-j)} + \varepsilon_{(t+h)}^h, \tag{3.6}$$

where F_{t-k} represents quarterly factors and α_k^h are the corresponding coefficients. Models that include quarterly factors are called Factor ADL-MIDAS (FADL-MIDAS) models throughout the study.

The second type of factors is extracted from daily financial series. Estimations are carried with factors both from all series and from separate financial data classes. These factors are high frequency variables and are inserted as $X_{(m-j,t)}$ in Equations 3.5 and 3.6.

In the empirical part of the study, ADL-MIDAS and FADL-MIDAS are compared with their non-MIDAS counterparts in order to measure the added value of the MIDAS method. The counterpart models can be given as:

$$Y_{t+h} = \beta_0^h + \sum_{k=0}^{(q_Y-1)} \rho_k^h Y_{(t-k)} + \sum_{j=0}^{(q_X-1)} \sum_{i=0}^{(m-1)} \beta_{(i+j*m)} X_{(m-i,t-j)} + \varepsilon_{(t+h)}^h, \tag{3.7}$$

$$Y_{t+h} = \beta_0^h + \sum_{k=0}^{(q_Y-1)} \rho_k^h Y_{(t-k)} + \sum_{k=0}^{(q_F-1)} \alpha_k^h F_{(t-k)} + \sum_{j=0}^{(q_X-1)} \sum_{i=0}^{(m-1)} \beta_{(i+j*m)} X_{(m-i,t-j)} + \varepsilon_{(t+h)}^h. \tag{3.8}$$

Equations 3.7 and 3.8 are labelled as ADL and Factor ADL (FADL) models respectively.

3.2.3. Forecast Combinations

As a part of the forecasting procedure, individual forecasts are combined by using forecast combination methods suggested in the literature. Combining individual forecasts by a pre-specified weighting rule has shown to improve forecast accuracy (Bates and Granger, 1969). This conclusion is reached by the assumption that individual forecasts are unbiased. Intuition behind the forecast gain by combination is that one forecast might include information which is not considered by the others and a better forecast can be generated by combining different information sets. In addition to that, as pointed out by Hendry and Clements (2004) and Stock and Watson (2004) forecast combinations can deal with model instability and structural breaks.[3]

Assume that R is the number of h-step ahead forecasts made for Y_t at time t. Then, the combination of forecasts, $\hat{Y}_{(t+h)}^{c_R}$, can be written as

$$\hat{Y}_{(t+h)}^{c_R} = \sum_{r=1}^{R} w_{r,t}^c \hat{Y}_{(r,t+h)}, \tag{3.9}$$

where the superscript c_R denotes the combination of R forecasts, $\hat{Y}_{(r,t+h)}$ is the forecast from model r, and $w_{r,t}^c$ is the combination weight for the forecast from model r. There are methods suggested in the literature to decide on the weights of individual forecasts. It can be as simple as assigning

[3] For an overview of the forecast combination literature, please see Timmermann (2006).

equal weights to each model (i.e. $w^c_{r,t} = 1/R$). This study employs discounted mean squared forecast error (DMSFE)[4] forecast combination method. With this method, forecast weights can be calculated as follows:

$$w^c_{r,t} = \frac{(\lambda_{r,t})^{\kappa}}{\sum_{r=1}^{R}(\lambda_{r,t}^{-1})^{\kappa}}, \ \lambda_{r,t} = \sum_{\tau=T_0}^{t-h} \delta^{t-h-\tau}(Y_{t-h} - \hat{Y}_{r,\tau+h})^2, \tag{3.10}$$

where $\delta \in [0,1]$ is the discount factor and κ is 1 or 2. The method takes into account the historical performance of a model and as δ gets higher, the comparative importance of recent forecast accuracy gets higher. When $\delta = 1$, the DMSFE forecast combination method boils down to MSFE forecast combination method. In this study, δ is taken as 0.9 and κ as 2.

One of the issues in the forecast combination literature is the selection of forecasts to combine (Timmermann, 2006; Aiolfi and Timmermann, 2006; Elliott et al., 2015). In the literature there is no consensus on how to proceed. Therefore, we first combine forecasts of all series and daily factors. Then, forecasts from different financial data classes are combined to see their performances. Finally, based on their root mean squared forecast error (RMSFE) performances, best series for each horizons are selected and combination of these forecasts is analyzed.

The forecasting stage of the empirical research includes several steps. At the first step, for every daily financial series or factor and for each model (e.g. ADL-MIDAS and FADL-MIDAS), forecasts are calculated for different lag lengths. Afterwards; for each high frequency variable, the best performing lag specification is selected based on Akaike Information Criterion (AIC) and RMSFE performances. At the last step, forecasts are combined by using the DMSFE method.

Within quarter forecasts are made by using the MIDAS with leads model. MIDAS with leads model was first used by Clements and Galvão (2008) and Kuzin et al. (2011) in a monthly-quarterly mixed data context. To illustrate the method within the daily-quarterly context, assume that we want to obtain 1-month ahead forecast for a quarterly variable. In that case, we are 2 months into the quarter of interest and have financial data of 44 working days. Let J_x denote the number of months that passed in the quarter (i.e. for the current example, $J_x = 2$). Then, the ADL-MIDAS with leads can be written as:

$$\begin{aligned} Y_{t+h} = \beta_0^h + \sum_{k=0}^{(q_Y-1)} \rho_k^h Y_{(t-k)} + \beta_1^h \Bigg[& \sum_{i=(3-J_x)*m/3}^{(m-1)} \omega(\theta^h, i-m) X_{(m-i,t+1)} + \\ & \sum_{j=0}^{(q_X-1)} \sum_{i=0}^{(m-1)} \omega(\theta^h, i+j*m) X_{(m-i,t-j)} \Bigg] + \varepsilon^h_{(t+h)}, \end{aligned} \tag{3.11}$$

where the first term in the brackets represent the leads and the second term represents the lags (i.e. information that belongs to the previous quarters).

In the forecasting literature, nowcasting[5] refers to within period of forecasts and updating them when new information becomes available. Andreou et al. (2011) note two main differences between MIDAS with leads and nowcasting. First, while nowcasting gives an update for the current quarter, MIDAS with leads can provide direct forecasts not only for the current quarter but also for longer horizons. Second difference is related to how models that do nowcasting (e.g. state-space

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4 We have received best results from this combination method.

5 Another term used in the forecasting literature is *backcasting* which refers to making forecasts for a certain period using data that become available after that certain period ends. This is usually the case for quarterly GDP growth forecasts with monthly data where GDP growth is announced with approximately 3 month lag while monthly data become available with one or two month lags.

models) and MIDAS with leads handle arrival of new information. Issues such as announcement dates, missing data, and ragged end are taken into account in the state-space models. Furthermore, effects of macroeconomic announcements can also be analyzed with Kalman filters. However, daily financial data are available on "daily" basis and do not require updates. This study does not deal with the noted problems and assume that all news effect is already reflected by the daily data.

3.2.4. Comparing Predictive Accuracy

Predictive accuracy of forecasts is compared by using the Diebold-Mariano (Diebold et al., 1995) (DM) test with squared forecast errors. Since we have a small number of forecasts, small sample adjustment of the DM test by Harvey et al. (1997) (HLN) is employed. It is specified as:

$$\text{HLN} = \left(\frac{T+1-2h+h(h-1)/T}{T}\right)^{-1/2} DM, \tag{3.12}$$

where T is the number of forecasts, h is the forecast horizon, and DM is the original DM statistic. HLN follows a Student-t distribution with $T-1$ degrees of freedom (Harvey et al., 1997).

As it can be observed in the models that are used in the forecasting GDP growth, some of the models are nested in others. One issue noted about the DM test in the literature is that when comparing two nested models, the critical values are not asymptotically normally distributed and shown to be undersized (McCracken, 2007). Clark and West (2007) (CW) develop a test statistic which can be used to compare out-of-sample forecast accuracy of two nested models. The null hypothesis of the test is that nesting model and the nested model have equal predictive accuracy and the alternative hypothesis is that the nesting model performs better than the nested model. Based on their simulation studies, Clark and West (2007) define two critical values for their CW statistics. If the test statistic is bigger that 1.282, the p-value of the test statistic is between 0.05 and 0.10; and if the test statistic is bigger than 1.645, the p-value is between 0.01 and 0.05.

In addition to HLN and CW tests, robustness of the results is checked with forecast encompassing and mean squared adjusted test statistics (Clark and McCracken, 2001; McCracken, 2007; Clark and McCracken, 2010) when the bigger model includes additional variables.

3.3. Data

Data are retrieved from *Datastream* using several databases and the most recently available data have been used for the regressions at the time of writing. The study focuses on the quarter-on-quarter Turkish GDP growth between 2000-Q2 and 2016-Q2. GDP data are from the TURKSTAT database. The length of the series is 65 and last 25 data points of the series (i.e. GDP growth data from 2010-Q2 till 2015-Q1) are selected to evaluate out-of-sample performance of MIDAS models. The initial window size is, thus, 40 (i.e. initial estimation sample is from 2000-Q2 till 2010-Q1) and forecasts are made with a recursive window.

Quarterly factors are extracted from six quarterly series which are listed in Table 3.11. [6] The data for these quarterly series are available since 1989-Q2. The Total import and export series are transformed as first difference of their logarithms and remaining quarterly series are used in their original form, which gives quarter-on-quarter growth rate. The factors are extracted using the PCA

[6] The selection of the series is solely based on the data availability.

with a window size of 40. Only first lag of the first factor, which explains 50% total variation in quarterly series, is used in the FADL-MIDAS and FADL regressions.

Daily financial series which run from 3 January 2000 to 30 June 2016 consist of 3 asset classes and a corporate risk class. There are 41 commodity, 35 equity, and 12 foreign exchange series in the asset classes and 10 corporate risk series with a length of 4301. Daily series used in the study are listed in Tables 3.12-3.15.

An additional *foreign corporate risk* class is used in order to account for the regional and global risk on GDP growth. There are 106 series in this class and they are given in Table 3.16. The motivation of including the class stems from the possible linkages within trade, investment and growth for a small open economy. High international risk might negatively influence trade and investment flows and thereby the domestic GDP growth.

The daily data series are transformed to obtain return series in percentage terms as follows:

$$x_t = log(\frac{X_{t-1}}{X_t}) * 100; \tag{3.13}$$

where x_t denotes log daily return at time t. The series are then tested for stationarity.

5 daily factors are extracted for all of the 204 series and for each financial data class separately. The window size used in factor extraction is 40. These factors explain 55%-18%, 46%-16%, 30%-10%, 19%-2%, 22%-5*10^{-6}%, and 26%-0.03% of total variation in all series, commodities, equities, foreign exchange series, domestic corporate risk, and foreign corporate risk series respectively.

Daily series and all quarterly series except GDP growth are winsorized at the 1% level in order to avoid any outlier effect.

3.4. Empirical Results

We analyze two types of models: models with financial data (ADL and ADL-MIDAS) and models with financial data and macro factors (FADL and FADL-MIDAS). We evaluate forecasting performance of these models with respect to benchmark autoregressive model with lag one (AR(1)) using RMSFE in order to determine the contribution of financial data to forecasting GDP growth. Additionally, we try to find out to what extent employing quarterly factors and MIDAS models in forecasting GDP growth of Turkey provide forecasting gains.

The selection of the benchmark model in model comparisons relies on the results of Marcellino (2008), who show that if the linear models prove to strong benchmarks for out-of-sample forecasting if they are correctly specified. For the Turkish GDP growth, a linear time-series model is specified based on the AIC and the Bayesian information criterion (BIC). According to the information criteria given in Tables 3.1, the minimum values for both the AIC and the BIC are received form the AR(1) model with a constant; therefore, this model is selected to be the benchmark model.

The forecast results are reported in three subgroups as 1-month ahead, 2-month ahead, 3-month ahead nowcasts and forecasts; and horizons beyond two-quarter ahead, namely, 3-quarter and 4-quarter ahead forecasts. Time left in certain quarter in monthly terms is considered in labeling the forecasts. In order to illustrate the distinction between these forecast horizons, assume that we want to make forecasts for 2013-Q1 and 2013-Q2. The forecast for the first quarter of 2013 done at the beginning of the first quarter (i.e. only use data from the previous periods and not from 2013-Q1) is labeled as 3-month ahead nowcast, the one done at the end of the first month is labeled as 2-month ahead nowcast, and the one done at the end of the second month is labelled as 1-month ahead nowcast. Forecasts done for 2013-Q2 in 2013-Q1 is labeled as forecasts and again the time left in 2013-Q1 in month-wise labels the forecasts (e.g. forecast done for 2013-Q2 at the beginning of 2013-Q1 is labeled as 3-month ahead forecast).

Firstly, we evaluate contribution of using financial data in forecasting real GDP growth. Top panels of Table 3.2 include forecast combinations with 204 daily series while combinations with 5 daily factors are given at the bottom panels. The results with macro factors (FADL and FADL-MIDAS) are given after the results without macro factors (ADL and ADL-MIDAS). The table presents the RMSFE of the benchmark model and RMSFE of the combined forecasts of the two types of models with respect to the RMSFE of the benchmark. If the ratio is less than one, it is interpreted as an improvement of the underlying forecast upon the benchmark. The results reveal that all models with financial data perform better than the benchmark model for all forecast horizons. To be explicit, in case of 1-month ahead nowcast, for the daily series, the ADL and ADL-MIDAS improve upon the AR by 2% and 17%, respectively. In Table 3.3, predictive ability of MIDAS models with respect to the AR(1) is compared by using the HLN and CW tests. The results are similar and show that financial data provide statistically significant forecasting gains over the benchmark.

Secondly, we compare forecasting performance of ADL-MIDAS and FADL-MIDAS models over the corresponding ADL and FADL models so that we aim to assess predictive ability of MIDAS models for quarterly real GDP growth. RMSFE performances of these models are given in Table 3.2. An initial comparison show that ADL-MIDAS models perform better than ADL models in all cases. Similarly, performance of FADL-MIDAS models is better than FADL models. The statistical significance of the differences between the models are tested by HLN and CW tests.[7] Corresponding test statistics are given in Table 3.4. In these tests, ADL models are compared with ADL-MIDAS models and FADL models with FADL-MIDAS models. According to the HLN test results, MIDAS models do not consistently beat the non-MIDAS models. On the other hand, according to the CW test statistics, the ADL-MIDAS and FADL-MIDAS models perform statistically better except for one case (i.e. FADL vs. FADL-MIDAS at 1-month ahead forecast).

Thirdly, we evaluate the performance of quarterly macroeconomic factors in forecasting GDP growth. For almost all MIDAS and non-MIDAS models, quarterly factors provide forecasting gains over the corresponding ADL and ADL-MIDAS models for both daily series and daily factors combinations and for each forecast horizon (Table 3.2). Test statistics for the significance of better performance of the FADL-MIDAS models against ADL-MIDAS models are given in Table 3.5. Regarding the observation on Table 3.2, the test statistics imply that the quarterly factors significantly improve the MIDAS forecasts only with the daily series and only for the 2-month ahead forecasts.

Fourthly, we investigate forecasting performance of each financial data class. In Table 3.6, RMSFE of each financial data class with respect to the benchmark model is reported. FADL-MIDAS models with the daily factors show the best performance both for most of the horizons. For example, for three month ahead nowcasts, FADL-MIDAS models with forex factors improve upon

[7] In addition to HLN and CW tests, for robustness purposes, forecast encompassing and mean squared adjusted test statistics are reported in Appendix 3.5. Tables 3.26-3.33 report HLN , CW, ENC_t, ENC_F, MSE_t, and MSE_F test statistics with their accompanying bootstrapped significance levels.

the benchmark by 19%. For three month ahead forecasts, the combinations of the factors extracted from separate asset classes provide 17% improvement over the benchmark. The improvement goes up to 28% for the 4-quarter ahead forecasts with the forecast combination of the equity factors.

Lastly, we try to identify whether some small group of series become prominent among 204 daily series in terms of forecasting gains in order to search for evidence for the argument that the results can be replicated by a small number of daily series. Forecast combination performances of the best 5 and 10 series for each horizon are given in Table 3.7. The table shows that forecasts do not improve in comparison to the results reported before. HLN and CW test statistics comparing the forecasts of best 5 series are given in Table 3.8 and the test statistics show that the FADL-MIDAS model forecasts statistically perform better than the combination of the best performing series.

Tables 3.9 and 3.10 reports the first 5 best series for each horizon based on their RMSFE performances. The table shows that, within the daily financial series, some of the equity series, especially FTSE Oil & Gas index, are very useful in forecasting the Turkish GDP growth with both ADL-MIDAS and FADL-MIDAS models. At the longer horizons, the foreign corporate bond indecies dominate the table. This might be a period specific phenomenon but the predictive ability of both equity and foreign corporate bond series should be further analyzed.

It can be observed on the tables that as the forecast horizon increases, the performance of the MIDAS models gets better compared to the benchmark. This is due to the deterioration of the performance of the benchmark model. The RMSFE of the AR(1) goes up to 1.33 at the 4-quarter ahead forecasts from 1.08 at the 1-quarter ahead forecasts. Therefore, the MIDAS models produce arguable more stable forecasts within horizons than the benchmark model. For the nowcasts, where the performance of the benchmark is the best, forecasts of the best MIDAS models and the benchmark are plotted in Figures 3.1-3.3.

Overall, the RMSFE comparisons show that better results are received with the combination of a small set of daily factors extracted from separate financial data classes. The result implies that the dimensions of the financial data can be reduced and the Turkish economy can be tracked by using a small set of daily factors.

The results suggest that the framework used in the study works significantly better than naive models. Our findings indicate that employing daily financial data improve forecasting performance of two types of model. Besides, with financial data one does not have to wait for updates of the dataset. MIDAS regression models provide forecasts gains compared to the models using simple aggregation schemes, and in most of the cases the gain is substantial. Consistent with the findings of previous studies (Stock and Watson, 2003; Andreou et al., 2013), quarterly factors provide forecasting gains over the benchmark models for all forecast horizons and for all financial data classes. However, the models considered here do not make use of any monthly data that were shown to forecast Turkish GDP data quite well in the past. By adding monthly variables in Equation 3.6 and updating the forecasts after monthly data releases, the performances of the models can further be improved.

Finally, we may compare our results with one of the limited studies about forecasting Turkish GDP growth, which is Akkoyun and Günay (2012). However, the direct comparison is not possible since we employ different estimation and forecasting period. Thus, we only mention about advantage of our framework over their models. Akkoyun and Günay (2012) employ small scale dynamic factor model and forecast quarterly GDP growth with monthly data by following Kalman filter approach. They find that some combination of hard indicators such as industrial production, export and import quantity indices and soft indicators such as PMI and PMI new orders have predictive power for the output growth. In last two years, correlation among GDP growth and the monthly data decreased (see Box 4.1 in the third inflation report of 2015 for details (CBRT, 2015)) which leads to decline in the performance of these models. Instead, we extract information from large set of daily financial data and make use of historical performance of the data in generating forecasts. Therefore, we can say that the methodology applied in this study is more robust to movements in individual series and deterioration of explanatory power in time.

3.5. Conclusions

In this study, our aim is to incorporate the information in daily financial data about the future state of the Turkish economy. To this end, the Mixed Data Sampling (MIDAS) models are used for the first time in generating nowcasts and forecasts for quarterly Turkish GDP growth in the analysis. We follow the approach introduced by Andreou et al. (2013) and employ 204 daily financial data consisting of 4 major financial data classes: commodity price, equity, foreign exchange and corporate risk.

Our results suggest that MIDAS regression models and forecast combination methods provide considerable advantage in exploiting information from daily financial data compared to the models using simple aggregation schemes when forecasting the quarterly GDP growth. Additionally, incorporating daily financial data into the analysis improves our forecasts substantially. These indicate that both the information content of the financial data and flexible data-driven weighting scheme of MIDAS regressions play a significant role for forecasting real GDP growth. Besides, consistent with the findings of previous studies (Stock and Watson, 2003; Andreou et al., 2013), quarterly factors lead to forecasting gains over the benchmark models for all forecast horizons and for all financial data classes. Additionally, the analysis of best performing series reveals the usefulness of daily factors from separate financial data classes in forecasting the Turkish GDP growth. This implies that daily factor series might be a good indicator for the Turkish GDP growth and be used as a daily index to track economic activity. Further research might be carried out by incorporating monthly hard and soft data into the analysis since previous studies prove their significance in improving the nowcasting performance.

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Tables

Table 3.1: Lag selection

	AIC	BIC
AR(1)	105.04	107.21
AR(2)	106.69	111.04
AR(3)	108.06	114.58
AR(4)	109.00	117.70
AR(1), constant	**99.98**	**104.33**
AR(2), constant	101.87	108.40
AR(3), constant	103.87	112.57
AR(4), constant	101.95	112.83

GDP growth lag selection

Table 3.2: RMSFE comparisons for MIDAS and non-MIDAS models

Type of Series	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
AR(1)	1.08	1.08	1.08	1.10	1.10	1.10	1.12	1.33
Daily Series								
ADL	0.93	0.92	0.98	0.96	0.91	0.88	0.94	0.75
ADL-MIDAS	0.80	0.80	0.83	0.91	0.83	0.87	0.78	0.69
FADL	0.78	0.90	0.95	0.92	0.87	0.88	0.92	0.74
FADL-MIDAS	0.78	0.76	0.81	0.87	0.80	0.84	0.78	0.68
Daily Factors								
ADL	0.96	0.98	0.93	0.93	0.91	0.92	0.93	0.65
ADL-MIDAS	0.89	0.85	0.82	0.90	0.82	0.88	0.92	0.59
FADL	0.95	0.96	0.90	0.92	0.89	0.92	0.90	0.63
FADL-MIDAS	0.89	0.84	0.80	0.87	0.81	0.86	0.88	0.55

Forecast combination results of ADL-MIDAS and FADL-MIDAS models for all daily series and factors. The first line gives the RMSFE of the AR(1) model with no constant. Other cells include the relative RMSFE of combined forecasts to the AR(1) model.

Table 3.3: HLN and CW test statistics for AR(1) vs MIDAS models

AR(1) vs.	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
HLN								
ADL-MIDAS	1.52	1.42	1.34	1.15	0.94	0.89	1.07	0.97
FADL-MIDAS	1.47	1.36	1.22	1.14	0.90	0.87	1.06	0.97
CW								
ADL-MIDAS	1.73^{**}	1.50^{*}	1.43^{*}	1.71^{**}	1.56^{*}	1.56^{*}	1.38^{*}	1.45^{*}
FADL-MIDAS	1.62^{*}	1.42^{*}	1.34^{*}	1.74^{**}	1.61^{*}	1.58^{*}	1.42^{*}	1.48^{*}
Daily Factors								
HLN								
ADL-MIDAS	1.42	1.87^{*}	1.96^{*}	1.48	0.88	0.88	0.75	1.54
FADL-MIDAS	1.15	1.47	1.75^{*}	1.21	0.84	0.87	0.70	1.37
CW								
ADL-MIDAS	2.10^{**}	2.19^{**}	2.34^{**}	2.16^{**}	1.52^{*}	1.58^{*}	1.41^{*}	1.89^{**}
FADL-MIDAS	1.86^{**}	1.85^{**}	1.96^{**}	2.05^{**}	1.53^{*}	1.66^{*}	1.42^{*}	1.82^{**}

Harvey-Leybourne-Newbold (HLN) and Clark-West (CW) test statistics for comparison of AR(1) benchmark model and MIDAS model forecast combination performances with all daily series and factors. For HLN, * p<0.10, ** p<0.05, *** p<0.01; and for CW, *0.05< p<0.10, ** 0.01<p<0.05.

Table 3.4: HLN and CW test statistics non-MIDAS vs. MIDAS models

ADL and FADL vs.	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
HLN								
ADL-MIDAS	1.25	1.16	1.35	1.22	1.74^{*}	0.31	1.03	1.27
FADL-MIDAS	1.50	1.33	1.47	1.23	1.84^{*}	0.77	1.14	1.15
CW								
ADL-MIDAS	1.48^{*}	1.30^{*}	1.48^{*}	1.71^{**}	2.11^{**}	0.93	1.49^{*}	1.40^{*}
FADL-MIDAS	1.89^{**}	1.47^{*}	1.66^{**}	1.78^{**}	2.20^{**}	1.25	1.70^{**}	1.40^{*}
Daily Factors								
HLN								
ADL-MIDAS	1.20	1.75^{*}	1.93^{*}	0.59	1.12	0.82	0.15	0.66
FADL-MIDAS	1.07	1.85^{*}	1.96^{*}	0.86	1.25	0.95	1.46	0.64
CW								
ADL-MIDAS	1.92^{**}	1.99^{**}	2.42^{**}	1.52^{**}	1.84^{**}	1.59^{*}	1.73^{**}	1.72^{**}
FADL-MIDAS	1.86^{**}	2.19^{**}	3.13^{**}	1.55^{*}	2.06^{**}	1.79^{**}	1.57^{*}	1.58^{*}

Harvey-Leybourne-Newbold (HLN) and Clark-West (CW) test statistics for comparison of non-MIDAS and MIDAS model forecast combination performances with all daily series and factors. For HLN, * p<0.10, ** p<0.05, *** p<0.01; and for CW, *0.05< p<0.10, ** 0.01<p<0.05.

Table 3.5: HLN and CW test statistics for ADL-MIDAS vs. FADL-MIDAS models

ADL-MIDAS vs. FADL-MIDAS	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
HLN	0.33	0.92	0.35	0.67	0.58	0.67	0.28	0.54
CW	0.65	1.37*	0.82	1.15	1.17	1.15	0.84	0.88
Daily Factors								
HLN	-0.00	0.34	0.68	0.59	0.31	0.36	0.56	0.68
CW	0.46	0.88	1.28	1.07	0.79	1.03	0.96	1.21

Harvey-Leybourne-Newbold (HLN) and Clark-West (CW) test statistics for comparison of ADL-MIDAS and FADL-MIDAS model forecast combination performances with all daily series and factors. For HLN, * $p<0.10$, ** $p<0.05$, *** $p<0.01$; and for CW, *$0.05< p<0.10$, ** $0.01<p<0.05$.

Table 3.6: RMSFE comparisons for MIDAS models, separate financial data classes

Type of Series	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
AR(1)	1.08	1.08	1.08	1.10	1.10	1.10	1.12	1.33
Daily Series								
Equities								
ADL-MIDAS	**0.81**	0.84	0.88	0.91	0.83	0.91	0.90	0.76
FADL-MIDAS	**0.81**	0.81	0.86	0.87	0.82	0.87	0.89	0.74
Commodities								
ADL-MIDAS	0.86	0.93	1.03	0.91	0.86	0.85	0.93	0.77
FADL-MIDAS	0.86	0.92	1.01	0.89	0.86	0.85	0.91	0.76
Forex								
ADL-MIDAS	0.97	1.03	1.05	1.04	0.92	0.93	0.90	0.75
FADL-MIDAS	0.93	0.99	1.05	1.02	0.90	0.91	0.89	0.73
Corporate Risk (Turkey)								
ADL-MIDAS	1.03	0.89	0.97	0.91	0.94	1.00	1.00	0.81
FADL-MIDAS	1.00	**0.77**	0.96	0.89	0.88	0.96	0.99	0.80
Corporate Risk (Foreign)								
ADL-MIDAS	0.93	0.89	0.90	0.96	0.88	0.96	0.75	0.70
FADL-MIDAS	0.92	0.87	0.88	0.92	0.85	0.93	**0.74**	0.68
Daily Factors								
Separate Asset Classes								
ADL-MIDAS	0.84	0.84	0.84	0.86	0.81	0.85	0.88	0.69
FADL-MIDAS	0.82	0.81	0.82	**0.83**	0.78	0.81	0.81	0.67
Equities								
ADL-MIDAS	0.93	0.87	0.86	0.87	0.81	0.87	0.85	0.66
FADL-MIDAS	0.92	0.86	0.85	0.86	**0.76**	0.89	0.81	**0.62**
Commodities								
ADL-MIDAS	0.86	0.86	0.81	0.89	0.93	0.86	0.86	0.68
FADL-MIDAS	0.83	0.80	**0.76**	0.86	0.90	0.84	0.83	0.68
Forex								
ADL-MIDAS	**0.81**	0.85	0.90	0.88	0.78	0.91	0.93	0.75
FADL-MIDAS	**0.81**	0.83	0.88	0.89	0.81	0.89	0.78	0.72
Corporate Risk								
ADL-MIDAS	0.92	0.93	0.88	0.95	0.91	0.89	0.92	0.72
FADL-MIDAS	0.87	0.92	0.88	0.91	0.85	**0.79**	0.88	0.74
Corporate Risk (Foreign)								
ADL-MIDAS	0.84	0.86	0.90	0.90	0.82	0.86	0.97	0.77
FADL-MIDAS	0.86	0.82	0.86	0.87	0.79	0.82	0.86	0.73

Forecast combination results of ADL-MIDAS and FADL-MIDAS models for separate financial data classes and factors derived from these classes. The first line gives the RMSFE of the AR(1) model with no constant. Other cells include the relative RMSFE of combined forecasts to the AR(1) model.

Table 3.7: RMSFE comparisons for MIDAS models with best series

	Forecast Horizon							
	Nowcast			Forecast				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
AR(1)	1.08	1.08	1.08	1.10	1.10	1.10	1.12	1.33
Best Series Combinations								
Daily Series								
Best 5 Series (ADL-MIDAS)	0.84	0.85	0.77	0.91	0.83	1.02	0.90	0.76
Best 5 Series (FADL-MIDAS)	0.84	0.84	0.73	0.97	0.82	0.85	0.91	0.76
Best 10 Series (ADL-MIDAS)	0.85	0.87	0.79	0.94	0.88	0.92	0.89	0.72
Best 10 Series (FADL-MIDAS)	0.84	0.83	0.73	0.91	0.84	0.81	0.90	0.71
Daily Factors								
Best 5 Factors (ADL-MIDAS)	0.99	0.89	0.74	0.69	0.73	0.85	0.82	0.65
Best 5 Factors (FADL-MIDAS)	0.88	0.79	0.74	0.88	0.89	0.92	0.86	0.70
Best 10 Factors (ADL-MIDAS)	0.92	0.87	0.78	0.71	0.71	0.84	0.84	0.66
Best 10 Factors (FADL-MIDAS)	0.82	0.82	0.74	0.80	0.87	0.82	0.84	0.64

Forecasts combination results of FADL-MIDAS models the for the best 5 and 10 daily series. The first line gives the RMSFE of the AR(1) model with no constant. Other cells include the relative RMSFE of combined forecasts to the AR(1) model.

Table 3.8: HLN and CW test statistics for best series vs. FADL-MIDAS models

FADL-MIDAS vs. Best Series	Forecast Horizon							
	Nowcast			Forecast				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
HLN	-0.39	-1.12	0.99	-0.50	-0.94	-2.38**	-1.53	-0.75
CW	0.62	0.03	2.43**	1.43*	1.33*	-1.40	-0.28	0.93
Daily Factors								
HLN	0.72	-0.12	0.35	-0.62	-0.30	-5.21***	-0.28	-1.56
CW	2.68**	2.02**	2.24**	1.28	1.26	-1.02	1.46	0.64

Harvey-Leybourne-Newbold (HLN) and Clark-West (CW) test statistics for comparison of forecast combination of best 5 series and FADL-MIDAS model forecast combination performances. The statistics are calculated using the small sample adjustment for the test. For HLN, * p<0.10, ** p<0.05, *** p<0.01; and for CW, *0.05< p<0.10, ** 0.01<p<0.05.

Table 3.9: The best series ranked based on their RMSFE performances for each MIDAS model and horizon

	Best Performing Series-1	
	Nowcast	
3-m	**2-m**	**1-m**
ADL-MIDAS		
FTSE TURKEY OIL & GAS PROD $ - PRICE INDEX	FTSE TURKEY OIL & GAS PROD $ - PRICE INDEX	CGBI WGBI WORLD AA 10-20Y($) - TOT RETURN IND
BIST NATIONAL 100 - PRICE INDEX	FTSE W TURKEY NONLIFE INSUR $ - PRICE INDEX	CGBI WGBI WORLD Non-Euro 5+y ($) - TOT RETURN IND
FTSE W TURKEY FORESTRY & PAP $ - PRICE INDEX	CBOE SPX VOLATILITY VIX (NEW) - PRICE INDEX	FTSE TURKEY OIL & GAS PROD $ - PRICE INDEX
FTSE W TURKEY GENERAL INDS $ - PRICE INDEX	FTSE W TURKEY ELTRO/ELEC EQ $ - PRICE INDEX	ML MOVE 1M BOND VOLATILITY INDEX - PRICE INDEX
CBOE SPX VOLATILITY VIX (NEW) - PRICE INDEX	BIST NATIONAL 100 - PRICE INDEX	CGBI WGBI WORLD AA 10+Y ($) - TOT RETURN IND
	Forecast	
3-m	**2-m**	**1-m**
FTSE TURKEY OIL & GAS PROD $ - PRICE INDEX	FTSE W TURKEY HEALTH CARE $ - PRICE INDEX	LME-Aluminium Alloy Cash U$/MT
BOFA ML U$ GLB HY IDX ($) - TOT RETURN IND	FTSE W TURKEY GENERAL INDS $ - PRICE INDEX	CGBI EMUSDGBI-C 5-10 YEARS INDEX - TOT RETURN IND
BARCLAYS EM MID.EAST TURKEY	FTSE TURKEY OIL & GAS PROD $ - PRICE INDEX	CGBI EMUSDGBI 1-5 YEARS INDEX - TOT RETURN IND
BARCLAYS EM TURKEY FIXED RATE	CGBI EMUSDGBI 1-5 YEARS INDEX - TOT RETURN IND	BOFA ML U$ GLB HY IDX ($) - TOT RETURN IND
BARCLAYS EM TURKEY INTL ISSUE	FTSE W TURKEY FORESTRY & PAP $ - PRICE INDEX	CGBI EMUSDGBI 5-10 YEARS INDEX - TOT RETURN IND
	Nowcast	
3-m	**2-m**	**1-m**
FADL-MIDAS		
FTSE TURKEY OIL & GAS PROD $ - PRICE INDEX	FTSE TURKEY OIL & GAS PROD $ - PRICE INDEX	CGBI EMUSDGBI INV.GRADE INDEX - TOT RETURN IND
FTSE W TURKEY FORESTRY & PAP $ - PRICE INDEX	JPM EMBI GLOBAL TURKEY - TOT RETURN IND	FTSE TURKEY OIL & GAS PROD $ - PRICE INDEX
BIST NATIONAL 100 - PRICE INDEX	JPM EMBI GLB.DIVERS TURKEY - TOT RETURN IND	CGBI WGBI WORLD Non-Euro 5+y ($) - TOT RETURN IND
Cocoa-ICCO Daily Price US$/MT	FTSE W TURKEY NONLIFE INSUR $ - PRICE INDEX	FTSE W TURKEY NONLIFE INSUR $ - PRICE INDEX
FTSE TURKEY FINANCIALS $ - PRICE INDEX	BARCLAYS EM TURKEY INTL ISSUE	CGBI WGBI WORLD AA 10-20Y($) - TOT RETURN IND
	Forecast	
3-m	**2-m**	**1-m**
FTSE TURKEY CON & MAT $ - PRICE INDEX	FTSE W TURKEY HEALTH CARE $ - PRICE INDEX	FTSE W TURKEY HEALTH CARE $ - PRICE INDEX
FTSE TURKEY TELECOM $ - PRICE INDEX	JPM ELMI+ TURKEY ($) - TOT RETURN IND	FTSE TURKEY BEVERAGES $ - PRICE INDEX
FTSE W TURKEY CHEMICALS $ - PRICE INDEX	FTSE TURKEY OIL & GAS PROD $ - PRICE INDEX	LME-Aluminium Alloy Cash U$/MT
FTSE TURKEY FINANCIALS $ - PRICE INDEX	FTSE TURKEY BEVERAGES $ - PRICE INDEX	S&P GSCI INDL Metals 1MTH Fwd Cap PI - PRICE INDEX
BOFA ML U$ GLB HY IDX ($) - TOT RETURN IND	CGBI EMUSDGBI 1-5 YEARS INDEX - TOT RETURN IND	S&P GSCI INDL Metals 3 MTH Fwd Cap PI - PRICE INDEX

Table 3.10: The best series ranked based on their RMSFE performances for each MIDAS model and horizon

Best Performing Series-2	
Forecast	
3-q	**4-q**
ADL-MIDAS	
CGBI WGBI WORLD AA 10-15Y($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 3-7y ($) - TOT RETURN IND
CGBI WGBI WORLD AA 1-10Y($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 3-5y ($) - TOT RETURN IND
CGBI WGBI WORLD AA ($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 5-7y ($) - TOT RETURN IND
CGBI WGBI WORLD AA 1-3Y ($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 1-3y ($) - TOT RETURN IND
CGBI WGBI WORLD AA 10-20Y($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 7-10y ($) - TOT RETURN IND
FADL-MIDAS	
CGBI WGBI WORLD AA 10-15Y($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 3-7y ($) - TOT RETURN IND
CGBI WGBI WORLD AA 10-20Y($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 3-5y ($) - TOT RETURN IND
CGBI WGBI WORLD AA 1-10Y($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 5-7y ($) - TOT RETURN IND
CGBI WGBI WORLD AA ($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 7-10y ($) - TOT RETURN IND
CGBI WGBI WORLD AA 1-3Y ($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 1-3y ($) - TOT RETURN IND

Table 3.11: Quarterly series used in the study.

	Name
Quarterly Series	TK EXPORTS F.O.B. TOTAL AS A % OF GDP SADJ
	TK IMPORTS F.O.B. TOTAL AS A % OF GDP SADJ
	TK PRODUCTION - TOTAL INDUSTRY EXCL. CONSTRUCTION SADJ
	TK HOURLY EARN: MFG SADJ
	TK MONETARY AGGREGATE M1 SADJ
	TK PASSENGER CAR REGISTRATIONS SADJ

Table 3.12: Daily commodity series used in the study.

	Name
Commodities	Cocoa-ICCO Daily Price US$/MT
	LME-Copper Grade A Cash U$/MT
	LME-Aluminium 99.7% Cash U$/MT
	LME-Nickel Cash U$/MT
	LME-Copper, Grade A 3 Months U$/MT
	LME-Aluminium 99.7% 3 Months U$/MT
	LME-Aluminium Alloy Cash U$/MT
	LME-Lead Cash U$/MT
	LME-SHG Zinc 99.995% Cash U$/MT
	LME-Nickel 3 Months U$/MT
	LME-Tin 99.85% Cash U$/MT
	LME-Lead 3 Months U$/MT
	LME-Tin 99.85% 3 Months U$/MT
	OPEC Oil Basket Price U$/Bbl
	S&P GSCI Enhanced Commodity PI - PRICE INDEX
	S&P GSCI 3 Mth Fwd Silver PI - PRICE INDEX
	S&P GSCI 3 Mth Fwd Sugar PI - PRICE INDEX
	S&P GSCI Agr Dynamic Roll Capped PI - PRICE INDEX
	S&P GSCI E27 WTI PI - PRICE INDEX
	S&P GSCI ENE Dynamic Roll PI - PRICE INDEX
	S&P GSCI EqualWeight Select PI - PRICE INDEX
	S&P GSCI IM Dynamic Roll Capped PI - PRICE INDEX
	S&P GSCI INDL MTLS DYM Roll PI - PRICE INDEX
	S&P GSCI INDL MTLS DYM Roll PI ER - EXCESS RETURN
	S&P GSCI LIVSTK DYM Roll PI - PRICE INDEX
	S&P GSCI PREC. MTLS DYM Roll PI - PRICE INDEX
	S&P GSCI PREC. MTLS DYM Roll PI ER - EXCESS RETURN
	S&P GSCI AGRI&Livstk 1 MTH Fwd PI - PRICE INDEX
	S&P GSCI Agri&livstk 3 MTH Fwd PI - PRICE INDEX
	S&P GSCI INDL Metals 1MTH Fwd Cap PI - PRICE INDEX
	S&P GSCI INDL Metals 3 MTH Fwd Cap PI - PRICE INDEX
	LME-Nickel 15 Months U$/MT
	LME-Lead 15 Months U$/MT
	LME-Aluminium 99.7% 15 Months U$/MT
	LME-Aluminium 99.7% 27 Months U$/MT
	LME-Aluminium Alloy 15 Months U$/MT
	LME-Copper, Grade A 15 Months U$/MT
	LME-Copper, Grade A 27 Months U$/MT
	LME-SHG Zinc 99.995% 15 Months U$/MT
	LME-SHG Zinc 99.995% 27 Months U$/MT
	LME-Tin 99.85% 15 Months U$/MT

Table 3.13: Daily equity series used in the study.

	Name
Equities	FTSE W TURKEY EQT IVST INS $ - PRICE INDEX
	FTSE TURKEY $ - PRICE INDEX
	FTSE TURKEY FINANCIALS $ - PRICE INDEX
	FTSE TURKEY INDUSTRIALS $ - PRICE INDEX
	FTSE TURKEY TELECOM $ - PRICE INDEX
	FTSE TURKEY MINING $ - PRICE INDEX
	FTSE TURKEY BANKS $ - PRICE INDEX
	FTSE TURKEY BASIC MATS $ - PRICE INDEX
	FTSE TURKEY BEVERAGES $ - PRICE INDEX
	FTSE TURKEY CON & MAT $ - PRICE INDEX
	FTSE TURKEY CONSUMER GDS $ - PRICE INDEX
	FTSE TURKEY CONSUMER SVS $ - PRICE INDEX
	FTSE TURKEY INDUSTRIAL MET $ - PRICE INDEX
	FTSE TURKEY OIL & GAS $ - PRICE INDEX
	FTSE W TURKEY CHEMICALS $ - PRICE INDEX
	FTSE W TURKEY ELECTRICITY $ - PRICE INDEX
	FTSE W TURKEY HEALTH CARE $ - PRICE INDEX
	FTSE W TURKEY NONLIFE INSUR $ - PRICE INDEX
	FTSE TURKEY TRAVEL & LEIS $ - PRICE INDEX
	FTSE TURKEY AUTO & PARTS $ - PRICE INDEX
	FTSE TURKEY FD & DRUG RTL $ - PRICE INDEX
	FTSE TURKEY OIL & GAS PROD $ - PRICE INDEX
	FTSE W TURKEY ELTRO/ELEC EQ $ - PRICE INDEX
	FTSE TURKEY FD PRODUCERS $ - PRICE INDEX
	FTSE W TURKEY FORESTRY & PAP $ - PRICE INDEX
	FTSE W TURKEY GENERAL INDS $ - PRICE INDEX
	FTSE TURKEY INDS TRANSPT $ - PRICE INDEX
	FTSE W TURKEY LEISURE GDS $ - PRICE INDEX
	FTSE TURKEY TCH H/W & EQ $ - PRICE INDEX
	CBOE SPX VOLATILITY VIX (NEW) - PRICE INDEX
	CBOE OEX VOLATILITY VXO (OLD) - PRICE INDEX
	ML MOVE 1M BOND VOLATILITY INDEX - PRICE INDEX
	ML MOVE 3M BOND VOLATILITY INDEX - PRICE INDEX
	S&P 500 LOW VOLATILITY - PRICE INDEX
	BIST NATIONAL 100 - PRICE INDEX

Table 3.14: Daily foreign exchange rate series used in the study.

	Name
Foreign Exchange	NEW TURKISH LIRA TO US $ (TK) - EXCHANGE RATE
	NEW TURKISH LIRA TO EURO - EXCHANGE RATE
	NEW TURKISH LIRA TO UK £ (TK) - EXCHANGE RATE
	NEW TURK.LIRA TO 100 JAPANESE YEN(TK) - EXCHANGE RATE
	NEW TURKISH LIRA TO AUSTRALIAN $(TK) - EXCHANGE RATE
	NEW TURKISH LIRA TO CANADIAN $ (TK) - EXCHANGE RATE
	NEW TURKISH LIRA TO DANISH KRN.(TK) - EXCHANGE RATE
	NEW TURKISH LIRA TO KUWAITI DNR.(TK) - EXCHANGE RATE
	NEW TURKISH LIRA TO NORWEG. KRN.(TK) - EXCHANGE RATE
	NEW TURKISH LIRA TO SAUDI RIYAL (TK) - EXCHANGE RATE
	NEW TURKISH LIRA TO SWEDISH KRN.(TK) - EXCHANGE RATE
	NEW TURKISH LIRA TO SWISS FRANC (TK) - EXCHANGE RATE

Table 3.15: Daily corporate risk (Turkey) series used in the study.

	Name
Corporate Risk (Turkey)	CGBI EMUSDGBI TURKEY - TOT RETURN IND
	CGBI EMUSDGBI-C TURKEY - TOT RETURN IND
	CGBI EMUSDGBI-E TURKEY - TOT RETURN IND
	CGBI EMUSDGBI-CE TURKEY - TOT RETURN IND
	JPM EMBI GLOBAL TURKEY - TOT RETURN IND
	JPM EMBI GLB.DIVERS TURKEY - TOT RETURN IND
	BARCLAYS EM MID.EAST TURKEY
	BARCLAYS EM TURKEY FIXED RATE
	BARCLAYS EM TURKEY INTL ISSUE
	JPM ELMI+ TURKEY ($) - TOT RETURN IND

Table 3.16: Daily corporate risk (foreign) series used in the study.

	Name	
Corporate Risk (Foreign)	BOFA ML GLOBAL GVT INDEX ($) - TOT RETURN IND	CGBI WGBI WORLD AAA/AA 15+Y ($) - TOT RETURN IND
	CGBI WGBI WORLD ALL MATS ($) - TOT RETURN IND	CGBI WGBI WORLD AAA/AA 20+Y ($) - TOT RETURN IND
	CGBI WGBI WORLD 7-10Y (U$) - TOT RETURN IND	CGBI WGBI WORLD AAA/AA 3-5Y ($) - TOT RETURN IND
	CGBI WGBI WORLD 10+Y (U$) - TOT RETURN IND	CGBI WGBI WORLD AAA/AA 3-7Y ($) - TOT RETURN IND
	CGBI WGBI WORLD 10-15Y ($) - TOT RETURN IND	CGBI WGBI WORLD AAA/AA 5+Y ($) - TOT RETURN IND
	CGBI WGBI AAA/AA ($) - TOT RETURN IND	CGBI WGBI WORLD AAA/AA 5-7Y ($) - TOT RETURN IND
	CGBI WGBI AAA/AA (L) - TOT RETURN IND	CGBI WGBI WORLD AAA/AA 7+Y ($) - TOT RETURN IND
	CGBI WGBI WORLD 1-10Y ($) - TOT RETURN IND	CGBI WGBI WORLD AAA/AA 7-10Y ($) - TOT RETURN IND
	CGBI WGBI WORLD 1-3Y (U$) - TOT RETURN IND	CGBI WGBI WORLD G3 ALL MATS ($) - TOT RETURN IND
	CGBI WGBI WORLD 1-5Y ($) - TOT RETURN IND	CGBI WGBI WORLD G5 ALL MATS ($) - TOT RETURN IND
	CGBI WGBI WORLD 10 MKT ALL MATS($) - TOT RETURN IND	CGBI WGBI WORLD G7 ALL MATS ($) - TOT RETURN IND
	CGBI WGBI WORLD 10MK X US ALL MATS($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 1-3y ($) - TOT RETURN IND
	CGBI WGBI WORLD 15+Y ($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 10+y ($) - TOT RETURN IND
	CGBI WGBI WORLD 3-5Y (U$) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 3-5y ($) - TOT RETURN IND
	CGBI WGBI WORLD 3-7Y($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 3-7y ($) - TOT RETURN IND
	CGBI WGBI WORLD 5+Y ($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 5-7y ($) - TOT RETURN IND
	CGBI WGBI WORLD 5-7Y ($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO 7-10y ($) - TOT RETURN IND
	CGBI WGBI WORLD AA ($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO ALL MATS($) - TOT RETURN IND
	CGBI WGBI WORLD AA 1-10Y($) - TOT RETURN IND	CGBI WGBI WORLD NON EURO ALL MATS($) - TOT RETURN IND
	CGBI WGBI WORLD AA 1-3Y ($) - TOT RETURN IND	CGBI WGBI WORLD NON US$ 1-10Y ($) - TOT RETURN IND
	CGBI WGBI WORLD AA 1-5Y ($) - TOT RETURN IND	CGBI WGBI WORLD NON US$ 10-15Y ($) - TOT RETURN IND
	CGBI WGBI WORLD AA 10-15Y($) - TOT RETURN IND	CGBI WGBI WORLD NON US$ 15+Y ($) - TOT RETURN IND
	CGBI WGBI WORLD AA 10+Y ($) - TOT RETURN IND	CGBI WGBI WORLD NON US$ 5+Y ($) - TOT RETURN IND
	CGBI WGBI WORLD AA 10-20Y($) - TOT RETURN IND	CGBI WGBI WORLD NON US$ ALL MATS ($) - TOT RETURN IND
	CGBI WGBI WORLD AA 15+Y ($) - TOT RETURN IND	CGBI WGBI WORLD NON-US$ 5-7Y ($) - TOT RETURN IND
	CGBI WGBI WORLD AA 20+Y ($) - TOT RETURN IND	CGBI WGBI WORLD NONJ AAA ALL MATS($) - TOT RETURN IND
	CGBI WGBI WORLD AA 3-5Y ($) - TOT RETURN IND	CGBI WGBI WORLD Non US$ 1-3Y ($) - TOT RETURN IND
	CGBI WGBI WORLD AA 3-7Y ($) - TOT RETURN IND	CGBI WGBI WORLD Non US$ 10+Y ($) - TOT RETURN IND
	CGBI WGBI WORLD AA 5+Y ($) - TOT RETURN IND	CGBI WGBI WORLD Non US$ 3-5Y ($) - TOT RETURN IND
	CGBI WGBI WORLD AA 5-7Y ($) - TOT RETURN IND	CGBI WGBI WORLD Non US$ 3-7Y ($) - TOT RETURN IND
	CGBI WGBI WORLD AA 7+Y ($) - TOT RETURN IND	CGBI WGBI WORLD Non US$ 7-10Y($) - TOT RETURN IND
	CGBI WGBI WORLD AA 7-10Y($) - TOT RETURN IND	CGBI WGBI WORLD Non-Euro 5+y ($) - TOT RETURN IND
	CGBI WGBI WORLD AAA ($) - TOT RETURN IND	ML EUROPE CONVERTIBLE BOND - TOT RETURN IND
	CGBI WGBI WORLD AAA 1-10Y($) - TOT RETURN IND	JPM GLOBAL GOVT.BND IN US$ - TOT RETURN IND
	CGBI WGBI WORLD AAA 1-3Y ($) - TOT RETURN IND	JPM GLOBAL GOVT.BND X.U.S.A.IN US$ - PRICE INDEX
	CGBI WGBI WORLD AAA 1-5Y ($) - TOT RETURN IND	S&P LEVERAGED LOAN INDEX - TOT RETURN IND
	CGBI WGBI WORLD AAA 10+Y ($) - TOT RETURN IND	BARCLAYS CUSTOM IG CORP INDEX
	CGBI WGBI WORLD AAA 10-15Y ($) - TOT RETURN IND	CGBI EMUSDGBI INDEX - TOT RETURN IND
	CGBI WGBI WORLD AAA 10-20Y ($) - TOT RETURN IND	BARCLAYS GOVERNMENT 1-3Y INDEX
	CGBI WGBI WORLD AAA 15+Y ($) - TOT RETURN IND	CGBI EMUSDGBI B RATED INDEX - TOT RETURN IND
	CGBI WGBI WORLD AAA 20+Y ($) - TOT RETURN IND	CGBI EMUSDGBI BB RATED INDEX - TOT RETURN IND
	CGBI WGBI WORLD AAA 3-5Y ($) - TOT RETURN IND	CGBI EMUSDGBI CCC RATED INDEX - TOT RETURN IND
	CGBI WGBI WORLD AAA 3-7Y ($) - TOT RETURN IND	CGBI EMUSDGBI INV.GRADE INDEX - TOT RETURN IND
	CGBI WGBI WORLD AAA 5+Y ($) - TOT RETURN IND	CGBI EMUSDGBI 1-5 YEARS INDEX - TOT RETURN IND
	CGBI WGBI WORLD AAA 5-7Y ($) - TOT RETURN IND	CGBI EMUSDGBI 10+ YEARS INDEX - TOT RETURN IND
	CGBI WGBI WORLD AAA 7+Y ($) - TOT RETURN IND	CGBI EMUSDGBI 5-10 YEARS INDEX - TOT RETURN IND
	CGBI WGBI WORLD AAA 7-10Y ($) - TOT RETURN IND	CGBI EMUSDGBI SUB INV.GRADE INDEX - TOT RETURN IND
	CGBI WGBI WORLD AAA/AA 1-10Y ($) - TOT RETURN IND	CGBI EMUSDGBI-C 1-5 YEARS INDEX - TOT RETURN IND
	CGBI WGBI WORLD AAA/AA 1-3Y ($) - TOT RETURN IND	CGBI EMUSDGBI-C 10+ YEARS INDEX - TOT RETURN IND
	CGBI WGBI WORLD AAA/AA 1-5Y ($) - TOT RETURN IND	CGBI EMUSDGBI-C 5-10 YEARS INDEX - TOT RETURN IND
	CGBI WGBI WORLD AAA/AA 10+Y ($) - TOT RETURN IND	BOFA ML U$ GLB HY IDX ($) - TOT RETURN IND
	CGBI WGBI WORLD AAA/AA 10-15Y($) - TOT RETURN IND	BOFA ML ER. NON FIN HY IDX ($) - TOT RETURN IND
	CGBI WGBI WORLD AAA/AA 10-20Y($) - TOT RETURN IND	BOFA ML BB-B GLB NON FIN HY IDX ($) - TOT RETURN IND

Figures

Figure 3.1: FADL-MIDAS 3-month ahead nowcasts

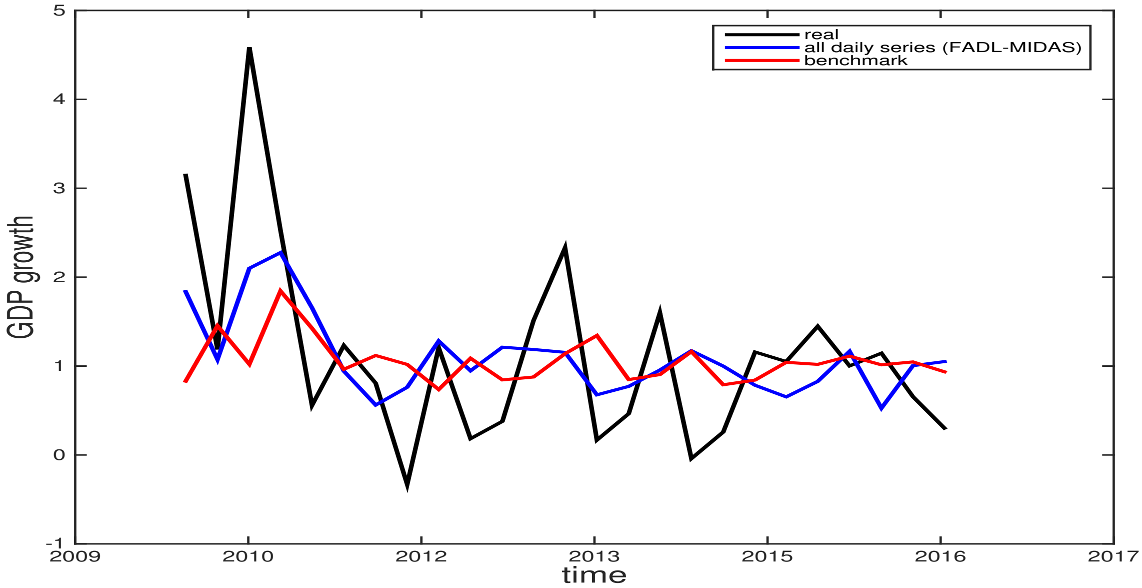

Figure of real GDP growth data and daily forecasts combinations with DMSFE weighting. The combined forecasts are 3-m ahead forecasts from the FADL-MIDAS model with all daily series.

Figure 3.2: FADL-MIDAS 2-month ahead nowcasts

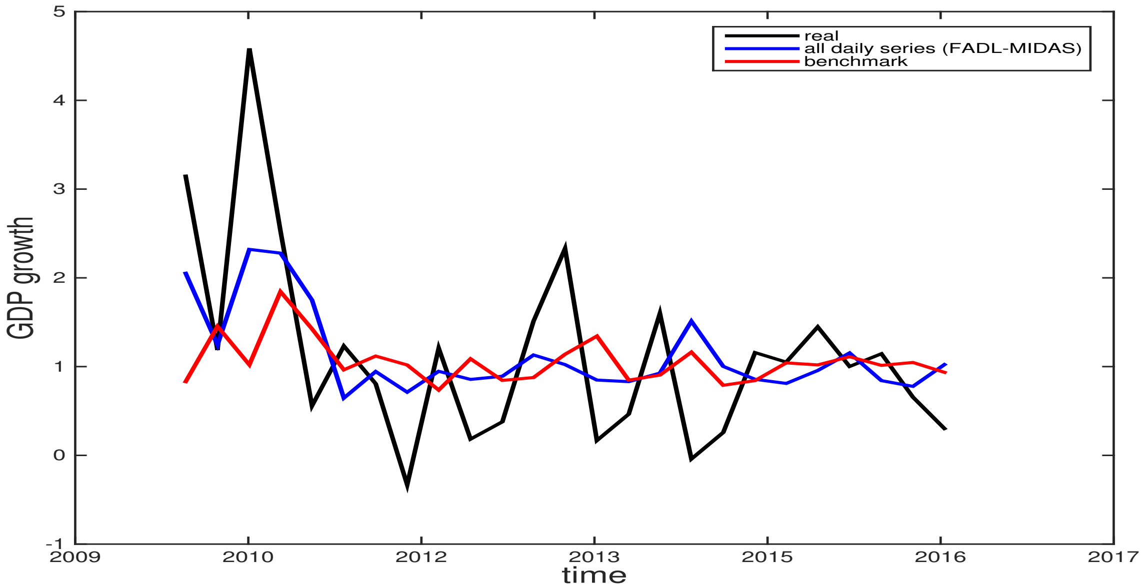

Figure of real GDP growth data and daily forecasts combinations with DMSFE weighting. The combined forecasts are 2-m ahead forecasts from the FADL-MIDAS model with all daily series.

Figure 3.3: FADL-MIDAS 1-month ahead nowcasts

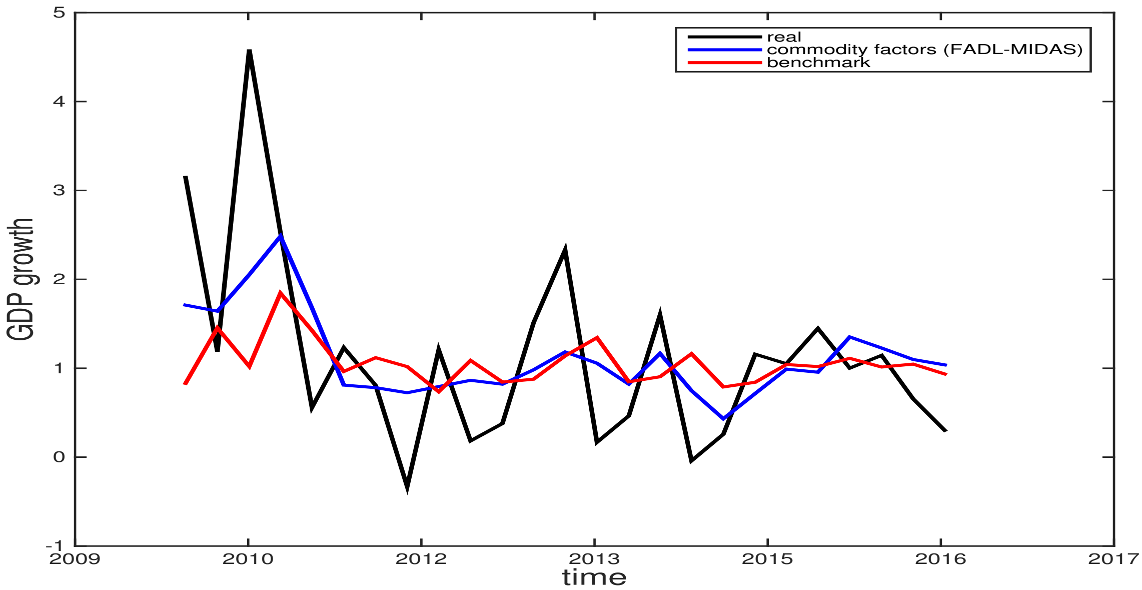

Figure of real GDP growth data and daily forecasts combinations with DMSFE weighting. The combined forecasts are 1-m ahead forecasts from the FADL-MIDAS model with daily factors extracted from commodity asset class.

Appendix

A. Non-MIDAS model forecasts and HLN–CW tests for financial data classes

Table 3.17: RMSFE comparisons for non-MIDAS models, separate financial data classes

Type of Series	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
AR(1)	1.08	1.08	1.08	1.10	1.10	1.10	1.12	1.33
Daily Series								
Equities								
ADL	0.88	0.94	0.98	0.95	0.87	0.89	0.95	0.79
FADL	**0.86**	0.91	0.94	**0.90**	**0.86**	0.86	0.93	0.77
Commodities								
ADL	0.94	0.95	0.98	0.98	0.89	**0.84**	0.95	0.80
FADL	0.92	0.92	0.95	0.96	0.88	0.86	0.93	0.77
Forex								
ADL	0.96	0.96	1.01	0.98	0.95	0.96	0.94	0.78
FADL	0.93	0.93	0.99	0.94	0.90	0.93	0.92	0.76
Corporate Risk (Turkey)								
ADL	0.96	1.00	1.00	0.95	0.93	0.96	0.96	0.78
FADL	0.92	0.97	0.96	**0.90**	0.88	0.93	0.94	0.75
Corporate Risk (Foreign)								
ADL	0.96	0.94	1.00	0.97	0.94	0.93	0.93	0.75
FADL	0.93	0.92	0.97	0.93	0.91	0.90	0.91	0.73
Daily Factors								
Separate Asset Classes								
ADL	0.95	0.95	0.95	0.96	0.93	0.92	0.92	0.77
FADL	0.94	0.92	0.90	0.94	0.90	0.90	0.89	0.75
Equities								
ADL	0.99	0.94	0.93	0.95	0.96	0.97	0.91	0.74
FADL	0.97	**0.90**	0.91	0.94	0.95	0.95	**0.87**	**0.71**
Commodities								
ADL	0.98	0.98	0.96	0.94	0.94	0.95	0.89	0.77
FADL	0.93	0.92	**0.87**	0.93	0.91	0.93	**0.87**	0.76
Forex								
ADL	0.95	0.93	0.98	0.96	0.97	0.95	0.94	0.81
FADL	0.93	0.92	0.96	0.94	0.93	0.93	0.91	0.79
Corporate Risk								
ADL	0.97	0.97	0.97	0.98	0.94	0.96	0.96	0.80
FADL	0.97	0.96	0.93	0.96	0.90	0.92	0.93	0.78
Corporate Risk (Foreign)								
ADL	0.91	0.97	0.94	0.95	0.91	0.87	0.94	0.77
FADL	0.91	0.93	0.90	0.93	0.88	0.86	0.91	0.74

Forecast combination results of ADL and FADL models for separate financial data classes and factors derived from these classes. The first line gives the RMSFE of the AR(1) model with no constant. Other cells include the relative RMSFE of combined forecasts to the AR(1) model.

Table 3.18: HLN test statistics for non-MIDAS vs. MIDAS models, separate financial data classes

ADL and FADL vs.	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
Equities								
ADL-MIDAS	0.42	0.56	1.08	0.35	0.85	-0.41	0.76	0.95
FADL-MIDAS	0.35	0.57	0.83	0.37	0.97	-0.41	0.71	0.90
Commodities								
ADL-MIDAS	0.37	0.10	-0.37	1.07	0.42	-0.17	0.33	2.94***
FADL-MIDAS	0.34	0.01	-0.46	1.34	0.37	0.14	0.50	0.43
Forex								
ADL-MIDAS	-0.05	-0.56	-0.44	-1.09	0.40	0.34	1.55	1.91*
FADL-MIDAS	0.02	-0.37	-0.60	-1.21	0.00	0.78	1.27	1.60
Corporate Risk (Turkey)								
ADL-MIDAS	-0.67	0.96	0.27	0.48	-0.12	-0.30	-0.89	-1.26
FADL-MIDAS	-0.72	1.20	0.08	0.06	-0.01	-0.21	-0.76	-1.08
Corporate Risk (Foreign)								
ADL-MIDAS	0.39	0.94	0.78	0.12	1.45	-1.39	0.95	0.77
FADL-MIDAS	0.09	1.17	0.92	0.16	1.26	-0.98	1.05	0.68
Daily Factors								
Separate Asset Classes								
ADL-MIDAS	1.90*	1.90*	1.67	1.41	1.92*	2.09**	1.47	1.36
FADL-MIDAS	1.99*	1.54	1.81*	1.68	2.18**	2.07**	1.10	1.35
Equities								
ADL-MIDAS	1.59	1.30	1.56	1.36	2.12**	1.31	1.94*	1.19
FADL-MIDAS	1.67	1.23	1.19	1.66	2.90***	1.30	1.70	1.44
Commodities								
ADL-MIDAS	1.46	1.52	2.06**	1.37	0.10	1.13	0.43	1.29
FADL-MIDAS	1.23	1.12	1.79*	1.48	0.27	1.18	0.64	0.82
Forex								
ADL-MIDAS	1.49	1.64	0.90	0.49	1.37	0.82	1.07	0.78
FADL-MIDAS	1.44	1.66	0.92	0.30	1.15	1.09	1.00	1.04
Corporate Risk (Turkey)								
ADL-MIDAS	0.68	0.40	0.85	0.61	0.44	0.98	0.41	1.26
FADL-MIDAS	0.98	0.46	0.66	0.78	0.75	1.08	0.39	0.70
Corporate Risk (Foreign)								
ADL-MIDAS	1.37	1.28	0.50	1.28	2.06**	0.15	-0.52	0.06
FADL-MIDAS	0.99	1.24	0.70	0.86	2.30**	0.90	0.72	0.31

Harvey-Leybourne-Newbold (HLN) test statistics for comparison of non-MIDAS and MIDAS model forecast combination performances with separate financial data classes and factors derived from these classes. * p<0.10, ** p<0.05, *** p<0.01.

Table 3.19: CW test statistics for non-MIDAS vs. MIDAS models, separate financial data classes

ADL and FADL vs.	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
Equities								
ADL-MIDAS	1.51*	1.35*	1.40*	0.98	1.93**	2.72**	1.24	1.40*
FADL-MIDAS	1.65**	1.42*	1.33*	0.98	2.27**	2.11**	1.19	1.65**
Commodities								
ADL-MIDAS	1.23	1.03	0.79	1.31*	0.96	0.39	1.02	1.57*
FADL-MIDAS	1.36*	1.04	0.75	1.64*	0.93	0.82	1.31*	1.11
Forex								
ADL-MIDAS	0.81	0.73	0.25	-0.27	0.95	1.23	1.97**	2.75**
FADL-MIDAS	0.79	0.55	0.17	-0.39	0.47	1.67**	1.63*	2.95**
Corporate Risk (Turkey)								
ADL-MIDAS	1.58*	1.55*	1.42*	1.47*	0.95	1.06	0.79	1.18
FADL-MIDAS	1.39*	1.80**	1.13	1.18	1.42*	1.14	0.67	0.76
Corporate Risk (Foreign)								
ADL-MIDAS	1.19	1.34*	1.45*	1.17	2.44**	-0.02	1.47*	1.00
FADL-MIDAS	1.10	1.91**	1.81**	1.14	2.02**	0.34	1.65**	1.04
Daily Factors								
Separate Asset Classes								
ADL-MIDAS	1.96**	2.02**	1.77**	1.57*	1.99**	2.44**	1.83**	2.03**
FADL-MIDAS	2.10**	1.60*	1.92**	1.79**	2.29**	2.25**	1.75*	2.04**
Equities								
ADL-MIDAS	2.06**	1.93**	2.17**	1.61*	2.43**	1.96**	3.09**	2.06**
FADL-MIDAS	2.66**	1.32*	1.52*	1.90**	3.10**	2.25**	2.97**	2.50**
Commodities								
ADL-MIDAS	1.92**	1.86**	2.60**	1.83**	0.61	1.81**	1.00	2.20**
FADL-MIDAS	1.72**	1.42*	2.55**	1.86**	0.88	1.81**	1.71**	1.57*
Forex								
ADL-MIDAS	1.71**	2.43**	1.17	1.19	1.69**	1.69**	0.95	1.34*
FADL-MIDAS	1.90**	2.35**	1.13	1.17	1.80**	2.46**	1.79**	1.84**
Corporate Risk (Turkey)								
ADL-MIDAS	1.52*	1.01	1.42*	1.34*	1.06	1.52*	0.82	2.29**
FADL-MIDAS	1.49*	0.94	1.69**	1.42*	1.50*	1.36*	0.79	1.61*
Corporate Risk (Foreign)								
ADL-MIDAS	2.36**	2.17**	1.23	1.90**	2.12**	1.61*	-0.18	0.87
FADL-MIDAS	2.06**	1.93**	1.67**	1.46*	2.26**	2.33**	1.47*	1.14

Clark-West (CW) test statistics for comparison of non-MIDAS and MIDAS model forecast combination performances with separate financial data classes and factors derived from these classes. *0.05< p<0.10, ** 0.01<p<0.05.

Table 3.20: HLN test statistics for AR(1) vs. MIDAS models, separate financial data classes

AR(1) vs.	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
Equities								
ADL-MIDAS	0.93	0.82	0.88	0.62	0.88	0.79	1.00	1.35
FADL-MIDAS	0.94	0.84	0.79	0.77	0.88	0.79	0.81	1.39
Commodities								
ADL-MIDAS	0.59	0.33	-0.16	0.82	0.78	0.83	0.55	0.93
FADL-MIDAS	0.58	0.33	-0.05	0.84	0.77	0.81	0.67	0.78
Forex								
ADL-MIDAS	0.37	-0.24	-0.49	-0.82	0.78	0.77	1.04	1.55
FADL-MIDAS	0.51	0.04	-0.33	-0.32	0.76	0.80	1.25	0.80
Corporate Risk (Turkey)								
ADL-MIDAS	-0.27	0.74	0.28	0.85	0.61	0.52	-0.46	0.13
FADL-MIDAS	0.02	0.95	0.32	0.59	0.65	0.55	-0.06	0.19
Corporate Risk (Foreign)								
ADL-MIDAS	1.41	1.44	0.87	0.82	0.88	0.77	0.99	0.63
FADL-MIDAS	1.49	1.52	0.90	0.94	0.82	0.75	1.01	0.70
Daily Factors								
Separate Asset Classes								
ADL-MIDAS	1.89*	1.77*	1.64	1.17	0.93	0.97	1.35	1.48
FADL-MIDAS	1.52	1.33	1.44	1.05	0.89	0.91	1.17	1.24
Equities								
ADL-MIDAS	1.68	1.50	1.45	1.20	0.93	0.83	1.87*	1.61
FADL-MIDAS	1.11	1.17	1.19	0.93	0.95	0.79	1.42	1.49
Commodities								
ADL-MIDAS	1.64	1.46	1.85*	2.02*	0.79	0.97	1.11	1.65
FADL-MIDAS	1.29	1.24	1.73*	1.16	0.79	0.94	1.21	1.05
Forex								
ADL-MIDAS	1.60	1.57	0.92	0.54	0.88	0.85	0.84	0.82
FADL-MIDAS	1.32	1.28	0.87	0.44	0.81	0.79	1.13	0.93
Corporate Risk (Turkey)								
ADL-MIDAS	0.87	0.64	0.93	0.58	0.74	0.86	0.65	1.21
FADL-MIDAS	0.93	0.55	0.92	0.64	0.71	0.82	0.58	0.86
Corporate Risk (Foreign)								
ADL-MIDAS	1.53	1.20	1.23	1.04	0.89	0.90	0.52	0.65
FADL-MIDAS	1.36	1.09	1.31	1.13	0.88	0.90	0.92	0.82

Harvey-Leybourne-Newbold (HLN) test statistics for comparison of AR(1) benchmark model and MIDAS model forecast combination performances with separate financial data classes and factors derived from these classes. * p<0.10, ** p<0.05, *** p<0.01.

Table 3.21: CW test statistics for AR(1) vs. MIDAS models, separate financial data classes

AR(1) vs.	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
Equities								
ADL-MIDAS	1.60*	1.49*	1.34*	1.31*	1.50*	1.50*	1.48*	2.36**
FADL-MIDAS	1.50*	1.40*	1.31*	1.45*	1.52*	1.47*	1.57*	2.21**
Commodities								
ADL-MIDAS	1.57*	1.22	1.02	1.20	1.57*	1.67**	1.11	1.46*
FADL-MIDAS	1.55*	1.18	1.05	1.32*	1.58*	1.67*	1.24	1.48*
Forex								
ADL-MIDAS	1.18	0.71	0.22	0.46	1.40*	1.43*	1.58*	2.33**
FADL-MIDAS	1.16	0.81	0.56	1.16	1.45*	1.44*	2.06**	1.44*
Corporate Risk (Turkey)								
ADL-MIDAS	0.65	1.46*	1.34*	2.06**	1.49*	1.40*	2.17**	1.64*
FADL-MIDAS	0.72	1.55*	1.14	1.84**	1.60*	1.44*	1.94**	1.66**
Corporate Risk (Foreign)								
ADL-MIDAS	2.24**	1.86**	1.67**	1.76**	1.58*	1.50*	1.36*	1.24
FADL-MIDAS	2.12**	1.74**	1.56*	1.95**	1.64*	1.58*	1.38*	1.29*
Daily Factors								
Separate Asset Classes								
ADL-MIDAS	1.96**	1.81**	1.71**	1.59*	1.53*	1.57*	1.70**	1.71**
FADL-MIDAS	1.66**	1.41*	1.51*	1.59*	1.56*	1.62*	1.61*	1.62*
Equities								
ADL-MIDAS	2.13**	1.94**	1.77**	1.68**	1.58*	1.54*	2.38**	1.94**
FADL-MIDAS	1.54*	1.50*	1.44*	1.42*	1.63*	1.60*	2.01**	1.82**
Commodities								
ADL-MIDAS	2.07**	1.67**	2.19**	2.29**	1.46*	1.62*	1.49*	1.99**
FADL-MIDAS	1.64*	1.39*	1.79**	1.84**	1.53*	1.67**	1.79**	1.60*
Forex								
ADL-MIDAS	1.82**	2.00**	1.22	1.31*	1.62*	1.55*	1.36*	1.24
FADL-MIDAS	1.68**	1.63*	1.12	1.41*	1.69**	1.59*	1.61*	1.58*
Corporate Risk (Turkey)								
ADL-MIDAS	1.41*	1.00	1.38*	1.44*	1.35*	1.45*	1.13	1.60*
FADL-MIDAS	1.31*	0.95	1.24	1.59*	1.43*	1.54*	1.21	1.60*
Corporate Risk (Foreign)								
ADL-MIDAS	2.08**	1.78**	1.80**	1.64*	1.53*	1.64*	1.30*	1.28*
FADL-MIDAS	1.98**	1.48*	1.87**	1.89**	1.56*	1.68**	1.52*	1.33*

Clark-West (CW) test statistics for comparison of AR(1) benchmark model and MIDAS model forecast combination performances with separate financial data classes and factors derived from these classes. *0.05< p<0.10, ** 0.01<p<0.05.

Table 3.22: HLN test statistics for ADL-MIDAS vs. FADL-MIDAS models, separate financial data classes

ADL-MIDAS vs. FADL-MIDAS	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
Equities	0.33	0.64	0.28	1.00	0.81	0.79	0.22	0.44
Commodities	0.11	0.21	0.37	0.51	0.36	0.30	0.76	0.27
Forex	0.51	0.41	0.01	0.76	0.64	0.63	0.18	0.63
Corporate Risk (Turkey)	0.54	1.05	0.25	0.22	0.95	0.70	0.20	0.32
Corporate Risk (Foreign)	0.67	1.04	0.64	0.82	0.48	0.60	0.45	1.17
Daily Factors								
Separate Asset Classes	0.35	0.43	0.48	0.44	0.52	0.57	0.89	0.42
Equities	0.22	0.31	0.16	0.17	1.23	-0.80	0.54	0.74
Commodities	0.47	0.72	0.98	0.49	0.78	0.39	0.57	0.57
Forex	0.00	0.18	0.57	-0.15	-0.57	0.37	1.13	0.58
Corporate Risk (Turkey)	0.76	0.17	-0.23	0.42	0.59	0.70	0.45	-0.46
Corporate Risk (Foreign)	-0.93	0.56	0.72	1.13	0.71	0.91	1.02	0.88

Harvey-Leybourne-Newbold (HLN) test statistics for comparison of ADL-MIDAS and FADL-MIDAS model forecast combination performances with separate financial data classes and factors derived from these classes. * p<0.10, ** p<0.05, *** p<0.01.

Table 3.23: CW test statistics for ADL-MIDAS vs. FADL-MIDAS models, separate financial data classes

ADL-MIDAS vs. FADL-MIDAS	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
Equities	0.65	1.18	0.67	1.64**	1.27	1.25	0.74	0.89
Commodities	0.53	0.71	1.05	0.92	0.64	0.58	1.29*	0.66
Forex	1.18	1.22	0.52	1.37*	1.15	1.08	0.64	1.20
Corporate Risk (Turkey)	1.07	1.62*	1.12	1.10	1.75**	1.52*	0.60	0.77
Corporate Risk (Foreign)	1.15	1.58*	1.17	1.22	1.10	1.19	1.01	1.40*
Daily Factors								
Separate Asset Classes	0.98	0.96	1.10	1.01	1.05	1.17	1.14	0.95
Equities	0.69	0.89	1.00	0.81	1.98**	0.34	1.29*	1.20
Commodities	1.03	1.14	1.64*	0.88	1.36*	1.51*	1.58*	1.58*
Forex	0.78	1.12	1.13	0.78	0.62	1.82**	1.35*	1.21
Corporate Risk (Turkey)	1.70*	1.15	0.39	0.96	1.13	1.36*	0.91	0.40
Corporate Risk (Foreign)	-0.02	1.35*	1.75**	1.98**	1.43*	1.66*	1.26	1.32*

Clark-West (CW) test statistics for comparison of ADL-MIDAS and FADL-MIDAS model forecast combination performances with separate financial data classes and factors derived from these classes. *0.05< p<0.10, ** 0.01<p<0.05.

Table 3.24: HLN test statistics for best series vs. FADL-MIDAS models, separate financial data classes

FADL-MIDAS vs. Best Series	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
Equities	-0.39	-0.33	1.33	-0.28	-0.15	-1.48	-0.17	-0.18
Commodities	0.11	0.46	1.90	-0.26	0.40	-2.30**	0.13	-0.01
Forex	0.96	1.01	2.82***	1.21	0.89	-2.14**	-0.24	-0.53
Corporate Risk (Turkey)	1.87*	-0.57	1.86*	-0.14	0.34	-0.49	1.12	0.32
Corporate Risk (Foreign)	0.75	0.24	2.04*	0.12	0.30	-2.19**	-1.31	-0.49
Daily Factors								
Separate Asset Classes	-0.36	-0.46	0.97	-0.89	-1.11	-3.66***	-1.55	-1.06
Equities	0.99	0.08	1.18	-0.58	-1.86*	-2.19**	-1.49	-1.87*
Commodities	-0.19	-0.53	-0.19	-0.73	0.83	-6.13***	-1.60	-0.76
Forex	-0.51	-0.19	1.77*	-0.09	-0.33	-3.00***	-1.64	-0.47
Corporate Risk (Turkey)	0.26	0.76	1.61	0.02	0.16	-1.55	-0.21	-0.21
Corporate Risk (Foreign)	0.27	-0.24	1.07	-0.54	-0.63	-4.09***	-0.61	-0.37

Harvey-Leybourne-Newbold (HLN) test statistics for comparison of forecast combination of best 5 series and FADL-MIDAS model forecast combination performances with separate financial data classes and factors derived from these classes. *0.05< p<0.10, ** 0.01<p<0.05.

Table 3.25: CW test statistics for best series vs. FADL-MIDAS models, separate financial data classes

FADL-MIDAS vs. Best Series	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
Equities	0.62	0.29	2.88**	1.27	2.56**	0.31	2.67**	2.32**
Commodities	1.74**	1.86**	2.88**	1.04	2.34**	-0.19	2.44**	2.04**
Forex	1.90**	1.85**	3.03**	2.64**	2.34**	-0.63	2.56**	2.03**
Corporate Risk (Turkey)	4.47**	1.53*	2.71**	1.46*	2.51**	1.00	3.45**	2.35**
Corporate Risk (Foreign)	2.29**	2.09**	2.87**	2.58**	2.09**	0.26	-0.41	1.22
Daily Factors								
Separate Asset Classes	1.57*	1.30*	2.42**	0.79	0.81	-1.53	1.15	0.76
Equities	2.32**	2.35**	2.72**	1.07	0.93	-0.27	1.74**	-0.18
Commodities	1.84**	0.95	1.41*	1.51**	2.92**	-1.24	1.48*	1.11
Forex	1.47*	2.09**	4.02**	1.64*	1.25	-0.34	0.92	1.65**
Corporate Risk (Turkey)	1.78**	2.40**	2.53**	1.86**	1.81**	-0.92	1.86**	1.50*
Corporate Risk (Foreign)	1.45*	1.60*	1.72**	0.89	0.93	-0.46	2.06**	1.47*

Clark-West (CW) test statistics for comparison of forecast combination of best 5 series and FADL-MIDAS model forecast combination performances with separate financial data classes and factors derived from these classes. *0.05< p<0.10, ** 0.01<p<0.05.

B. Robustness Checks

In addition to HLN and CW tests, robustness of the results is checked with forecast encompassing and mean squared adjusted test statistics (Clark and McCracken, 2001; McCracken, 2007; Clark and McCracken, 2010) when the bigger model includes additional variables. These cases include the comparison of AR(1) model with ADL-MIDAS and FADL-MIDAS models; and ADL-MIDAS models with FADL-MIDAS models. In the former comparison, the bigger model includes quarterly factor terms in addition to the AR(1) term. In the latter comparison, the bigger model includes additional quarterly factor variables.

Let $\hat{\varepsilon}_{0,t+h}$ denote the h-step ahead forecast error from the benchmark model (e.g. AR(1)) and $\hat{\varepsilon}_{1,t+h}$ denote the forecast error from the model to be compared. Define $\hat{d}_{t+h} = \hat{\varepsilon}^2_{0,t+h} - \hat{\varepsilon}^2_{1,t+h}$, $\hat{c}_{t+h} = \hat{\varepsilon}_{0,t+h}(\hat{\varepsilon}_{0,t+h} - \hat{\varepsilon}_{1,t+h})$, and $\hat{\sigma}^2_1 = (P-h+1)\sum_{t=R}^{T-h}\hat{\varepsilon}^2_{1,t+h}$. Then, the encompassing and mean squared adjusted test statistics can be written as the following:

$$\text{ENC-t} = \frac{P^{-1/2}\sum_{t=R}^{T-h}\hat{c}_{t+h}}{\hat{S}_{cc}^{1/2}}, \tag{3.14}$$

$$\text{ENC-F} = \frac{\sum_{t=R}^{T-h}\hat{c}_{t+h}}{\hat{\sigma}^2_1}, \tag{3.15}$$

$$\text{MSE-t} = \frac{P^{-1/2}\sum_{t=R}^{T-h}\hat{d}_{t+h}}{\hat{S}_{dd}^{1/2}}, \tag{3.16}$$

$$\text{MSE-F} = \frac{\sum_{t=R}^{T-h}\hat{d}_{t+h}}{\hat{\sigma}^2_1}, \tag{3.17}$$

where $\hat{S}_{cc}$ and $\hat{S}_{dd}$ denote Newey and West (1987) heteroskedasticity and autocorrelation consistent variance for $\hat{c}_{t+h}$ and $\hat{d}_{t+h}$ respectively, P is the number of out-of-sample forecasts, and R is the initial window size. According to the Monte Carlo simulations of Busetti and Marcucci (2013), ENC-F to the be the most powerful tests within test statistics. For cases where the assumptions of the test statistics do not hold, Clark and McCracken (2010) describe a bootstrapping algorithm. In our study, we use the described bootstrap method with 10,000 repetitions. Results of these test are given below.

Table 3.26: ENC-t tests for AR(1) vs. MIDAS models

AR(1) vs.	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
All Daily Series								
ADL-MIDAS	1.93**	1.69***	1.51***	2.16***	2.14***	2.20***	1.63**	1.69**
FADL-MIDAS	1.80**	1.58***	1.41***	2.16***	2.21**	2.25**	1.67**	1.72**
Equities								
ADL-MIDAS	1.72**	1.58**	1.48**	1.57**	1.94**	1.89**	1.81**	2.18**
FADL-MIDAS	1.61**	1.48**	1.40**	1.74**	1.99**	1.91**	1.84***	2.38**
Commodities								
ADL-MIDAS	1.67**	1.31**	1.10**	1.47***	2.22**	2.35**	1.38**	1.60**
FADL-MIDAS	1.67**	1.28**	1.13**	1.59**	2.24**	2.34**	1.53**	1.67**
Forex								
ADL-MIDAS	1.08**	0.78**	0.22**	0.38**	1.97**	2.06***	1.87***	2.53***
FADL-MIDAS	1.14**	0.86**	0.57**	1.04**	2.05**	1.99**	1.76**	2.30***
Corporate Risk (Turkey)								
ADL-MIDAS	0.55**	1.41**	1.13**	2.23***	2.13**	2.00**	1.61**	1.83**
FADL-MIDAS	0.68**	1.60**	0.99**	2.06**	2.25**	2.05**	1.95**	1.86**
Corporate Risk (Foreign)								
ADL-MIDAS	2.34**	2.20**	1.71**	1.75**	2.15**	2.10**	1.56**	1.39**
FADL-MIDAS	2.26***	2.07***	1.61**	2.26**	2.25**	2.25**	1.59**	1.45**
Daily Factors								
All Daily Factors								
ADL-MIDAS	2.28***	2.29***	2.44***	2.37***	2.12***	2.29***	1.71**	2.18***
FADL-MIDAS	1.98***	1.95***	2.06**	2.32***	2.13**	2.36**	1.65**	2.05**
Seperate Asset Classes								
ADL-MIDAS	2.06**	1.96**	1.81**	1.96***	2.15***	2.23***	1.99***	2.16***
FADL-MIDAS	1.74**	1.54**	1.61**	1.91**	2.20**	2.31**	1.91**	1.96***
Equities								
ADL-MIDAS	2.00***	2.05**	1.98***	2.10***	2.20***	2.12**	2.57***	2.32***
FADL-MIDAS	1.45**	1.60**	1.58**	1.77**	2.22**	2.18**	2.27**	2.12***
Commodities								
ADL-MIDAS	2.26***	1.74**	2.17***	2.17***	2.10**	2.37***	1.85**	2.26***
FADL-MIDAS	1.79***	1.53**	1.93**	2.08***	2.19**	2.44***	2.11**	1.86***
Forex								
ADL-MIDAS	2.01**	2.39***	1.42**	1.62**	2.26**	2.12**	1.43***	1.52**
FADL-MIDAS	1.85**	1.82**	1.28**	1.69**	2.31**	2.22**	1.95**	1.86**
Corporate Risk (Turkey)								
ADL-MIDAS	1.34**	1.02**	1.38**	1.59**	1.83**	2.02**	1.39**	2.01***
FADL-MIDAS	1.34**	1.04**	1.25**	1.84**	2.03**	2.20**	1.45**	1.84**
Corporate Risk (Foreign)								
ADL-MIDAS	2.06***	1.59**	1.57**	1.78***	2.17**	2.39**	0.99**	1.68**
FADL-MIDAS	1.87***	1.54**	1.75**	2.03***	2.21**	2.45**	1.77***	1.65**

ENC-t test statistics comparing AR(1) model with other models used in the study. The statistics are calculated using the small sample adjustment for the test. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 3.27: ENC-F tests for AR(1) vs. MIDAS models

AR(1) vs.	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
All Daily Series								
ADL-MIDAS	10.19***	9.15***	7.27***	3.98**	22.12***	17.71***	10.15**	8.53**
FADL-MIDAS	10.94***	12.23***	8.47***	6.93**	27.24***	21.79***	11.40**	10.30**
Equities								
ADL-MIDAS	13.88***	11.46**	6.89**	5.42**	23.54***	16.17***	3.62**	4.63**
FADL-MIDAS	14.03***	13.88***	8.39**	8.08**	25.84***	19.39***	5.43**	6.60**
Commodities								
ADL-MIDAS	14.74**	9.06**	5.20**	3.98***	23.31***	22.33***	2.87**	3.40**
FADL-MIDAS	15.38**	10.26**	6.57**	5.57***	25.14***	24.16***	4.31**	4.83**
Forex								
ADL-MIDAS	2.43**	2.41**	0.54**	0.45**	15.84***	14.68***	3.91**	3.89**
FADL-MIDAS	4.39**	4.57**	2.05**	1.64**	18.34***	16.64***	5.53**	6.54**
Corporate Risk (Turkey)								
ADL-MIDAS	1.41**	6.74**	3.64**	6.50**	17.16**	12.49**	2.47**	5.27**
FADL-MIDAS	2.57**	19.46**	3.71**	10.38**	23.36***	15.67**	4.64**	6.52**
Corporate Risk (Foreign)								
ADL-MIDAS	3.67**	5.29**	6.45**	2.98**	18.16***	13.12**	14.83***	10.57**
FADL-MIDAS	3.78**	6.01***	6.99**	6.08**	24.25***	17.29**	15.82***	12.35**
Daily Factors								
All Daily Factors								
ADL-MIDAS	5.25**	6.06***	8.20***	5.07***	24.21***	19.26***	3.67**	19.30***
FADL-MIDAS	5.80**	7.36***	9.29***	7.13***	27.58***	22.44***	7.07**	27.98***
Separate Asset Classes								
ADL-MIDAS	6.21**	6.15***	6.06***	6.65**	24.49***	20.00***	3.81**	6.75**
FADL-MIDAS	7.55**	8.40**	7.52**	9.86**	30.03***	26.38***	8.79***	9.74***
Equities								
ADL-MIDAS	2.35**	5.38**	6.19**	5.91**	26.53***	19.66***	5.87**	9.55***
FADL-MIDAS	3.02**	6.75**	6.88**	7.79**	30.89***	20.71***	9.11***	13.36***
Commodities								
ADL-MIDAS	6.51***	5.62***	7.93***	5.02**	15.72***	19.44***	5.44**	8.01**
FADL-MIDAS	8.34**	10.03**	11.62**	8.06**	19.25***	23.46***	7.54**	10.52***
Forex								
ADL-MIDAS	9.20**	8.10***	4.47**	9.67**	28.90***	16.46***	2.68**	5.03**
FADL-MIDAS	10.36**	8.33***	6.10**	12.51**	30.43***	20.54***	11.93**	8.56**
Corporate Risk (Turkey)								
ADL-MIDAS	3.63**	3.08**	6.00**	3.58**	16.95***	16.12***	3.00**	6.10**
FADL-MIDAS	6.79**	4.67**	5.27**	7.46**	26.64***	30.42***	6.84**	6.53**
Corporate Risk (Foreign)								
ADL-MIDAS	7.68**	6.34***	4.13**	4.22**	25.10***	21.20***	1.38**	3.62**
FADL-MIDAS	6.38**	9.93***	6.27**	6.49**	30.30***	25.96***	6.06***	7.17**

ENC-F test statistics comparing AR(1) model with other models used in the study. The statistics are calculated using the small sample adjustment for the test. * p<0.10, ** p<0.05, *** p<0.01.

Table 3.28: MSE-t tests for AR(1) vs. MIDAS models

AR(1) vs.	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
All Daily Series								
ADL-MIDAS	1.59***	1.48***	1.40***	1.62***	1.87***	1.88***	1.41***	1.30***
FADL-MIDAS	1.53***	1.42***	1.27***	1.52***	1.81***	1.81***	1.36**	1.26**
Equities								
ADL-MIDAS	0.97**	0.85**	0.92**	0.74**	1.66***	1.48**	1.23**	1.17***
FADL-MIDAS	0.98**	0.88**	0.83**	0.93**	1.68***	1.53**	0.91**	1.27***
Commodities								
ADL-MIDAS	0.61**	0.34**	-0.17**	1.12***	1.54**	1.64***	0.76	1.17***
FADL-MIDAS	0.61**	0.35**	-0.06**	1.10***	1.49**	1.57**	0.92**	0.93**
Forex								
ADL-MIDAS	0.38**	-0.24**	-0.51**	-0.80**	1.55**	1.58***	1.43***	1.93***
FADL-MIDAS	0.53**	0.04**	-0.35**	-0.27**	1.50***	1.54***	1.02**	1.47***
Corporate Risk (Turkey)								
ADL-MIDAS	-0.28**	0.77**	0.29**	0.91	1.29**	1.11**	-0.29**	0.18**
FADL-MIDAS	0.02**	0.99**	0.34**	0.69**	1.37**	1.18**	-0.06**	0.25**
Corporate Risk (Foreign)								
ADL-MIDAS	1.47***	1.50***	0.90**	0.78**	1.75***	1.59***	1.25**	0.81**
FADL-MIDAS	1.55***	1.58***	0.94**	1.23***	1.66***	1.51**	1.27**	0.90**
Daily Factors								
All Daily Factors								
ADL-MIDAS	1.48***	1.95***	2.04***	1.77***	1.76***	1.80***	0.83**	1.75***
FADL-MIDAS	1.20***	1.54***	1.82***	1.48***	1.66***	1.71***	0.77**	1.59***
Separate Asset Classes								
ADL-MIDAS	1.97**	1.84***	1.71***	1.56***	1.88***	1.99***	1.84***	1.99***
FADL-MIDAS	1.58**	1.38**	1.50***	1.29***	1.77***	1.81***	1.47***	1.51***
Equities								
ADL-MIDAS	1.75***	1.56***	1.51***	1.66***	1.82***	1.66***	2.28***	2.10***
FADL-MIDAS	1.16**	1.22**	1.24**	1.22***	1.89***	1.51***	1.68***	1.80***
Commodities								
ADL-MIDAS	1.71***	1.52***	1.93***	1.79***	1.60***	2.01***	1.55***	1.92***
FADL-MIDAS	1.35***	1.29***	1.80***	1.33***	1.55***	1.85***	1.59***	1.23***
Forex								
ADL-MIDAS	1.67***	1.63***	0.95**	0.70**	1.82***	1.70***	1.07***	1.09***
FADL-MIDAS	1.38**	1.34***	0.91**	0.54**	1.55**	1.49***	1.42***	1.06**
Corporate Risk (Turkey)								
ADL-MIDAS	0.91**	0.67	0.97***	0.75***	1.47**	1.76***	0.82**	1.65***
FADL-MIDAS	0.97**	0.57**	0.95***	0.74**	1.40***	1.65***	0.71**	1.05**
Corporate Risk (Foreign)								
ADL-MIDAS	1.60***	1.25***	1.28***	1.34***	1.78***	1.89***	0.31	0.85**
FADL-MIDAS	1.42***	1.13***	1.36***	1.41***	1.74***	1.83***	1.18***	0.98**

MSE-t test statistics comparing AR(1) model with other models used in the study. The statistics are calculated using the small sample adjustment for the test. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 3.29: MSE-F tests for AR(1) vs. MIDAS models

AR(1) vs.	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
All Daily Series								
ADL-MIDAS	14.46***	13.62***	11.58***	5.04**	28.15***	23.26***	14.18***	10.89***
FADL-MIDAS	15.68***	17.82***	12.79***	8.07***	32.16***	26.78***	14.86***	12.29***
Equities								
ADL-MIDAS	12.84***	10.20***	7.56***	5.01**	27.46***	19.17***	4.64**	4.31***
FADL-MIDAS	13.57***	12.72***	8.47***	7.73***	29.89***	23.47***	5.22**	6.02***
Commodities								
ADL-MIDAS	8.62**	3.92**	-1.43**	5.51***	24.08***	25.31***	2.72**	4.01***
FADL-MIDAS	8.80**	4.33**	-0.57**	6.90***	24.87***	26.17***	4.24**	4.67**
Forex								
ADL-MIDAS	1.79**	-1.49**	-2.52**	-1.90**	18.16***	16.91***	5.06***	5.04***
FADL-MIDAS	3.94**	0.40**	-2.50**	-0.74**	19.85***	18.86***	5.67**	7.50***
Corporate Risk (Turkey)								
ADL-MIDAS	-1.35**	6.42***	1.74**	5.02***	16.46***	11.42**	-0.99**	0.91**
FADL-MIDAS	0.17**	16.93***	2.34**	6.33**	21.73***	14.62***	-0.33**	1.65**
Corporate Risk (Foreign)								
ADL-MIDAS	4.00***	6.43***	6.13***	1.88**	21.88***	14.28***	17.90***	9.50***
FADL-MIDAS	4.51***	8.13***	7.20***	4.69**	26.17***	16.83***	18.87***	11.45***
Daily Factors								
All Daily Factors								
ADL-MIDAS	6.48***	9.25***	12.16***	5.91***	29.27***	22.74***	3.43**	24.55***
FADL-MIDAS	6.47***	10.38***	14.33***	7.87***	30.83***	24.55***	6.28**	32.41***
Separate Asset Classes								
ADL-MIDAS	10.84**	10.45***	10.30***	9.04***	31.02***	26.11***	5.87***	10.62***
FADL-MIDAS	12.07***	12.82***	12.20***	11.08***	34.64***	30.80***	11.65***	12.66***
Equities								
ADL-MIDAS	3.96***	7.73**	8.63***	8.10***	31.26***	23.05***	8.69***	14.81***
FADL-MIDAS	4.56***	9.19***	9.46***	8.76***	38.34***	21.35***	11.78***	19.29***
Commodities								
ADL-MIDAS	9.06***	8.84***	12.70***	6.42***	17.36***	24.46***	7.46***	11.62***
FADL-MIDAS	11.18***	14.04***	18.40***	8.88***	20.06***	26.85***	9.86***	11.94***
Forex								
ADL-MIDAS	13.38***	10.00***	5.53**	7.11**	35.13***	19.26***	3.04***	5.41***
FADL-MIDAS	13.40***	10.86***	7.51**	6.41**	30.67***	21.06***	14.46***	7.62**
Corporate Risk (Turkey)								
ADL-MIDAS	4.59**	3.77***	7.42***	2.89**	19.33***	20.71***	3.44**	7.93***
FADL-MIDAS	8.35***	4.55**	7.04***	5.19**	25.43***	33.59***	5.92**	5.96**
Corporate Risk (Foreign)								
ADL-MIDAS	10.72***	8.71***	6.19***	5.77***	29.90***	24.43***	0.70**	3.67**
FADL-MIDAS	8.49***	11.96***	9.13***	7.94***	33.81***	28.84***	7.30***	7.44**

MSE-F test statistics comparing AR(1) model with other models used in the study. The statistics are calculated using the small sample adjustment for the test. * p<0.10, ** p<0.05, *** p<0.01.

Table 3.30: ENC-t tests for ADL-MIDAS vs. FADL-MIDAS models

ADL-MIDAS vs. FADL-MIDAS	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
All Daily Series	0.62**	1.28**	0.76**	1.19**	1.23**	1.19**	0.81**	0.93**
Equities	0.62***	1.06**	0.63**	1.53**	1.21**	1.32**	0.69**	0.94**
Commodities	0.45**	0.61**	0.90**	0.97**	0.58**	0.58**	1.27***	0.65**
Forex	1.11**	1.09**	0.52**	1.32**	1.13**	1.01**	0.65**	1.23**
Corporate Risk (Turkey)	1.07**	1.76**	1.09**	1.30**	1.65***	1.41**	0.66**	0.82**
Corporate Risk (Foreign)	1.07**	1.47**	1.07**	1.36**	1.22**	1.13**	0.97**	1.52**
Daily Factors								
All Daily Factors	0.41**	0.81**	1.32**	0.97**	0.81**	1.18**	0.97**	1.22**
Separate Asset Classes	0.93**	1.02**	1.07**	1.04**	1.04**	1.15**	1.24**	0.99**
Equities	0.65**	0.93**	0.99**	0.85**	2.08***	0.32**	1.24**	1.27***
Commodities	0.98**	1.28**	1.73**	0.93**	1.29**	1.52**	1.64***	0.57**
Forex	0.75**	0.96*−*	1.09**	0.79**	0.64**	1.64***	1.50**	1.19**
Corporate Risk (Turkey)	1.77**	1.18**	0.32**	1.05**	1.17**	1.33**	0.98**	0.41**
Corporate Risk (Foreign)	-0.02**	1.59**	1.44**	1.69**	1.37**	1.61**	1.35**	1.40**

ENC-t test statistics comparing ADL-MIDAS and FADL-MIDAS models using same series. The statistics are calculated using the small sample adjustment for the test. * p<0.10, ** p<0.05, *** p<0.01.

Table 3.31: ENC-F tests for ADL-MIDAS vs. FADL-MIDAS models

ADL-MIDAS vs. FADL-MIDAS	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
All Daily Series	0.43**	1.85**	0.80**	1.26**	1.43**	1.26**	0.55**	0.76**
Equities	0.43**	1.43**	0.73**	1.70**	0.77**	1.53**	0.72**	1.29**
Commodities	0.26**	0.50**	1.01**	0.96**	0.38**	0.35**	1.03***	0.64**
Forex	1.93**	2.36**	0.73**	0.96**	0.86**	1.00**	0.78**	1.75**
Corporate Risk (Turkey)	1.49**	8.28***	1.02**	2.52**	2.35**	1.85**	0.95**	0.76**
Corporate Risk (Foreign)	0.31**	0.91**	0.65**	2.18**	1.84**	1.39**	0.53**	0.87**
Daily Factors								
All Daily Factors	0.31**	0.93**	1.35**	1.33**	0.72**	0.99**	1.91**	3.37**
Separate Asset Classes	1.10**	1.91**	1.35**	1.60**	1.38**	2.14**	3.21**	1.56**
Equities	0.72**	1.61**	1.74**	1.17**	2.49***	0.32**	2.41**	2.21***
Commodities	1.58**	3.63**	3.41**	1.77**	1.14**	1.70**	2.09**	1.18**
Forex	0.84**	1.31**	1.46**	1.14**	1.25**	2.96**	7.61**	2.02**
Corporate Risk (Turkey)	3.90**	2.13**	0.18**	2.43**	3.37**	6.12**	2.11**	0.45**
Corporate Risk (Foreign)	-0.02**	4.00**	2.08**	1.53**	1.31**	1.76**	4.47***	2.76**

ENC-F test statistics comparing ADL-MIDAS and FADL-MIDAS models using same series. The statistics are calculated using the small sample adjustment for the test. * p<0.10, ** p<0.05, *** p<0.01.

Table 3.32: MSE-t tests for ADL-MIDAS vs. FADL-MIDAS models

ADL-MIDAS vs. FADL-MIDAS	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
All Daily Series	0.34***	0.96***	0.37**	0.88***	0.83***	0.88***	0.30**	0.59**
Equities	0.34***	0.67**	0.29**	0.99**	0.91***	1.09***	0.22**	0.53**
Commodities	0.11**	0.22	0.39***	0.58***	0.30	0.34	0.83***	0.28**
Forex	0.54	0.43**	0.01**	0.83***	0.62**	0.63	0.20**	0.70***
Corporate Risk (Turkey)	0.56**	1.09***	0.26**	0.28	1.16***	0.86***	0.24**	0.38
Corporate Risk (Foreign)	0.70***	1.08***	0.66***	0.85***	0.79***	0.67**	0.48***	1.26***
Daily Factors								
All Daily Factors	-0.00**	0.35**	0.70**	0.58**	0.40**	0.56	0.64	0.79***
Separate Asset Classes	0.36**	0.45	0.50**	0.48**	0.61***	0.62***	0.98***	0.44
Equities	0.23**	0.32***	0.17**	0.18**	1.38***	-0.39**	0.57***	0.80***
Commodities	0.49**	0.75**	1.02**	0.52***	0.89**	0.49***	0.68***	0.05**
Forex	0.01**	0.19	0.59***	-0.16**	-0.43**	0.22**	1.19***	0.56**
Corporate Risk (Turkey)	0.79***	0.18**	-0.24**	0.46**	0.65***	0.90***	0.53**	-0.56**
Corporate Risk (Foreign)	-0.97**	0.58	0.75**	1.06***	0.95**	1.03***	1.05***	0.87***

MSE-t test statistics comparing ADL-MIDAS and FADL-MIDAS models using same series. The statistics are calculated using the small sample adjustment for the test. * p<0.10, ** p<0.05, *** p<0.01.

Table 3.33: MSE-F tests for ADL-MIDAS vs. FADL-MIDAS models

ADL-MIDAS vs. FADL-MIDAS	**Forecast Horizon**							
	Nowcast			**Forecast**				
	3-m	**2-m**	**1-m**	**3-m**	**2-m**	**1-m**	**3-q**	**4-q**
Daily Series								
All Daily Series	0.48***	2.72**	0.82**	1.82**	1.89***	1.82***	0.43**	0.97**
Equities	0.48***	1.79**	0.69**	2.27**	1.16***	2.43***	0.49**	1.46**
Commodities	0.13**	0.36***	0.91***	1.14***	0.40**	0.43	1.37***	0.57**
Forex	2.00**	2.00**	0.02**	1.25***	0.98**	1.16**	0.51**	2.05**
Corporate Risk (Turkey)	1.60**	8.37***	0.56**	1.09**	3.18***	2.19***	0.69**	0.72**
Corporate Risk (Foreign)	0.44***	1.36***	0.86***	2.62***	2.29***	1.62***	0.56***	1.41**
Daily Factors								
All Daily Factors	-0.01**	0.82**	1.46***	1.58***	0.72**	0.95**	2.50**	3.97***
Separate Asset Classes	0.86**	1.67**	1.34**	1.49**	1.62**	2.29**	4.68**	1.43**
Equities	0.52**	1.12***	0.62**	0.50**	3.15***	-0.88**	2.29***	2.81***
Commodities	1.56**	3.84**	3.78**	1.96***	1.60**	1.21***	1.85***	0.22**
Forex	0.01**	0.61***	1.62***	-0.54**	-1.85**	1.02**	10.18***	1.81**
Corporate Risk (Turkey)	3.18***	0.68**	-0.29**	2.06**	3.44***	7.05***	2.18**	-1.49**
Corporate Risk (Foreign)	-1.56**	2.41**	2.35**	1.76***	1.78**	2.23**	6.42***	3.29**

MSE-F test statistics comparing ADL-MIDAS and FADL-MIDAS models using same series. The statistics are calculated using the small sample adjustment for the test. * p<0.10, ** p<0.05, *** p<0.01.

4

Currency Interventions: Multiple Aims, Multiple Horizons*

Abstract

This study reviews the literature on some methodological issues in modeling currency interventions in the light of the recent economic developments in emerging markets. The issues we identify as the most important and controversial ones are channels of influence, endogeneity of interventions, secret interventions, motivations of decision makers, and the impact of interventions over multiple horizons. Objectives of policymakers depending on multiple time horizons are not simultaneously studied in the literature due to technical difficulties of working with mixed-frequency data. This is a serious drawback in modeling policy reaction functions of central banks, particularly in emerging markets. We argue that this technical problem can be solved with methods that are used to model mixed-frequency data in the time series econometrics literature.

Keywords: exchange rate, currency intervention, central banking, emerging markets
JEL code: F31, E58, G15, C22, C53

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4.1. Introduction

Large scale interventions by central banks in the foreign exchange market can be traced back to the 19th century. However, by the end of the 20th century most advanced economies have not been regularly intervening on the foreign exchange market (Fratzscher, 2005). Notable exceptions are Japan and Switzerland that rely on currency interventions because of the exceptional cases of their economies. Accordingly, we currently observe currency interventions as a regularly used policy tool mainly in emerging markets. Policymakers in emerging markets have been using currency interventions on a regular basis when the exchange rate was an explicit or implicit target of monetary policy, for avoiding excessive exchange rate fluctuations, and for their currency reserve management. Particularly the two latter motivations have gained importance in the aftermath of the global financial crisis. The role and the effectiveness of the policy have been much debated in the literature, while there is no methodological guide on modeling interventions. This study gives a review of the issues that make modeling currency interventions challenging, summarize existing methods that deal with these issues, and discuss possible solutions to the shortcomings of those methods.

The historical record of foreign exchange intervention reports that monetary authorities in advanced economies such as the US, the UK, Germany, and France have been in the currency markets for a long time. Coordinated and individual interventions of these countries to balance exchange rate levels were observed since the 19th century till the break of the Bretton Woods System and after the signing of the Plaza Agreement (Bordo et al., 2007) and during the period of the former Exchange Rate Mechanism (ERM) of the European Monetary System between 1979 to 1998[1] (Sarno and Taylor, 2001). However, these countries have not been intervening to the markets for the last 15 years. A reason for their withdrawal from the currency markets is that the foreign exchange markets in advanced economies are so thick that currency interventions would be dwarfed, and thus would be inefficient (Fratzscher et al., 2015).

Some advanced economies still intervene to the currency markets with reasons that are unique to their own markets. In Japan the policy rate has been at the zero lower bound since the mid '90s and thus dropped out as a suitable policy instrument available to the Bank of Japan (BoJ). Accordingly, the BoJ made use of currency interventions to react to economic fluctuations during a period when the policy rate fails to stimulate the economy. However, the BoJ has not been intervening on the foreign exchange market for a couple of years now. The most recent intervention in the Japanese market was in November 2011 and the Japanese authorities[2] sold 14 trillion Yens to buy US Dollars in that year in order to prevent appreciation of the Japanese currency. Another advanced country that recently intervened on the currency market is Switzer-land. The country has been perceived as a safe haven after the global financial crisis and the European sovereignty debt crisis. In order to prevent a sharp appreciation of the Swiss Franc against the Euro at levels that were not in line with economic fundamentals, the Swiss National Bank pegged the value of the Swiss Franc against the Euro, and had to intervene to the market constantly, which lead to the

[1] The central banks in the European Monetary System were obliged to intervene, when the exchange rate was approaching the margins of the bands. Note that the ERM was followed by the ERM II, in service since 1999. The only current members are Denmark, and the Eurozone. Again, both central banks are obliged to intervene if the exchange rate deviates too much from the central parity.

[2] Throughout the study (monetary) authorities, policymakers and central banks will be used interchangeably because it is not always the central banks who decide on interventions. In Japan for instance, as in some other countries, the central bank executes intervention decisions taken by the Ministry of Finance.

accumulation of currency reserves.[3] The Swiss National Bank reduced their interventions when the cap of 1.2 Swiss Franc per Euro was abolished in January 2015.

Different from the most advanced economies policymakers in the emerging economies are still using currency interventions as a policy tool based on motivations as discussed below. The use of currency interventions has even increased its prominence amongst emerging markets in the aftermath of the global financial crisis. With the beginning of the Quantitative Easing (QE) program by the US, which also started discussion[4] on "*currency wars*", central banks of several emerging countries, such as Brazil, Russia and Turkey intervened more frequently to the currency market to prevent an appreciation of their own currency versus the US Dollar and accumulated US Dollar reserves. But when the Federal Reserve in 2013 announced the end of QE in 2013 and political and economic crises shattered several emerging markets, their central banks started intervening in the opposite direction and sold US Dollar to avoid a sharp depreciation of the domestic currency.

Even though there is no consensus on the exact role and efficiency of currency interventions, practices of policymakers at central banks, and theoretical and empirical studies agree on the relevance of currency interventions as a policy tool. Policymakers' motivations for and the practice of currency interventions are discussed by Neely (2008) and Mohanty and Berger (2013). According to these survey studies, central bankers use interventions in order to stabilize the level of the exchange rate and dampen its volatility, and as a tool to reach their inflation targets. Participants of the surveys state that most of the time they perceive their interventions to the markets as being "successful". The non-trivial role of currency interventions has been emphasized in some recent macroeconomic studies but these studies are not able to address all of the questions posed on their role and significance.[5] Theoretical models of Ghosh et al. (2016), Maggiori and Gabaix (2015), and Cavallino (2015) indicate that currency interventions have a complementary role to monetary policy and they smooth the effect of shocks to an economy. Empirical studies such as Dominguez (1998), Kim (2003), Kearns and Rigobon (2005), and Beine et al. (2007a) show that currency interventions can indeed have an effect on the exchange rate.

The aim of this study is to review the literature on the methodological issues of intervention modeling and to point out the shortcomings of the models in explaining the role of the currency interventions in emerging markets considering recent developments in global financial markets. Monetary authorities are the central agent in intervention modeling. Several aspects of modeling such as the definition of the central bank's loss function, the timing of interventions, channels of influence, secrecy of interventions, and the interaction of interventions and monetary policy require information from the policymakers' perspective. In order to retrieve this information, some authors conducted surveys with policymakers. Neely (2000), Neely (2008), Archer et al. (2005), and Mohanty and Berger (2013) survey motivations and beliefs of fi banks on interventions and try to identify the changes in these motivations over time. Therefore, the issues noted in the study are organized in a way to reflect problems noted in these surveys and for each issue, the results of

[3] The amount of foreign exchange reserves of the Swiss National Bank were around 41 billion USD at the end of 2008, around 217 billion USD at the end of 2010 and 488 billion USD at the end of 2013.

[4] In September 2010, the Brazilian Finance Minister Guido Mantega accused the US to start a currency war with the QE program (Wolf, 2010). The central idea in this claim is that the US Dollar depreciated after the to this, central banks around the world took measures to protect their currencies.

[5] Most of the empirical literature is on the efficiency of interventions on exchange rate level and volatility. This study will not consider the "efficiency" *per se*. It is about how to model interventions in general depending on the context of a research interest. For detailed literature review on the efficiency problem, see Neely and Weller (2007), Menkhoff (2013), and Brause (2011).

the surveys are noted where available and convenient to the discussion.

Results of the study suggest that some of the issues in currency intervention modeling are well understood and for some others, further research is needed. Issues such as channels of influence and endogeneity problem have attracted extensive research in the literature. On the other hand, the study of policymakers' motivations, which potentially differ depending on the time horizon, in a unified framework has not gained much interest. This is due to the practical difficulties of working with data at different frequencies. Policymakers use interventions for several objectives alongside with other policy instruments. In order to avoid working with different horizons for the policymakers' objectives, the empirical literature focuses on one of the objectives instead of working with several objectives at the same time. The recent time series econometrics literature shows that it is possible to study these objectives simultaneously using mixed-frequency data models.

The paper proceeds as follows: Section 4.2 reviews better understood issues in the currency intervention modeling. Section 4.3 explains how interventions are used for multiple purposes by policymakers. Section 4.4 describes the common approach in the literature that deals with specific objectives at specific time frequencies. Section 4.5 discusses the multiple aims and multiple horizons problem in the context of mixed-frequency data modeling, and finally Section 4.6 concludes.

4.2. Well-Documented Issues

4.2.1. The Channels of Influence

The theoretical literature suggests three channels through which the currency intervention affects the exchange rate. These are the portfolio balancing, the signaling, and the noise-trading (or coordination) channel.

These transmission channels are discussed as the first one of the issues and in a relatively detailed fashion to give a background on the subsequent discussions.

The portfolio balancing channel theory is built upon the portfolio balancing model of exchange rates. According to the model, domestic investors choose the amount of domestic bonds, and foreign bonds they are holding. The model assumes that foreign and domestic assets are imperfect substitutes. When performing a sterilized intervention[6] the monetary authorities will provide or withdraw liquidity to the monetary base in order to offset the change caused by the currency intervention. Accordingly the relative supplies of domestic and foreign bonds in the economy will change and private agents adjust their portfolio. Finally the spot exchange rate will adjust (Sarno and Taylor, 2001). This means that different from a non-sterilized intervention it is here the composition of money supply rather than its level that affects the exchange rate.

In a world of perfect capital mobility and high financial integration, the assumption of imperfect substitutability of assets may not hold. If households are indifferent between holding domestic and foreign assets, then sterilized interventions will not be efficient since it is the amount of total assets that matter for the households and not the composition. If one assumes that the portfolio balancing channel is the channel through which interventions really work, the close-to-perfect sub-

[6] Discussions on the implications of non-sterilized currency interventions agree on that these interventions influence policy rates and exchange rates. Furthermore, sterilization of intervention is common practice among monetary authorities (Dominguez and Frankel, 1993; Taylor, 1992). Therefore this study will exclusively cover problems with sterilized intervention modeling.

stitutability of advanced country bonds might be another argument to explain why advanced countries have not been intervening to the currency markets besides the already mentioned argument of thick markets. On the other hand, the same argument might be used in favor of interventions in emerging market economies where international financial integration is still relatively low.

However, Sarno and Taylor (2001) note that imperfect substitution is not a sufficient condition for the theory to work, if Ricardian Equivalence (RE) (McCulloch, 1888; Barro, 1974; Seater, 1993) holds. The RE hypothesis suggests that the method of government financing does not matter for the aggregate demand because whether the financing is through taxes or bond issuing, the public is aware that either they will be taxed today or in the future (i.e. if the government issues bonds today, the public will be taxed in the future in order to pay the bonds). In such a world, the sterilized currency interventions are "swaps in the currency composition" of the assets the public holds, so they should not be effective (Dominguez, 2009). Therefore, even if domestic and foreign assets are assumed to be imperfect substitutes, analyses with the portfolio balancing channel should be carried out with caution.

The signaling channel assumes that policymakers influence the expectations on the future monetary policy by currency interventions (Kaminsky and Lewis, 1996). The theory goes back to Mussa (1981) and assumes that the exchange rates as asset prices are forward-looking. After a deviation from the desired level of the exchange rate, policymakers intervene to the markets to signal that they will change the policy rate to align with the exchange rate to the desired level. Market participants understand the signal, adjust their expectations, and accordingly their positions based on the future monetary policy: exchange rate level changes. Credibility and time consistency of monetary policy are preconditions of the signaling channel because otherwise market players will not trust the information conveyed by interventions or will believe that the central bank will not be willing or able perform the signaled policy, and interventions will not be efficient.

This channel gives a theoretical case in which currency interventions might be efficient even the assumptions of the portfolio balancing channel fail. However, it does not explain motivations for secret interventions and the changing amount and persistency of interventions. If a central bank uses interventions as a tool for signaling, then all interventions should be visible to the public, while they are in reality (see Section 4.2.3) sometimes carried out secretly. Differences in the amount and frequency[7] of currency interventions can be explained by differences in the credibility of monetary authorities: those ones with a lower credibility could be forced to intervene more often and with higher amounts in order to achieve the same effect. The economic literature however, has not yet picked up this point.

The central idea in the noise-trading or coordination channel is the existence of heterogeneous expectations in the foreign exchange market and the role of central banks in communicating information to the market players (Sarno and Taylor, 2001; Taylor, 2005; Reitz and Taylor, 2008; Beine et al., 2009). The market is assumed to be composed of noise traders and fundamentalists. Noise-traders are daily or intra-daily traders that base their decisions on what they think are news, trends, and patterns in the currency market. Their trading strategies are not consistent with economic fundamentals. Fundamentalists or rational traders "make their decisions based on news (facts, forecasts, etc.). Noise traders make decisions based on anything else." (Thaler and De Bondt, 1993, p. xvii). The fundamentalists try to maximize profits by selling a currency when they believe it is overvalued and buying when it is undervalued (i.e. they exploit the arbitrage

[7] Properties of the intervention data will be discussed in Section 4.4.

opportunity in the markets and pull the exchange rates aligned with the economic fundamentals). Agents may move from one group of traders to the other.

The coordination channel may become relevant when the exchange rate has moved away from its fundamental value due to the influence of noise traders. Although they know that the exchange rate is misaligned, the rational traders' ability and willingness to bring the price back to the fundamental level is limited, because they are afraid of the noise trader risk, i.e. the risk that noise traders keep the exchange rate away from the fundamental level for a long time.[8]

When suffering from such a coordination failure (Howitt, 2003), the central bank might intervene to signal that the currency is actually misaligned and market participants should adjust their positions in line with the central bank to avoid a failure of the market (i.e. the central bank coordinates the behaviors of currency traders). As Reitz and Taylor (2008) point out, this requires the interventions to be reported, since a transparent intervention gives stronger signals than secret ones. Furthermore the coordination effect might be even strengthened by communication in form of 'oral intervention' (Fratzscher, 2006). As Égert (2007) and (Frömmel and Pintér, 2011) show for the case of the Hungarian National Bank, central bank communication can move the exchange rate even in emerging economies.

Neely (2008) and Mohanty and Berger (2013) ask monetary authorities about how they perceive the relative importance of the three channels. In both surveys, the signaling (or expectations) channel is seen to be the channel that is most efficient while the portfolio balancing channel is seen to be the least efficient one. According to Neely (2008), monetary authorities in countries with floating exchange rates also agree to the relevance of the noise-trading channel. For the signaling channel, Mohanty and Berger (2013) make a distinction between expectations on "the future monetary policy" and "future exchange rate and interventions". Expectations on the future exchange rates and further interventions are seen more important than the expectations on a possible policy rate change.

The relation with other issues

The assumptions of the channels of effectiveness have implications on other modeling problems that should be noted here. First, central bank objectives are explicitly defined in studies assuming the portfolio balancing channel to be relevant. Bhattacharya and Weller (1997), Vitale (1999), Lee (2011), Ghosh et al. (2016), and Cavallino (2015) are some of the studies that define central bank loss functions based on assumed central bank objectives. For example, Bhattacharya and Weller (1997) assume that central banks aim at reaching a target exchange rate level and interventions are costly; so the loss function includes both the deviation from the target and the cost of interventions. Other studies, such as Ghosh et al. (2016), explicitly include macroeconomic objectives in the central bank's loss function together with intervention costs and exchange rate variables. If the role of central banks is not distinguished from other market players such as in the noise-trading models, central banks are implicitly assumed to aim at changing exchange rate levels without referring to any explicit target (Neely and Weller, 2007; Westerhoff, 2003).

Second, in the signaling and noise-trading channels, interventions do not have any explicit relation with macroeconomic and policy variables. In these models, the currency interventions are

[8] This problem becomes worse when "brain and capital" are separated, i.e. when the trader has to rely on his or her credibility in the view of the investors. But also agency problems within an organization may have the same effect, "if the boss of an organization is unsure of the ability of the subordinate" (Shleifer and Vishny, 1997, p. 47).

assumed to have an endogenous relation only with the exchange rates. Exceptions are Lee (2011) and Vitale (2011), where exchange rates and thus the decision to intervene depend on economic fundamentals. Unlike the macroeconomic literature on currency interventions, however, economic fundamentals are not explicitly noted.[9]

Third, in the signaling channel literature; Bhattacharya and Weller (1997), Vitale (1999), and Vitale (2011) discuss the information content of interventions and perception of signals by the market. The difference of Bhattacharya and Weller (1997) from other models is that secrecy in this study is derived from the model results instead of being one of the assumptions. Vitale (1999), and Vitale (2011) compare cases when central banks hide their interventions and when they announce them. As discussed above, the signaling channel does not explain the observed differences in the scale of interventions. Neely (2008) finds that policymakers basically agree that the size of interventions increases their probability of success. Bhattacharya and Weller (1997) argue that central banks should always keep the scale of interventions secret to have the upper hand in speculation. Based on this result, one can argue that by intervening at different scales, central banks avoid giving a pattern of interventions that would reveal their strategy which could be exploited by the market players and leave the interventions futile. However, this argument requires reasons for central banks to announce their interventions such as credibility (Fratzscher et al., 2015).

4.2.2. Endogeneity Problem

The endogeneity problem in currency intervention modeling refers to the contemporaneous relation of foreign exchange rate interventions and exchange rate movements. Neely (2008) notes that central banks have different indicators for interventions and reaction times to the indicators might change depending on situation. Even so, endogeneity of interventions and exchange rate is not out of question, and persists to be an important component of currency intervention modeling.

The extent of the quantitative impact of ignoring the endogeneity is calculated for the Japanese interventions by Chen et al. (2012). The starting point of the study is that even though interventions are carried out intra-daily, intervention data are available at daily frequencies. Their simulation study suggests that in case endogeneity of the variables is considered, coefficients of the effect of interventions on exchange rates are found to be twice as large as those reported in the previous literature. Thus, endogeneity can introduce a substantial bias in estimated coefficients.

One common method to avoid the problem early in the literature and still sometimes used is to retrieve exchange rate data in a way that would avoid the problem. For instance, Dominguez (1998) considers interventions of the Federal Reserve, Bundesbank, and BoJ, and uses New York market close data for exchange rates. By doing so, it is warranted that the interventions of Bundesbank and BoJ are pre-determined for the US markets on a certain day because of the time difference between countries, and the interventions of the FED are pre-determined for the others.

Another method that has been proposed in the literature is the instrumental variable approach (Hillebrand et al., 2009). This method, however, requires a lot of care concerning the instrumental variables, most notable finding appropriate instruments to be employed.

Kearns and Rigobon (2005) present an innovative solution to the problem for special cases.

[9] When necessary, studies give details of the economic fundamentals that are used in exchange rate modeling. For instance, for the empirical part of their study Beine et al. (2009) define how fundamentalists predict exchange rates.

In their model, interventions and exchange rates are allowed to influence each other in separate equations, and intervention is carried out only when a "shadow intervention" threshold is passed. The setup is identified with the assumption that BoJ and Reserve Bank of Australia (RBS) have changed their intervention policies during the period under consideration. The same setup would not be identified for countries that have not experienced a similar change.

Further links between interventions and economic fundamentals in the context of exchange rate modeling, exchange rate pass-through, and the interaction between financial markets and the real economic variables have been discussed in the literature. Policymakers report that they might use interventions in order to influence variables other than exchange rates (Mohanty and Berger, 2013), but the intention is always to influence the target variable indirectly via the exchange rates.

Recently, more general frameworks have been developed to analyze the links between the currency interventions and other macroeconomic variables. One such study is presented by Ghosh et al. (2016), who conclude that the currency interventions and monetary policy can be used as complementary policies. In a recent study that tries to explain international liquidity movements by international risk sharing, Maggiori and Gabaix (2015) explain implications of currency interventions to the real economy and financial markets without defining objectives for governments. In Cavallino (2015), who uses the Gamma Model framework of Maggiori and Gabaix (2015) to explain the relation of capital flows with monetary policy and currency interventions, central banks optimizes a function for net transfers to households which includes both intervention and monetary policy terms. These models provide promising guidelines to understand the macroeconomic role of the currency interventions.

4.2.3. Secrecy

Secrecy is argued to increase the impact of interventions. Interestingly, survey results on the secrecy of interventions agree that secret interventions are common. In Archer et al. (2005), the ratio of central banks preferring secret interventions is 40%; in Neely (2008), this ratio is 50% while in Mohanty and Berger (2013), 15 out of 21 respondent central banks report that they never pre-announce their interventions. Even though the ratio is not consistent, these responses shed doubt on the intervention data used in empirical studies. In empirical research, one should either use data from central banks that formally announce their interventions or use methods that would reveal secret interventions.

Most of the studies in the literature use assumptions on secrecy given by the channels of influence. An important contribution on the secrecy puzzle is given by Bhattacharya and Weller (1997). Their model implies that secrecy on interventions and secrecy on the scale of interventions should be distinguished. Bhattacharya and Weller (1997) note that in order the interventions to be efficient; the scale of interventions should never be announced. The intuition behind this result is that if a central bank gives full information about its target level, then it will lose its advantage and "the surprise" component of interventions. Therefore, some central banks announce the time and amount of interventions. A central bank may not announce any of its interventions, or announce some of them, or all of them might publicly. These choices depend on the credibility of central banks. As most theories suggest, a lack of credibility is a motivation for secret intervention, less credible monetary authorities will intervene secretly or hide some of their interventions. If there is doubt on the intervention practices of a central bank, then either an approximation of interventions (e.g. change in foreign reserves) or methods that would reveal interventions from market data (see, for instance, Beine et al. (2007a) for a method to recover secret interventions from Reuters wire services) should be used.

Ignoring other issues in the literature, for the secrecy issue, macroeconomic modeling of currency interventions proposes a solution. Starting from the fact that intervention is a part of balance sheet activities, simplified models include the changes in the foreign exchange reserves as the currency interventions. In Levy-Yeyati et al. (2013) for instance, first, net changes in reserves in dollars are defined as the difference between foreign assets and the sum of foreign liabilities and government deposits. Then, yearly currency interventions are defined as the annual average of the monthly change in the change in reserves divided by monetary base of the previous month. Nevertheless, the frequency of the proposed measure is not intuitive considering central bank objectives are more focused on short and medium runs.

4.3. The Motivations of Monetary Authorities

Friedman (1953) argues that a successful intervention is one that is profitable for the central bank, but policymakers strongly disagree that profitability is a motivation for interventions. Neely (2008) notes that interventions are assumed to bring profit to central banks since- in theory - they sell (buy) a currency, which is overvalued (undervalued) based on their evaluations. In both surveys by Neely (2000) and Neely (2008), profit is not reported as a motivation. In addition to that, Neely (2008) points out that this is the case even though policymakers believe that they can profit at every horizon of trading.

According to the policymakers, currency intervention has multiple objectives and cause-effect relations in markets other than the foreign exchange market. These objectives are listed by Neely (2000) as "resisting short-term trends in exchange rates and correcting long-term misalignments from fundamental values". Mohanty and Berger (2013) ask their respondents to rank seven objectives which are "curbing excessive exchange rate market speculation, maintaining market stability, discouraging sharp capital flows, foreign exchange reserve management, smoothing the impact of commodity price fluctuations, maintaining or enhancing competitiveness, and alleviating foreign exchange funding shortages of banks and corporations". Objectives of the policymakers change depending on economic conditions and sometimes more than one objective might be considered.

4.3.1. Exchange Rate Related Purposes

Exchange rate related purposes are the most studied objectives in the theoretical and empirical literature on currency interventions. Responses to the central bank surveys show that interventions are used to affect the exchange rate in various ways. However, influencing the volatility of exchange rates turns out to be the primary objective of most central banks. Trend smoothing and limiting capital flow pressure appear to be the second and third objectives respectively. The latter objective is reported to be very important especially during 2008-2009 (i.e. at the beginning of the global financial crisis and the QE programme of the US)[10] Mohanty and Berger (2013). Multiple objectives of central banks show that currency intervention decisions are influenced by developments in other markets such as equity markets as long as they have an influence on exchange

[10] It is important to note that the date of the Mohanty and Berger (2013) questionnaire is February 2013, which means that it was conducted before the US announcement of ending the QE. The announcement resulted capital outflows from emerging markets and exchange rate fluctuations; so the importance of the noted objective might have increased again after 2013.

rates. Furthermore, Neely (2008) reports that central banks "strongly agree" that the currency interventions are influential in the markets.

4.3.2. Foreign Exchange Reserve Management

Foreign exchange reserve management is relevant to the intervention modeling for two reasons. First, while accumulating currency reserves is costly, central banks should keep some of their reserves for purposes other than explicit currency market considerations. These are ensuring the capacity for supporting the domestic currency in the future, servicing foreign currency liabilities and debt obligations, and precautionary savings against emergencies are among the reasons that countries keep foreign exchange reserves (Nugée, 2000). Costs of holding reserves depend on how they are funded. Foreign reserves are funded by domestic assets and if we understand reserves as a portfolio rather than a policy tool, the cost of holding reserves depends on yields of foreign assets forming the reserves, and the yields of domestic assets that funded the reserves. Then, an immediate question on the existence of binding constraints on foreign exchange reserves arises. Is there a maximum or minimum amount of reserve level for interventions to be carried?

It turns out that such binding constraints may be ignored in intervention modeling. This is due the implications of low and high level of foreign exchange reserves. Low level of foreign exchange reserves might imply that state of intervening country economy might be beyond the adjustments that would be brought by interventions (e.g. a currency crisis). Regarding the upper bound constraint on foreign exchange reserves, emerging market economies are empirically found to be below their optimal level of reserves. Therefore, there would not be any practical implications of an upper constraint for these countries

Second, when analyzing the efficiency of currency interventions, neglecting motivations that are not directly related to the exchange rates might mitigate the true effect of interventions on the exchange rates. International finance literature suggests that emerging market economies try to optimize their foreign exchange reserve to GDP ratios as an insurance of their economies against sudden stops in capital flows (Jeanne and Ranciere, 2011; Calvo et al., 2012). The optimization of the international reserves implies the accumulation of more reserves for the most of the emerging economies. (Calvo et al., 2012).[11] Evidence on the possibility that the reserve accumulation motivation of central banks might bias results in studies on the effectiveness of currency interventions that are motivated by exchange rate concerns is provided by Dominguez et al. (2013) for the Czech Republic. Their findings suggest that interventions motivated by reserve accumulation also affect the exchange rate, if they are carried out frequently, and that a significant impact is not observed when interventions are infrequent. Therefore, motivations other than exchange rates, especially foreign reserve accumulation for emerging markets, should be accounted for when modeling currency interventions.

4.3.3. Relation with Other Policy Instruments

The relation of interventions with other policy instruments relies on the fact that a desired effect on the exchange rate can be reached by different policies. If, by instance, the monetary authorities wishes to dampen an appreciation of the domestic currency due to capital inflows, they can (i) purchase foreign currency on the currency market, thus intervene, (ii) make domestic bonds less

[11] In East Asian countries, there seems to be an over accumulation of reserves.

attractive by lowering their policy rate, or (iii) impose capital controls.

All these instruments have costs and benefits based on their efficiency and repercussions on financial markets and the real economy. Policymakers have to account for these costs and benefits, thus, interlink policy decisions.

The surveys try to identify the relation of interventions with other policy measures. At a moderate level, policymakers agree that currency intervention might be a substitute for other policies ((Neely, 2008). Qualitative responses in Mohanty and Berger (2013) and a quantitative experiment of the authors show that monetary policies might conflict with interventions. There is also consensus that capital controls and macro prudential policies successfully supported interventions after the global financial crisis. Taken all together, these results imply the linkage of interventions with other policy tools, policy constraints, and market structure.

In most theoretical models, interventions are expressed as endogenous to exchange rates and sometimes to other variables. Macroeconomic modeling takes interventions as changes in balance sheets of central banks (i.e changes in foreign exchange reserves). Therefore, interventions can be endogenous to capital flows Cavallino (2015), inflation expectations, and growth levels Kumhof (2010). Through the loss functions of central banks, these models also present how monetary policy and currency interventions can be interchangeably used as policy tools depending on the strength of exogenous shocks and their weights in the loss functions (Ghosh et al., 2016).

4.4. Intervention Data and Timing of Interventions

Intervention data is characterized by some key properties that have to be taken into consideration in modeling. These are the interventions' irregular frequency and occurrence in clusters, their varying amount, and their timing.

Regarding the *irregular frequency and clustering of interventions*, in a very recent and comprehensive analysis of the efficiency of interventions, Fratzscher et al. (2015) compile a detailed currency intervention dataset from 33 countries from advanced and emerging markets, such that they are able to describe general characteristics of the intervention data. The dataset shows that the interventions occur in sequences or clusters and are observed on 19.1% of the total trading days. Purchases of the foreign currency (which do not require foreign currency reserves) are dominating with 76.1% of the interventions in the dataset.

Figure (4.1) plots daily intervention data for Japan (01 April 1991–30 September 2015) and Turkey (31 January 2006–30 September 2015). As it can be observed on the graphs, there are periods without interventions in both cases. These periods are most of the time short, but can also exceed a year, such as the period between 25 January 2012 and 10 June 2013 in Turkey. The key message of these clusters is that interventions should be modeled in a way that central banks are not always active in the currency market.

The literature addresses this issue by the assumption that there are costs to interventions such as in the case of Kearns and Rigobon (2005) or other pre-defined rules for interventions. For Japan, Ito and Yabu (2007) assume that there are political costs to Yen sales and purchases. The intuition behind the assumption is that interventions of the Bank of Japan first have to be approved by the Japanese Ministry of Finance and once an intervention has been approved, interventions on the subsequent days will be less costly.

The modeling framework in Lee (2011) gives a trigger rule for interventions. Interventions are assumed to be triggered when exchange rates are above/below certain thresholds determined by model parameters.[12]

Beine et al. (2009) explain the *varying amount of interventions* and assume that the exchange rate is a function of foreign exchange reserves along with other variables, such as the shares of chartists and fundamentalists in the market. In their model a leaning-against-the-wind intervention is a function of the previous period's exchange rate. Such an approach is intuitive since it has the flexibility that size of interventions will depend on the scale of changes in exchange rates; however, a central bank might adjust its reaction based on other financial and real economy factors which would make a time-varying rule–if a rule is desired to be used at all–more convenient.

In the plots of the intervention data of Japan and Turkey, it can be seen that amount of interventions can sometimes be much higher than interventions in other times. The maximum amount of interventions are 8 trillion Yen and 5.4 billion USD for Japan and Turkey respectively for the given periods, while the average amounts are 213 billion Yen and 65.5 million USD. Policymakers agree that market conditions are influential on the size of interventions (Neely, 2000, 2008). Empirical applications should, therefore, consider the differences in the amounts of interventions.

Finally, the *timing of interventions* refers to the time when interventions are carried in the markets. Most central banks report that they can respond quickly to developments on the currency market; but for some others, the response time might get longer, if there has not been a recent intervention (Neely, 2008). Assuming that the authorities announce interventions, two closely related issues can be noted on the timing of interventions. The first one is about the efficiency of interventions and the other is about the medium and long-term motivations of central banks.

For most countries the exact timing of interventions during the day is not available. The precise timing of interventions is imperative according to theories assuming that interventions are effective via intra-day trading (i.e. noise-trading). If exact timing is not available, the estimated effect of interventions on exchange rates might be biased (Chen et al., 2012).

Similarly, the question of when interventions show their effect is critical. If exchange rates react to interventions at short horizons only after an intervention is implemented, then estimates at lower frequencies might give biased results and mitigate effects of interventions.[13,14,15]

The objectives of policymakers differ in horizons and theoretical studies show that short vs. medium-term distinction is crucial for the central bank objectives. The difference stretches from short-term (e.g. instantaneous effect on exchange rate level or volatility at the intra-day level) to long-term objectives (e.g. accumulate foreign exchange rate reserves). The common practice in the literature is to focus on the horizon of the objective and adjust intervention data accordingly. If, for instance, macroeconomic implications of interventions are studied, quarterly aggregated data of currency interventions are used (Levy-Yeyati et al., 2013; Blanchard et al., 2015; Ghosh et al., 2016). This practice is motivated by the fact that many macroeconomic variable data are available only at the quarterly frequency.

Working with intervention data at frequencies different from the frequencies of objectives might lead to restrictions for researchers that try to identify reaction functions of policymakers.

[12] Models that use thresholds can be used in analyzing interventions in countries such as the Russian Federation, which specify floors and ceiling for exchange rates to intervene, without imposing a formal peg.

[13] The issue is also linked to the discussion of the efficiency and purposes of interventions. If interventions are effective only in short-term; then, it cannot be used as a tool to defend long-term targets.

[14] Intra-day approach is mostly used to investigate the effect of interventions on exchange rate volatility.

[15] Similarly, aggregation of daily intervention data to be used with lower frequency variables might have the same consequence.

Financial variables that prompt central banks to intervene in the currency markets such as short-term and long-term exchange rate targets (Ito and Yabu, 2007) can easily be incorporated to the policy reaction functions of central banks. If short-term and long-term (or medium term, or all of them at once) objectives are thought to be important for decision-making of central banks such as in the case of the Czech Republic studied by Dominguez et al. (2013), then a researcher should find a way to track variables in different frequencies. To our best knowledge, this has not been done in the literature.

4.5. Mixed-Frequency Data Modeling

Table 4.1 summarizes the theoretical and empirical studies on currency interventions based on the motivations of the policymakers and the frequencies of data used in the studies. In some of the theoretical studies such as Maggiori and Gabaix (2015), there is not an explicit data frequency but these studies are classified by the frequency of the most restrictive data series that might be used. Maggiori and Gabaix (2015) is built up as a macro model, for instance, so it is subsumed under "Quarterly" frequency. The purpose of the table is to visualize the gaps in the literature.

We can summarize the features of the literature given in the table in three conclusions. First, most of the studies use intra-daily or daily data. Intervention data are usually available at the daily level so it is natural to see more studies under "Daily" frequency. Studies that aim to measure the effectiveness of the interventions at the time of the intervention (or around the time of intervention) and have the necessary dataset use intra-daily datasets. Studies that use quarterly datasets usually retrieve currency interventions from observed changes in international reserves instead of accumulating daily interventions carried out in a certain quarter or they use other definitions of quarterly interventions (Levy-Yeyati et al., 2013). Second, studies that focus on international reserves use quarterly data due to its relation to other macroeconomic variables that are announced quarterly. Third, generalized autoregressive conditional heteroscedasticity (GARCH) models and its extensions allow researchers to analyze the impact of interventions on both return and volatility of exchange rates; so it is not uncommon to see that these two motivations are studied together (Almekinders and Eijffinger, 1996; Guimarães-Filho and Karacadag, 2004; Suardi, 2008). Yet, there is only one study in which exchange rate and international reserves related motivations are investigated together (Dominguez et al., 2013).

The table points to a gap in the literature for studying exchange rate related motivations together with the quarterly announced international reserves.[16] From the perspective of central bank objectives, the previous section argues that it is difficult to handle all objectives of policymakers simultaneously in a single framework because that requires using high frequency financial data with low frequency macro variables. At the theoretical level, multiple objectives can be studied with models that interlink currency interventions to other financial and macroeconomic variables such as the Gamma model framework (Maggiori and Gabaix, 2015; Cavallino, 2015), which allows to analyze the real economy and financial markets together, or DSGE modeling.

The problem in this model is that real economic variables are mostly not observable at financial data frequencies; so in order to test the validity of implications of the model, one should either aggregate financial data or use end-of-period observations for financial data. Another ap-

[16] Studies refer to the ratio of international reserves to GDP and the limitation on international reserves originates from the announcement frequency of GDP data. International reserves as a stock variable might be available at higher frequencies (e.g. monthly or weekly).

proach, which has not gained attention in the literature yet, is to use data at their own frequencies, hence work in a mixed-frequency data setting. The time series econometrics literature gives two methods to handle mixed-frequency data: Kalman filters and Mixed-Frequency Data Sampling (MIDAS) models. These two different approaches offer separate solutions to the problems that consist mixed-frequency data.

Kalman filters have a wide range of applications, mostly in macroeconomic forecasting. Kalman filter method applications, as for example used in Kuzin et al. (2011) and Mariano and Murasawa (2003), interpolate low frequency variables bases on pre-defined schemes so that for each high frequency data point, there are real or interpolated low frequency data. Empirical applications using this approach show that it has significant forecasting power in comparison with the previously used methods in the literature.

In its basic form, a MIDAS model is a single equation framework that uses weighting polynomial functions to aggregate high frequency data, and thus solve both the data aggregation bias and parameter proliferation problems in dealing with mixed-frequency data (Ghysels et al., 2004, 2007). MIDAS models are shown to generally perform better than simple aggregation schemes and they have found entrance to a wide area of applications in the forecasting literature after their introduction. They have been used in volatility and macroeconomic forecasting based on both macro variables and financial data.

Comparisons of Kalman filters and MIDAS models show that the models are characterized by some distinctive features. In simple frameworks, Kalman filters are found to be more efficient while on the other hand, MIDAS models are less prone to specification errors (Andreou et al., 2011; Bai et al., 2013). For the case of currency interventions, one of the models can be selected based on the problem under consideration.

Considering the example of a researcher that wants to model policymakers' motivations spanning different horizons given at the end of previous section, we can sketch how these models can be used in a hypothetical case. Assume that a researcher wants to test whether a central bank is motivated to intervene on the currency market by both reserve accumulation and exchange rate deviations at the daily level. Foreign exchange reserve data are not available at the daily frequency. Therefore, one can first generate daily forecasts using one of the mixed-frequency data methods specifying a forecast model. Then, these daily forecasts can be used as a proxy to measure the central bank's reaction to daily changes in the foreign exchange reserves.

4.6. Conclusions

This study reviews methodological issues in currency intervention modeling and identifies potential solutions to issues that have not yet been solved in the literature.

The portfolio balancing, signaling, and noise-trading channels gives theoretical explanations on how currency interventions work and they have all been thoroughly studied in the literature. The portfolio balancing channel needs more strict assumptions than the other two channels. However, all three channels can be used in modeling currency interventions in the emerging markets.

Some progress has been made on the endogeneity of interventions, its relation with other economic variables and policy tools for specific cases, but further research is needed to find a more generalized solutions for the issues. For emerging market economies, the interventions' relation with the monetary policy and macro prudential policies should not be ignored.

The empirical literature and central bank surveys make it clear that the currency interventions are used to reach goals that span multiple horizons. Identifying motivations of central banks over time is crucial in order to isolate the effect and success of currency interventions for each motivation. An area of future research might deal with working with these motivations in a single framework by using Kalman filters or MIDAS models.

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Tables

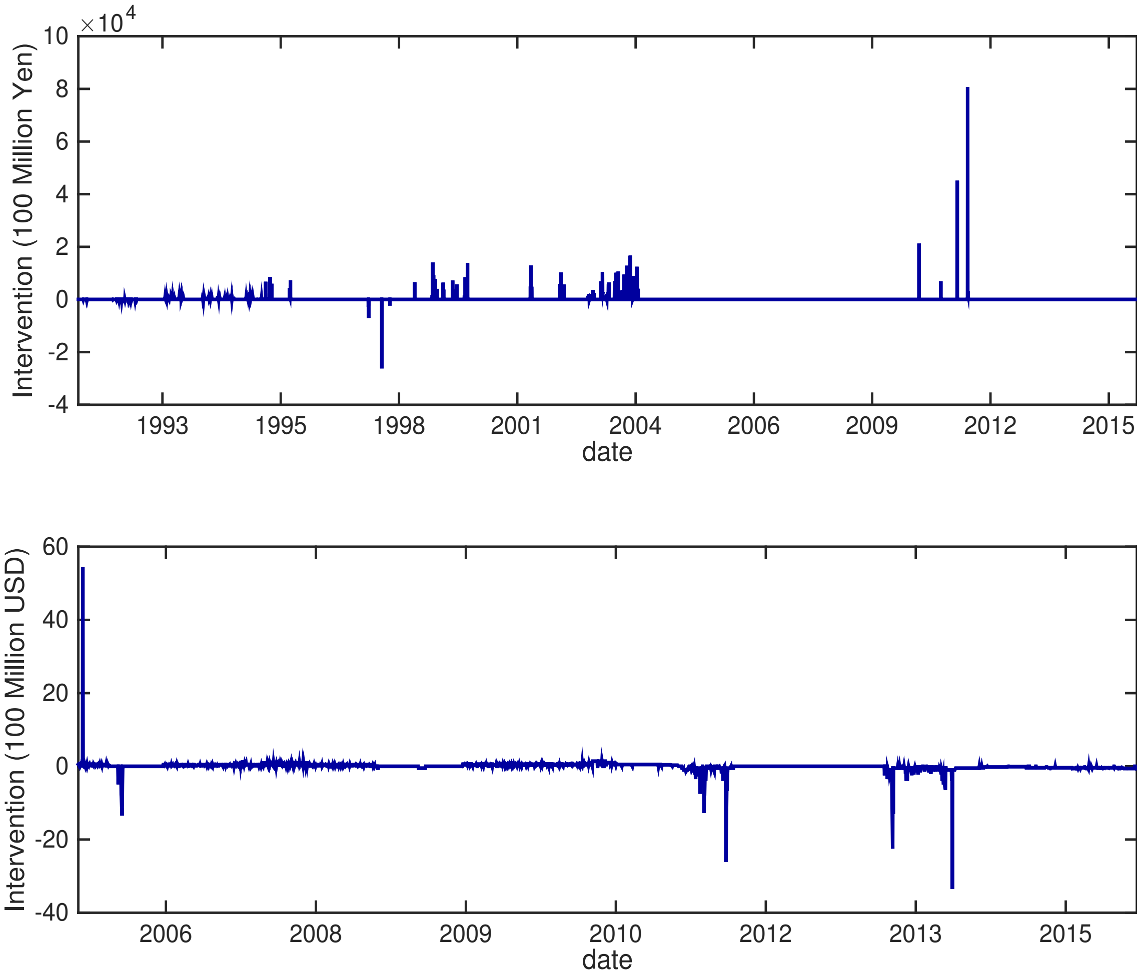
Table 4.1: The literature on the currency interventions

	Frequency				
Variable(s) under consideration	**Intra-daily**	**Daily**	**Weekly**	**Monthly**	**Quarterly**
FX Return	Payne and Vitale (2003), Neely (2005), Chen et al. (2012)	Ito (2002), Fatum and M Hutchison (2003), Kearns and Rigobon (2005), Chaboud and Humpage (2005), Ito and Yabu (2007), Fratzscher (2008), Reitz and Taylor (2008), Reitz and Taylor (2012)	Beine et al. (2009)	Kim (2003), Beine et al. (2007a), Taylor (2004), Taylor (2005)	Lee and Lai (2011), Levy-Yeyati et al. (2013), Blanchard et al. (2015), Cavallino (2015), Maggiori and Gabaix (2015), Ghosh et al. (2016)
FX Volatility	Dominguez (2006), Hillebrand et al. (2009), Beine et al. (2007b), Gnabo et al. (2009)	Dominguez (1998), Dominguez (2006), Rogers and Siklos (2003)			
Int. Reserves					Jeanne and Ranciere (2011), Calvo et al. (2012)
FX Return-FX Volatility	Almekinders and Eijffinger (1996), Dominguez (2003), Dominguez and Panthaki (2007), Pasquariello (2010)	Kim et al. (2000), Guimarães-Filho and Karacadag (2004), Domaç and Mendoza (2004), Akıncı et al. (2005), Herrera and Özbay (2005), Fratzscher (2006), Fatum and Hutchison (2006), Disyatat and Galati (2007), Suardi (2008), Kamil (2008), Onder and Villamizar (2015), Fratzscher et al. (2015)	Beine et al. (2003)		
FX Return-Int. Reserves		Dominguez et al. (2013)			

Tabulation of the studies on currency interventions based on the motivations of policymakers and the data frequencies used by the authors. The rows group the studies based on three main motivations (i.e. foreign exchange return and volatility, and international reserves) and combinations of these three that have been studied in the literature. The table can seen as an update of the table given at the end of Neely (2005) without the survey studies and with an extra dimension of the motivations. Beine et al. (2009) uses a bi-weekly data set but included under the "Weekly" column to optimize the table space. Dominguez (2006) is included under both "Intra-daily" and "Daily" columns because the study measures the effects of the currency interventions at both frequencies.

Figures

Figure 4.1: Daily currency interventions



Daily currency interventions for Japan and Turkey. Top panel: intervention amounts for Japan in 100 million Yen for the period 01 April 1991–30 September 2015 (*Source: Federal Reserve Database*), bottom panel: intervention amounts for Turkey in 100 million USD for the period 31 January 2006–30 September 2015 (*Source: The Central Bank of the Turkish Republic database*).

5

Daily Currency Interventions in Emerging Markets: Incorporating Reserve Accumulation to the Reaction Function*

Abstract

This study considers emerging market central bank interventions motivated by international reserve management. Emerging market central banks use currency intervention as a policy tool against exchange rate movements and accumulate international reserves as an insurance against sudden stops or reversals in capital flows. To account for both of these motivations, the model of Ito and Yabu (2007), which is exclusively based on exchange rate targeting, is extended to include the international reserves-to-GDP ratio at a daily frequency. Daily values of the ratio are forecast using the Mixed Data Sampling (MIDAS) model and exchange rate returns. Compared with the benchmark model, we find that the MIDAS model performs better in forecasting the reserve-to-GDP ratio. The extended model is estimated by using the floating exchange rate regime period data of Turkey. We identify breaks in the Turkish intervention policy, and the reserve-to-GDP variable in the extended model is found to have a significant role in the intervention reaction function.

Keywords: currency intervention, international reserves, emerging markets, Turkey, mixed data sampling

JEL classification: F31, E58, G15, C22, C53

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5.1. Introduction

Currency intervention has been a policy tool regularly used by emerging market central banks in floating exchange rate regimes. The relevance of interventions has been evident during and after the global financial crisis during which emerging markets have experienced large capital flows because of the Quantitative Easing (QE) policies in developed countries. Considering the fact that central banks are not profit driven, theoretical motivations for currency interventions include exchange rate and international reserve management related purposes. Unlike the few advanced economies who still use currency interventions, such as Japan, both purposes are relevant for emerging markets. However, most of the studies in the literature focus on the exchange rate related purposes. The relation of interventions and international reserves is usually discussed in a context that is disconnected from the exchange rate related motivations. This study extends an intervention policy reaction function developed for advanced economies to include an international reserve component. In this way, the new reaction function is able to address concerns of emerging market economies. It is shown that the extended model captures interventions in Turkey better than the model solely based exchange rates.

Exchange rate interventions have kept their popularity in emerging markets and some advanced economies as a short-term remedy for fluctuations in currency markets. Advanced economies such the US, the UK, Germany, and France, sometimes individually and sometimes in coordination, intervened on currency markets after the Plaza Accord in order to avoid extreme depreciations or appreciations of their currencies.[1] Interventions in deep currency markets (i.e. advanced economies) are considered to have a non-significant impact, whereas in emerging markets the currency markets are thinner.[2]

A further motivation for emerging economies to employ interventions is to accumulate international reserves. Emerging market central banks try to optimize international reserves as an insurance against sudden stops in capital flows (Calvo et al., 2012; Jeanne and Ranciere, 2011) or as a mechanism that would make up for the underdeveloped financial markets (Dominguez, 2010) in exchange for the opportunity cost of the spread between public sector bonds over interest earned from international reserves held. Obstfeld et al. (2010) point out the possibility that capital flights might be financed by withdrawals of bank deposits. In this case, the monetary base will shrink rapidly and will lead to a crisis if the central bank does not have enough international reserves to sustain the demands as the lender of last resort. Similarly, Frankel and Saravelos (2012) present empirical evidence that countries with higher international reserves were more successful in weathering the global financial crisis compared to the countries with low levels of reserves.

A market participant interested in the probability and efficiency of a central bank intervention might get biased results if she exclusively focuses on one of these two motivations. For instance, as shown by Dominguez et al. (2013) for the case of Czech Koruna (CZK), interventions that are not primarily intended to affect the exchange rate but carried out by reserve management purposes might indeed influence the exchange rates depending on the frequency of interventions. They find that frequent interventions motivated for reserve accumulation affect the exchange rates. The re-

1 Although this was not the first period of frequent central bank interventions in advanced economies, it is of particular importance since it occurred after the breakdown of the Bretton Woods system, when no consensus on exchange rate stability was reached. For a historical account to currency interventions, see Bordo et al. (2007).

2 For surveys on central bankers beliefs that currency interventions are efficient, see Neely (2008) and Mohanty and Berger (2013).

sults of the study imply that if all interventions are treated equally and reserve management related interventions are not distinguished, an efficiency analysis will give biased results during a period when there are frequent interventions for reserve management. Therefore, the significance of each motivation of central banks should be clarified and interventions for each motivation should be isolated for a more accurate efficiency analysis of currency interventions.

The contribution of our study to the literature is threefold. First, we extend the infrequent intervention model of Ito and Yabu (2007) by assuming that policymakers optimize a weighted loss function of deviations of exchange rate from a target level and of reserve-to-GDP ratio from a fixed optimal level of reserves. Second, we calculate daily forecasts for reserve-to-GDP ratios, which is a variable that is available only at the quarterly level since it requires GDP data.

Third, as an empirical contribution and illustration, we analyze currency interventions of the Central Bank of the Republic of Turkey (CBRT) during the floating exchange rate regime. Turkey is selected as an empirical case because it is an emerging market that has been intervening to the currency markets both for exchange rate and reserve accumulation purposes, it is one of the countries with the largest optimal reserves-actual reserve gap (Calvo et al., 2012), its intervention data are publicly available, and the CBRT announcements indicate possible changes in its motivations so that implications of the model estimates can be compared with the announcements.

There are four main findings of the study. First, at the daily level, it is possible to generate forecasts for the quarterly reserve-to-GDP ratio that perform better than the benchmark model. Improvements of the forecasts are shown to reach up to 45% of the benchmark model performance. Second, we identify structural breaks in the reaction function of the CBRT. Structural break tests imply there are fragmentations of the CBRT reaction data both for the extended model and the original Ito and Yabu (2007) model. Therefore, analyzing the full sample period might be misleading. Third, the daily reserve-to-GDP variable is found to be significant in the full sample and in the sub-samples, while a comparable pattern is not observed for the exchange rate variables. Fourth, with the extended model, market participants can distinguish false alarms of interventions more successfully. The noise-to-signal ratio analyses show that the extended model gives lower ratios in comparison to the model only with exchange rates. The improvement with the extended model goes up to 20% for US Dollar (USD) purchases.

The study is organized as follows: Section 5.2 gives an overview of interventions by the CBRT and their motivation. Section 5.3 derives the infrequent intervention model with reserve-to-GDP levels and notes its interpretation. Section 5.4 summarizes the dataset used and calculates daily reserve-to-GDP forecasts. Section 5.5 tests structural breaks in the policy function, while Section 5.6 reports the estimation results. The final section concludes.

5.2. Intervention Motivations

5.2.1. Intervention Motivations in Emerging Markets

Motivations of policymakers for interventions have been investigated by surveys carried out with central bankers and in the theoretical literature. According to the practices noted in the surveys, addressing developments in the exchange rates either in the level or the volatility have been the top priorities of policymakers (Neely, 2008; Mohanty and Berger, 2013). Furthermore, "discouraging short term capital flows" and foreign exchange reserve management have been noted as other important motivations of central banks (Mohanty and Berger, 2013).

The recent literature that relate currency interventions to capital flow shocks (Cavallino, 2015; Ghosh et al., 2016; Blanchard et al., 2015) and reserve accumulation behavior of emerging markets against sudden-stops (Calvo et al., 2012; Jeanne and Ranciere, 2011) imply that reserve ratios are crucial for intervention decisions. Therefore, for emerging market economies, a currency intervention reaction function that would include both exchange rate and foreign exchange reserve related purposes would be more relevant from a market participants' point of view, instead of deriving a reaction function for each purpose separately.

5.2.2. Intervention Policy of the CBRT

The CBRT has adopted a floating exchange rate regime in 2001. After the breakout of the 2001 financial crisis in Turkey, the floating exchange rate regime has been introduced on 22 February 2001 and as one of the many following financial reforms, the law regulating the CBRT has been amended to give the bank more independence. The CBRT has been intervening in the currency market sporadically with changing motivations under administrations of all three governors until 2015.[3] Description of the CBRT interventions and reasons for selection of the reaction function components used in the study are given in this section.

Currency interventions of the CBRT are either announced interventions with auctions or unannounced direct interventions. In the interventions with auctions, time and maximum amount of foreign exchange to be purchased (sold) are announced beforehand. Sometimes, the number of planned auctions in a certain month is announced as additional information, but the CBRT always reserves the right to stop the interventions or start them as it sees viable. Thus, announced interventions are not deterministic in practice. Unannounced interventions are communicated to the public on the day they are performed and the amounts of the interventions are announced after 15 days of the intervention day. The number of unannounced interventions is small compared to the number of announced interventions.

The amounts of unannounced interventions have been larger than those of the announced ones. Foreign exchange amounts purchased/sold vary between 9 million USD to 2.25 billion USD. There have been cases in which unannounced interventions are 3 or 9 million USD but they are usually more than 300 million USD and in one case reached 5.4 billion USD. Details of the intervention data of the CBRT are given in Section (5.4).

After 2011, the CBRT has devised other unconventional monetary policy tools in addition to currency interventions. The reserve option mechanism (ROM) has been introduced during late 2011 as a stabilizing policy tool (Değerli and Fendoğlu, 2015). At the beginning of 2014, after the sudden depreciation of the Turkish Lira (TRY) against the USD, the CBRT started directly financing the foreign exchange demands of the oil importing state owned enterprises. These policy changes should be addressed in studies on effectiveness of currency interventions or dropped from the sample (Onder and Villamizar, 2015).

The CBRT has been cautious in its communications with respect to the floating exchange rate regime and the aim of currency interventions. Most of the time, the aim is put as "increasing market volatility and calming disorderly markets". The wording of the exchange rate policy of the CBRT has been changed after 2012. The CBRT's "Monetary and Exchange Rate Policy for 2013", which is published in December 2012 (CBRT, 2012), repeats the central bank's message

[3] The governors of the CBRT from 2001 till 2015 are Süreyya Serdengeçti (14/03/2001-14/03/2006), Durmuş Yılmaz (18/04/2006-13/04/2011) and Erdem Başçı (14/04/2011-19/04/2016).

of "no target" but also includes the statement "...Nonetheless, with a view to limiting the risks to the financial stability, the CBRT does not remain unresponsive to the excessive appreciation or depreciation of the TL...". The statement implies that even though the CBRT does not have a strict target for the exchange rate as in the case of a fixed exchange rate or pegged regime, it does make its comparisons of "excessive appreciation or depreciation" with an interval in mind. In some of the press releases regarding interventions (CBRT, 2009) and exchange rate policy texts (CBRT, 2007a), the need for building foreign exchange reserve as an emerging market economy has been noted by pointing at the "right" periods to do so.

Despite the recent literature given above on the connection of interventions and capital flows; Figures (5.1) and (5.2), which include quarterly net capital flows to Turkey and quarterly net interventions by the CBRT respectively, show why an approach based on capital flows may not be the correct approach for the case of Turkey. Intuitively, net capital inflows (outflows) should decrease (increase) the USD/TRY exchange rate level and based on the movement in the exchange rate; the CBRT should increase (decrease) its foreign exchange reserves, which means it intervenes to the market by purchasing (selling) USD.[4] However; counter intuitively, the figures show that the CBRT intervened to the markets only by selling USD after 2011 even though there are persistent capital inflows to Turkey after this date. Besides, in the ad hoc classification of Blanchard et al. (2015) based on the reaction to capital flows, Turkey is classified as a non-intervener country. Therefore, an approach directly based on capital inflows is not taken here.

In addition to the referred literature on the reserve accumulation in emerging economies, a reaction function based on deviations from an exchange rate target and reserve optimization is selected for two reasons. The first reason is that intuitively the target in this reaction function does not mean a level of exchange rate that is to be protected as in a fixed exchange rate regime; but it rather refers to a smoothed path for the exchange rate based on the history. Indeed, such attempts by policymakers to smooth the impact of the shocks in the currency markets are found to be very effective (Fratzscher et al., 2015).

The same reasoning of an "implicit target for smoothness" can be applied to other periods unless the motivation for currency interventions is explicitly communicated differently. Such a period started after 2006 in which the CBRT's press releases about currency interventions motivated by exchange rate reserve management. During this period, the CBRT explicitly announced that the main motivation for some of the interventions is reserve accumulation referring to the need of strong international reserves for emerging markets.

The second reason is related to the traceability of the central bank behavior. From a market participant point of view, a target level of exchange rate based on short and long-term deviations is much easier to track than volatility of exchange rates, which might be subject to model specification errors. There is no consensus on how to model the volatility. In the Turkish case for instance studies that include deviations from exchange rate volatility use different specifications of GARCH models (Guimarães-Filho and Karacadag, 2004; Herrera and Özbay, 2005). A better estimate of the volatility can be obtained using the intraday data; but genuine data for computing the so-called realized volatility may not be available at all for an outsider. Furthermore, market participants do not have information on the model of the CBRT for measuring volatility. On the other hand, historical exchange rate data is easily accessible, reliable and tractable.

Moreover; although the CBRT notes excessive volatility in the currency market as the main

[4] The exchange rate of TRY at time t is expressed in terms of 1 USD.

motivation, results of the limited studies on Turkey show that exchange rate volatility is not a significant motivation of interventions. For the first three years of the floating exchange rate (i.e. 2001-2003), Guimarães-Filho and Karacadag (2004) find that the CBRT's interventions are not motivated by the deviations in the exchange rate return and volatility from their previous month's values. For the period 1993-2003, Herrera and Özbay (2005) study the motivations of the CBRT with a Tobit model. By restricting their research only to short-term variables, they find that the CBRT interventions are not motivated by short-term deviations from the exchange rate return and volatility, which supports the findings of Guimarães-Filho and Karacadag (2004). Recently, Onder and Villamizar (2015) find that the effect of interventions on exchange rate volatility is small and short lived, while they have a larger significant effect on exchange rate returns.

5.3. A Model of Infrequent Intervention with Reserve Targeting

Based on the Almekinders and Eijffinger (1996) model of intervention, Ito and Yabu (2007) develop a model of infrequent interventions that aims to capture the motivation of the Bank of Japan's currency interventions between 1991 and 2002. Here, the model of Ito and Yabu (2007) is extended by adding a component of international reserves to the objective function.

Let s_t represent the log of USD/TRY exchange rate at time t. The central bank is assumed to have the following objective function:

$$\min_{Int_t} \; E[(\alpha(s_t - s_t^T)^2 + \beta(Q_t(\Delta s_t, \Lambda_{t-1}) - G_t)^2)|\Omega_{t-1}] \tag{5.1}$$

where s_t^T is the target level of the USD/TRY exchange rate at time t, Ω_{t-1} is the information available at time $t-1$, G_t is the target level of foreign reserve-to-GDP ratio, and Int_t is volume of currency intervention. G_t is assumed to be exogenous and constant at level $G_t = a$. The coefficients α and β are the weights of the exchange rate target gap and the reserve ratio target gap respectively with $\alpha, \beta \geq 0$. $Q_t(\Delta s_t, \Lambda_{t-1})$ gives the level of reserve-to-GDP ratio at time t based on first difference of the exchange rate return, Δs_t, and a matrix of variables, Λ_{t-1}, that might play a role in determination of the ratio. As it is shown in Section 5.4.1, Λ_{t-1} is assumed to consist of lags of Δs_t and some quarterly variables. $Q_t(\Delta s_t, \Lambda_{t-1})$ is assumed to be linear in Δs_t as follows:

$$Q_t(\Delta s_t, \Lambda_{t-1}) = \kappa \Delta s_t + R_{t-1}(\Lambda_{t-1}) + v_t, \tag{5.2}$$

where κ denotes the effect of Δs_t on the reserve-to-GDP ratio, $R_{t-1}(\Lambda_{t-1})$ denotes the component of the ratio that is not related to Δs_t, and v_t is an i.i.d error.

A critical aspect of modeling currency interventions is the assumptions on the exchange rate movements. The literature suggests that a number of factors such as interest rates and money supplies differentials, commodity prices, and order flows might affect exchange rate levels. In a recent literature review, Rossi (2013) studies the exchange rate predictability with different forecast horizons, predictors, model specifications, and evaluation methods. According to the review, the predictability of the models depend on all of these factors and the Random Walk (RW) without a drift appears to be the strongest benchmark model. Particularly, at the daily level, the evidence against the RW model is limited to a number of studies and exchange rate pairs (Rime et al., 2010; Ferraro et al., 2015). Therefore, the policymakers are assumed to model the exchange rate movements as a RW and try to influence the exchange rates by interventions as follows[5]:

$$s_t = s_{t-1} + \rho Int_t + u_t. \tag{5.3}$$

It has to be noted that the RW assumption will be kept throughout the study and only interventions are assumed to effect exchange rates. USD purchases and sales are denoted by (+) and (-) respectively because the motivation in purchases is assumed to be increasing s_t while in sales, the motivation is to decrease s_t.

Using (5.3), $Q_t(\Delta s_t, \Lambda_{t-1})$ can be written in terms of intervention as follows[6]:

$$Q_t(Int_t, \Lambda_{t-1}) = \eta Int_t + R_{t-1}(\Lambda_{t-1}) + v_t, \tag{5.4}$$

where $\eta = \kappa\rho$ and denotes the effect of interventions on reserve levels. As USD purchases (sales) increase (decrease) the value of $Q_t(Int_t, \Lambda_{t-1})$, η has to be positive, which implies that coefficients κ and ρ should have the same sign.

The minimization problem in (5.1) can be solved by using (5.3) and (5.4). The optimal level of currency intervention, Int_t^*, can be written as:

$$Int_t^* = \frac{a\beta\eta}{\alpha\rho^2 + \beta\eta^2} - \frac{\alpha\rho}{\alpha\rho^2 + \beta\eta^2}(s_{t-1} - s_t^T) - \frac{\beta\eta}{\alpha\rho^2 + \beta\eta^2}R_{t-1}(\Lambda_{t-1}),$$

which can be simplified to

$$Int_t^* = -\frac{\alpha\rho}{\alpha\rho^2 + \beta\eta^2}(s_{t-1} - s_t^T) + \frac{\beta\eta}{\alpha\rho^2 + \beta\eta^2}(a - R_{t-1}(\Lambda_{t-1})). \tag{5.5}$$

The first term in the equation denotes the effect of deviations of exchange rate from the target level. The sign of this coefficient depends on the sign of ρ. Holding other parameters constant, the interpretation of ρ is similar to Ito and Yabu (2007). Assuming that USD is purchased (sold) when TRY appreciates (depreciates) against the USD, leaning–against–the–wind behavior of central banks implies that $\rho > 0$ (i.e. s_t increases (decreases) after purchases (sales) of USD). Similarly, leaning-with-the-wind implies $\rho < 0$. In the extended model, the parameter is weighted by the relative importance of other variables. The second term in Equation (5.5) denotes the effect of the gap between the optimal and the current level of reserve-to-GDP levels. The coefficient of this term is positive. Thus, as the optimal level of reserve-to-GDP increases (decreases), the optimal level of currency intervention will increase (decrease), and as $R_{t-1}(\Lambda_{t-1})$ increases (decreases), the optimal intervention level will decrease (increase). The parameters α and β weigh the deviations based on their importance in the objective function. The term $\alpha\rho^2 + \beta\eta^2$ in the denominators of the coefficients normalizes the effects. Note that if $\beta = 0$ and $\alpha = 1$, the second term in the equation drops and the equation boils down to the optimal level of intervention given in Ito and Yabu (2007).

Jeanne and Ranciere (2011) show that most of the emerging market economies, except the Asian countries in their sample, have smaller reserve-to-GDP ratios than the optimal value. There-

[5] For advanced economies, Yilmaz (2003) shows that during periods of coordinated currency interventions, the exchange rates deviate from the martingale property. Some deviations from the RW assumption are included as robustness checks in Section (5.7).

[6] Note that $\Delta s_t = (s_t - s_{t-1}) = (s_{t-1} + \rho Int_t - s_{t-1}) = \rho Int_t$.

fore, for an emerging country in which $a > R_{t-1}(\Lambda_{t-1})$, the model is expected to explain the foreign currency purchases by the central banks better than sales.

For the sake of simplicity, in the rest of the study, a is normalized to 0 and Equation (5.5) is expressed in a compact form as follows:

$$Int_t^* = A(s_{t-1} - s_t^T) + BR_{t-1}(\Lambda_{t-1}). \tag{5.6}$$

where

$$A = -\frac{\alpha\rho}{\alpha\rho^2 + \beta\eta^2}, \text{ and} \tag{5.7}$$

$$B = -\frac{\beta\eta}{\alpha\rho^2 + \beta\eta^2}. \tag{5.8}$$

The exchange rate target is assumed to be composed of five elements that capture the short-term and long-term movements in the exchange rate. Short-term elements are the previous day's and previous month's exchange rates, s_{t-2} and s_{t-21} respectively. Long-term elements are the 1, 3, and 5-year moving averages, which are defined as

$$s_t^{kMA} = \frac{1}{k260} \sum_{i=0}^{k260-1} s_{t-i}, \tag{5.9}$$

where $k = 1,3,5$ and a year is assumed to have 260 business years. Then the target exchange rate can be written as follows:

$$s_t^T = \delta_1 s_{t-2} + \delta_2 s_{t-21} + \delta_3 s_{t-1}^{long} \tag{5.10}$$

where

$$s_t^{long} = c_1 s_t^{1MA} + c_2 s_t^{3MA} + c_3 s_t^{5MA}. \tag{5.11}$$

The coefficients of the target exchange rate and long-term exchange rate are normalized to one which means that $\delta_1 + \delta_2 + \delta_3 = 1$, and $c_1 + c_2 + c_3 = 1$. Using the definitions of the target exchange rate level and the long term exchange rate, the optimum level of intervention in Equation (5.6) can be written as:

$$\begin{aligned} Int_t^* =& \gamma_1(s_{t-1} - s_{t-2}) + \gamma_2(s_{t-1} - s_{t-21}) + \gamma_3(s_{t-1} - s_{t-1}^{1MA}) \\ &+ \gamma_4(s_{t-1} - s_{t-1}^{3MA}) + \gamma_5(s_{t-1} - s_{t-1}^{5MA}) + \gamma_6 R_{t-1}(\Lambda_{t-1}) \end{aligned} \tag{5.12}$$

where $\gamma_1 = \delta_1 A$, $\gamma_2 = \delta_2 A$, $\gamma_3 = \delta_3 c_1 A$, $\gamma_4 = \delta_3 c_2 A$, $\gamma_5 = \delta_3 c_3 A$, and $\gamma_6 = B$.

In this form, the model implies that policymakers will react to exchange rate movements continuously. However, as it can be observed on Figures (5.3) and (5.4) that present Turkish intervention data, it is an empirical fact that there might spells of interventions or just a stand alone intervention. Ito and Yabu (2007) capture the possibility of non-frequent interventions by introducing political costs to the model. For the Japanese case, the intuition of political costs is based on the necessity of an approval by the Ministry of Finance for the Bank of Japan to start interventions. The approval of the initial intervention is assumed to decrease the costs of the following interventions. In Turkey, the CBRT independently decides on interventions; so the preceding intuition is not valid for the Turkish case. On the other hand, as noted in the survey of Neely (2008); except one bank, central banks are in general very quick to make an intervention even there has not been an intervention in the previous day. Therefore, the motivation suggested by Ito and Yabu (2007) seems to apply to the very special case of the Bank of Japan rather that the general situation, and particularly not to the case of the CBRT.

Instead, public announcements on the auctions for currency interventions justify a similar cost effect for the case of Turkey. As noted in the previous section, the CBRT sometimes chooses to intervene to the markets with unannounced interventions; but usually use auctions whose rules are predetermined. However, the end date is left undetermined by the note that the CBRT has the right to end the auctions when they see the continuation unnecessary. The public announcement of these interventions is taken as the cost of interventions and it is assumed that subsequent interventions are more likely since the cost does not apply to them.

The cost function, C_t, is defined as

$$C_t = \begin{cases} C_1^P - C_2 I(Int_{t-1} > 0) & \text{if } \ Int_t > 0 \\ C_1^S - C_2 I(Int_{t-1} < 0) & \text{if } \ Int_t < 0 \end{cases} \tag{5.13}$$

where $C_1^P > 0$ is the cost of purchasing USD, $C_1^S > 0$ is the cost of selling USD, and $I(.)$ is the indicator function that is used to indicate if there is an intervention of the same kind in the previous period. The intuitively correct case for facilitation of interventions is $C_2 > 0$ which corresponds to the situation where an intervention in period $t-1$ decreases the cost of intervention at time t. The cost of intervention can also be modeled as a fixed amount for both USD sales and purchases as in Kearns and Rigobon (2005), but here costs are assumed to be different for both directions in order to account for asymmetric effects of interventions.

The central bank will make its intervention decisions by comparing the costs and benefits of interventions given in Equations (5.13) and (5.12) respectively. Different cases implied by these comparisons can be written as follows:

$$IInt_t = \begin{cases} -1 & \text{if } \ Int_t^* + \varepsilon_t < \mu_1 + \gamma_7 I(Int_{t-1} < 0) \\ 0 & \text{if } \ \mu_1 + \gamma_7 I(Int_{t-1} < 0) < Int_t^* + \varepsilon_t < \mu_2 - \gamma_7 I(Int_{t-1} > 0) \\ 1 & \text{if } \ \mu_2 - \gamma_7 I(Int_{t-1} > 0) < Int_t^* + \varepsilon_t \end{cases} \tag{5.14}$$

where μ_1 and μ_2 are the cut-off levels for USD sales and purchases respectively, and $\varepsilon_t \sim N(0, \sigma^2)$.[7] Assuming the sign of the intervention at time t is never different from the intervention sign at time $t-1$[8], intervention decisions can be re-written in the form of an ordered probit model as:

$$IInt_t = \begin{cases} -1 & \text{if } \ y_t^* < \mu_1 \\ 0 & \text{if } \ \mu_1 < y_t^* < \mu_2 \\ 1 & \text{if } \ \mu_2 < y_t^* \end{cases} \tag{5.15}$$

7 For the model only with exchange rate targeting, Ito and Yabu (2007) put the sign conditions on the cut-off levels as $\mu_1 < 0$ and $\mu_2 > 0$. Intuitively, the value of the optimal intervention will be pushed downward by the negative effect of the new $\gamma_6 R_{t-1}(\Lambda_{t-1})$ term. Therefore, a sign restriction on the cut-off levels is not employed here.

8 This assumption is validated for the intervention data of CBRT. A purchase (sale) of USD is always followed by a purchase (sale) or no intervention period.

where $y_t^* = X_t\gamma + \varepsilon_t$ and

$$\begin{aligned} X_t\gamma =&\gamma_1(s_{t-1}-s_{t-2})+\gamma_2(s_{t-1}-s_{t-21})+\gamma_3(s_{t-1}-s_{t-1}^{1MA}) \\ &+\gamma_4(s_{t-1}-s_{t-1}^{3MA})+\gamma_5(s_{t-1}-s_{t-1}^{5MA})+\gamma_6 R_{t-1}(\Lambda_{t-1})+\gamma_7 IInt_{t-1} \end{aligned} \tag{5.16}$$

It has to be noted that by using the ordered probit model in Equation (5.15), we can only estimate standardized values of the coefficients which are $\gamma_i^* = \gamma/\sigma$ and $\mu_i^* = \mu_i/\sigma$ which means that δ and c values can be calculated as $\delta_1 = \gamma_1^*/(\sum_{i=1}^5 \gamma_i^*)$, $\delta_2 = \gamma_2^*/(\sum_{i=1}^5 \gamma_i^*)$, $\delta_3 = (\sum_{z=3}^5 \gamma_z^*)/(\sum_{i=1}^5 \gamma_i^*)$, $c_j = \gamma_{j+2}^*/(\sum_{i=3}^5 \gamma_i^*)$ for $j = 1,2,3$ but A and ρ cannot be identified. Similarly, a standardized value for B is given by the estimations; but η, along with the parameters α and β, is not identified. This model is referred as the "extended model" and the version of the model without the reserve variable is referred as the "Ito & Yabu model".

Ito and Yabu (2007) note that the model they give can be seen as a "reaction function with neutral bands". Within the neutrality bands, the central bank will not react to exchange rate movements. With the new variable added to the model, it is now a reaction function that reacts also to the international reserves accumulated as a ratio to GDP until the time of intervention decision. Below the negative band, the central bank will react by selling USD and above the positive band, it will react by purchasing USD. γ_1 and γ_2 coefficients denote reactions based on the short-term deviations; γ_1, γ_2, and γ_3 are the long-term deviation coefficients; γ_6 is coefficient of existing reserves, and γ_7 is the momentum coefficient, which tells that an intervention is more likely today if there was an intervention on the previous day. A positive value of γ_7 means that the likelihood of an intervention today increases based on the existence of a previous day intervention .

A reaction function without the neutrality bands can be given as the following:

$$\begin{aligned} IInt_t =&\phi_0+\phi_1(s_{t-1}-s_{t-2})+\phi_2(s_{t-1}-s_{t-21})+\phi_3(s_{t-1}-s_{t-1}^{1MA}) \\ &+\phi_4(s_{t-1}-s_{t-1}^{3MA})+\phi_5(s_{t-1}-s_{t-1}^{5MA})+\phi_6 R_{t-1}(\Lambda_{t-1})+\upsilon_t \end{aligned} \tag{5.17}$$

which is the linearization of the preceding probit model with a constant (Ito and Yabu, 2007). This linear model is called as "conventional extended model" and the version of the model without the reserve variable is referred as "conventional model" throughout the study.

5.4. Data

The initial dataset includes New York closing spot rates for the USD/TRY exchange rate starting from 26 March 2001 to 16 October 2015. It starts just after the CBRT decided to implement a floating exchange rate regime on 22 February 2001. The first month of the floating exchange rate regime is not included in the data set because of the sharp devaluation of the TRY in the immediate period.[9] The USD/TRY exchange rate is plotted in Figure (5.5) with the 1, 3, and 5-year moving average values for the whole sample.

Intervention data are retrieved from the CBRT database. There are 2314 days with interventions. Unannounced interventions are less frequent and are announced on the day they are carried out but the amounts of interventions are given 15 days after the interventions. For this type of interventions, the CBRT is partially following the policy recommendations of Bhattacharya and

[9] Blanchard et al. (2015) take the period for Turkey starting from 2003-Q3. This might be another approach to start the daily dataset.

Weller (1997) who argue that efficiency of interventions is at the maximum when an intervention is announced but the amount is not. The delay in the announcement of the amount is not relevant for the ordered probit regression analysis, which only works with the information whether an intervention is occurred or not.

There are 2305 auctions and 27 direct unannounced interventions in the dataset, which means that on some days the CBRT used both auctions and direct interventions. 1496 of the interventions are purchases and 818 are sales of the USD. The maximum amount of an intervention on a single day is 5441 million USD, which was a purchase, while the minimum amount is 5 million USD, which is again a purchase. For the sales, the maximum amount is 3351 million USD and the minimum amount is 10 million USD.

The OLS and ordered probit regressions do not use the whole dataset. As it is described below, the sample is split into an estimation and a forecast sample to generate forecasts for the reserve-to-GDP ratios. The estimation period ends on 31 December 2005. The rest of the sample after this date until 30 September 2015 is used in the regressions. The end of the sample is chosen to be 30 September 2015 because this is the final date on which quarterly data, and therefore the reserve-to-GDP ratio, are available. The dataset used in ordered probit regressions consists of 2522 days. There are 1018 USD purchase and 679 USD sale days during the time period that sums up to 1697 intervention days. The maximum amounts of purchases and sales are 5.5 billion USD and 3.3 billion USD respectively.

5.4.1. Daily reserve-to-GDP ratio forecasts

Estimating the model in (5.15) requires the use of the daily $R_{t-1}(\Lambda_{t-1})$ series. However, such a series is not available at the daily level since the calculation of the series uses quarterly GDP data.[10] In order to carry out the regression analysis, a synthetic $R_{t-1}(\Lambda_{t-1})$ series is calculated by using the Mixed Data Sampling (MIDAS) model.[11] For each day in a quarter, forecasts for the end of quarter's reserve-to-GDP ratio are calculated and the values are brought together to generate the necessary series. Since the reserve-to-GDP ratio is treated as a quarterly variable from now on, for notational convenience the subscript t of the reserve-to-GDP ratio is replaced with $d = 1, 2, \ldots, D$ where D is the maximum number of quarters in the dataset.

There are other methods to work with mixed frequency date in the time series econometrics literature but the MIDAS model is selected as the method of forecasting for two reasons. First, it handles the mixed data with a single equation in a parsimonious fashion and allows us to write the daily reserve-to-GDP forecasts in a functional form that is given in Equation (5.4). Second, Andreou et al. (2011) and Bai et al. (2013) show that the MIDAS model is less prone to specification errors than its competitor, state-space models.

In its simplest form, a MIDAS model for a quarterly series of interest, Q_d, can be written as follows:

$$Q_d = \psi_0 + \psi_1 \sum_{j=0}^{(q_S-1)} \sum_{i=0}^{(m-1)} \omega(\theta, i + j*m) S_{(m-i,d-j)} + \nu_{(d)}, \tag{5.18}$$

10 Besides employing the approach we have here, the closest series to the real $R_{t-1}(\Lambda_{t-1})$ can be calculated using the quarter end values for the reserve-to-GDP-ratio and daily exchange rate returns. Such a series is used in the probit model estimations and we get similar results we present here. The advantage of the MIDAS approach is that it can give daily forecasts by including more data in a concise manner.

11 For the properties of the MIDAS models, please see Ghysels et al. (2004), Ghysels et al. (2007), and Foroni and Marcellino (2013).

where q_x is the number of low frequency lags, ψ_j is the corresponding coefficient for the aggregated high frequency variable at low frequency lags, m is the fixed number of high frequency periods in one single low frequency period, (i,d) is the i^{th} lagged high frequency period in the low frequency period d, $S_{(i,d)}$ is the high frequency variable (e.g. daily series), and $\omega(\theta, i + j*m)$ is the polynomial distributed lag function that depends on the hyper parameter θ. There are various functional specifications for the polynomial function ω, but the Almon distributed lag polynomial is used in this study.[12] The polynomial function can be written as:

$$\omega(\theta,i) = \sum_{p=0}^{n_p} \theta_p i^p, \tag{5.19}$$

and assumes that the weight of the i^{th} lag can be calculated with underlying $(n_p + 1)$ hyper parameters $\theta = (\theta_0, \ldots, \theta_p)$. n_p is taken to be 2 in the calculations.

Forecasts for the reserve-to-GDP ratios are calculated by MIDAS with leads. The MIDAS with leads methodology allows us to calculate forecasts for the end of the quarter we are in as move through the quarter. "Lead" refers to the data used within the quarter that a forecast is made. For instance, if one wants to make a forecast at the 10^{th} day of the quarter for the end of the quarter[13], these 10 days are called leads. Days that belong to the previous quarter/s are called lags.

The high frequency variable, S, is taken as daily exchange rate returns. Exchange rate return and daily lags are selected to be the high frequency variable to ensure the appearance of Δs_t in Equation (5.4). An Autoregressive (AR) term and quarterly factor series are also added in the estimations. The performance of the forecasts are improved by using the first lag of one quarterly factor that is extracted from six quarterly macroeconomic series (Stock and Watson, 2002; Andreou et al., 2013).

The MIDAS with leads forecast equation can be given as follows:

$$\begin{aligned} Q_{d+h} = \psi_0^h + \sum_{r=0}^{(q_Q-1)} \zeta_r^h Q_{(d-r)} + \sum_{r=0}^{(q_F-1)} \tau_r^h F_{(d-r)} + \psi_1^h \Bigg[\sum_{i=(3-J_{\Delta s})*m/3}^{(m-1)} \omega(\theta^h, i-m) \Delta s_{(m-i,d+1)} \\ + \sum_{j=0}^{(q_{\Delta s}-1)} \sum_{i=0}^{(m-1)} \omega(\theta^h, i+j*m) \Delta s_{(m-i,d-j)} \Bigg] + \nu_{(d+h)}^h, \end{aligned} \tag{5.20}$$

where h is the forecast horizon; ζ_r is the coefficient of the AR term and q_Q is the number of lags of the low frequency variable; F_{d-r} is the quarterly factor at time F_{d-r}, τ_r and and q_F are the corresponding coefficient and lag number of the quarterly factors; $J_{\Delta s}$ and $q_{\Delta s}$ are the number of leads and lags of exchange rate returns respectively. Finally, the autoregressive lag is taken to be 1. The forecast horizon, h, is fixed to one quarter since we do not need further forecast horizons. However, a forecast calculated at the n^{th} day of a quarter is called the $(65-n)$-day ahead forecast for ease of expression, where $n = 1, 2, \ldots, 65$.

After the estimation of the model parameters and decision on the weights of the lags, the weight of the Δs_t on a specific date can be separated in order to write the equation in form of Equation (5.4). The constant, AR term, factors and lags of the exchange rate returns are stacked

12 Calculations are made also with Beta polynomial and exponential Almon lag polynomial functions. The Almon lag polynomial gives the best results in terms of forecasting performance and speed. Results retrieved using other functions are available upon request.

13 This forecasts might also be called a 55-day ahead forecast assuming that there are 65 days in a quarter.

into the matrix $\hat{\Lambda}_{t-1}$ so that

$$\hat{Q}^t = \hat{\psi}_1 \omega(\hat{\theta}, t)\Delta s_t + \hat{R}^{t-1}(\hat{\Lambda}_{t-1})$$

which is the forecast of the end-of-quarter reserve-GDP-ratio at time t. The superscript t identifies the series as a forecast series. From this equation, the variable that is used in the ordered probit regressions can be written as follows:

$$\hat{R}^{t-1}(\hat{\Lambda}_{t-1}) = \hat{Q}^t - \hat{\psi}_1 \omega(\hat{\theta}, t)\Delta s_t \tag{5.21}$$

The quarterly series we use for calculating the quarterly factor are imports and exports as a share of GDP, production (excluding construction), hourly earnings, monetary aggregate (M1), and passenger car registrations. The factors are extracted by using the Principal Component Analysis (PCA) with a window size of 40. Already the first one these factors explains 51% of the total variation in the quarterly series. Other factors explain 34%, 18%, 7%, and 2% respectively. We only report the forecasts results using the first factor, which delivered the best results.

Quarterly series and the daily exchange rate return are winsorized at the 1% level in order to prevent any outlier effects.

Quarterly changes in the international reserves of the CBRT are given in Figure (5.6) and the reserve-to-GDP series are plotted in Figure (5.7). Both the ratio series and the exchange rate return series are tested for a unit root before performing the regressions.

The number of leads and lags that are used to calculate the forecasts may vary. Here, the number of leads and lags are selected based on the root mean squared forecast error (RMSFE) of different specifications. The selection procedure of the leads and lags follows three steps. At the first step, we calculate 1 to 65-day ahead forecasts with a recursive window scheme and the RMSFE of the forecasts are gathered. Then, for each lag and within the quarter forecast horizon, the RMSFE performances are compared with the benchmark AR(1) model with a constant. At the final step, the lag value that gives the best average performance is selected. Table (5.1) reports RMSFE values of the forecasts for several forecast horizons and lags with respect to the benchmark model. The performance of the forecast is up to 45% better compared to the benchmark model. The estimated Almon polynomial lag functions are given in Figure (5.8).

The best average performance is received from lag 95 with an average performance of 0.6. The $\hat{R}^{t-1}(\hat{\Lambda}_{t-1})$ series is generated by using this lag.[14] Figure (5.9) plots the generated $\hat{R}^{t-1}(\hat{\Lambda}_{t-1})$ series against the real reserve-to-GDP series.

5.5. Identifying Structural Breaks

During the estimation periods for the probit regressions, there have been notable domestic and global events that may have change the intervention policy of the CBRT. First; since the beginning of 2006, the governor of the CBRT changed twice. Durmuş Yılmaz was appointed as the governor on 14 March 2006 and Erdem Başçı was appointed on 14 April 2011. The governors' policy objectives might play a role in the currency intervention policies (Ito and Yabu, 2007). Second, the global financial crisis started in 2008 after the collapse of the Lehman Brothers and the Federal Reserve started the first round their QE policy, which continued until 2014 with two renewed

[14] 95 is the sum of the leads and lags used in the forecasts.

rounds. Turkey had negative quarter–on–quarter GDP growth rates in the last quarter 2008 and first quarter of 2009 with -5.9% and -5.6% respectively, which are the lowest growth rates since the banking crisis in 2001. The financial crisis and both the start and end of the QE policy has implications on the capital flows to Turkey, hence reserve management. Finally, at the start of 2014, the CBRT implemented new policies to cope with the deviations in the exchange rate and started to support the USD need of the state owned oil-importing firms directly.

The possibility of changes in the intervention policy of the CBRT is first analyzed by the methodology introduced by Andrews (1993) who shows that the existence, statistical significance, and location of one structural break point can be tested by using F or Wald statistics, and simulates asymptotic critical values. Accordingly, for the linear version of the probit model is used as given in Equation (5.17), we calculate recursive Chow test F-statistics for every point within the middle 80% of the data (i.e. the first and last 10% are trimmed following Andrews (1993)). Figure (5.10) gives the calculated F-statistics. The maximum value is received at on date 04 August 2011 which implies a structural break at this date. The conventional model gives the same break date, but with higher value of the statistics.

Considering the number of events that might have caused policy changes, the existence of multiple structural breaks is tested by the Bai and Perron (2003a) (BP) test for an unknown number of structural breaks. For the BP test, the maximum number of structural breaks is taken as 5, the trimming ratio is 0.1, and the errors are assumed to be heteroskedastic. We start by applying the BP test to the linear model including both the exchange rate and reserves. Table (5.2) displays the test statistics for each number of breaks. The critical values for the test statistics are given in Bai and Perron (2003b). Bai and Perron (2003a) note that the sequential procedure gives better results for the number of structural breaks; so the break points suggest by this procedure is taken as a reference.[15] The dates of the breaks estimated by the sequential procedure are 24 September 2007, 03 August 2011, and 19 June 2013.

The first structural break point coincides to a period when the CBRT increased the maximum amount of auctions from 45 million USD to 90 million USD due to the capital inflows to Turkey due to the evaluation of the housing and credit markets abroad (CBRT, 2007b). In 2008, after the global financial crisis, buying auctions are suspended and selling auctions have continued for a while. Foreign reserve concerns mark the period before and after the global financial crisis. The second suggested structural break point is at a time when the CBRT announced that it would intervene to the markets when seen necessary. This announcement came in August 2011 after the announcement of suspension of interventions in July 2011. The second round of the US QE ended in the second quarter of 2011, and the interventions are directed to address uncertainty in the foreign exchange market. Finally, on the last structural break date, the conditional termination of the QE based on positive economic data was announced and it was noted that the programme could be wrapped in 2014. The announcement and subsequent termination of the QE programme created upward movements in the currency markets, and the CBRT has increased the amount of interventions. For the further analysis we proceed using these three break points and four sub-periods accordingly. In contract to the extended model the procedure suggests 4 break points for the benchmark model with only exchange rates, the original (Ito and Yabu, 2007) model, see Table (5.3).

[15] The table also gives the estimates of the number of structural breaks from LWZ and BIC. These values are 4 and 5 respectively.

5.6. Estimation Results

5.6.1. Linear regression results

The linear regressions results of Equation (5.17) with Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) errors are given in Table (5.4). Results of the conventional model are given in Table (5.5) for comparison. According to the R^2 values, the explanatory power of the conventional model with reserves is the smallest in the last period of the sample. The final sub-period in the sample has been marked with the political risk and introduction of new policy measures by the CBRT to deal with the movements in the currency markets; therefore, the low performance of the model in the last period is expected. A more complex model might be needed to capture the events of the last period.

The coefficient of momentum variable, ϕ_7, is significant in the full sample and in all sub-sample regressions. The positive sign of the coefficient implies that the cost of interventions decreases if there is an intervention on the previous day. The size of the coefficient gets smaller in time and is the smallest in the last sub-period implying that the predictability of a future intervention based on the current day intervention decreases over time.

The reserve variable coefficient, ϕ_6, is significant in the full sample and for the first three sub-sample regressions. The negative sign is in line with the implications of the model and implies that as the amount of reserve accumulated before the day of intervention, intervention will decrease. Our initial assumption on the reserve variable is that it would explain the USD purchases in a better way in Turkey. The size of the coefficient is the largest in the third subsample in which there has been no USD purchases carried out. This suggests that in the third sub-sample, there is indeed an over accumulation of reserves compared to the optimal level and it contradicts the assumption that Turkey, as an emerging country, has always a deficit in the reserve-to-GDP ratio and should be inclined to accumulate reserves continuously.

None of the exchange rate variable coefficients is significant at the full sample; while for the conventional model, 3-year and 5-year moving average variable coefficients are significant. Coefficient for the deviations from the previous day, ϕ_1, is never significant in any regressions of neither of the conventional extended and conventional models. This result is in line with the CBRT announcements saying that the bank does not intervene based on short-term movements in the exchange rates. For the extended model, coefficients for the deviations from the 1-year and 3-year moving average are significant for the first three sub-samples while the 5-year term has a significant effect in the first two sub-samples. The signs of the exchange rate variable coefficients are not significant through regressions suggesting that relative importance and weight of the variables in the objective function change depending on the circumstances of certain periods.

5.6.2. Ordered probit estimations

The results of the ordered probit regressions of the extended model for the full sample and the four sub-samples are given in Table (5.6), whereas probit regression results for the Ito & Yabu model are reported in Table (5.7) for comparison. The tables contain coefficient estimates, cut-off point estimates (i.e. estimates of μ_1 and μ_2), and Pseudo-R^2 or *McFadden's* R^2 for each regression.

Fitted values of the probit regressions are given in Figures (5.11) and (5.12) with the estimated cut-off point estimates for the full sample and sub-samples respectively. Changes in the cut-off values within periods can be observed on the graphs. For the USD purchases, the estimated cut-off value for the first period is lower and for the second period is higher than the estimated cut-off point for the USD purchases in the full sample regression. For the USD sales, the estimated cut-off points are lower in the first and third periods, and higher in the second and fourth periods than the estimated cut-off point in the full sample regression. The lower (higher) cut-off point for the USD purchases (sales), the higher the probability that the CBRT is intervening to the markets. The band for intervention (i.e. the area between the cut-off points) is the narrowest for the second period (i.e. 25/09/2007–03/08/2011); so, only based the band width, the CBRT would be expected to be in the currency markets with the highest probability during this period.

The coefficient of the momentum variable, γ_7^*, is significant at the 1% level and has the expected positive sign in all of the regressions implying that an intervention today increases the possibility of an intervention tomorrow. Size comparison of the coefficient within periods suggest that after the introduction of new measures by the CBRT such as ROM in the third period and directly supplying oil importing state-owned firms in the fourth period has decreased the influence of the momentum variable.

The coefficient of the reserve variable, γ_6^*, is significant in the full sample and in the first three sub-sample period regression. The coefficient has the theoretically expected sign. It is the smallest and insignificant in the last sub-sample period regression. In the final sub-sample, the cut-off point estimator is not significant either indicating that the extended model performs poorly in explaining the intervention behavior of the CBRT in this sub-sample period. However, considering the developments in the last period of the sample, this results comes as no surprise to us and indicates the necessity of analyzing this period in more detailed fashion, which is out of the scope of this study. The size of the coefficient is the largest in the first and third sub-sample period regressions. Starting from the end of the first period and during the second period, the CBRT has explicitly announced the aim of some interventions as accumulating international reserves by point outing the need for strong reserves in emerging market economies; so, intuitively we expect the coefficient to be largest in size in these two periods. The coefficient is indeed the largest in the first sub-sample period regression; however, the coefficient in the second period is not one of the largest on the contrary to our expectations. The robustness checks show the coefficient is indeed robust to different model specifications only in the second sub-sample period; but during this sub-sample period, the strength of the variable might have been mitigated by the concerns on the international risk on currency markets during the global financial crisis.

Significance of the reserve variable is tested with a Wald test with the null hypothesis that the variable does not have an affect on the reaction of the CBRT, $H_0 : \gamma_6^* = 0$ (i.e. the CBRT reacts according to the Ito & Yabu model), with the respective samples. The null hypothesis can be rejected at the 1% significance level for the full sample while the significance level drops to 5% for the first three sub-sample periods. For the last period, the test statistic suggests that we do not have enough evidence to reject the null hypothesis at a significant level. Hence, even though we cannot compare the extended model with the Ito & Yabu model directly because of the different structural breaks, we see the statistically significant affect of the reserve-to-GDP ratio in the reaction function.

Similar to the linear regression results, we observe a significant effect of the reserve variable in the third sub-sample period in which no USD purchases take place, justifying the evidence for the possibility that the CBRT chose to reduce its international reserves depending on the certain conditions of the period.

We cannot derive direct conclusions based on the coefficient estimates of the exchange rate variables since they are weighted values rather than the real effects of the exchange rate variables on interventions. Nevertheless, values of target exchange rate variable coefficients (i.e. δ and c) can be calculated by using the standardization conditions and by fixing non-significant terms to 0. Calculated δ and c values for the extended model are given in Table (5.8). δ_1,δ_2, and δ_3 correspond to the comparative weights of the deviation from previous day, deviation from previous month, and deviation from the long-term target level in the estimation function respectively. As it can be seen in the table, in the second and third sub-sample periods, only the long-term exchange rate variables are significant (i.e. $\delta_3 = 1$). In the final period, only significant coefficient is δ_2. However, the signs of and sizes of the coefficients change depending on the estimation period. The positive weight of the 5-year moving average term transforms to negative in the second and third periods. In these two periods, the 3-year moving average term has a positive effect with a larger size compared to the weight of the 5-year moving average term implying that the 3-year moving average term has a more decisive role in these periods while in the first period this role has been divide into all terms.

Comparisons based on the Pseudo-R^2 values indicate that the explanatory power of the model changes over time. It has to be noted that the pseudo-R^2 of ordered probit regressions is not directly comparable with the OLS R^2. Therefore, even though the pseudo-R^2 values reported in Table (5.6) are smaller than the R^2 values from the conventional regressions, it does not necessarily imply that their explanatory power is smaller. Veall and Zimmermann (1996) show that Pseudo-R^2 values of the probit models are smaller than the OLS R^2. The Pseudo-R^2 reported for the probit model regressions actually correspond to a very high explanatory power for the full sample and two of the sub-samples. According to the R^2 values, the extended model has the smallest explanatory power in the last period as expected and due to the developments in this period noted above. The explanatory power of the model in the second period comparatively weaker than it is in the first and third periods, probably based on the risks brought by the global financial crisis.

Therefore, the probit model regression results for the extended model provide evidence for the economically significant influence of the international reserve accumulation behavior of the CBRT until mid-2013 whereas the regression results for the 05/08/2011-19/06/2013 period raise questions on the presumption that an emerging market economy has a continuous tendency to accumulate reserves.

5.6.3. Noise-to-signal analysis

The implications of the sub-sample probit regressions can further be analyzed with a noise-to-signal analysis (Ito and Yabu, 2007) in order to see how well the model performs in predicting future interventions. Using the probability of an intervention that is calculated after each probit regression, one can calculate early warnings (i.e. intervention/no-intervention days correctly predicted by the model) or false alarms (i.e. intervention/no-intervention days incorrectly signaled by the model) with the noise-to-signal ratio methodology introduced by Kaminsky and Reinhart (1999). The smaller a noise-to-signal ratio, the better a model performs in signaling future interventions. A description of the noise-to-signal ratio calculation and a breakdown of the results are given in Appendix (5.8).

Noise-to-signal ratios of both model for all sub-sample periods and a comparison of the models are reported in Table (5.9). In the first two sub-sample periods in which there are both USD purchases and sales, the noise-to-signal ratios from the extended model are smaller for the interventions by sales. This is an unexpected result since our initial assumption is that the model would better explain/predict USD purchases. However, in the breakdown of the results in Table (5.18), we see that the performance in the USD sales is due to the prediction of days without interventions rather than days with interventions. The number of days with USD sales is 4 in the first period and 20 in the second period while the numbers are 289 and 515 for the USD purchases for the respective periods. Therefore, the model safely assumes that there will not be USD sales in the future and we have lower noise-to-signal ratios for these two periods. Nevertheless, it has to be noted that when the number of days with USD sales increases in the third period, the performance of the model is still good and in the last period, it deteriorates; but the changes in the performance should not be taken as a direct evidence against the extended model with USD sales because as we argued earlier, we do not expect a very significant performance in the last period.

Comparisons of the extended model to the model only with exchange rates give little intuition about the relative performances of the models. According to the full sample comparisons, the extended model performs 5% better than the model only with exchange rates for USD purchases and 18% better for the USD sales interventions. At the sub-sample level, a direct comparison of the model performances is not possible since the number of structural break points is different. As a short-cut for comparison, if the we take the second and third period of the FX model as one period and average the noise-to-signal ratios, we see that during this time period, the extended model performs 20% better than the model only with exchange rates for USD purchases and 51% better for the USD sales interventions. In the last two periods during which there have been only USD sale interventions, extended model performs comparatively worse. However, these comparisons are blurred by the different segmentation of the sample.

The noise-to-signal analysis justifies our conclusions from the previous section and provides new insights. Even though the model is assumed to give better results for USD purchases based on the empirical evidence on emerging markets reserve accumulation behavior, the performance of the model for USD sales indicate that the extended model can explain both sides of the interventions. The performance of the model in the USD sales is driven by the low values of noise in the calculations which might be due to the small number of interventions by USD sales.

5.7. Robustness Checks

The robustness of the probit model regressions are checked by changing the specification of the exchange rate target, adding the exchange rate volatility in the regressions as a possible factor that would motivate the CBRT for interventions, and including interest rate differentials and macroeconomic news as deviations from the RW assumption for the exchange rate models.

The probit regressions results for the extended model given in Section (5.6) uses a fixed specification of exchange rate target that is previously used by Ito and Yabu (2007). Even though this specification covers a wide range of possibilities, the actual target may not include some of the short or long-term target elements. In order to test the robustness of the results for the reserve-to-GDP ratio, probit regressions are carried out by dropping each exchange rate target variable, and short-term and long-term components of the target separately. The columns (1)-(7) of the Tables (5.10)-(5.14) report the regression results for the full sample and sub-sample periods. The reserve-to-GDP ratio coefficient has the expected sign in all exchange rate target and sample specifications. The coefficient is significant in all specifications for the full sample and the second sub-sample period. In the third period, the coefficient loses its significance only when the long-term target component is dropped. The significance of the coefficient is not robust to different specifications of the target exchange rate; however, as it is reported in Table (5.6), in this period, all exchange rate target coefficients expect the deviation from the previous day are significant. Finally, the coefficient is not significant in the fourth sub-sample period regressions as expected.

The volatility of exchange rate has been note as one of the important motivations for currency interventions. In order to test the robustness of the results, the daily realized volatility of the USD/TRY exchange rate has been calculated as the square of the exchange rate returns. The volatility variable is included in the regressions and in another set of regressions, the first lag of the variable is also added to see the impact of the previous day volatility in the intervention behavior. The coefficient of the volatility variable is denoted by γ^*_{vol} in the regressions. The columns (8) and (9) of the Tables (5.10)-(5.14) report the regression results. The reserve-to-GDP ratio coefficient has the expected the sign and significant for both model specifications and in all sample specifications expect the fourth sub-sample period. In the last sub-sample period, the coefficient has the correct sign but insignificant as expected.

The fundamental models of exchange rates assume that inflation rate, money supply, and interest rate differentials decide the exchange rate levels. In order to test the robustness of the results based on the fundamental models at the daily level, only the interest rate differential is included in the regressions due to data availability and two different interest rate variables are calculated. The first variable is calculated by taking the difference of the overnight interest rates on deposits in Turkey and US. The second variable is calculated by taking the difference of the 3-month interest rate on deposits in Turkey and the US 3-month Treasury bill rate. The coefficients of the variable are denoted as $\gamma^*_{overnight}$ and γ^*_{3M} respectively. The variables are included in the regressions separately. The columns (10) and (11) of the Tables (5.10)-(5.14) report the regression results with the interest rate variables. The reserve-to-GDP ratio coefficient loses its significant only in the third period and with inclusion of the overnight interest rate differential variable.

The macroeconomic data announcements in Turkey and the US are included in the regressions to see if the CBRT indeed reacts to some domestic or foreign macroeconomic developments that might be picked up by the reserve-to-GDP ratio variable. The new variables are two dummy variables that take a value of 1 if there is a macroeconomic data announcement on a specific date or 0 otherwise. Economic calendar data for the US GDP, consumer price index, and unemployment data are retrieved from the US Bureau of Economic Analysis and Bureau of Labor Statistics. For Turkey, the calendar data for the same macroeconomic indicators are retrieved from the Turkish Statistical Institute. In the US macroeconomic news variable, FED policy rate change dates are also included considering the impact of these decisions on small economics but the policy rate data are not included for Turkey based on the literature arguing that interventions might signal policy rate changes (Kaminsky and Lewis, 1996), and interventions and policy rate are complementary tools (Ghosh et al., 2016). The news variable coefficients for Turkey and the US are denoted as $\gamma^*_{TRYNews}$ and γ^*_{USNews} respectively. The column (12) of the Tables (5.10)-(5.14) reports the regression results with the news variables. The sign and significance of the reserve variable is robust to the inclusion of the news variables in the full sample and the first three sub-sample specifications.

The final columns of the Tables (5.10)-(5.14) include regression results for a big model that includes all robustness check variables excepts the overnight interest rate differential that does not turn out to be significant in other specifications. The results are robust to this specification in the full sample and the first two sub-sample periods. In the third sub-sample period specification, the coefficient loses its significance.

To our best knowledge, there has not been an attempt in the literature to identify the reserve accumulation behavior of the central banks at the daily frequency. Therefore, the validity of the forecasts generated by the MIDAS with leads might be a concern. It can be argued that the policy makers assess the sufficiency of their foreign exchange reserves based on the end of period forecasts that rely on already available metrics. In order to isolate this concern, a forecast series that assume the end of period reserves-to-GDP ratio is calculated by using the already available GDP and foreign exchange reserves data. For Turkey, the reserves data is publicly available at the weekly frequency, so the forecast for the end of period ratio is updated every week and uses the GDP data from the previous period.

The weekly updated forecast series, the MIDAS forecasts, and the real values for the end of period reserve-to-GDP ratios are plotted in Figure (5.13). As it can be seen on the graph, there are differences between series over time and the relative performance is of the forecast series cannot be visually assessed for some periods. For the series plotted in the graph, the RMSFE of the MIDAS series is 0.0269 while the RMSFE of the weekly updated series is 0.0317; thereby, the MIDAS forecasts have a 15% better performance than the weekly updated series.

Similar to the series generated by the MIDAS with leads, the weekly updated forecasts are tested to see whether they prompt central banks to intervene in the currency markets. The structural break tests with the forecasts variable reports there are 5 structural breaks in the policy reaction function. The ordered probit regression results for the full sample and 6 sub-sample periods are reported in Table (5.15). The sign of the weekly updated variable coefficient is expected to have a negative sign since a low (high) level of expected end of period reserve-to-GDP ratio would prompt the CBRT to buy (sell) foreign exchange reserves. Even though the variable coefficient has the correct sign and significant in the full sample specification, the sign is positive in the sub-sample specifications and the coefficient loses its significance. We think the difference between the MIDAS series and the weekly updated series comes from first, because of the difference in the forecast performances, and second, because the variable specified with the MIDAS model is able to capture a component that is more intuitive for the current reserve accumulation behavior. Furthermore, the MIDAS specification that is employed in this study already uses the already available quarterly data.

Therefore, the robustness checks show that the results for the extended model are robust in the full sample and the second sub-sample period for all model specifications considered. The robustness in the second sub-sample period is an expected results based on the announcements of the CBRT on currency accumulations in this period. The first sub-sample period regression results are sensitive to the target exchange rate level specifications due to the significance of these variables in this period. The currency accumulation announcements in this period are close to the beginning of the second sub-sample period and we think this might be the reason why the model is not able to show the significance of the variable in a robust way. In the third sub-sample period, the significance of the variable is sensitive to the inclusion of the long-term exchange rate target that is shown to be significant in this period. Additionally, it is shown that a naive approach to the end of period reserve-to-GDP ratio fails to deliver a better forecast performance than the MIDAS forecasts and it is not significant in the sub-sample ordered probit regressions.

5.8. Conclusions

This study extends a model of infrequent interventions to include reserve accumulation motivation in emerging markets. The model implies that policymakers react to short and long-term movements in the currency markets while often at the same time aim at achieving an optimal level of reserve-to-GDP ratio that would insure themselves against sudden-stops in capital flows. Implications of the model are tested by the CBRT currency intervention data during the floating exchange rate regime period.

The model requires the use of the reserve-to-GDP ratio, which is not available at a daily frequency. A daily series of reserve-to-GDP ratio is generated using the MIDAS methodology with leads. Forecasts generated by this method are shown to perform better than the benchmark model.

The policy function is tested for structural breaks due to the events that might have potentially caused changes in the CBRT intervention policy during the sample period. There are three structural break points found that divide the dataset into four sub-sample periods. Ordered probit regression results show that the reserve variable is significant in the full sample and in the first three sub-sample periods covering the floating exchange rate regime period until 20 June 2013. After this date, only the momentum variable is found to be significant. In the noise-to-signal ratio analysis, the performance of the extended model in estimating the USD sales might be due to the low frequency of interventions by sales. A set of robustness checks show that the sign of the variable coefficient is robust to different model specifications and the significance of the coefficient is only in the full sample and the second sub-sample period in which the motivation of the CBRT for reserve accumulation is explicit.

Further research on the model might include application of the model to other emerging market economies that intervene on currency markets and are motivated to accumulate international reserves. Another research path might focus on improving the daily forecast performances that would potentially give better estimates for the reserve variable in the model. The model presented in the study assumes that currency interventions influence both the reserve levels and exchange rates on the contrary of the limited empirical evidence that show depending on the intervention strategy, interventions that aim to accumulate reserves may not influence exchange rates. The model can be modified to identify these strategies and check the reaction functions separately. It can also be extended to include other motivations such as exchange rate volatility. Finally, the normalization of the optimal reserve level can be dropped and a dynamic model can be studied in which optimal level of reserves can be modified quarterly based on new macroeconomic data. If one can see the movements in the optimal reserve-to-GDP level, this research would also be illuminating to see the reasons behind the high performance of the extended model in estimating the USD sales.

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Tables

Table 5.1: MIDAS forecast performances

Horizon	Lag				
	81	...	95	...	132
1	0.658	...	0.576	...	0.588
2	0.675	...	0.571	...	0.582
3	0.667	...	0.557	...	0.560
4	0.636	...	0.536	...	0.550
5	0.633	...	0.534	...	0.545
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
61	0.688	...	0.684	...	0.629
62	0.679	...	0.699	...	0.649
63	0.731	...	0.747	...	0.672
64	0.738	...	0.777	...	0.705
65	0.789	...	0.822	...	0.723
Mean	0.614	...	**0.600**	...	0.625

Root mean squared error (RMSFE) values of the MIDAS with leads forecasts of the quarterly reserve-to-GDP ratios. Horizon refers to the daily distance from the end of the quarter at the time when the forecast is made. Lag refers to the to the total number of daily data used in the current and previous quarters. There are either 64 or 65 working days in a given quarter in the dataset, thus a quarter is assumed to have 65 working days to account for the longest possible quarters. The values in the table are the ratios of the forecasts to the RMSFE of the benchmark model, AR(1) model with a constant. The value in bold refers to the minimum value averaged over all horizons and the corresponding lag value, 95, is used in the calculation of the daily reserve-to-GDP variable.

Table 5.2: Structural break test with unknown number of breaks, the conventional extended model

$SupF_t(1)$	$SupF_t(2)$	$SupF_t(3)$	$SupF_t(4)$	$SupF_t(5)$
518.08***	82899.02***	231921.04***	249005.76***	8605.78***
$SupF_t(2\|1)$	$SupF_t(3\|2)$	$SupF_t(4\|3)$	$SupF_t(5\|4)$	
11972.00***	2042.20***	71.50***	13.00**	
$UDMax$	$WDMax(5\%)$	$WDMax(10\%)$		
249005.76***	249005.76	249005.76		
Number of Breaks Selected				
Sequential procedure	3			
LWZ	4			
BIC	5			

Bai and Perron (2003a) (BP) structural break test with an unknown number of breaks for the conventional reaction function with the reserve ratio variable, the conventional extended model. Results from the sequential procedure are used in the subsequent calculations. In case of this model, the sequential procedure gives 2 structural breaks at the 10, 5, and 2.5, and 1% significance levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.3: Structural break test with unknown number of breaks, the conventional model

$SupF_t(1)$	$SupF_t(2)$	$SupF_t(3)$	$SupF_t(4)$	$SupF_t(5)$
6449.23***	5045896.84***	-523503.06	-3108675.99	2231104.06***
$SupF_t(2\|1)$	$SupF_t(3\|2)$	$SupF_t(4\|3)$	$SupF_t(5\|4)$	
5100.07***	1463.33***	95.72***	98.96***	
$UDMax$	$WDMax(5\%)$	$WDMax(10\%)$		
5045896.84***	5045896.84	5045896.84		
		Number of Breaks Selected		
Sequential procedure	4			
LWZ	4			
BIC	5			

Bai and Perron (2003a) (BP) structural break test with unknown number of breaks for the conventional reaction function only with the exchange rate deviation variables, the conventional model. Results from the sequential procedure are used in the subsequent calculations. In case of this model, the sequential procedure gives 4 structural breaks at the 10, 5, 2.5% and 1% significance levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.4: OLS regressions, the conventional extended model

	Full Sample	31/01/06-24/09/07	25/09/07-03/08/11	05/08/11-19/06/13	20/06/13-30/09/15
ϕ_1	-0.58	0.52	0.14	0.22	0.55
	(-0.78)	(0.36)	(0.15)	(0.08)	(0.50)
ϕ_2	-0.11	0.73***	0.38	1.25*	-0.59*
	(-0.60)	(3.44)	(1.33)	(1.84)	(-1.67)
ϕ_3	0.22	-1.26**	0.63**	-3.16**	-0.55
	(0.96)	(-2.41)	(2.19)	(-2.18)	(-0.84)
ϕ_4	-0.24	2.91***	-6.13***	-6.13***	1.10
	(-0.79)	(2.84)	(-6.19)	(-2.75)	(1.33)
ϕ_5	-0.15	-4.54***	4.30***	4.07	-0.70
	(-0.61)	(-3.94)	(5.18)	(1.49)	(-1.27)
ϕ_6	-2.00***	-1.96**	-1.23**	-2.67***	-0.12
	(-8.78)	(-2.29)	(-2.36)	(-2.89)	(-0.26)
ϕ_7	0.82***	0.62***	0.55***	0.43***	0.35***
	(56.34)	(9.69)	(13.29)	(5.01)	(4.28)
ϕ_0	0.93***	1.08***	0.83***	1.12***	-0.51**
	(8.83)	(2.85)	(3.67)	(2.95)	(-2.08)
N	2522	429	1009	489	595
R^2	0.89	0.78	0.70	0.73	0.15

Classical OLS regression results for the conventional reaction function with the reserve variable, the conventional extended model, given in Equation (5.17):

$$\begin{aligned} IInt_t =& \phi_0 + \phi_1(s_{t-1} - s_{t-2}) + \phi_2(s_{t-1} - s_{t-21}) + \phi_3(s_{t-1} - s_{t-1}^{1MA}) \\ &+ \phi_4(s_{t-1} - s_{t-1}^{3MA}) + \phi_5(s_{t-1} - s_{t-1}^{5MA}) + \phi_6 R_{t-1}(\Lambda_{t-1}) + \phi_7 IInt_{t-1} + \upsilon_t. \end{aligned}$$

t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.5: OLS regressions, the conventional model

	Full Sample	31/01/06-29/08/07	30/09/08-03/08/09	04/08/09-22/07/11	25/07/11-19/06/13	20/06/13-30/09/15
ϕ_1	-0.73	-0.65	0.81	-0.074	-0.61	0.57
	(-0.94)	(-0.48)	(0.74)	(-0.05)	(-0.22)	(0.52)
ϕ_2	-0.21	0.64***	-0.26	-0.85*	1.32*	-0.58*
	(-1.12)	(2.96)	(-0.84)	(-1.75)	(1.93)	(-1.67)
ϕ_3	-0.11	-1.07**	1.00***	0.82*	-6.47***	-0.62
	(-0.47)	(-1.97)	(3.01)	(1.67)	(-4.86)	(-1.18)
ϕ_4	0.94***	1.62*	5.43***	2.42**	-11.2***	1.17
	(3.46)	(1.95)	(2.78)	(2.02)	(-5.15)	(1.54)
ϕ_5	-1.24***	-3.11***	-7.88***	-1.99**	11.3***	-0.76
	(-5.24)	(-3.53)	(-4.05)	(-2.05)	(4.96)	(-1.53)
ϕ_6						
ϕ_7	0.90***	0.68***	0.45***	0.20***	0.47***	0.35***
	(92.39)	(10.87)	(6.56)	(2.84)	(6.06)	(4.29)
ϕ_0	0.019***	0.23***	0.069*	0.76***	0.025**	-0.58***
	(3.11)	(4.62)	(1.80)	(10.67)	(2.31)	(-7.05)
N	2522	412	503	514	498	595
R^2	0.89	0.80	0.81	0.060	0.71	0.15

Classical OLS regression results for the conventional reaction function only with the exchange rate deviation variables, the conventional model, given as follows:

$$\begin{aligned} IInt_t =& \phi_0 + \phi_1(s_{t-1} - s_{t-2}) + \phi_2(s_{t-1} - s_{t-21}) + \phi_3(s_{t-1} - s_{t-1}^{1MA}) \\ &+ \phi_4(s_{t-1} - s_{t-1}^{3MA}) + \phi_5(s_{t-1} - s_{t-1}^{5MA}) + \phi_7 IInt_{t-1} + \upsilon_t. \end{aligned}$$

t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.6: Probit regressions, the extended model

	Full Sample	31/01/06-24/09/07	25/09/07-03/08/11	05/08/11-19/06/13	20/06/13-30/09/15
γ_1^*	-2.63	12.4	0.21	-0.73	7.73
	(-0.61)	(1.13)	(0.04)	(-0.05)	(0.62)
γ_2^*	-0.37	12.3***	1.36	5.95	-6.27*
	(-0.33)	(2.85)	(0.86)	(1.27)	(-1.80)
γ_3^*	0.66	-25.7***	2.70	-11.7	-2.85
	(0.38)	(-3.21)	(1.42)	(-0.76)	(-0.50)
γ_4^*	0.50	41.0***	-25.8***	-151.8***	7.93
	(0.22)	(3.36)	(-4.40)	(-3.37)	(1.15)
γ_5^*	-2.96	-53.3***	18.0***	131.4***	-4.87
	(-1.41)	(-3.96)	(3.34)	(3.07)	(-1.07)
γ_6^*	-12.5***	-15.5**	-6.55**	-11.3**	-3.11
	(-9.73)	(-2.06)	(-2.04)	(-2.10)	(-0.66)
γ_7^*	2.67***	1.74***	1.82***	1.05***	1.45***
	(34.21)	(7.21)	(13.69)	(3.63)	(5.98)
μ_1	-7.47***	-12.8***	-5.98***	-8.94***	-1.49
	(-12.59)	(-3.90)	(-4.33)	(-3.95)	(-0.63)
μ_2	-3.94***	-5.61*	-2.20		
	(-6.92)	(-1.76)	(-1.62)		
N	2522	430	1008	489	595
Pseudo R^2	0.76	0.74	0.59	0.73	0.19

Regression results for the extended probit model with the reserve ratio variable, the extended model, which is given by the Equations (5.15) and (5.16):

$$IInt_t = \begin{cases} -1 & \text{if} \quad y_t^* < \mu_1 \\ 0 & \text{if} \quad \mu_1 < y_t^* < \mu_2 \\ 1 & \text{if} \quad \mu_2 < y_t^* \end{cases}$$

where $y_t^* = X_t\gamma + \varepsilon_t$ and

$$\begin{aligned} X_t\gamma = & \gamma_1(s_{t-1} - s_{t-2}) + \gamma_2(s_{t-1} - s_{t-21}) + \gamma_3(s_{t-1} - s_{t-1}^{1MA}) \\ & + \gamma_4(s_{t-1} - s_{t-1}^{3MA}) + \gamma_5(s_{t-1} - s_{t-1}^{5MA}) + \gamma_6 R_{t-1}(\Lambda_{t-1}) + \gamma_7 IInt_{t-1}. \end{aligned}$$

t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.7: Probit regressions, the Ito & Yabu model

	Full Sample	31/01/06-29/08/07	30/09/08-03/08/09	04/08/09-22/07/11	25/07/11-19/06/13	20/06/13-30/09/15
γ_1^*	-4.20	-0.61	6.45	0.95	-3.03	7.83
	(-0.98)	(-0.07)	(0.93)	(0.08)	(-0.19)	(0.63)
γ_2^*	-1.34	11.8**	-2.35	-6.28*	5.46	-6.20*
	(-1.22)	(2.29)	(-1.01)	(-1.77)	(1.26)	(-1.78)
γ_3^*	-0.20	-21.9**	5.16**	7.23	-27.5**	-4.14
	(-0.12)	(-2.48)	(2.02)	(1.50)	(-2.34)	(-0.86)
γ_4^*	6.99***	28.7**	57.6***	19.8**	-158.3***	9.47
	(3.58)	(2.29)	(2.66)	(2.00)	(-5.31)	(1.52)
γ_5^*	-9.15***	-41.2***	-71.5***	-18.1*	147.4***	-6.31
	(-5.07)	(-3.00)	(-3.27)	(-1.90)	(5.44)	(-1.63)
γ_6^*						
γ_7^*	2.94***	1.97***	1.57***	0.88***	1.13***	1.45***
	(40.85)	(7.61)	(7.39)	(3.77)	(3.90)	(5.98)
μ_1	-1.72***	-5.75***	-2.25***		-4.00***	0.078
	(-26.00)	(-4.66)	(-6.85)		(-9.23)	(0.34)
μ_2	1.54***	0.80***	2.91***	-0.86***		
	(26.40)	(2.88)	(5.52)	(-3.45)		
N	2522	412	503	514	498	595
Pseudo R^2	0.74	0.75	0.73	0.082	0.73	0.18

Regression results for the probit model only with the exchange rate deviation variables, the Ito & Yabu model, which is given as

$$IInt_t = \begin{cases} -1 & \text{if } \; y_t^* < \mu_1 \\ 0 & \text{if } \; \mu_1 < y_t^* < \mu_2 \\ 1 & \text{if } \; \mu_2 < y_t^* \end{cases}$$

where $y_t^* = X_t \gamma + \varepsilon_t$ and

$$\begin{aligned} X_t \gamma = & \gamma_1 (s_{t-1} - s_{t-2}) + \gamma_2 (s_{t-1} - s_{t-21}) + \gamma_3 (s_{t-1} - s_{t-1}^{1MA}) \\ & + \gamma_4 (s_{t-1} - s_{t-1}^{3MA}) + \gamma_5 (s_{t-1} - s_{t-1}^{5MA}) + \gamma_7 IInt_{t-1}. \end{aligned}$$

t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.8: Probit regressions, extended model coefficients

	Full Sample	31/01/06-24/09/07	25/09/07-03/08/11	05/08/11-19/06/13	20/06/13-30/09/15
δ_1	0.000	0.000	0.000	0.000	0.000
δ_2	0.000	-0.479	0.000	0.000	1.000
δ_3	0.000	1.479	1.000	1.000	0.000
c_1	0.000	0.676	0.000	0.000	0.000
c_2	0.000	-1.079	3.308	7.441	0.000
c_3	0.000	1.403	-2.308	-6.441	0.000

Results for the δ and c coefficient calculations for the extended probit model with the reserve ratio variable, the extended model. The calculations are made by using the estimated results in Table (5.7) and formulas given in the text: $\delta_1 = \gamma_1^*/(\sum_{i=1}^5 \gamma_i^*)$, $\delta_2 = \gamma_2^*/(\sum_{i=1}^5 \gamma_i^*)$, $\delta_3 = (\sum_{z=3}^5 \gamma_z^*)/(\sum_{i=1}^5 \gamma_i^*)$, $c_j = \gamma_{j+2}^*/(\sum_{i=3}^5 \gamma_i^*)$ for $j = 1,2,3$. In the calculations, the coefficients that are not significant are taken as 0. A value of 1 for the δ_i terms imply that all of the weight is on that specific variable i.

Table 5.9: Noise-to-signal ratios and relative performances

	extended model			the Ito & Yabu model	
	Purchase	Sale		Purchase	Sale
Full Sample	0.038	0.009	Full Sample	0.039	0.011
31/01/06-24/09/07	0.043	0.003	31/01/06-29/08/07	0.050	0.005
			30/09/07-03/08/09	0.064	0.002
25/09/07-03/08/11	0.169	0.001	04/08/09-22/07/11	0.358	
05/08/11-19/06/13		0.019	25/07/11-19/06/13		0.016
20/06/13-30/09/15		0.300	20/06/13-30/09/15		0.252

Noise-to-signal ratios and comparative performances of the models with, extended model, and without, the Ito & Yabu, the reserve ratio variable for the full sample and the five sub-sample periods. The noise-to-signal ratios for the USD purchase and sales interventions are calculated as described in Appendix (5.8). Lower values of the noise-to-signal ratio indicate better performances.

Table 5.10: Robustness checks, the full sample period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
γ_1^*		-2.92		-2.62	-2.64	-2.75	-2.87	-2.54	-2.06	-2.52	-2.35	-2.79	-1.34
		(-0.70)		(-0.61)	(-0.61)	(-0.63)	(-0.66)	(-0.59)	(-0.48)	(-0.58)	(-0.54)	(-0.65)	(-0.31)
γ_2^*	-0.51			-0.20	-0.40	-0.43	-1.02	-0.52	-0.44	-0.28	-0.30	-0.37	-0.086
	(-0.46)			(-0.20)	(-0.35)	(-0.38)	(-1.02)	(-0.46)	(-0.38)	(-0.24)	(-0.25)	(-0.32)	(-0.07)
γ_3^*	0.65	0.40	0.35		0.84	1.21		0.64	0.66	0.65	0.42	0.66	0.45
	(0.38)	(0.26)	(0.23)		(0.56)	(0.73)		(0.37)	(0.38)	(0.37)	(0.23)	(0.38)	(0.25)
γ_4^*	0.52	0.85	0.70	0.89		-2.60***		0.43	0.48	-0.31	-1.02	0.49	-1.00
	(0.23)	(0.39)	(0.32)	(0.45)		(-3.01)		(0.19)	(0.21)	(-0.13)	(-0.43)	(0.22)	(-0.43)
γ_5^*	-2.99	-3.26	-3.12	-3.12	-2.56***			-2.91	-2.95	-2.45	-1.90	-2.97	-1.93
	(-1.42)	(-1.58)	(-1.51)	(-1.53)	(-3.18)			(-1.39)	(-1.41)	(-1.18)	(-0.92)	(-1.41)	(-0.93)
γ_6^*	-12.5***	-12.3***	-12.5***	-12.5***	-12.6***	-13.3***	-13.4***	-12.5***	-12.5***	-12.5***	-12.5***	-12.5***	-12.5***
	(-9.73)	(-9.76)	(-9.87)	(-9.72)	(-10.12)	(-10.48)	(-10.48)	(-9.72)	(-9.72)	(-9.77)	(-9.74)	(-9.73)	(-9.76)
γ_7^*	2.66***	2.67***	2.66***	2.67***	2.67***	2.68***	2.75***	2.67***	2.67***	2.66***	2.65***	2.67***	2.65***
	(34.23)	(34.41)	(34.47)	(34.22)	(34.28)	(34.75)	(36.16)	(34.19)	(34.16)	(34.06)	(33.92)	(34.22)	(33.93)
γ_{vol}^*								74.8	84.5				19.5
								(0.55)	(0.60)				(0.14)
$\gamma_{vol}^*(Lag)$									-49.7				-120.9
									(-0.35)				(-0.86)
$\gamma_{overnight}^*$										0.021			
										(1.31)			
γ_{3M}^*											0.029**		0.031**
											(2.09)		(2.17)
$\gamma_{TRYNews}^*$												0.073	0.075
												(0.64)	(0.67)
γ_{USNews}^*												0.092	0.097
												(0.89)	(0.96)
μ_1	-7.49***	-7.40***	-7.49***	-7.46***	-7.52***	-7.86***	-7.84***	-7.46***	-7.46***	-7.30***	-7.21***	-7.46***	-7.18***
	(-12.59)	(-12.66)	(-12.74)	(-12.58)	(-13.11)	(-13.32)	(-13.27)	(-12.58)	(-12.58)	(-12.02)	(-11.83)	(-12.56)	(-11.79)
μ_2	-3.96***	-3.87***	-3.96***	-3.93***	-3.99***	-4.32***	-4.33***	-3.93***	-3.93***	-3.76***	-3.65***	-3.92***	-3.62***
	(-6.93)	(-6.91)	(-7.05)	(-6.92)	(-7.30)	(-7.71)	(-7.73)	(-6.90)	(-6.91)	(-6.44)	(-6.23)	(-6.88)	(-6.18)
N	2522	2541	2542	2522	2522	2522	2522	2522	2522	2522	2522	2522	2522
Pseudo R^2	0.76	0.75	0.75	0.76	0.76	0.75	0.75	0.76	0.76	0.76	0.76	0.76	0.76

Robustness checks for the extended probit model with the reserve ratio variable, the extended model, for the full sample period. Models (1)-(7) test the robustness of the reserve-to-GDP ratio variable to different exchange rate target specifications by dropping the exchange rate variables from the model one-by-one and and as short-term and long-term targets. Models (8) and (9) test the robustness of the variable against the inclusion of the exchange rate volatility, which is calculated as the square of the exchange rate returns, and the first lag of the volatility variable. Models (10) and (11) test the robustness of the variable against the inclusion of an interest rate variable that is first calculated as the difference between the overnight interest rates of Turkey and the US, and then the difference between the 3-month ahead interest rate on deposits in Turkey and the 3-month T-bill rate in the US. Model (12) tests the robustness of the variable against the inclusion of the macroeconomic data announcements for Turkey (GDP, inflation rate, unemployment rate) and the US (GDP, inflation rate, unemployment rate, and changes in policy rate). Finally, Model (13) checks the robustness against the inclusion of all the employed variables with a preference for the 3-month ahead interest rate difference. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.11: Robustness checks, the first sub-sample period (31/01/06-24/09/07)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
γ_1^*		14.8		10.8	6.00	2.32	-3.09	12.2	17.4	9.03	15.7	12.8	20.6*
		(1.32)		(0.93)	(0.57)	(0.22)	(-0.34)	(1.14)	(1.44)	(0.92)	(1.40)	(1.16)	(1.70)
γ_2^*	12.9***			0.047	1.78	0.74	-3.96***	12.3***	12.3***	8.75*	14.3***	12.4***	14.2***
	(2.91)			(0.02)	(0.90)	(0.42)	(-2.77)	(2.86)	(2.92)	(1.85)	(2.80)	(2.79)	(2.75)
γ_3^*	-25.2***	-15.0***	-12.8***		-8.74*	-9.20*		-25.8***	-23.5***	-21.5***	-29.0***	-25.7***	-26.2***
	(-3.23)	(-2.74)	(-2.60)		(-1.65)	(-1.72)		(-3.14)	(-2.99)	(-2.79)	(-3.22)	(-3.17)	(-2.94)
γ_4^*	39.0***	27.7***	23.1***	13.4**		-9.29***		41.3***	38.1***	53.9***	37.2***	42.1***	35.6***
	(3.39)	(3.13)	(3.01)	(2.56)		(-2.77)		(3.27)	(3.18)	(3.34)	(2.80)	(3.37)	(2.64)
γ_5^*	-50.6***	-38.9***	-34.0***	-28.5***	-12.5***			-53.6***	-50.5***	-65.5***	-50.4***	-54.5***	-48.9***
	(-4.05)	(-4.01)	(-4.14)	(-4.12)	(-3.65)			(-3.87)	(-3.83)	(-3.92)	(-3.52)	(-3.98)	(-3.40)
γ_6^*	-13.9*	-10.7	-10.2	-16.6**	-3.61	1.42	-4.22	-15.7**	-14.5*	-18.1**	-15.1**	-16.2**	-15.1**
	(-1.89)	(-1.59)	(-1.55)	(-2.29)	(-0.42)	(0.16)	(-0.76)	(-2.10)	(-1.94)	(-2.19)	(-2.00)	(-2.14)	(-1.99)
γ_7	1.80***	1.99***	2.01***	1.98***	2.04***	2.28***	2.99***	1.74***	1.76***	1.65***	1.78***	1.74***	1.80***
	(7.74)	(9.10)	(9.50)	(8.56)	(9.19)	(10.48)	(15.38)	(7.19)	(7.23)	(6.64)	(7.38)	(7.07)	(7.33)
γ_{vol}^*								49.2	152.4				212.7
								(0.23)	(0.66)				(0.87)
$\gamma_{vol}^*(Lag)$									-570.1*				-627.5*
									(-1.91)				(-1.95)
$\gamma_{overnight}^*$										-0.22			
										(-1.60)			
γ_{3M}^*											0.084		0.077
											(0.97)		(0.83)
$\gamma_{TRYNews}^*$												-0.12	-0.13
												(-0.39)	(-0.42)
γ_{USNews}^*												0.50***	0.49**
												(2.69)	(2.47)
μ_1	-11.9***	-9.98***	-9.49***	-11.4***	-6.22*	-3.70	-4.33*	-12.8***	-12.2***	-15.9***	-11.8***	-13.1***	-11.7***
	(-3.84)	(-3.30)	(-3.29)	(-3.58)	(-1.65)	(-0.94)	(-1.89)	(-3.89)	(-3.83)	(-3.68)	(-3.34)	(-3.97)	(-3.29)
μ_2	-4.91	-3.59	-3.43	-6.44**	-1.15	0.99	-0.46	-5.68*	-5.30*	-9.14**	-4.37	-5.88*	-4.51
	(-1.58)	(-1.29)	(-1.25)	(-2.10)	(-0.31)	(0.26)	(-0.20)	(-1.80)	(-1.67)	(-2.11)	(-1.21)	(-1.84)	(-1.22)
N	430	449	450	430	430	430	430	430	430	430	430	430	430
Pseudo R^2	0.73	0.72	0.71	0.72	0.71	0.70	0.65	0.74	0.74	0.74	0.74	0.74	0.74

Robustness checks for the extended probit model with the reserve ratio variable, the extended model, for the first sub-sample period. Models (1)-(7) test the robustness of the reserve-to-GDP ratio variable to different exchange rate target specifications by dropping the exchange rate variables from the model one-by-one and and as short-term and long-term targets. Models (8) and (9) test the robustness of the variable against the inclusion of the exchange rate volatility, which is calculated as the square of the exchange rate returns, and the first lag of the volatility variable. Models (10) and (11) test the robustness of the variable against the inclusion of an interest rate variable that is first calculated as the difference between the overnight interest rates of Turkey and the US, and then the difference between the 3-month ahead interest rate on deposits in Turkey and the 3-month T-bill rate in the US. Model (12) tests the robustness of the variable against the inclusion of the macroeconomic data announcements for Turkey (GDP, inflation rate, unemployment rate) and the US (GDP, inflation rate, unemployment rate, and changes in policy rate). Finally, Model (13) checks the robustness against the inclusion of all the employed variables with a preference for the 3-month ahead interest rate difference. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.12: Robustness checks, the second sub-sample period (25/09/07-03/08/11)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
γ_1^*		1.15		0.26	-0.51	-0.35	-0.71	-0.024	0.40	0.55	0.36	-0.63	-0.74
		(0.23)		(0.05)	(-0.10)	(-0.07)	(-0.14)	(-0.00)	(0.07)	(0.10)	(0.07)	(-0.12)	(-0.14)
γ_2^*	1.37			1.96	0.19	0.30	0.20	1.58	1.68	1.28	1.63	1.45	1.80
	(0.91)			(1.33)	(0.12)	(0.19)	(0.14)	(0.95)	(0.98)	(0.82)	(1.03)	(0.92)	(1.05)
γ_3^*	2.70	3.28*	3.31*		1.87	2.87		2.71	2.74	3.69*	3.85**	2.69	3.87**
	(1.42)	(1.89)	(1.91)		(0.89)	(1.35)		(1.43)	(1.44)	(1.96)	(2.01)	(1.41)	(2.01)
γ_4^*	-25.8***	-24.3***	-24.2***	-25.1***		-5.85***		-25.3***	-25.0***	-6.47	-8.95	-26.0***	-8.71
	(-4.42)	(-4.13)	(-4.18)	(-4.23)		(-3.91)		(-4.21)	(-4.16)	(-0.74)	(-1.01)	(-4.38)	(-0.98)
γ_5^*	17.9***	16.5***	16.4***	18.2***	-4.23***			17.4***	17.2***	-1.21	1.12	18.0***	0.82
	(3.35)	(3.09)	(3.12)	(3.33)	(-3.22)			(3.18)	(3.13)	(-0.15)	(0.13)	(3.32)	(0.10)
γ_6^*	-6.55**	-6.68**	-6.68**	-6.27*	-14.2***	-11.6***	-19.9***	-6.72**	-6.76**	-9.42***	-9.23***	-6.52**	-9.30***
	(-2.04)	(-2.08)	(-2.08)	(-1.92)	(-4.70)	(-3.66)	(-7.45)	(-2.06)	(-2.07)	(-2.76)	(-2.71)	(-2.03)	(-2.71)
γ_7^*	1.82***	1.83***	1.84***	1.84***	1.97***	1.91***	2.12***	1.81***	1.81***	1.77***	1.78***	1.81***	1.77***
	(13.74)	(13.89)	(14.02)	(13.92)	(15.49)	(14.76)	(17.39)	(13.64)	(13.62)	(13.08)	(13.12)	(13.61)	(13.02)
γ_{vol}^*								-89.9	-88.2				-29.9
								(-0.67)	(-0.65)				(-0.22)
$\gamma_{vol}^*(Lag)$									-51.8				7.97
									(-0.35)				(0.05)
$\gamma_{overnight}^*$										-0.086***			
										(-2.80)			
γ_{3M}^*											-0.065***		-0.066***
											(-2.59)		(-2.60)
$\gamma_{TRYNews}^*$												0.19	0.19
												(1.01)	(0.97)
γ_{USNews}^*												0.18	0.21
												(1.05)	(1.19)
μ_1	-5.98***	-6.01***	-6.01***	-5.90***	-8.82***	-7.82***	-11.2***	-6.07***	-6.09***	-7.95***	-7.75***	-5.94***	-7.76***
	(-4.33)	(-4.36)	(-4.36)	(-4.22)	(-6.56)	(-5.63)	(-9.01)	(-4.31)	(-4.32)	(-5.01)	(-4.94)	(-4.30)	(-4.93)
μ_2	-2.20	-2.24*	-2.24*	-2.06	-5.19***	-4.16***	-7.62***	-2.28	-2.30*	-4.06***	-3.87**	-2.15	-3.88**
	(-1.62)	(-1.65)	(-1.65)	(-1.50)	(-3.98)	(-3.06)	(-6.48)	(-1.64)	(-1.66)	(-2.62)	(-2.53)	(-1.58)	(-2.52)
N	1008	1008	1008	1008	1008	1008	1008	1008	1008	1008	1008	1008	1008
Pseudo R^2	0.59	0.59	0.59	0.59	0.58	0.59	0.57	0.59	0.59	0.60	0.60	0.60	0.60

Robustness checks for the extended probit model with the reserve ratio variable, the extended model, for the second sub-sample period. Models (1)-(7) test the robustness of the reserve-to-GDP ratio variable to different exchange rate target specifications by dropping the exchange rate variables from the model one-by-one and and as short-term and long-term targets. Models (8) and (9) test the robustness of the variable against the inclusion of the exchange rate volatility, which is calculated as the square of the exchange rate returns, and the first lag of the volatility variable. Models (10) and (11) test the robustness of the variable against the inclusion of an interest rate variable that is first calculated as the difference between the overnight interest rates of Turkey and the US, and then the difference between the 3-month ahead interest rate on deposits in Turkey and the 3-month T-bill rate in the US. Model (12) tests the robustness of the variable against the inclusion of the macroeconomic data announcements for Turkey (GDP, inflation rate, unemployment rate) and the US (GDP, inflation rate, unemployment rate, and changes in policy rate). Finally, Model (13) checks the robustness against the inclusion of all the employed variables with a preference for the 3-month ahead interest rate difference. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.13: Robustness checks, the third sub-sample period (05/08/11-19/06/13)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
γ_1^*		-0.24		-1.44	-1.53	-1.27	-14.8	0.37	10.8	-1.31	-1.42	-0.38	10.3
		(-0.01)		(-0.09)	(-0.09)	(-0.08)	(-0.81)	(0.02)	(0.66)	(-0.08)	(-0.09)	(-0.02)	(0.64)
γ_2^*	5.94			4.13	6.59	5.91	-6.21	6.33	5.85	5.24	5.64	6.43	5.67
	(1.27)			(1.12)	(1.53)	(1.40)	(-1.52)	(1.30)	(1.23)	(1.18)	(1.24)	(1.38)	(1.20)
γ_3^*	-11.8	0.47	0.44		-11.4	-8.33		-12.4	-12.1	-4.90	-4.00	-14.0	-2.07
	(-0.77)	(0.04)	(0.04)		(-0.84)	(-0.72)		(-0.80)	(-0.77)	(-0.32)	(-0.23)	(-0.93)	(-0.12)
γ_4^*	-151.7***	-168.6***	-168.5***	-181.3***		-21.5***		-148.6***	-160.8***	-183.7***	-160.1***	-154.7***	-184.1***
	(-3.40)	(-3.49)	(-3.54)	(-2.83)		(-3.35)		(-3.54)	(-3.24)	(-4.12)	(-3.57)	(-3.38)	(-3.21)
γ_5^*	131.4***	142.8***	142.7***	154.2**	-20.0**			128.4***	140.8***	157.0***	132.8***	135.2***	154.3***
	(3.09)	(3.11)	(3.15)	(2.50)	(-2.55)			(3.19)	(3.04)	(3.72)	(2.79)	(3.15)	(2.78)
γ_6^*	-11.3**	-10.8**	-10.8**	-13.2***	-16.5***	-16.2***	-4.44	-11.9**	-10.0*	-8.14	-9.93*	-10.8**	-8.03
	(-2.11)	(-1.97)	(-1.98)	(-2.90)	(-3.75)	(-3.92)	(-1.58)	(-2.17)	(-1.77)	(-1.23)	(-1.72)	(-2.09)	(-1.33)
γ_7^*	1.05***	1.11***	1.11***	1.08***	1.23***	1.18***	2.70***	1.05***	1.09***	1.06***	1.04***	1.04***	1.06***
	(3.66)	(3.68)	(3.72)	(3.70)	(4.32)	(4.11)	(12.93)	(3.62)	(3.65)	(3.65)	(3.61)	(3.59)	(3.58)
γ_{vol}^*								578.1	488.7				499.9
								(0.35)	(0.28)				(0.28)
$\gamma_{vol}^*(Lag)$									-2552.5*				-2618.1*
									(-1.89)				(-1.87)
$\gamma_{overnight}^*$										0.100			
										(0.87)			
γ_{3M}^*											0.12		0.16
											(0.67)		(0.89)
$\gamma_{TRYNews}^*$												0.10	0.033
												(0.24)	(0.08)
γ_{USNews}^*												-0.34	-0.28
												(-0.81)	(-0.64)
μ_1	-8.95***	-8.96***	-8.97***	-10.3***	-9.17***	-9.28***	-3.79***	-9.11***	-8.66***	-7.26**	-7.48**	-8.80***	-6.85*
	(-3.96)	(-3.78)	(-3.78)	(-5.46)	(-4.82)	(-5.12)	(-3.09)	(-3.96)	(-3.56)	(-2.10)	(-2.11)	(-3.99)	(-1.84)
N	489	489	489	489	489	489	489	489	489	489	489	489	489
Pseudo R^2	0.73	0.73	0.73	0.73	0.72	0.72	0.59	0.73	0.74	0.74	0.74	0.74	0.74

Robustness checks for the extended probit model with the reserve ratio variable, the extended model, for the third sub-sample period. Models (1)-(7) test the robustness of the reserve-to-GDP ratio variable to different exchange rate target specifications by dropping the exchange rate variables from the model one-by-one and and as short-term and long-term targets. Models (8) and (9) test the robustness of the variable against the inclusion of the exchange rate volatility, which is calculated as the square of the exchange rate returns, and the first lag of the volatility variable. Models (10) and (11) test the robustness of the variable against the inclusion of an interest rate variable that is first calculated as the difference between the overnight interest rates of Turkey and the US, and then the difference between the 3-month ahead interest rate on deposits in Turkey and the 3-month T-bill rate in the US. Model (12) tests the robustness of the variable against the inclusion of the macroeconomic data announcements for Turkey (GDP, inflation rate, unemployment rate) and the US (GDP, inflation rate, unemployment rate, and changes in policy rate). Finally, Model (13) checks the robustness against the inclusion of all the employed variables with a preference for the 3-month ahead interest rate difference. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.14: Robustness checks, the fourth sub-sample period (20/06/13-30/09/15)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
γ_1^*		4.66		7.67	7.76	7.52	8.29	7.51	9.71	7.02	6.65	7.71	8.66
		(0.40)		(0.62)	(0.64)	(0.61)	(0.67)	(0.59)	(0.64)	(0.56)	(0.52)	(0.63)	(0.58)
γ_2^*	-5.99*			-6.88*	-6.64*	-6.58*	-5.15	-5.80*	-5.70	-8.12*	-7.61*	-6.24*	-6.92*
	(-1.78)			(-1.90)	(-1.93)	(-1.93)	(-1.57)	(-1.65)	(-1.64)	(-1.95)	(-1.82)	(-1.83)	(-1.71)
γ_3^*	-2.83	-7.17	-7.02		3.06	1.67		-2.34	-1.93	1.25	0.44	-2.81	1.17
	(-0.49)	(-1.13)	(-1.12)		(0.86)	(0.42)		(-0.41)	(-0.34)	(0.18)	(0.06)	(-0.49)	(0.16)
γ_4^*	7.95	9.21	9.18	5.64		1.04		7.38	7.05	1.53	4.73	7.86	3.99
	(1.16)	(1.29)	(1.29)	(1.30)		(0.51)		(1.10)	(1.05)	(0.18)	(0.60)	(1.14)	(0.51)
γ_5^*	-4.85	-5.57	-5.53	-3.61	0.035			-4.53	-4.34	0.51	-1.96	-4.84	-1.57
	(-1.07)	(-1.20)	(-1.20)	(-1.13)	(0.03)			(-1.02)	(-0.98)	(0.09)	(-0.35)	(-1.06)	(-0.28)
γ_6^*	-3.14	-3.00	-3.02	-3.91	-5.56	-6.45	-4.27	-2.94	-3.02	-4.17	-3.38	-3.11	-3.28
	(-0.66)	(-0.60)	(-0.61)	(-1.00)	(-1.34)	(-1.57)	(-1.21)	(-0.63)	(-0.65)	(-0.93)	(-0.71)	(-0.66)	(-0.70)
γ_7^*	1.45***	1.47***	1.47***	1.46***	1.49***	1.48***	1.49***	1.47***	1.46***	1.43***	1.44***	1.44***	1.45***
	(6.02)	(6.11)	(6.13)	(6.05)	(6.24)	(6.22)	(6.25)	(6.05)	(5.95)	(5.91)	(5.95)	(5.93)	(5.90)
γ_{vol}^*								-2443.2	-2448.2				-2415.4
								(-1.25)	(-1.25)				(-1.24)
$\gamma_{vol}^*(Lag)$									-646.1				-598.5
									(-0.71)				(-0.66)
$\gamma_{overnight}^*$										-0.10			
										(-1.03)			
γ_{3M}^*											-0.080		-0.075
											(-0.82)		(-0.78)
$\gamma_{TRYNews}^*$												-0.12	-0.083
												(-0.39)	(-0.27)
γ_{USNews}^*												0.052	0.052
												(0.20)	(0.19)
μ_1	-1.51	-1.41	-1.42	-1.90	-2.68	-3.12	-2.00	-1.50	-1.56	-2.75	-2.23	-1.49	-2.25
	(-0.63)	(-0.56)	(-0.57)	(-0.95)	(-1.26)	(-1.48)	(-1.09)	(-0.64)	(-0.66)	(-1.23)	(-0.89)	(-0.62)	(-0.92)
N	595	595	595	595	595	595	595	595	595	595	595	595	595
Pseudo R^2	0.18	0.18	0.18	0.19	0.18	0.18	0.18	0.19	0.20	0.19	0.19	0.19	0.20

Robustness checks for the extended probit model with the reserve ratio variable, the extended model, for the fourth sub-sample period. Models (1)-(7) test the robustness of the reserve-to-GDP ratio variable to different exchange rate target specifications by dropping the exchange rate variables from the model one-by-one and and as short-term and long-term targets. Models (8) and (9) test the robustness of the variable against the inclusion of the exchange rate volatility, which is calculated as the square of the exchange rate returns, and the first lag of the volatility variable. Models (10) and (11) test the robustness of the variable against the inclusion of an interest rate variable that is first calculated as the difference between the overnight interest rates of Turkey and the US, and then the difference between the 3-month ahead interest rate on deposits in Turkey and the 3-month T-bill rate in the US. Model (12) tests the robustness of the variable against the inclusion of the macroeconomic data announcements for Turkey (GDP, inflation rate, unemployment rate) and the US (GDP, inflation rate, unemployment rate, and changes in policy rate). Finally, Model (13) checks the robustness against the inclusion of all the employed variables with a preference for the 3-month ahead interest rate difference. t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.15: Probit regressions, the extended model with the forecasts using weekly data

	Full Sample	First Sub-Sample	Second Sub-Sample	Third Sub-Sample	Fourth Sub-Sample	Fifth Sub-Sample	Sixth Sub-Sample
γ_1^*	-2.88	-14.6	12.1	4.79	-0.50	4.09	0.53
	(-0.67)	(-1.17)	(0.85)	(0.59)	(-0.05)	(0.21)	(0.05)
γ_2^*	-1.41	18.8	0.99	-2.42	-2.93	14.7***	-1.50
	(-1.24)	(1.60)	(0.22)	(-0.87)	(-0.78)	(3.19)	(-0.43)
γ_3^*	-1.67	11.6	10.1	4.91	15.1**	-63.2***	-6.85
	(-0.95)	(0.27)	(1.12)	(1.58)	(2.47)	(-4.04)	(-1.27)
γ_4^*	0.84	72.9**	68.7**	54.3	-9.59	-68.2***	13.4**
	(0.39)	(2.26)	(2.10)	(0.94)	(-0.89)	(-3.71)	(2.20)
γ_5^*	-3.58*	-133.5**	-76.8**	-67.8	0.10	80.7***	-10.2***
	(-1.89)	(-2.53)	(-2.15)	(-1.18)	(0.01)	(3.15)	(-2.66)
γ_6^*	-7.22***	2.48	3.82	1.85	6.20	4.18	1.09
	(-7.64)	(0.26)	(0.45)	(0.35)	(1.08)	(0.68)	(0.22)
γ_7^*	2.79***	2.23***	0.56*	1.99***	1.42***	1.93***	1.80***
	(36.99)	(5.70)	(1.72)	(7.62)	(7.42)	(8.04)	(8.86)
μ_1	-5.16***	-8.80*	2.90	-1.54	2.62	-1.12	0.18
	(-11.20)	(-1.93)	(0.76)	(-0.47)	(1.07)	(-0.43)	(0.07)
μ_2	-1.74***	0.25		3.78		4.12	
	(-3.96)	(0.07)		(1.13)		(1.54)	
N	2521	233	281	380	514	498	615
Pseudo R^2	0.75	0.85	0.097	0.80	0.25	0.73	0.33

Regression results for the extended probit model with the reserve ratio variable that has been created with weekly updated forecasts instead of the MIDAS methodology. The estimated model is as follows:

$$IInt_t = \begin{cases} -1 & \text{if } \; y_t^* < \mu_1 \\ 0 & \text{if } \; \mu_1 < y_t^* < \mu_2 \\ 1 & \text{if } \; \mu_2 < y_t^* \end{cases}$$

where $y_t^* = X_t\gamma + \varepsilon_t$ and

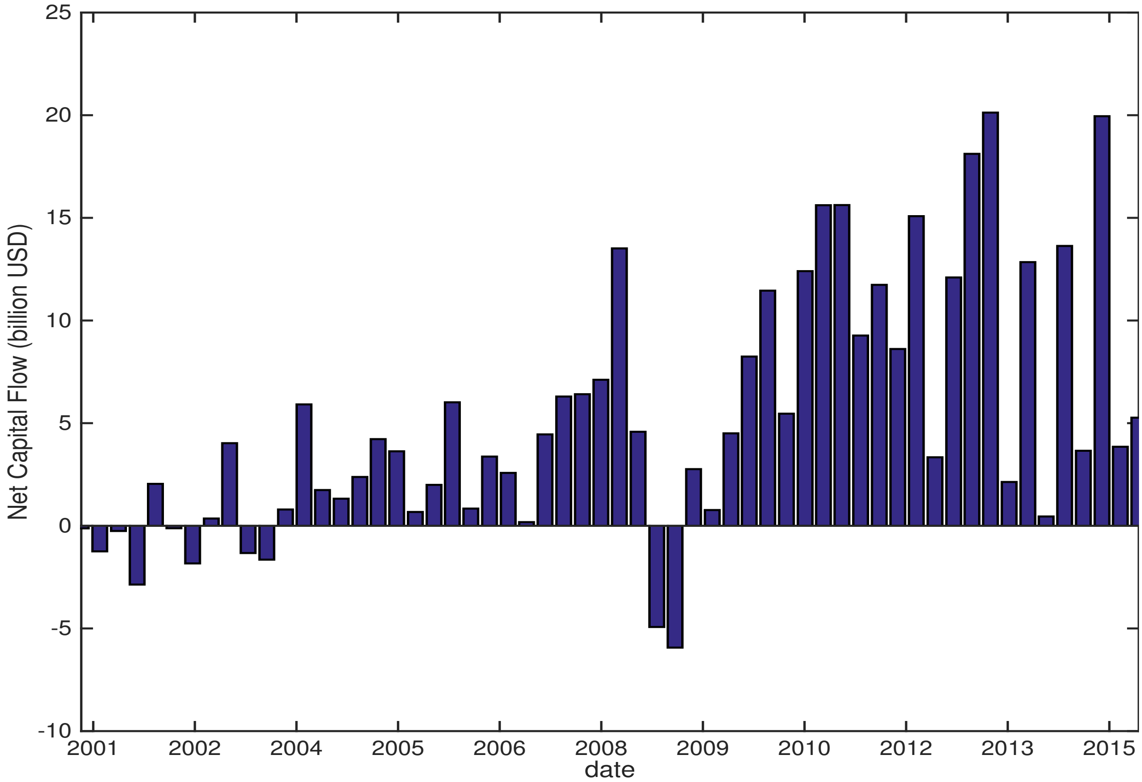
$$\begin{aligned} X_t\gamma =& \gamma_1(s_{t-1} - s_{t-2}) + \gamma_2(s_{t-1} - s_{t-21}) + \gamma_3(s_{t-1} - s_{t-1}^{1MA}) \\ &+ \gamma_4(s_{t-1} - s_{t-1}^{3MA}) + \gamma_5(s_{t-1} - s_{t-1}^{5MA}) + \gamma_6 R_t^{week} + \gamma_7 IInt_{t-1}. \end{aligned}$$

where R_t^{week} denotes the weekly updated forecasts variable for the end of quarter reserve-to GDP ratios.

t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

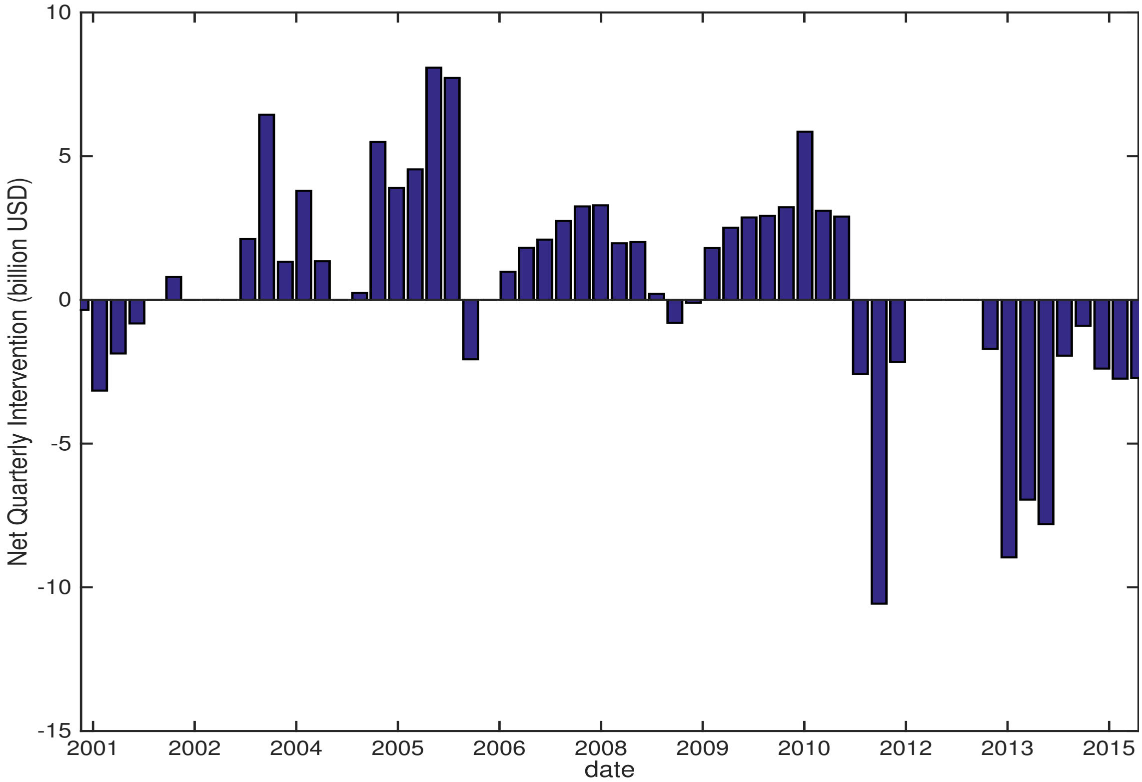
Figures

Figure 5.1: Capital flows



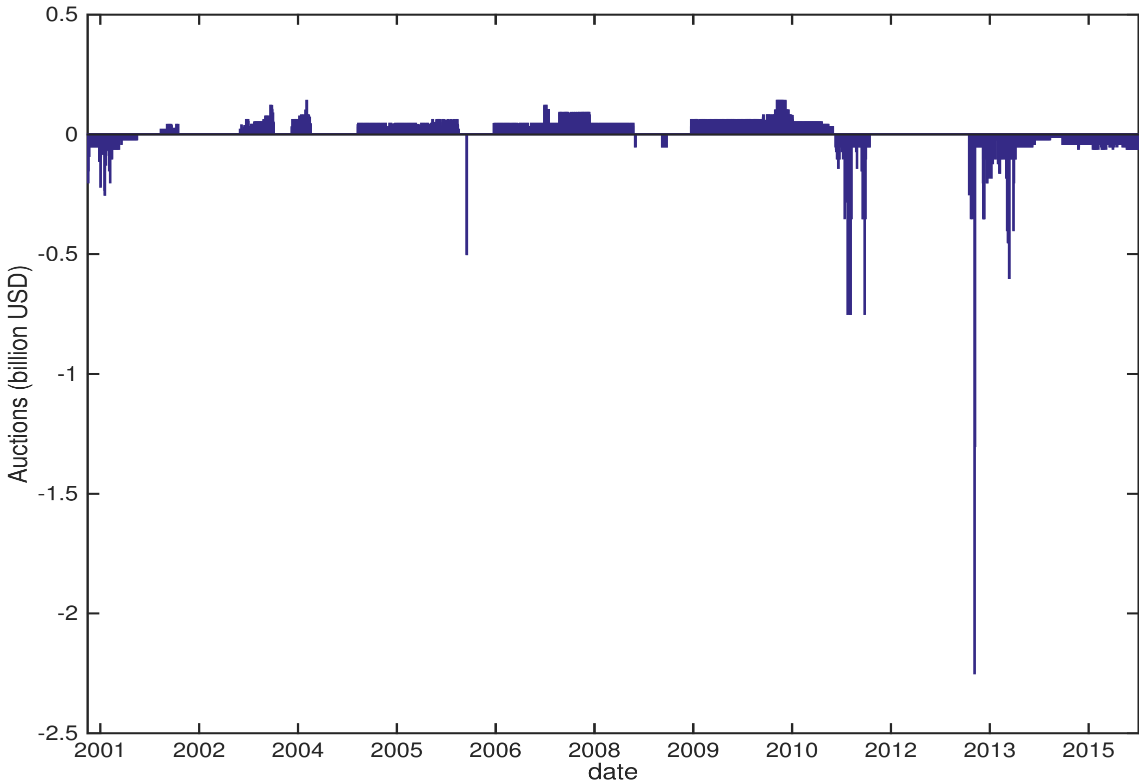
Quarterly capital flow data for the time period from 26 March 2001 to 16 October 2015. Positive values indicate capital inflows to Turkey while negative values are capital outflows from the country. *Source: The CBRT database*

Figure 5.2: Quarterly interventions



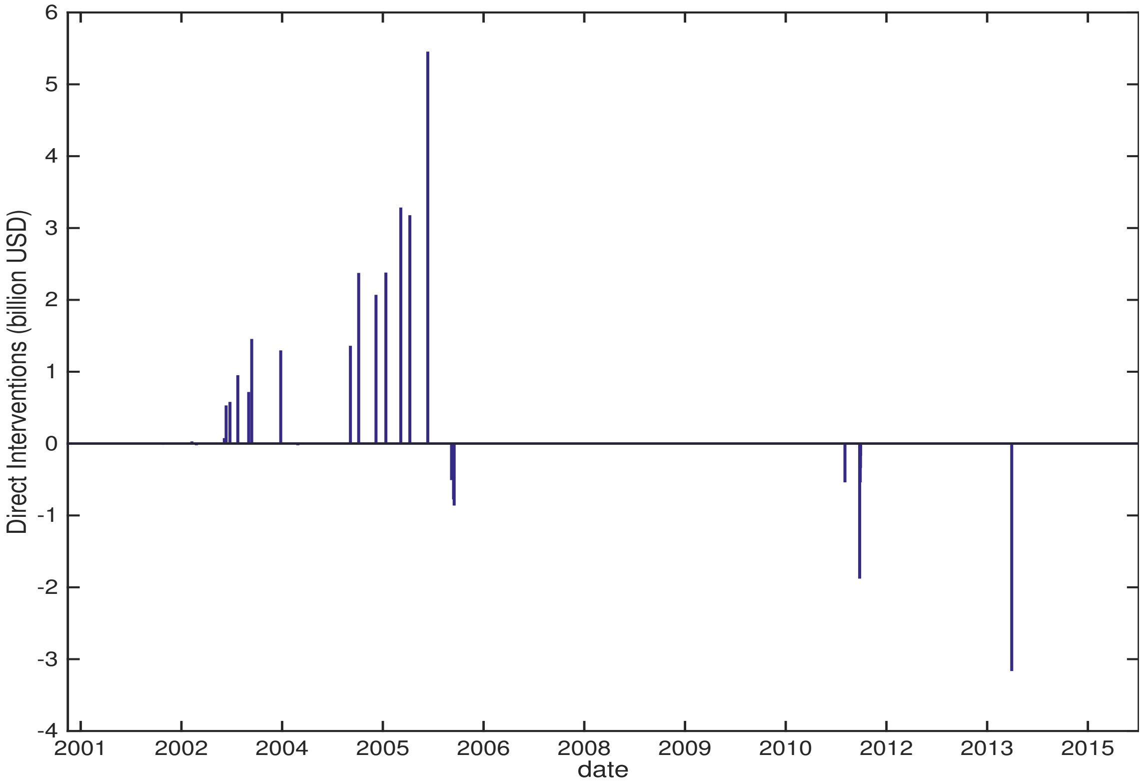
Total quarterly intervention data for the time period from 26 March 2001 to 16 October 2015. Positive values indicate USD purchases while the negative values are USD sales. *Source: The CBRT database*

Figure 5.3: Intervention data, auctions



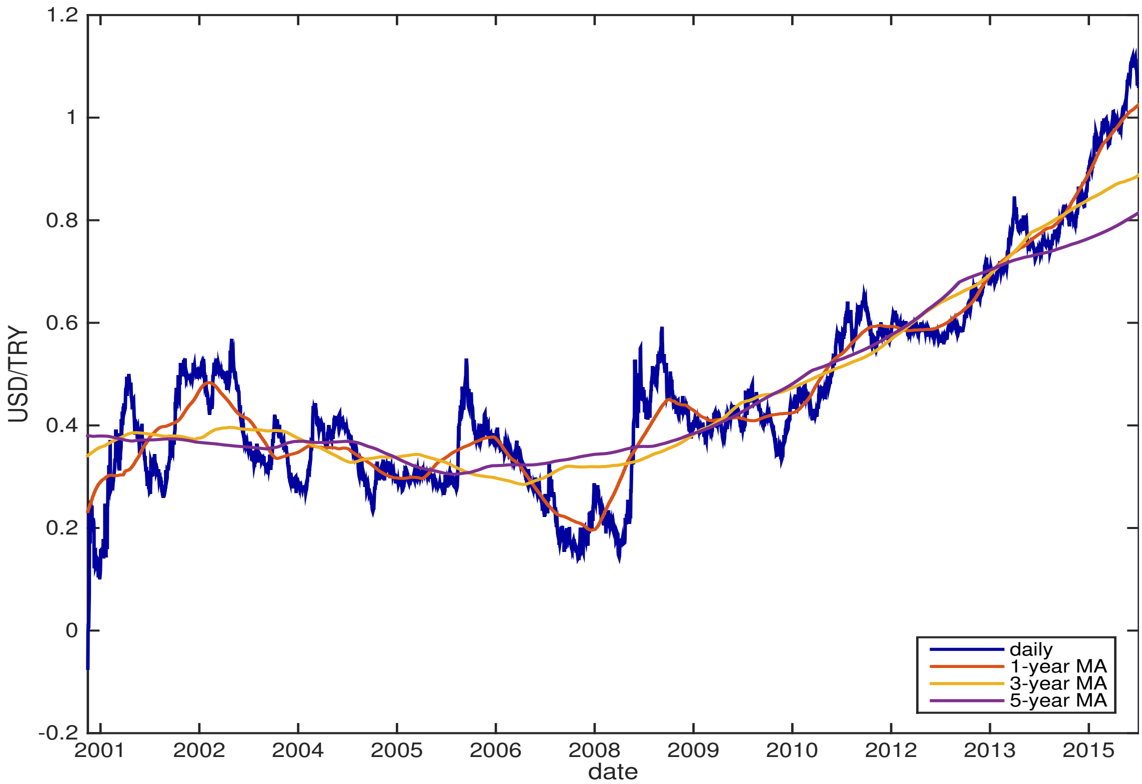
Interventions carried out by the CBRT with auctions. The data covers the time period from 26 March 2001 to 16 October 2015. Positive values indicate USD purchases while the negative values are USD sales. *Source: The CBRT database*

Figure 5.4: Intervention data, direct interventions



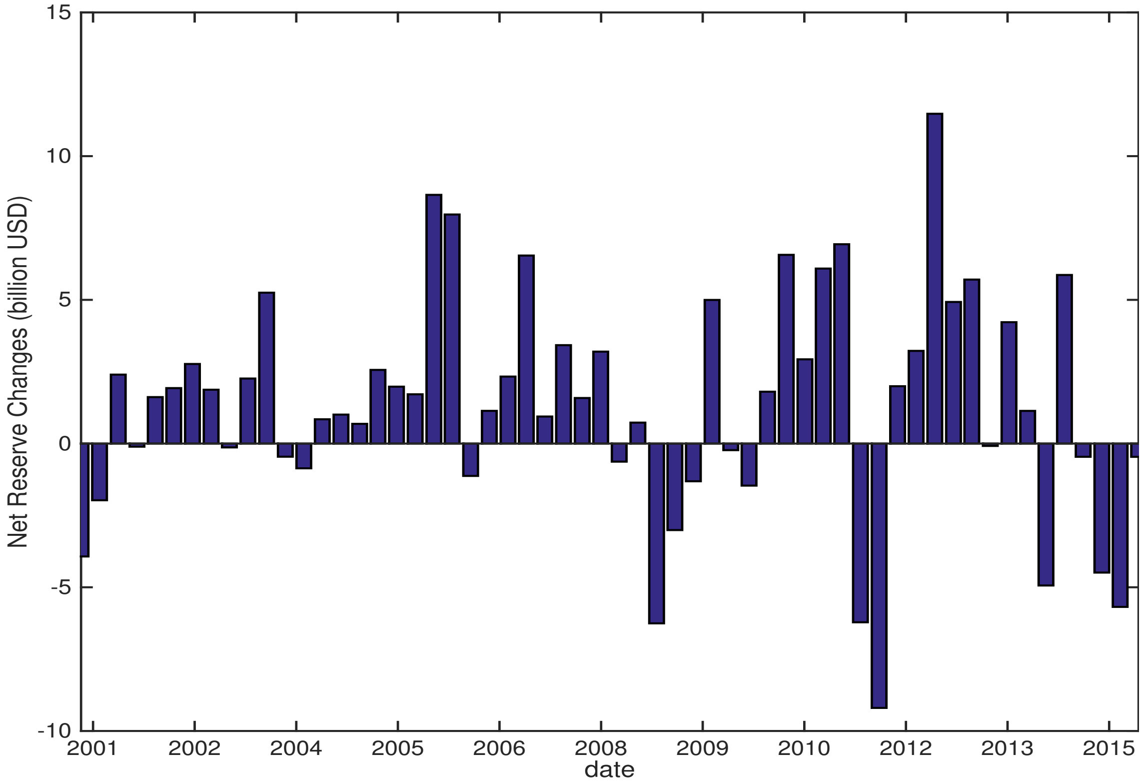
Direct interventions carried out by the CBRT. The data covers the time period from 26 March 2001 to 16 October 2015. Positive values indicate USD purchases while the negative values are USD sales. *Source: The CBRT database*

Figure 5.5: USD/TRY exchange rate



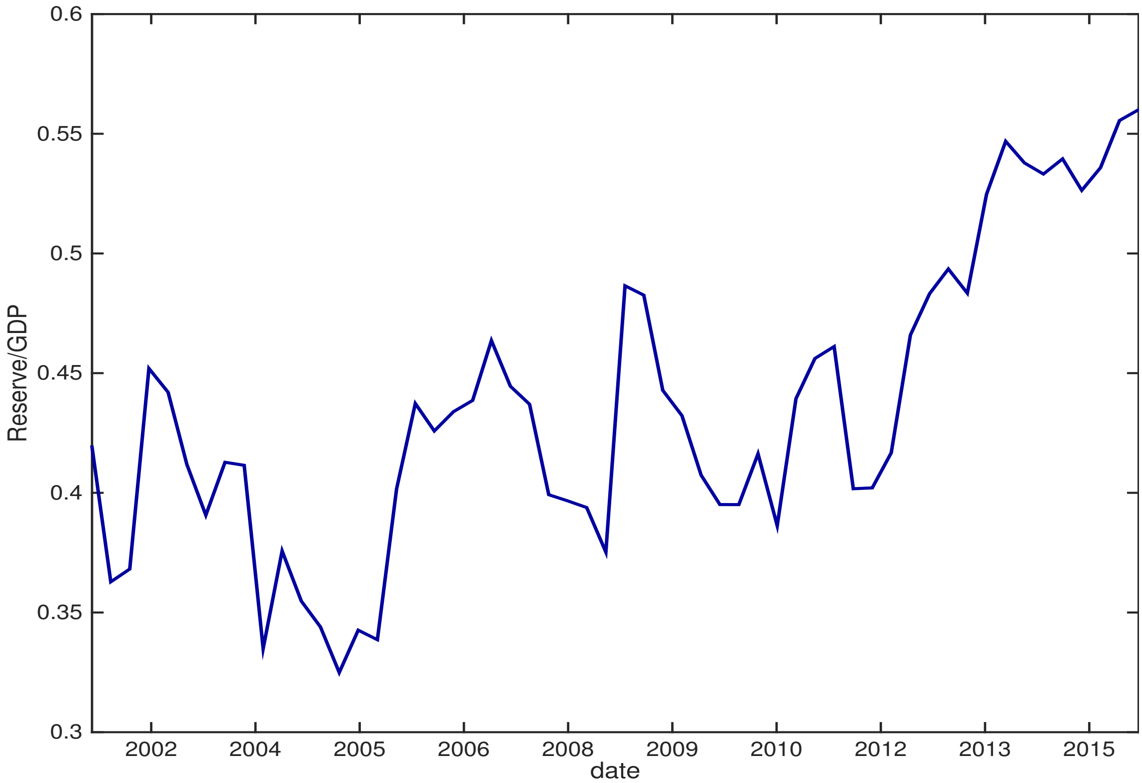
USD/TRY exchange rate values with 1-year, 3-year, and 5-year moving average values. *Source: The CBRT database and calculations of the authors.*

Figure 5.6: Foreign exchange reserves



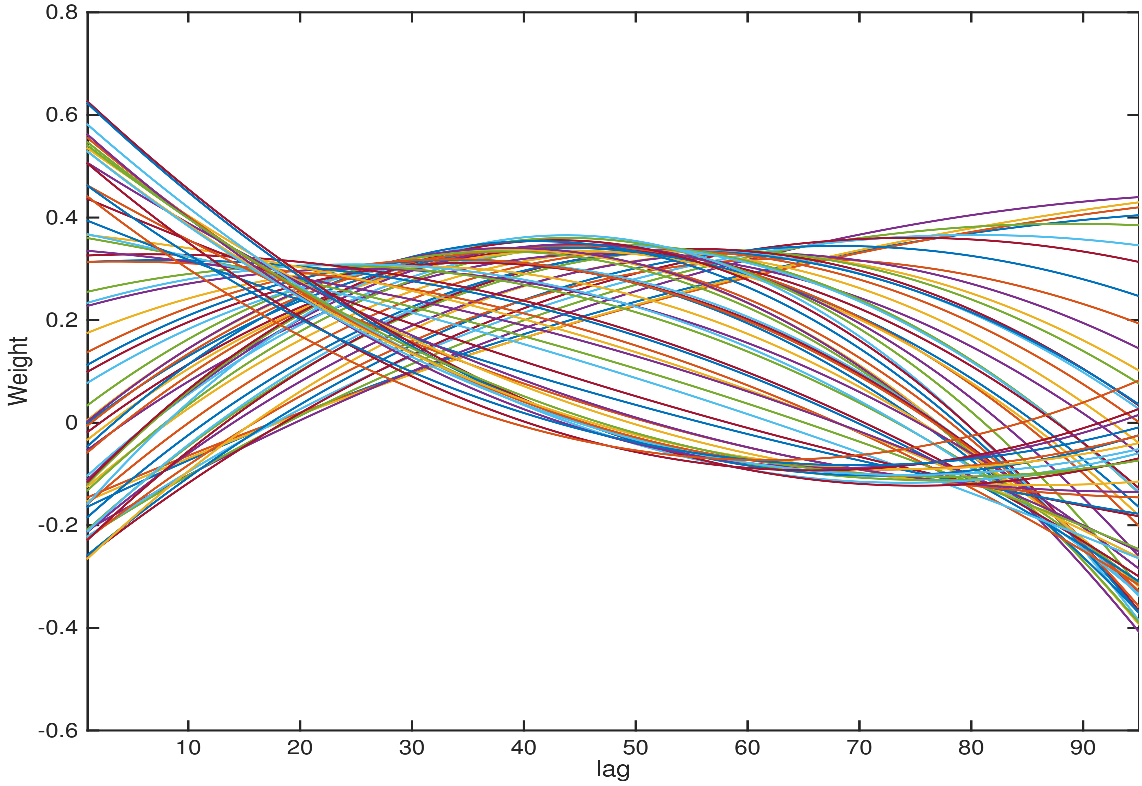
Quarterly change in international reserves of the CBRT for the time period from 26 March 2001 to 16 October 2015. *Source: The CBRT database*

Figure 5.7: International reserve-to-GDP ratio



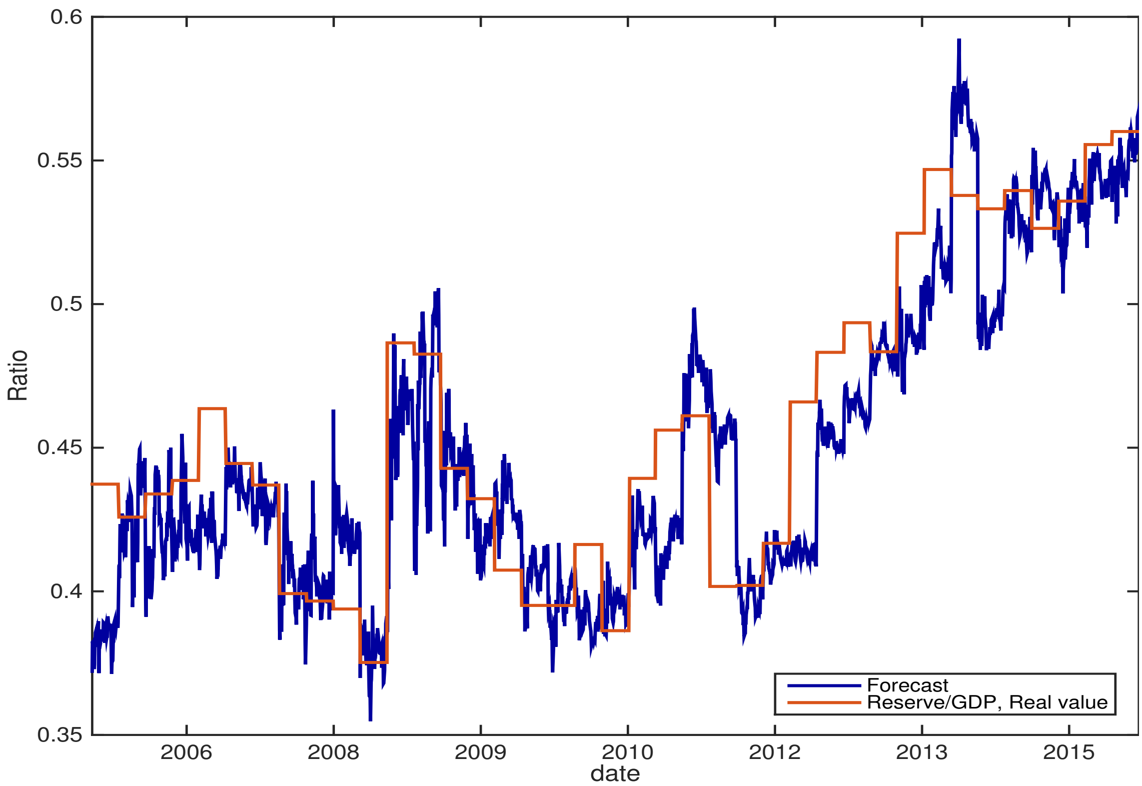
Quarterly ratio of the international reserves to GDP for the time period from 26 March 2001 to 16 October 2015. *Source: The CBRT database and calculations of the authors.*

Figure 5.8: MIDAS estimation, estimated weights



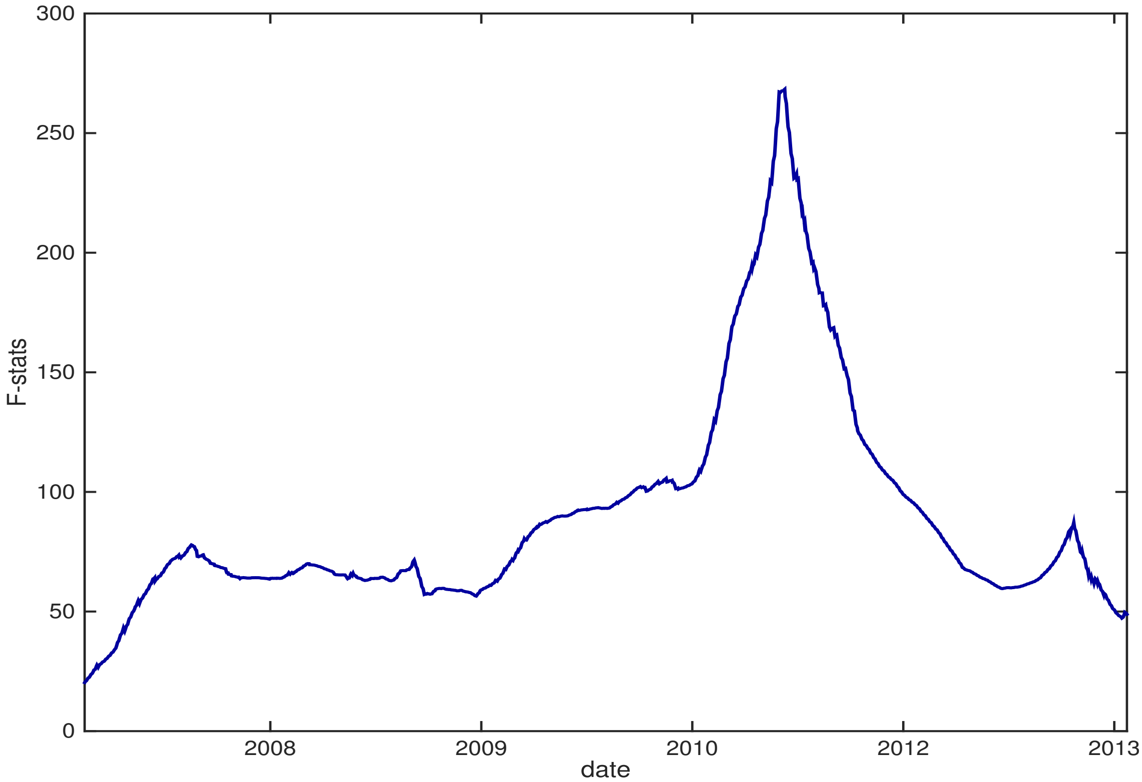
Estimated weights with the MIDAS with lead model for all forecast horizons. Almon distributed lag polynomial function with two hyper parameters is used in the estimations.

Figure 5.9: Daily $\hat{R}^{t-1}(\hat{\Lambda}_{t-1})$ values



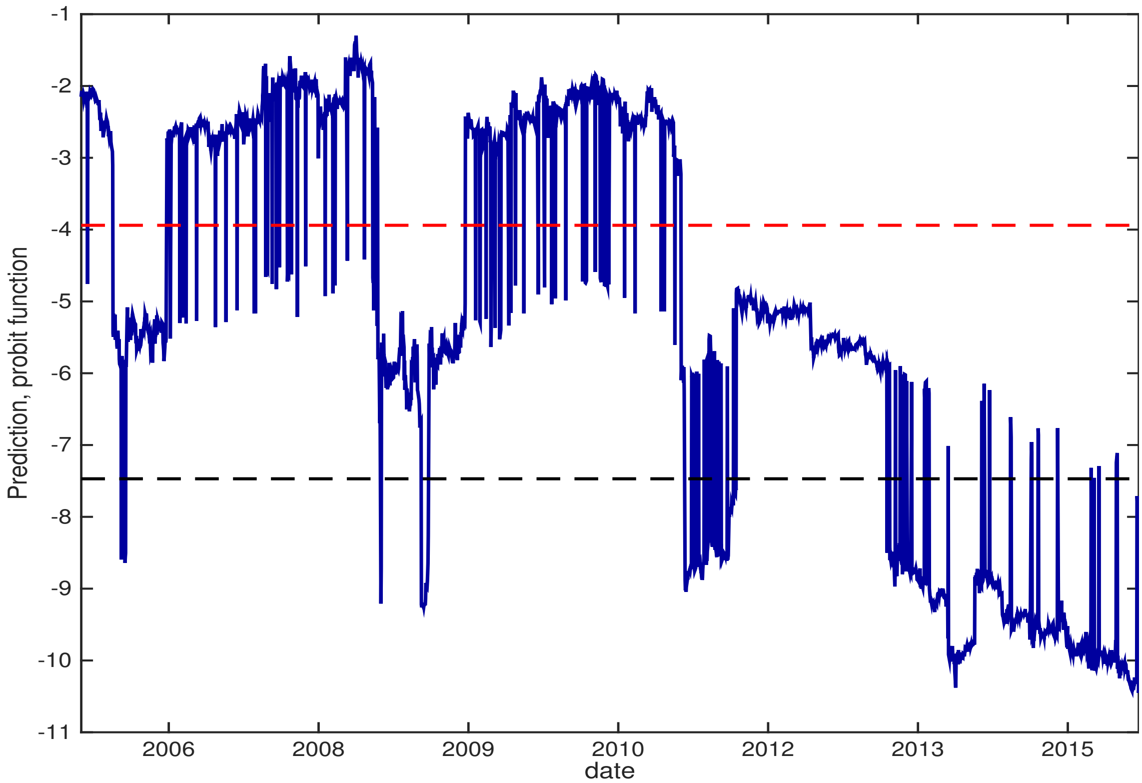
Plot of the calculated $\hat{R}^{t-1}(\hat{\Lambda}_{t-1})$ values with the quarterly reserve-to-GDP ratios for the forecast period, 02 January 2006 to 30 September 2015. $\hat{R}^{t-1}(\hat{\Lambda}_{t-1})$ values are plotted in blue and quarterly values are plotted in red.

Figure 5.10: Chow test statistics



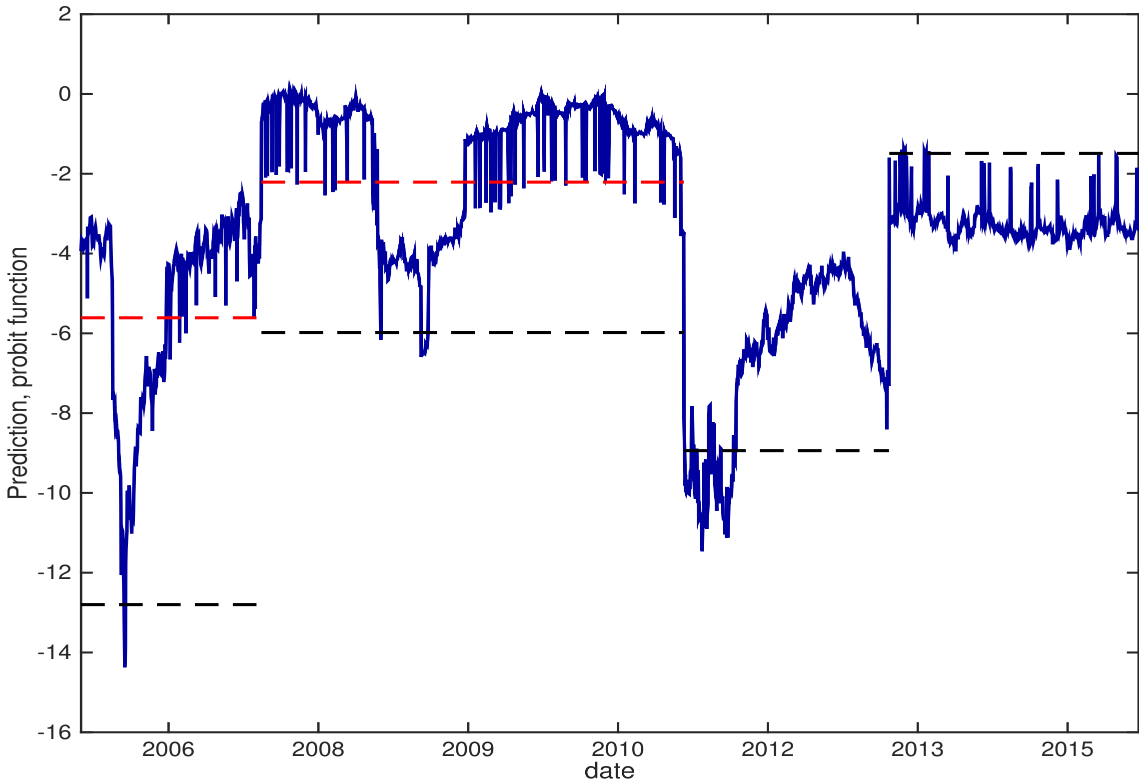
F-statistics of the Chow tests for the extended model estimation period, 02 January 2006 to 30 September 2015. The sample is trimmed at the 10% level.

Figure 5.11: Ordered probit regressions, fitted values, full sample



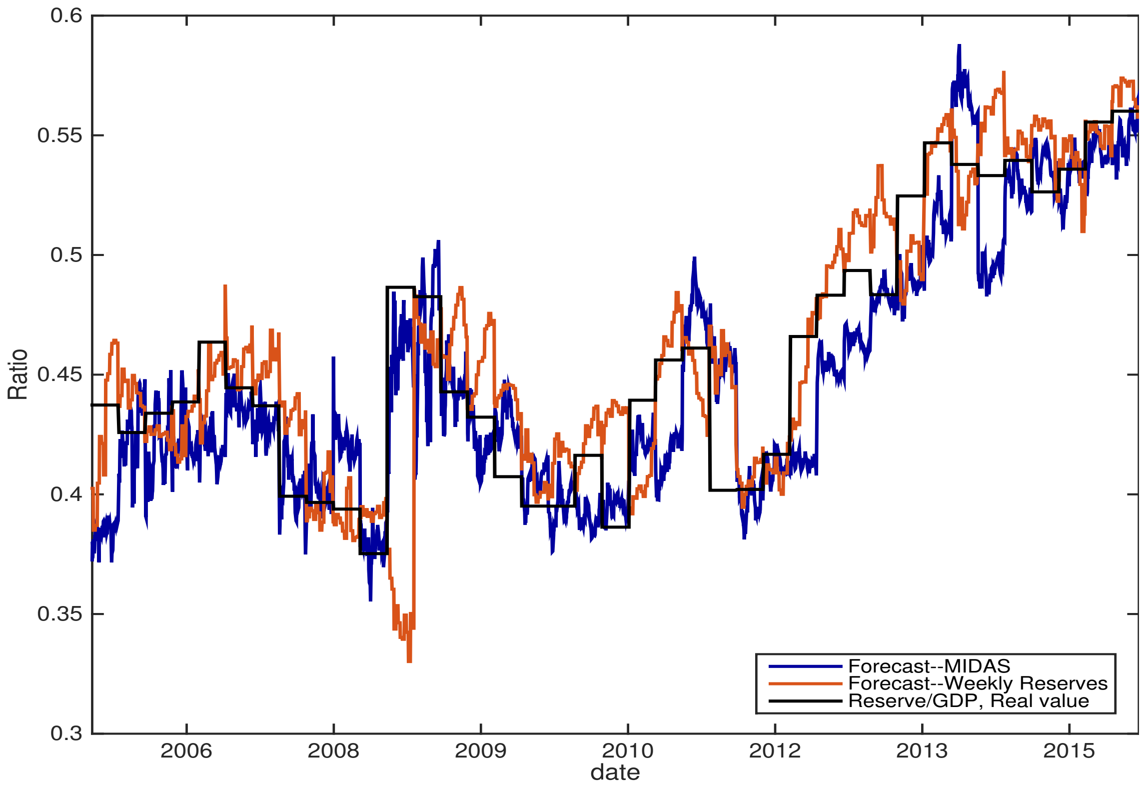
Predicted values and cut-off points for the full sample probit analysis. Dashed horizontal black line represents the estimated the cut-off point for the USD sales, $\hat{\mu}_1$, and Dashed horizontal red line represents the estimated the cut-off point for the USD purchases, $\hat{\mu}_2$. If the predicted value is smaller than the black line, the CBRT is likely to sale USD while it is higher than the red line, the central bank is likely to purchase USD.

Figure 5.12: Ordered probit regressions, fitted values, subsamples



Predicted values and cut-off points for the sub-sample probit analysis. Dashed horizontal black line represents the estimated the cut-off point for the USD sales, $\hat{\mu}_1$, and Dashed horizontal red line represents the estimated the cut-off point for the USD purchases, $\hat{\mu}_2$. If the predicted value is lower than the black line, the CBRT is likely to sale USD while it is higher than the red line, the central bank is likely to purchase USD. Notice that, there are no USD purchases in the third and fourth periods.

Figure 5.13: Daily reserve-to-GDP forecasts



Plot of the MIDAS forecasts, the forecasts generated using the weekly foreign exchange reserve levels, and the quarterly reserve-to-GDP ratios for the forecast period, 02 January 2006 to 30 September 2015. MIDAS values are plotted in blue, the forecasts using weekly data are plotted in red, and quarterly values are plotted in black.

Appendix: Noise-to-Signal Analysis Breakdown

Let Z_1 be the number of days an intervention signal is issued by the model and an intervention is carried by the policy makers, Z_2 be the number of days an intervention signal is issued but an intervention is not carried, Z_3 be the number of days an intervention signal is not issued but an intervention is carried, and Z_4 be the number of days neither an intervention signal is issued nor an intervention is carried. Then the signal ratio will be (Z_1/Z_1+Z_3) and the noise ratio or the false alarms will be (Z_2/Z_2+Z_4). A "cutoff" level of probability refers to the probability level that is taken to be the threshold for probit model probabilities to be taken as a signal of interventions. Small values of the cutoff level will increase the signal ratio but will also increase the noise ratio, which implies an intervention alarm every day as a theoretical possibility. Thus, a level of cutoff probability that will signal enough but not introduce much noise has to be chosen. In order to do that, Kaminsky and Reinhart (1999) propose to minimise $((Z_2/Z_2+Z_4))/((Z_1/Z_1+Z_3))$ while Ito and Yabu (2007) minimize just the Z_2/Z_1 level. These two are the same problem because the numbers of intervention and no-intervention days are constant in the dataset.

Table 5.16: Noise-to-signal analysis, calculation

	Intervention	No intervention
Signal issued	Z_1	Z_2
No signal issued	Z_3	Z_4
Total	Z_1+Z_3	Z_2+Z_4

$$\text{signal} = \frac{Z_1}{Z_1+Z_3}, \quad \text{noise} = \frac{Z_2}{Z_2+Z_4}, \quad \text{noise-to-signal} = \text{noise}/\text{signal}$$

Table 5.17: Noise-to-signal analysis, optimal cut-off points in %

	extended model			the Ito & Yabu	
	Purchase	Sale		Purchase	Sale
Full Sample	90	94	Full Sample	92	95
31/01/06-24/09/07	99	26	31/01/06-29/08/07	94	35
25/09/07-03/08/11	73	47	30/09/07-03/08/09	97	38
			04/08/09-22/07/11	96	
05/08/11-19/06/13		94	25/07/11-19/06/13		97
20/06/13-30/09/15		97	20/06/13-30/09/15		97

Table 5.18: Noise-to-signal ratio, breakdown.

	extended model					the Ito & Yabu			
	Purchase		Sale			Purchase		Sale	
Full sample					Full sample				
	Intervention	No intervention	Intervention	No intervention		Intervention	No intervention	Intervention	No intervention
Signal issued	811	45	423	10	Signal issued	708	41	314	9
No signal issued	207	1459	256	1833	No signal issued	310	1463	365	1834
Total	1018	1504	679	1843	Total	1018	1504	679	1843
31/01/06-24/09/07					31/01/06-29/08/07				
	Intervention	No intervention	Intervention	No intervention		Intervention	No intervention	Intervention	No intervention
Signal issued	48	1	3	1	Signal issued	197	5	2	1
No signal issued	241	140	1	425	No signal issued	76	134	2	407
Total	289	141	4	426	Total	273	139	4	408
					30/09/07-03/08/09				
						Intervention	No intervention	Intervention	No intervention
					Signal issued	91	5	18	1
					No signal issued	179	228	2	482
					Total	270	233	20	483
25/09/07-03/08/11					04/08/09-22/07/11				
	Intervention	No intervention	Intervention	No intervention		Intervention	No intervention	Intervention	No intervention
Signal issued	468	44	18	1	Signal issued	102	3		
No signal issued	47	235	2	987	No signal issued	373	36		
Total	515	279	20	988	Total	475	39		
05/08/11-19/06/13					25/07/11-19/06/13				
	Intervention	No intervention	Intervention	No intervention		Intervention	No intervention	Intervention	No intervention
Signal issued			26	2	Signal issued			15	1
No signal issued			70	391	No signal issued			81	401
Total			96	393	Total			96	402
20/06/13-30/09/15					20/06/13-30/09/15				
	Intervention	No intervention	Intervention	No intervention		Intervention	No intervention	Intervention	No intervention
Signal issued			259	5	Signal issued			246	4
No signal issued			300	31	No signal issued			313	32
Total			559	36	Total			559	36

Calculated values according to Table (5.16). These values are used to calculate noise-to-signal ratios reported in Table (5.9).

Samenvatting van het Proefschrift

Dit doctoraatsproefschrift getiteld "Essays on Nonlinear Time-Series Modeling and Financial Markets in Emerging Economies" is een verzameling van vijf essays welke empirische en theoretische bijdragen leveren tot de discussies over niet-lineaire tijdreeksmodellering en de prognose van financiële tijdsreeksen, internationale financiën, en de rol van centrale banken in wisselmarkten. De ultieme motivatie voor het proefschrift, welke omvat zit in het laatste hoofdstuk, is het verklaren van de motieven van centrale banken in opkomende markten om te interveniëren op de wisselmarkten. Andere hoofstukken vloeiden voort uit onderzoek naar dit onderwerp, al staan de eerste twee hoofdstukken op zichzelf. Het derde hoofdstuk voorziet de methodologie welke gebruikt wordt in het laatste hoofdstuk, en dit op gedetailleerde wijze en met een empirische toepassing. Het vierde hoofdstuk presenteert de literatuur welke geleid heeft tot de keuze van het kader waarop het laatste hoofdstuk van het proefschrift is gebouwd.

Het eerste hoofdstuk behandelt een praktische probleem in de econometrische literatuur rond niet-lineaire tijdreeksen. De afgelopen drie decennia werden wisselkoersinterventies van centrale banken werden de afgelopen drie decennia gemodelleerd met behulp van een wijde selectie van modellen. De "Smooth Transition Autoregressive Generalized Conditional Heteroskedasticity" (STAR-GARCH) was een van deze modellen. De literatuur rond de STAR-type modellen merkt twee praktische problemen op bij zijn gebruik van het model, namelijk, afhankelijkheid van de initiële waarden bij het schatten van het model en een hoge vertekening van de schatter voor de richtingscoëfficentparameter. Het "Iteratively Weighted Least Squares" (IWLS) algoritme wordt gezien als een robuust algoritme voor de selectie van de initiële waarden en voor het gebruik van een algemene set van niet-lineaire modellen met conditionele variantie. De literatuur toont aan dat het meest-waarschijnlijke-schatter-probleem opgelost kan worden met behulp van IWLS. De simulatiestudie in het eerste hoofdstuk toont aan dat het IWLS algoritme betere schattingen voor de STAR-GARCH parameters geeft in vergelijking met de gevestigde algoritmes gebruikt in de literatuur. De prestaties van het algoritme hangen af van de waarde van de richtingscoëfficentparameter. Als de richtingscoëfficentparameter heel hoog is, dan is de vertekening van de schatter van deze parameter hoog bij alle modellen. De voorspellingsoefeningen met wisselkoers- en aandelendata bieden verdere inzichten in de geval specifieke prestaties en superioriteit van het IWLS algoritme. De resultaten van het hoofdstuk voor wat betreft de voorspelbaarheid van wisselkoersrendementen motiveren het wisselkoersmodel gebruikt in Hoofdstuk 5.

Gedurende en in de nasleep van de recente globale financiële crisis hebben centrale banken van opkomende economieën voornamelijk vertrouwd op wisselmarktinterventies tegen ongewenste bewegingen in de nominale wisselkoersen als gevolg van sterke kapitaalstromen naar deze markten. Excessieve binnenlandse kredietgroei, waarvan de internationale financiële literatuur aangetoond heeft dat dit het meest belangrijke signaal is voor een financiële crisis, in opkomende economieën is een andere belangrijk gevolg van de hoge kapitaalstromen. Daarom vestigt het tweede hoofdstuk de aandacht op de determinanten van binnenlandse kredietgroei in opkomende economieën. Dit motiveert de context waarin de wisselkoersinterventies, verder in dit proefschrift, besproken zullen worden. Gebruikmakend van data op bankniveau en macro-economische indicators van Centraal en Oost-Europese landen (CEECs), wordt aangetoond dat de financiële hefboom van banken en de reële wisselkoers een significante impact hebben op de binnenlandse kredietgroei, en dat het effect genuanceerder is voor banken van buitenlandse eigendom.

Hoofdstuk 3 maakt gebruik van het Mixed Data Sampling (MIDAS) model voor de voorspelling van de Turks reëel Bruto Binnenlands Product (BBP) met behulp van dagelijkse financiële data. Reële BBP voorspellingen worden gegenereerd voor verschillende horizonten met de rendementen van aandelenprijzen, grondstoffenprijzen, wisselkoersen, en bedrijfsrisico's en dagelijkse factoren welke onttrokken worden uit deze tijdreeksen. De accuraatheid van de voorspellingen gebaseerd op de "root mean squared forecasting error" tonen aan dat de MIDAS modellen aanzienlijke voordelen hebben in termen van de accuraatheid van de voorspellingen, vergeleken met het referentiemodel en andere lineaire modellen. Het MIDAS model en de resultaten gepresenteerd in deze studie worden gebruikt in het laatste hoofdstuk van het proefschrift.

Hoofdstuk 4 is een omleiding langs de literatuur rond wisselkoersinterventies vanuit een methodologisch perspectief. Er bestaat een uitgebreide literatuur welke teruggaat tot de tweede helft van de jaren 1980. Het onderwerp werd rigoureus bestudeerd voor zowel ontwikkelde als opkomende markteconomieën. Het hoofdstuk vult een leegte in de literatuur door het catalogeren van de empirische en theoretische kaderwerken met betrekking tot specifieke problemen in de modellering van wisselkoersinterventies (e.g. transmissiekanalen en endogeniteitsproblemen) om verdere literatuur met betrekking tot het onderwerp te gidsen. Het hoofdstuk vestigt met name de aandacht op het gebrek aan analyses naar de beweegredenen van beleidsmakers bij het spreiden van wisselkoersinterventies over verschillende tijdshorizonten. Sommige empirische studies rond interventies argumenteren dat het isoleren van de beweegredenen mogelijk voordelen zou hebben voor studies die de efficiëntie van wisselkoersinterventies nagaan; echter, aangezien deze motieven vaak betrekking hebben op verschillende horizonten, kiezen de meeste studies ervoor om te gaan met één motivatie en één horizon tegelijkertijd. Er wordt opgemerkt dat het probleem opgelost kan worden met behulp van "mixed frequency data modeling" met methodes gesuggereerd in de tijdsreekseconometrie zoals MIDAS of Kalman filters.

Volgend op de beoordeling van de literatuur in het vorige hoofdstuk, bestuderen we in Hoofdstuk 5 twee motivaties voor centrale bank interventies in de valutamarkten van opkomende economieën. De eerste motivatie is het aanpassen van de wisselkoers naar een streefniveau en de tweede motivatie is de accumulatie van buitenlandse deviezenreserves als verzekering tegen plotse terugvallen in kapitaalinstromen. De reserves accumulatie motivatie wordt geïncorporeerd in de reactiefunctie van de beleidsmakers door het model van sporadische interventies, welke enkel wisselkoers targeting bevat, uit te breiden. De reserve accumulatie motivatie wordt voorgesteld als de afstand van de actuele reserves-tot-BBP ratio ten opzichte van het optimale niveau. Het model wordt geschat aan de hand van data met betrekking tot Turkije gedurende de glijdende wisselkoersperiode. Om het probleem met "mixed-data frequency" op te lossen, wordt er dagelijkse data van de reserve-tot-BBP ratio gegenereerd. De schattingsresultaten en een aantal robuustheidstests tonen dat, samen met afwijkingen van de lange-termijn wisselkoers doelstellingen, de reserve accumulatie een belangrijke drijfveer was tot midden 2013. Het resultaat heeft belangrijke implicaties voor studies die de effectiviteit van wisselkoersinterventies in Turkije, en de wisselkoersinterventies van opkomende economieën in het algemeen, in vraag stellen. De interventies die er op gericht zijn om reserves te accumuleren worden namelijk niet verwacht de wisselkoers te beïnvloeden. Indien de interventies die enkel gemotiveerd worden uit bezorgdheid omtrent de wisselkoers niet geïsoleerd worden, dan kan het zijn dat het geschatte effect van interventies op de wisselkoersen vertekend is. Bijgevolg, zou vanuit dit perspectief studies rond de effectiviteit van wisselkoersinterventies heroverwogen moeten worden vanuit dit perspectief.