ESTIMATING AND FORECASTING THE YIELD CURVE:
SRI LANKAN GOVERNMENT SECURITIES MARKET

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CANDIDATE’S DECLARATION

“I declare that this is my own work, and this thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any University or other institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text”

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"I have supervised and accepted this thesis for the submission of the degree"

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Dr. V. Welagedara   Date

DEDICATION

This thesis is dedicated to my parents
for their endless love, support and encouragement.

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First and foremost, I thank and pay respect to my parents who has been my pillars of strength giving me moral support at all times. My two younger brothers deserve my wholehearted thanks as well, for assisting me in so many ways, from helping to debug a code, to sharing their ideas, to simply being there whenever I needed their support.

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Thavisha Senarath Yapa

ABSTRACT

In this study, I evaluate two versions of the Nelson and Siegel (1987) model, namely the Nelson-Siegel model using the methodology presented in Diebold and Li (2006) and Nelson-Siegel-Svensson model (1994), with the purpose of fitting the current yield curve and forecasting the yield curve for the Sri Lankan government securities market.

The study finds that using the Svensson model which has an additional curvature factor compared to the Nelson -Siegel (Diebold and Li model) leads to a better in-sample fit of the term structure, and thus a better fit of the yield curve is observed. The superior in-sample fit of the Svensson model is clearly visible in the graphical outputs obtained and is further supported by the higher R^2 and lower RMSE associated with the Svensson model.
The results obtained are robust for recent events such as the COVID -19 pandemic that affected the country.

Forecasting performance of the two models, indicated opposite results compared to results obtained in the estimation of yield curves. Yield curves from Nelson-Siegel (Diebold and Li) model are predicted better compared to the Svensson model under both the short forecast horizon of one month and longer forecast horizon of six months. This is clearly exhibited in the lower RMSE associated with the Nelson -Siegel (Diebold and Li) model under the rolling window forecasting design that was applied using an AR(1) forecasting model.

Keywords: Yield curve, Term structure of interest rates, Nelson-Siegel, Diebold & Li, Svensson, Estimating, Forecasting.

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LIST OF ABBREVIATIONS

Abbreviation	Description
AIC	Akaike Information Criterion
AR	Auto Regressive
CBSL	Central Bank of Sri Lanka
ESS	Explained Sum of Squares
MAPE	Mean Absolute Prediction Error
NS Model	Nelson-Siegel model, using the methodology presented in Diebold and Li, 2006
OLS	Ordinary Least Squares
QAR	Quantile Autoregression
$\mathbf{R^2}$	Coefficient of Determination
RMSE	Root Mean Squared Error
SV Model	Nelson-Siegel-Svensson model
TSS	Total Sum of Squares

CHAPTER 1: INTRODUCTION

1.1 Introduction

The term structure of interest rates is the relationship between the interest rates and different terms or maturities. The visual representation of the term structure of interest rates is known as the yield curve. The graph displays the yield on the vertical axis and the time to maturity across the horizontal axis. The curve may take different shapes at different points in the economic cycle; Normal Yield Curve, Inverted Yield Curve, Steep Yield Curve, Flat Yield Curve, Humped Yield Curve. Yield curve shape indicates the market's expectations of future rate changes. The commonly seen yield curve shape is the Normal Yield Curve which is upward sloping and generally concave.

Interest rate term structures have a significant impact on economics and finance especially for financial institutions and governments. The yield curve is used as a proxy to gauge investor sentiment on the direction of the economy and is applied in predicting economic output and growth and many other vital economic & financial factors. Therefore, the ability to accurately estimate the current term structure of interest rates, or in other words, to accurately estimate the current yield curve, is of critical importance to many areas of economics and finance. Just as significant, is the capability to forecast the future term structure of interest rates.

1.1.1 Significance of the study

The purpose of this study is to arrive at the most suitable model that can be used, firstly, for estimating the current term structure of interest rates (Fitting the yield curve), and secondly, for forecasting the future term structure of interest rates (Forecasting the yield curve). This study will contribute to the finance sector, for instance, by providing a basis for banks and other financial institutions to decide on the most applicable model to use for estimating and forecasting the movement of the term structure of interest rates as it is vital for appraising the interest rate risk of banks and financial institutions. Because features and movements of the yield curve influence many economic factors of a nation, the analysis presented in this study will also be of importance to economists, data analysts and government policy makers in predicting key economic factors such as inflation, economic growth, exchange rate movements & consumer and business sentiment. The main contribution to the literature is applying this study to the Sri Lankan government securities market as only a very few studies of this type have been conducted in Sri Lanka. Most importantly, the estimating and forecasting methods used in this study have not been used in previous studies done in Sri Lanka. Another significant contribution to the literature is that, while most previous studies conducted in many countries support Svensson model's superiority in forecasting performance as compared to other Nelson and Siegel class models, the evidence from this study suggests that the Nelson and Siegel model (using the methodology presented in Diebold and Li, 2006) portrays better forecasting performance compared to the Svensson model, in the context of the Sri Lankan government securities market.

This study analyses the application of the two parametric models Nelson-Siegel model (using the methodology presented in Diebold and Li, 2006) and its extension Nelson-Siegel-Svensson (1994) model on the Sri Lankan government securities market. The two models will be used to fit the current yield curve as well as to forecast the future yield curve.

The Nelson and Siegel model (1987) and its extension the Nelson-Siegel-Svensson model (1994) are extensively used by central banks and other market participants as a model for the term structure of interest rates. It is evident from certain academic studies that the model can also be used as a valuable tool for forecasting the term structure (Diebold and Li, 2006).

According to BIS (2005), all term structure estimation models can be broadly categorized into parametric and spline-based approaches. Nelson-Siegel and its extension by Svensson are both parametric models and are also called function-based models because they are described as single-based functions that are defined over the entire maturity domain.

It is of great importance, that the most suitable model is applied to model and forecast the yield curve while avoiding inadequate models, as accurately fitting and forecasting the term structure of interest rates is the backbone of a smoothly functioning financial market.

1.2 Research Problem

Accurately fitting & forecasting the term structure of interest rates is pivotal to understanding the movement of interest rates in a country. Understanding the movement of interest rates in a developing country like Sri Lanka is a demanding task, given the illiquid bond market conditions & volatile economic conditions. Therefore, it is important that the model employed is a robust model and is the most applicable one to capture the behavior of the country's interest rates. This study will help determine the most suitable model out of the Nelson-Siegel model (using the methodology presented in Diebold and Li, 2006) and its extension Nelson-Siegel-Svensson (1994) model, through reliable fitting and forecasting of the yield curve. The two parametric models are widely used by market participants including central banks for fitting the term structure of interest rates. The ease in linearizing the model, greater flexibility, good fit and intuitive interpretation of the parameters and state variables, supported the selection of the two models.

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1.3 Objectives

There are two primary objectives of this study. First objective is to determine the model that can accurately estimate the current term structure of interest rates of the Sri Lankan government securities (Treasury bills & Treasury bonds). For this purpose, the two models Nelson-Siegel model (using the methodology presented in Diebold and Li, 2006) and its extension Nelson-Siegel-Svensson model (1994), is applied. The two models are compared based on graphical outputs, the coefficients of determination & prediction errors, to select the most suitable model.

The second objective of the study is to focus on exploring out-of-sample forecasting performance of the same two models; Nelson-Siegel model (using the methodology presented in Diebold and Li, 2006) and its extension Nelson-Siegel-Svensson model (1994) using Sri Lankan government security yields. The most applicable model for forecasting the Sri Lankan Treasury yield curve, is decided based on evaluation and comparison by a measurement of prediction accuracy.

Thus, the study will consist of two parts:

Part 1: Estimating the current term structure of interest rates (Fitting the yield curve)

Part 2: Forecasting the term structure of interest rates (Forecasting the yield curve)

1.4 Outline of the study

The thesis is structured as follows: Chapter 2 reviews the past literature and develops the main hypothesis of this study. Past literature includes studies done globally as well as studies done in Sri Lanka, and thus, highlights the literature gap in Sri Lanka. This chapter also presents the main hypothesis of the study, which consists of two separate hypotheses for the two parts of the study. Chapter 3 outlines the two theoretical models used in the study. A detailed description of the variables of each model is provided in this section. The data set and the methodology, including the forecasting framework employed, is described in Chapter 4. The data set and methodology used to compare the two models, under each of the two parts of this study is presented in this chapter. In Chapter 5, the results of the thesis are discussed. Utilizing both graphical outputs and statistical measures the results for the two parts of the study are discussed in this section. Final chapter of the study, Chapter 6 presents the conclusion, limitations, and the recommendations of the study.

CHAPTER 2: LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

2.1 Literature Review

The yield curve was introduced in the 1970s, after floating exchange rate systems were initiated in the US. Floating exchange rates made trading more sophisticated for bond traders and as a result traders started looking at bond yields in new ways. They began drawing a curve through the yields of all maturities instead of looking at each maturity as a different marketplace. The part of the curve closest to the present time became known as the short end and part of the curve represented by yields of bonds further out became known as the long end. Thus, the yield curve was developed and in turn facilitated studies on yield curve movement, modelling and forecasting among others.

The research evaluates the application of the two parametric models Nelson-Siegel model (using the methodology presented in Diebold and Li, 2006) and its extension Nelson-Siegel-Svensson (1994) model on the Sri Lankan government securities market. Furthermore, this study applies the forecasting methodology used by Reinicke (2019), to both models mentioned above, to evaluate the forecasting performance of the two models.

2.1.1 Nelson-Siegel model and the methodology presented in Diebold and Li, 2006)

The Nelson Siegel Model is used to express the yield curve at any point of time as a linear combination of the level, slope and curvature factors. The dynamics of these three factors drive the dynamics of the whole yield curve as mentioned by Diebold and Li (2006). The critical factor in determining the movement of term structures is the level factor according to Litterman and Scheinkman (1994). The slope factor tends to have an effect on short-term rates that is opposite to its effect on long term rates. The last factor is the curvature factor, because it causes the short and long ends to increase, while decreasing medium-term rates.

Nelson and Siegel (1987) parameterised the Nelson Siegel model and determined the best fitting values of the coefficients using linear least squares. The process was repeated over a grid of values for λ (time constant) to create the overall best fitting values. Annaert, Claes, Ceuster and Zhang (2012) called this procedure the grid search. Nelson and Siegel (1987) found the best fitting values of λ within the range of 50-100 and found that small values of λ are able to fit the curvature at low maturities because they correspond to rapid decay in the regressors. Consequently, large values of λ were found to produce slow decay in the regressors and fitted curvature over long maturity ranges though unable to follow extreme curvature at short maturities. Nelson and Siegel (1987) produced the best fit for US T-bills to be given by λ =40. However, while Nelson and Siegel constructed the parameter λ such that it can change with time, Diebold and Li (2006) argued that fixing the parameter for the entire time resulted in a very little loss of fit and thus concluded that λ_t should be fixed at 0.0609 thereby simplifying the estimation procedure and sharpening economic intuition.

2.1.2 Nelson and Siegel's criteria for an acceptable yield curve model

Nelson and Siegel (1987) also stated that the criteria for an acceptable yield curve model is that it is capable of predicting yields beyond the maturity period of the sample set used to fit it, because a function may be flexible enough to fit the data over a particular interval but may have very poor estimating properties when extrapolated outside that interval.

2.1.3 Features of the Nelson-Siegel model

Nelson Siegel Model produces term structure forecasts that appear much more accurate at long time periods than various standard benchmark forecasts, as found out by Diebold and Li (2006). Nelson Siegel model is however not consistent with the no-arbitrage property, i.e., consistency between the dynamic evolution of interest rates and the actual shape of the yield curve is not ensured at certain points as argued by Bjork and Christensen (1999).

Elen (2010) empirically tested whether the Nelson Siegel parameters legitimately computes the level, slope and curvature elements of a term structure by first producing a level, slope and curvature from observed yield data and then comparing them against the estimated parameters of the model. Elen (2010) then created a time series of the three factors of Nelson Siegel found by OLS and observed that the estimated factors and the defined factors followed the same pattern, hence concluding that based on Canadian yields, the three factors of Nelson Siegel were indeed level, curvature and slope.

2.1.4 The Nelson-Siegel-Svensson model and comparisons

The method of Svensson (1994) is more flexible and has a better fit than the original approach of Nelson and Siegel (1987) as observed by Laurini and Moura (2010). Gilli, Grobe and Schumann (2010) estimated the parameters of Nelson-Siegel-Svensson using the method formulated by Diebold and Li (2006) of fixing λ_1 and λ_2 and then estimate the rest of the parameters using a least squares algorithm. Gilli et al (2010) noted the need to have constraints when solving optimization problem of obtaining parameters to guarantee the computation of reasonable values, thus deduced that Nelson-Siegel-Svensson works well in interpolating observed yields.

Aljinović, Poklepović, and Katalinić (2012) compared the performance of Nelson-Siegel and Nelson-Siegel-Svensson models to find the best fit model to estimate the yield curve in the Croatian market using weekly yield data. For the comparison of the two models, the coefficient of determination(R^2), which gives details about the goodness of fit of a model, was used. T-tests at a 1% level of significance was performed and it was found out that Nelson-Siegel-Svensson model produced a better fit for Croatian term structure.

As observed by Michiel de Pooter (2007), the four-factor model, which adds a second slope factor to the three-factor Nelson-Siegel model, forecasts particularly well. Especially with a one-step state-space estimation approach the four-factor model produces accurate forecasts and outperforms competitor models across maturities and forecast horizons. Subsample analysis shows that this outperformance is also consistent over time.

2.1.5 In-sample fit and out-of-sample fit of extensions of the Nelson and Siegel model

Bliss (1996) highlighted the risks of using in-sample goodness of fit as the only criterion for comparing term structure estimation method. Bliss(1996) employed both parametric and non-parametric tests in comparing five term structure estimation methods and observed that the Unsmoothed Fama-Bliss is the best at an overall level, but also recommended that users fitting term structures parsimoniously need to look at either the Smoothed Fama-Bliss or the Extended Nelson Siegel methods. In-sample results give a mis-represented view of the performance of the term structure, because there is a risk of over-fitting the data and this can be removed by using out-of-sample tests to assess the estimation methods.

Michiel de Pooter (2007) examined the various extensions of the Nelson and Siegel (1987) model with the purpose of fitting and forecasting the term structure of interest rates and noted that using more flexible models leads to a better in-sample fit of the term structure; the out-of-sample predictability improves as well.

2.1.6 Modeling & forecasting the yield curve, Reinicke (2019)

Reinicke (2019) used three approaches to model and forecast the yield curve. The first approach was based on the Diebold and Li (2006)'s model, while the next two approaches were based on functional principal component analysis and Gaussian processes, respectively. The proposed methods were tested on two data sets; one data set comprising of data obtained from market-listed Bundeswertpapiere (federal securities) of the Federal Republic of Germany and the other set comprising of data derived from market quotations of Treasury securities by the United States. The forecast performance of the three approaches were compared using a measurement of prediction accuracy. It was concluded that the performance of principal components model was better suited for a variety of data sets as the performance did not vary significantly when applied to different data sets when compared with the Diebold and Li (2006) model. Reinicke (2019) also noted that, while the Gaussian processes model performed better in the shorter maturities, the principal components model performed better in the long-term maturity spectrum.

2.1.7 Literature in Sri Lanka

Dayarathne (2013) assesses the interest rate behavior with respect to selected economic factors in Sri Lanka using the Vector Error Correction Model. Dayarathne (2013) noted that the growth of Gross Domestic Production, change in Sri Lanka Rupee/ United States Dollar and Inflation showed short run as well as long run relationship with interest rates while Growth in Money Supply, growth in Domestic Debt and growth of the Private Credit Growth exhibited a short run relationship.

Aazim and Cooray (2010) examines the foundations of expectation hypothesis to ascertain monetary policy impact on daily market interest rates of Sri Lanka money and government securities market for the period 2000-2009. Aazim & Cooray (2010) observed that monetary policy impact monotonically decreases over the yield curve at the short-end and become segmented toward medium to long-term of the yield curve. Analyzed for heterogeneous economic environment, the impact appears to be weaker and increasingly segmented at times of financial and economic uncertainties.

Karunasena (2009) attempts to evaluate the outcomes and existing issues related to the development of the Sri Lankan bond market as well as the relevant measures and actions taken. The paper highlights that Sri Lanka has made a reasonable progress in developing a government bond market and a default-risk free benchmark yield curve but the country still has a long way to go in order to realize full benefits of a developed bond market.

Rathnasingha and Dayarathne (2021) focuses on constructing the most suitable model to fit the yield curve for the Sri Lankan Government Bond market; the Nelson and Siegel model has been used as the base model for this purpose. In addition to the traditional Nelson and Siegel model, the paper examines different discounting functions, applying the OLS technique, to construct the best fit model that enhances accuracy and predictability.

In the global domain, considerable research effort has been dedicated to the questions of how to optimally estimate, model and forecast the yield curve. However, in Sri Lanka, very few attempts have been made in estimating and forecasting the yield curve for the Sri Lankan government securities market. Furthermore, studies specific to the application of parametric models on the Sri Lankan government securities market can be hardly found in the literature in Sri Lanka. Rathnasingha and Dayarathne (2021) employs parametric models (Nelson and Siegel model as well as different discounting functions, applying the OLS technique) to construct the best fit yield curve model for the Sri Lankas government bond market. However, the estimating and forecasting techniques used in this study differs from the methods discussed in their paper, and importantly, the methods used in this study have not been employed in previous studies done in Sri Lanka. Thus, this study will help reduce the existing vacuum in Sri Lankan literature, with respect to research done on modelling and forecasting the yield curve using parametric models.

2.2 Hypothesis Development

Aim of this research is to evaluate the application of the two parametric models Nelson-Siegel model (using the methodology presented in Diebold and Li, 2006) and its extension Nelson-Siegel-Svensson (Svensson, 1994) model on the Sri Lankan government securities market. Both models are widely used in the global sphere and are standard extensions of the initial Nelson -Siegel model (1987).

First objective of this study is to determine the model that can accurately estimate the current term structure of interest rates of Sri Lankan government securities. The second objective of the study is to focus on exploring out-of-sample forecasting performance of the same two models for the Sri Lankan government securities market.

Thus, the study will consist of two parts:

Part 1: Estimating the current term structure of interest rates (Fitting the yield curve)
Part 2: Forecasting the term structure of interest rates (Forecasting the yield curve)

A separate null hypothesis and alternate hypothesis is developed for each part of the study; Hence the research will be based on two hypothesis scenarios.

Research Hypothesis: Part 1: Estimating the current term structure of interest rates (Fitting the yield curve)

H_0 : There is no significant difference in the performance of the two models in terms of estimating the current term structure of interest rates.

H_a : There is a significant difference in the performance of the two models in terms of estimating the current term structure of interest rates.

Research Hypothesis: Part 2: Forecasting the term structure of interest rates (Forecasting the yield curve)

H_0 : There is no significant difference in the forecasting performance of the two models

H_a : There is a significant difference in the forecasting performance of the two models

Amidst the substantial research available globally on the estimation and forecasting performance of various Nelson- Siegel class models, a number of studies have proven Svensson models superior performance given the improved flexibility and fit that comes by including a second curvature factor with a separate decay parameter. Some of the studies with positive feedback on the performance of the Svensson model are discussed briefly in the next few paragraphs.

The method of Svensson (1994) is more flexible and has a better fit than the original approach of Nelson & Siegel (1987) as observed by Laurini and Moura (2010).

Gilli et al (2010) pointed out that it is important to introduce constraints, when solving optimization problem of obtaining parameters, to make sure reasonable values are computed, thus inferred that Nelson-Siegel-Svensson works well in interpolating observed yields.

Aljinovic et al (2012) assessed the performance of Nelson-Siegel and Nelson-Siegel-Svensson models to find the most applicable model to fit the yield curve in the Croatian market and it was discovered that Nelson-Siegel-Svensson model produced a better fit for Croatian term structure.

As highlighted by Michiel de Pooter (2007), the four-factor Svensson model, demonstrated superior forecasting performance across maturities and forecast horizons compared to competitor models This superior performance was also consistent over time as shown in subsample analysis.

Thus, evidence from most previous studies suggest that the Svensson model performs better. The detailed description of the Nelson-Siegel model (using the methodology presented in Diebold and Li, 2006) and its extension Nelson-Siegel-Svensson (Svensson, 1994) model provided in the next chapter establishes the foundation to understand the structural differences of the two models that could be causing performance differences.

CHAPTER 3: THEORETICAL MODELS

3.1 Economic importance and features of the yield curve

In the study of treasury securities, obtaining accurate interest rate point estimates is vital as it is a key input for risk modeling and financial modeling. Dealers and traders base their investment decisions on conclusions derived from modelling and forecasting yield curves. On the other hand, analysts and economists base their research and findings on market expectations, risk premiums and demand and supply information of investors, by analyzing the movement of the yield curve.

The yield curve estimation methods are designed for the purpose of approximating one of the three key theoretical bond market constructs: the discount curve, the forward curve and the yield curve.

Let $P_t(\tau)$ denote the price of a τ-period bond, i.e., the present value at time t of Rs.1 receivable τ periods ahead and let $y_t(\tau)$ denote its continuously compounded yield to maturity. Based on the relationship between price and yield, the discount curve can be derived, and is defined as:

$$P_t(\tau) = e^{-\tau y_t(\tau)} . \qquad [3.1]$$

And, from the discount curve, the forward rate curve can be obtained, which is defined by:

$$f_t(\tau) = -\frac{P'_t(\tau)}{P_t(\tau)} . \qquad [3.2]$$

The relationship between the yield to maturity and the forward rate curve can be obtained by combining the presented equations, and is therefore defined as:

$$y_t(\tau) = \frac{1}{\tau}\int_0^{\tau} f_t\,(u)du\,. \qquad [3.3]$$

By deriving the representation of one of these constructs, the representations of the others can be automatically derived. This study focuses on the yield curve alone as most of the literature for interest rate term structure forecasting employs the yield curve. In practice, discount curves, forward curves and yield curves are not directly observable and therefore must be estimated from actually observed bond prices.

There are several important stylized facts about the yield curve as Diebold and Li (2006) mentions:

(1) "The average yield curve is increasing and concave"
(2) "The yield curve assumes a variety of shapes through time, including upward sloping, downward sloping, humped, and inverted humped"
(3) "Yield dynamics are persistent, and spread dynamics are much less persistent"
(4) "The short end of the yield curve is more volatile than the long end"
(5) "Long rates are more persistent than short rates"

3.2 Model Description

The theoretical context of the two parametric models employed in the thesis is discussed below.

3.2.1 Nelson-Siegel yield curve model (using the methodology presented in Diebold and Li, 2006)

The Nelson Siegel (1987) functional form is a convenient and parsimonious three-component exponential approximation that is used to derive the yield curve.
Diebold and Li (2006) works with the following forward rate curve developed by Nelson and Siegel (1987) and extended by Nelson and Siegel (1988).

$$f_t(\tau) = \beta_{1t} + \beta_{2t}e^{-\lambda_t\tau} + \beta_{3t}\lambda_t e^{-\lambda_t\tau} . \qquad [3.4]$$

Hence, the corresponding yield curve employed in their study is,

$$y_t(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau}\right) + \beta_{3t}\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau} - e^{-\lambda_t\tau}\right) \qquad [3.5]$$

The exponential decay rate is controlled by the parameter λ_t; while large values of λ_t lead to fast decay and fits the curve better at short maturities, small values of λ_t lead to slow decay and gives a better fit of the curve at long maturities. Furthermore, λ_t controls where the loading on β3t achieves its maximum. Diebold and Li (2006) set λ_t = 0.0609 for all t.

Diebold and Li (2006) interpret β_{1t}, β_{2t} and β_{3t} as three latent dynamic factors. The loading on β1t is constantly 1; hence it may be viewed as a long-term factor. The factor β2t has a loading equal to $(1 - e^{-\lambda_t\tau})/\,\lambda_t\tau$. It is a function that starts at 1 and then decays fast and monotonically to 0; hence it may be viewed as a short-term factor. The loading on β3t, $((1 - e^{-\lambda_t\tau})/\,\lambda_t\tau)$- $e^{\lambda_t\tau}$, starts at 0 (and is therefore not short-term), increases, reaches its maximum and then decays to zero (and is therefore not long-term); hence it may be viewed as a medium-term factor.

Diebold and Li (2006) provides another valuable interpretation of the three factors: i.e., the three factors, namely long-term, short-term, and medium-term, may also be explained in terms of level, slope and curvature of the yield curve.

The level of the yield curve is governed by the long-term factor β_{1t}. As the loading of β1t is the same across all maturities, a change in β_{1t} will change all yields equally, thus changing the yield curve level. Also $y_t(\infty) = \beta_{1t}$.

The short-term factor β_{2t} is associated with the yield curve slope. Diebold and Li (2006), defines factor β_{2t} as the ten-year yield minus the three-month yield. Additionally, it is noted that an increase in β_{2t} will raise short maturity yields more than long maturity yields, because the short rates load more powerfully on β_{2t}, thereby changing the yield curve slope.

At last, β_{3t} being the medium-term factor is connected to the yield curve curvature, which. Diebold and Li (2006) defines as twice the two-year yield minus the sum of the ten-year and three-month yields.

Furthermore, it is noted that an increase in β_{3t} will increase medium-term yields, thereby increasing yield curve curvature, but will only have a small effect on very short or very long yields, which load minimally on it.

3.2.2 Nelson-Siegel-Svensson yield curve model.

The four-factor Svensson (1994) model suggest improving the flexibility and fit for the Nelson-Siegel model by including a second hump-shape factor with a separate decay parameter, λ_{2t} , in addition to λ_{1t}. The resulting four-factor forward curve is given by:

$$f_t(\tau) = \beta_{1t} + \beta_{2t} \exp\left(-\frac{\tau}{\lambda_{1t}}\right) + \beta_{3t}\left(\frac{\tau}{\lambda_{1t}}\right)\exp\left(-\frac{\tau}{\lambda_{1t}}\right) + \beta_{4,t}\left(\frac{\tau}{\lambda_{2t}}\right)\exp\left(-\frac{\tau}{\lambda_{2t}}\right) \quad [3.6]$$

The resulting equation for the yield curve is then:

$$y_t(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1-\exp\left(-\frac{\tau}{\lambda_{1t}}\right)}{\left(\frac{\tau}{\lambda_{1t}}\right)}\right) + \beta_{3t}\left(\frac{1-\exp\left(-\frac{\tau}{\lambda_{1t}}\right)}{\left(\frac{\tau}{\lambda_{1t}}\right)} - \exp\left(-\frac{\tau}{\lambda_{1t}}\right)\right) +$$
$$\beta_{4t}\left(\frac{1-\exp\left(-\frac{\tau}{\lambda_{2t}}\right)}{\left(\frac{\tau}{\lambda_{2t}}\right)} - \exp\left(-\frac{\tau}{\lambda_{2t}}\right)\right) \quad [3.7]$$

The first term is a constant, equals β_{1t} and describes the long-term level of zero rates, because the contribution of the other two components disappears as τ approach infinity. The second component, $\left(\frac{1-\exp\left(-\frac{\tau}{\lambda_{1t}}\right)}{\left(\frac{\tau}{\lambda_{1t}}\right)}\right)$ establishes an exponential time decay that becomes slower the bigger λ_{1t} is. The third component, $\left(\frac{1-\exp\left(-\frac{\tau}{\lambda_{1t}}\right)}{\left(\frac{\tau}{\lambda_{1t}}\right)} - \exp\left(-\frac{\tau}{\lambda_{1t}}\right)\right)$ creates either a hump (if β_{3t} is positive) or a trough (if β_{3t} is negative) that occurs at a time governed by λ_{1t}. The additional fourth component, $\left(\frac{1-\exp\left(-\frac{\tau}{\lambda_{2t}}\right)}{\left(\frac{\tau}{\lambda_{2t}}\right)} - \exp\left(-\frac{\tau}{\lambda_{2t}}\right)\right)$, adds a second medium-term component to the Nelson-Siegel model. It adds a second hump (if β_{4t} is positive) or a trough (if β_{4t} is negative) that occurs at a time governed by λ_{2t}.Thus, the Svensson model can be used to fit term structure shapes with more than one local maximum or minimum along the maturity spectrum, with more ease.

CHAPTER 4: DATA AND METHODOLOGY.

4.1 Data

The first part of the study, that is, estimating the current term structure of interest rates is based on daily secondary market yield quotations of government securities of Sri Lanka. The second part of the study, which is, forecasting the term structure of interest rates, employs weekly data points obtained from the same data set as used for the first part of the study. This is done by extracting weekly observations from the end of each week, from the available daily data, thereby, converting the data set into a weekly data set. The forecasting framework in the second part of the study, requires stepwise moving through the entire data set repeating the prediction process. Doing this using daily data will be tedious and time consuming. Thus, for the second part of study the data set is shortened by extracting weekly data. A detailed description of the data set used under each part of the study is provided in the following section.

4.1.1 Data Description - Part 1: Estimating the current term structure of interest rates (Fitting the yield curve)

The analysis is done using daily secondary market yield quotations of government securities (Treasury bills and Treasury bonds) of Sri Lanka. The data was obtained from the official website of the Central Bank of Sri Lanka. Thus, data collection for this study is based on secondary research. The time span of the daily data selected is November 2014 till July 2020 in order to include periods of impact from exogenous factors such as the Easter Sunday attacks in April 2019 and the COVID-19 outbreak in 2020. A larger data set will help produce more accurate outcomes from the models and reduce the margin of error. The data set comprises of 1356 daily yield quotes for 13 terms of maturities: {3 months, 6 months, 1 year, 2 years, 3 years, 4 years, 5 years, 6 years, 8 years, 10 years, 15 years, 20 years, 30 years}. Observations with holidays and non-trading days were removed.

A three-dimensional plot of the daily yield curve data is provided in Figure 4.1. The substantial amount of temporal variation in the level is visible in the diagram. The variation in the slope and curvature is also visible in the diagram, but to a less significant degree. Descriptive statistics for the yield data is presented in Table 4.1. It is evident that the average yield curve is upward sloping, and that the long maturity yields are less volatile and more persistent than short maturity yields.

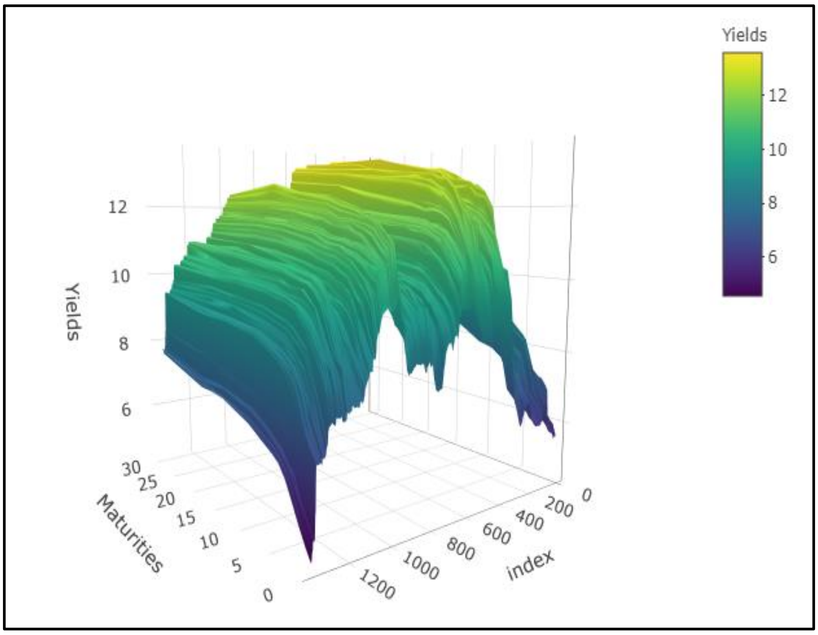


Figure 4.1: Daily yield curves of Sri Lankan Treasury securities from November 2014 to July 2020 across 13 maturities.

Index: Daily data points between November 2014 to July 2020. In other words, it is the observation number.

Table 4.1 Descriptive Statistics, yield curves

Maturity	Mean	Standard Dev.	Minimum	Maximum	$\hat{\rho}(30)$	$\hat{\rho}(365)$	$\hat{\rho}(900)$
R_3M	7.934	1.226	4.55	9.93	0.904	-0.349	-0.753
R_6M	8.353	1.409	4.63	10.68	0.910	-0.469	-0.723
R_1Y	8.819	1.565	4.8	11.15	0.915	-0.492	-0.726
R_2Y	9.222	1.664	5.19	11.98	0.921	-0.564	-0.755
R_3Y	9.763	1.477	5.59	12.44	0.896	-0.542	-0.730
R_4Y	10.017	1.448	6.03	12.69	0.889	-0.554	-0.726
R_5Y	10.179	1.415	6.3	12.73	0.883	-0.559	-0.710
R_6Y	10.314	1.368	6.44	12.84	0.878	-0.556	-0.708
R_8Y	10.469	1.315	6.63	12.87	0.868	-0.549	-0.707
R_10Y	10.617	1.293	6.84	13.07	0.851	-0.550	-0.686
R_15Y	10.828	1.246	7.15	13.24	0.851	-0.538	-0.704
R_20Y	11.019	1.222	7.15	13.5	0.846	-0.505	-0.697
R_30Y	11.238	1.182	7.61	13.58	0.851	-0.458	-0.668

Note: The descriptive statistics for daily yields at different maturities is presented above. The last three columns contain sample autocorrelations at displacements of 30 days (1 month), 365 days (12 months), and 900 days (30 months). The sample period is 11:2014–07:2020.

Diebold and Li, (2006) depicts a similar descriptive statistics table in their paper. When comparing the two descriptive statistics tables, the average yield increases with maturity in both studies, confirming the upward sloping shape of the yield curve embedded in both data sets. In the descriptive statistics table presented above, autocorrelations at displacements of 1 month is positive for all maturities while autocorrelations at displacements of 12 months and 30 months are negative for all maturities. In the descriptive statistics table presented in Diebold and Li, (2006), almost all autocorrelations are positive except for the negative autocorrelations found in the 3-, 6- and 9-month maturity buckets at displacements of 30 months. However, when analyzing the overall context, lower sample autocorrelation figures are derived at higher displacements, across all maturity buckets in both studies. It is therefore clear that the long-term rates are less volatile and more persistent than short-term rates.

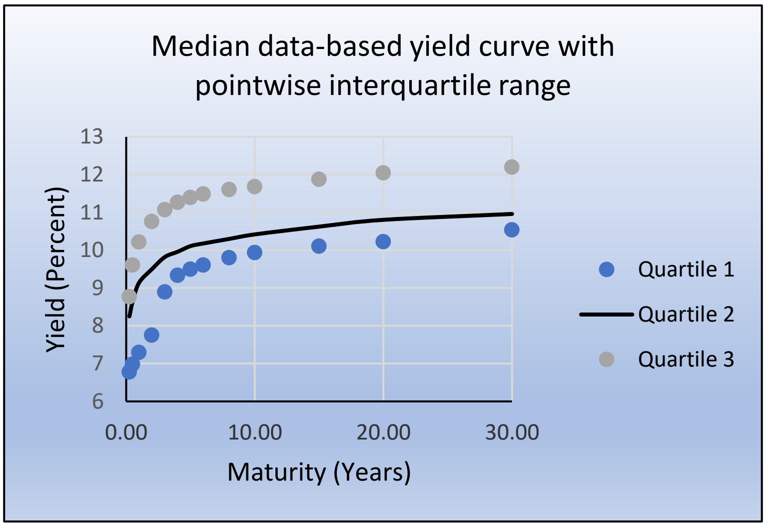


Figure 4.2 Median data-based yield curve with pointwise interquartile range.

For each maturity the median yield, the 25th percentile and the 75th percentile, is plotted.

The median data-based yield curve with pointwise interquartile range is depicted in Figure 4.2. The previously mentioned positive/upward sloping pattern is visible in it. The higher volatility in short-term rates compared to long-term rates, is visible as well. It is also noteworthy to highlight the asymmetric distributions of yields around their medians, along with a long right tail.

4.1.2 Data Description - Part 2: Forecasting the term structure of interest rates (Forecasting the yield curve)

The same data set used for estimating the yield curve (Part 1), with the same time span of November 2014 till July 2020, was employed for forecasting the yield curve as well. However, from the available daily data, weekly observations from the end of each week were extracted, converting the data set into a weekly data set. Therefore, weekly secondary market yield quotations of government securities of Sri Lanka were used in the forecasting process (Part 2). The data set then comprised of 296 weekly data points for the same 13 terms of maturities: {3 months, 6 months, 1 year, 2 years, 3 years, 4 years, 5 years, 6 years, 8 years, 10 years, 15 years, 20 years, 30 years}. Observations with holidays and non-trading days were removed. An illustration of the data set is given in Figures 4.3, 4.4(a) & 4.4(b).

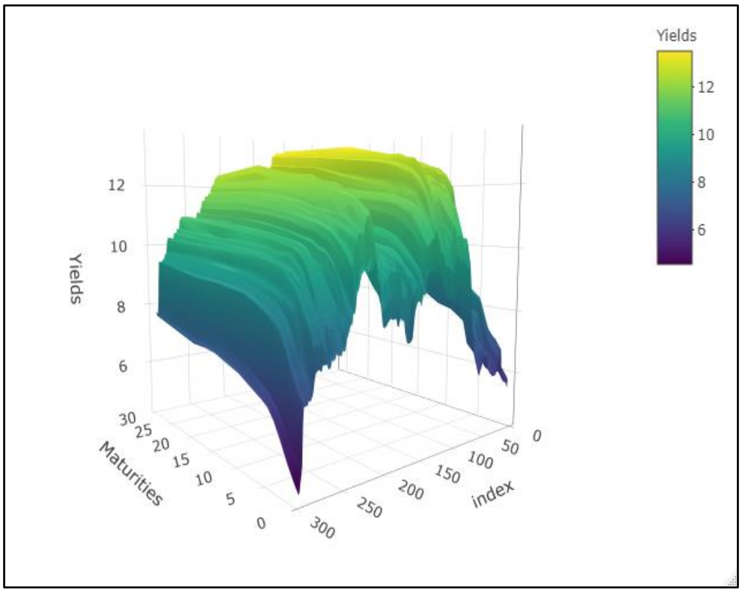


Figure 4.3: Weekly yield curves of Sri Lankan Treasury securities from November 2014 to July 2020 across 13 maturities.

Index: Weekly data points between November 2014 to July 2020. In other words, it is the observation number.

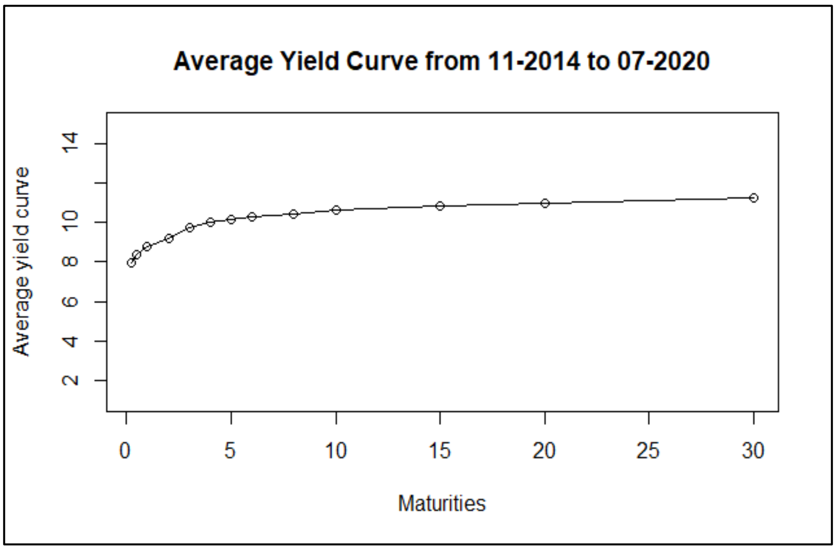


Figure 4.4: (a) Average yield curve (mean curve) from November 2014 to July 2020

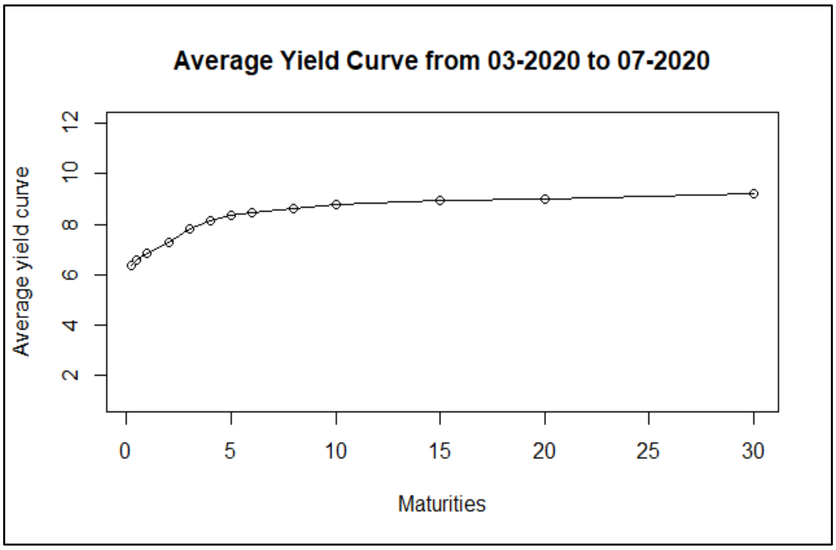


Figure 4.4: (b) Average yield curve (mean curve) of part of the data set: March 2020 to July 2020

The impact of the COVID – 19 pandemic was severe on the country's economy.
The Monetary Board of the Central Bank of Sri Lanka reduced policy rates by a cumulative of 250 basis points during the year up to mid July 2020 to induce further reductions in market lending rates and reinforce support to COVID-19 hit businesses as well as to the broader economy. The reduction in the level of the yield curve (parallel shift downwards) can be clearly seen in Figure 4.14- (b) as the average yield for that period only (March 2020 to July 2020), is lower at all maturities, compared to the average yield curve for the whole period (November 2014 to July 2020), which is at a higher level.

4.2 Methodology

The "YieldCurve" R package by Guirreri (2015) along with other functions of R, is used for both parts of this study, Fitting the yield curve using each model (1st part) and forecasting the yield curve using each model (2nd part).

Fit of the yield curve is evaluated by comparing the graphical yield curve outputs, R^2, and RMSE's of the two models.

The forecasting performance of the models are assessed by applying a forecasting study design similar to the one used by Reinicke (2019). In this study design, the forecasting approach is two-fold based on two methods: out-of-sample testing and cross validation. RMSE values of the two models will be used to arrive at the most suitable model for forecasting.

A point to note is that, in this package the parameter λ_t is not fixed but is estimated at every step in t, whereas in Diebold and Li (2006)'s work, λ_t is fixed. In this package, a λ is estimated at every forecasting step repeating for every maturity, maximizing the loading on β_{3t}. Then the beta values corresponding to this λ are estimated using the Ordinary Least Squares method. The parameter set with those beta values minimizing the residuals of the estimation model across all maturities is then selected.

Thus, in this study, in the estimation part of the current yield curve, the λ_t values in both the Nelson-Siegel model and Svensson model are estimated as explained above. However, in the forecasting part of the yield curve, a fixed value for $\lambda_t$is applied by taking the mean of all estimated λ_ts, in both the Nelson-Siegel model and Svensson model (note that Svensson model has two λ parameters [λ_{1t} & λ_{2t}]).

The "Nelson.Siegel (rate, maturity)" and "Svensson (rate, maturity)" functions of the "YieldCurve" R package are the two main functions used in this study.

The data set employed, and the methodology used under each part of the study is discussed in detail, in the following sections.

Part 1**:** Estimating the current term structure of interest rates (Fitting the yield curve)
Part 2**:** Forecasting the term structure of interest rates (Forecasting the yield curve)

Nelson-Siegel model, using the methodology presented in Diebold and Li, 2006, will be denoted by the abbreviation 'NS' and the Nelson-Siegel-Svensson model will be denoted by the abbreviation 'SV' henceforward.

4.2.1 Methodology - Part 1: Estimating the current term structure of interest rates (Fitting the yield curve)

The methods used to evaluate and compare the two parametric models' ability and accuracy in fitting the current yield curve is discussed below.

4.2.1.1 Model Comparison

In addition to comparing the graphical outputs of the fitted lines under each model, the Coefficient of Determination (R^2) and Root Mean Square Error (RMSE) is used to compare the accuracy and performance of the two models.

The Coefficient of Determination (R^2)

R^2 is a statistic that offers knowledge about the goodness of fit of a model. R^2 is the proportion of the variance in the dependent variable that is predictable from the independent variable(s). The coefficient of determination usually ranges between 0 and 1. An R^2 of 1 tells that the regression predictions fit the data perfectly. Therefore, closer the R^2 is to 1, the better the goodness of fit of a model.

$$R^2 = \frac{ESS}{TSS} = \frac{\Sigma \hat{y}_i^2}{\Sigma y_i^2} = \frac{b_1 \Sigma y_i x_{1i} + b_2 \Sigma y_i x_{2i}}{\Sigma y_i^2} \qquad [4.1]$$

where,
ESS: Explained sum of squares
TSS: Total sum of squares

Root Mean Square Error (RMSE)

RMSE is a measure of accuracy, that is frequently used in model comparison to measure the differences between values (sample or population values) estimated by a model and the values observed.; In more technical terms, RMSE tells how spread out the residuals are; where residuals are a measure of the distance between the regression line and the data points. In other words, it gives an idea of how concentrated the data is around the line of best fit. RMSE is never negative, and a value of 0 shows a perfect fit to the data although it is almost never achieved in practice. In general, a lower RMSE is considered better than a higher one.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N}} \quad [4.2]$$

$\sum_{i=1}^{N}(Predicted_i - Actual_i)^2$: Summation of the squared differences between the predicted value and actual of each data point.

N: Sample size

4.2.2 Methodology - Part 2: Forecasting the term structure of interest rates (Forecasting the yield curve)

4.2.2.1 Forecasting model.

Following the works of Diebold and Li (2006), Reinicke (2019) and De Pooter (2007), a first-order autoregressive process [AR(1) model] is used for forecasting the out-of-sample parameters for the NS model and SV model.

An autoregressive process of order p is a process where the realization β_t is a weighted sum of past realizations, i.e., β_{t-1}, β_{t-2},…, β_{t-p}. The first-order autoregressive process [AR(1) model] is given by:

$$\beta_t = \mu + \emptyset\beta_{t-1} + v_t \quad [4.3]$$

Where μ is the intercept, $\emptyset$ is the coefficient of the lagged value β_{t-1}, and v_t is the random error.

Using the AR(1) model function in the R package, coefficients $\beta_{1,t}$, $\beta_{2,t}$, $\beta_{3,t}$ for NS model and coefficients $\beta_{1,t}$, $\beta_{2,t}$, $\beta_{3,t}$, $\beta_{4,t}$ for SV model is forecasted.

In addition to employing an AR(1) model, this research follows the same forecasting study design applied by Reinicke (2019), in analyzing the forecasting performance of different models.

As described by Reinicke(2019), a detailed step by step breakdown of the forecasting approach used in her study is provided in the following section.

4.2.2.2 Description of study design

Reinicke (2019)'s forecasting approach consists of two steps that utilizes two methods, out-of-sample testing and cross validation. Out-of-sample testing is where the given data set is split into a training sample and a testing sample. Training sample is used for the initial parameter estimation and model selection while the testing sample is used to evaluate forecasting performance. Accordingly, data used for model fitting is not used in the forecasting process (Bergmeir, Hyndman and Koo (2018)). Illustrated in Figure 4.15 is the out-of-sample forecasting procedure. The overall yield curve data is represented by the blocks in the figure (in this study each block will represent one weekly data point). The training data is represented by the blue blocks and testing data by the grey blocks and the data that is not used by white blocks. In this example, the forecast horizon is 4 periods (h=4).

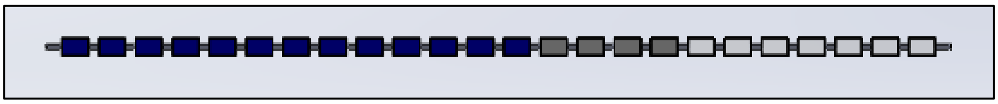


Figure 4.5: Illustration of out-of-sampling forecasting (basis for illustration, Reinicke, 2019 & Bergmeir et al., 2018)

The second method applies the forecasting procedure to K different training samples utilizing the K-fold cross validation method. On that account, a more accurate evaluation of the forecasting performance of a model can be made than evaluating the performance derived from a single modelling set-up.

Due to the presence of temporal relation in the data, the inability to randomly divide the data into training and testing samples, is highlighted in her study. As a solution, a rolling window setup of the training data with specified window length *l* is introduced. Through the rolling window setup, multiple forecasting models are produced. As explained in her thesis, based on the current window of data, forecasts for the successive h periods are made and the mean forecasting error over the entire curve is noted down. Moving through the entire data set, stepwise, repeating this forecasting process gives a measure for prediction accuracy for this method based on the set size, the number of weeks of the chosen rolling window, respectively.

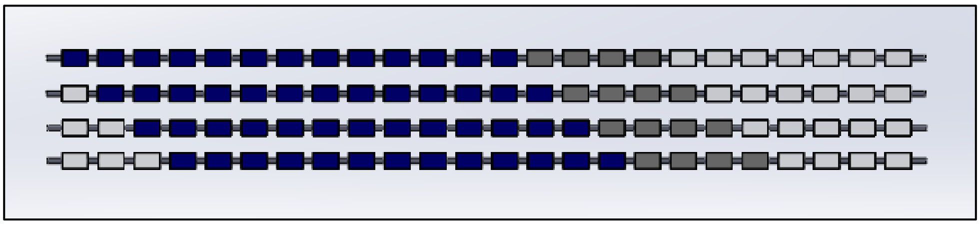


Figure 4.6: Illustration of forecasting procedure with stepwise shifting of the rolling window (basis for illustration, Reinicke, 2019)

Another area, she explores is the, the impact on forecasting performance of varying the training window size within the out of sample and cross validation testing framework. Figure 4.17 shows an example where the training window size is reducing by two steps. It is also mentioned, the steps by which the rolling window is reduced depends on the forecast horizon, h. Out of sampling testing with smaller rolling window means a higher number of models can be estimated shifting through the data, which in turn means that mean forecast error will be calculated over more estimated models.

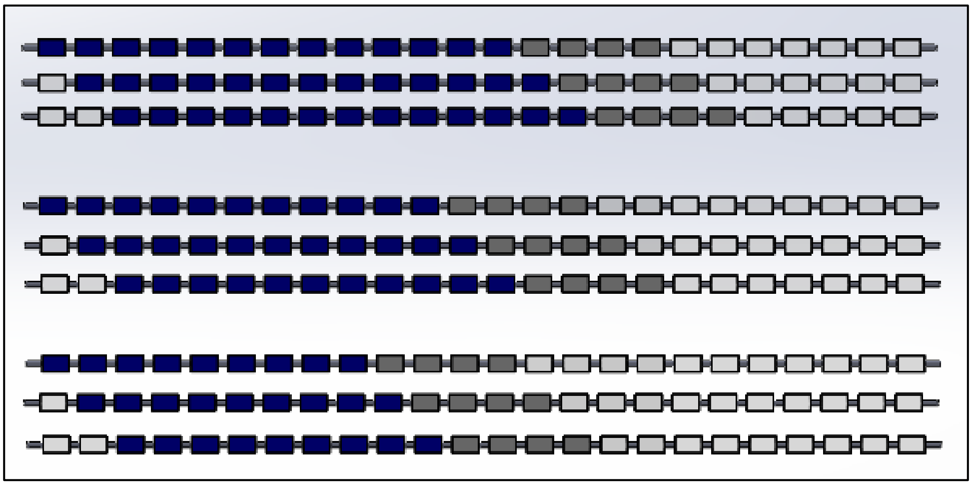


Figure 4.7: Illustration of varying size of training sample within out-of-sample and cross validation testing framework (basis for illustration, Reinicke, 2019).

Reinicke (2019), employs the above study design to evaluate the forecasting performance of three models: Factor model by Diebold and Li (2006), Functional Principal Component model & Gaussian Process Prior model. This study applies the same forecasting study design to the NS model (same as Reinicke's Factor model by Diebold and Li), and further extends it to the SV model, using Sri Lankan treasury securities yields. This study will also use forecasting horizons of h = 4 and h = 26 to reflect a 1-month and 6-month forecasting horizons.

Reinicke (2019) extends the above study design to higher order AR models in addition to the standard AR (1) model. However, this research is based on the standard AR(1) model only.

4.2.2.3 Measurement of prediction accuracy - Root Mean Square Error (RMSE)

Similar to the estimation part of the yield curve discussed in the first part of this chapter, RMSE will be used to examine the forecasting performance of the two models as well.

In a forecasting context, RMSE of a forecasted curve f_i is defined by:

$$RMSE_i = \sqrt{\frac{\sum_{\tau=1}^{m}(\hat{y}[\tau,i]-y[\tau,i])^2}{m}} \qquad [4.4]$$

Where,

$\hat{y}[\tau, i]$: forecasted yield for period i and maturity τ

$y[\tau, i]$: actual yield for period i and maturity τ

RMSE is viewed as a" standard measure in the financial literature for measuring and comparing the accuracy of interest rates prediction models" (Arbia and Di Marcantonio, 2015). It is also used by Diebold and Li (2006), Chen and Niu (2014), Sambasivan and Das (2017) & Reinicke (2019).

CHAPTER 5: RESULTS

5.1 Part 1: Estimating the current term structure of interest rates (Results)

As mentioned under Section 3.3, the "YieldCurve" R package by Guirreri (2015) along with other functions of R, is used to estimate the current term structure of interest rates (fitting the yield curve) for both the NS model and SV model.

5.1.1 Nelson-Siegel yield curve fit method - using the methodology presented in Diebold and Li, 2006.

As previously discussed under Section 3.2, the yield curve is fit using the three-factor model,

$$y_t(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau}\right) + \beta_{3t}\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau} - e^{-\lambda_t\tau}\right)$$

Figure 5.1 shows the graphical yield curve output of the actual (data-based) and fitted (model-based) daily average yield curves of the NS model.

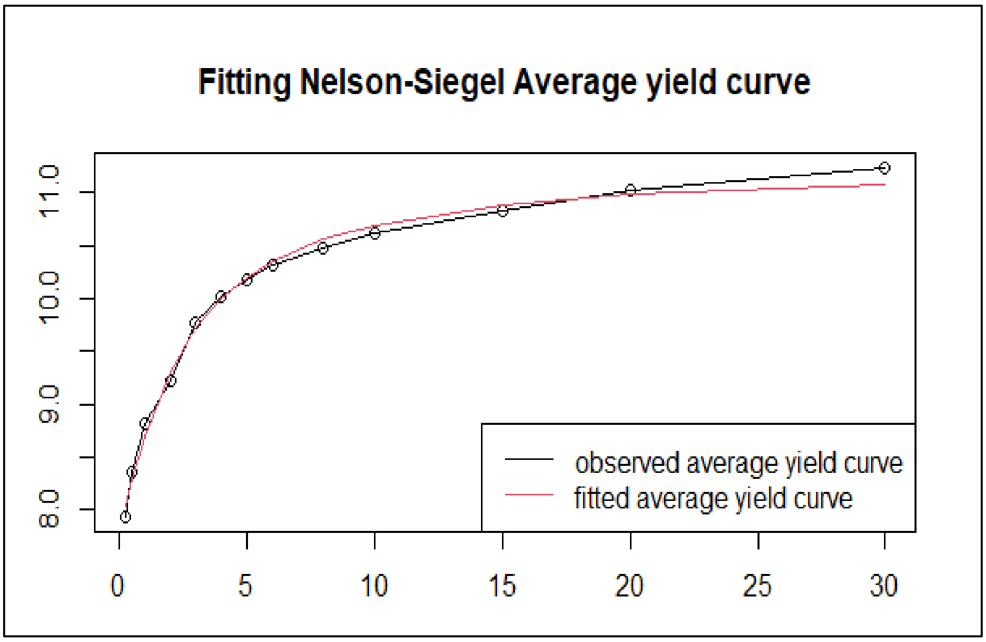


Figure 5.1: Graphical daily average yield curve output obtained using R function for the NS model.

Average yield data is represented by the y-axis and maturity data by the x-axis.

5.1.2 Nelson-Siegel-Svensson yield curve fit method.

As previously discussed under Section 3.2, the yield curve is fit using the four-factor model,

$$y_t(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1-\exp\left(-\frac{\tau}{\lambda_{1t}}\right)}{\left(\frac{\tau}{\lambda_{1t}}\right)}\right) + \beta_{3t}\left(\frac{1-\exp\left(-\frac{\tau}{\lambda_{1t}}\right)}{\left(\frac{\tau}{\lambda_{1t}}\right)} - \exp\left(-\frac{\tau}{\lambda_{1t}}\right)\right) +$$
$$\beta_{4t}\left(\frac{1-\exp\left(-\frac{\tau}{\lambda_{2t}}\right)}{\left(\frac{\tau}{\lambda_{2t}}\right)} - \exp\left(-\frac{\tau}{\lambda_{2t}}\right)\right)$$

Figure 5.2 shows the graphical yield curve output of the actual (data-based) and fitted (model-based) daily average yield curves of the four factor SV model.

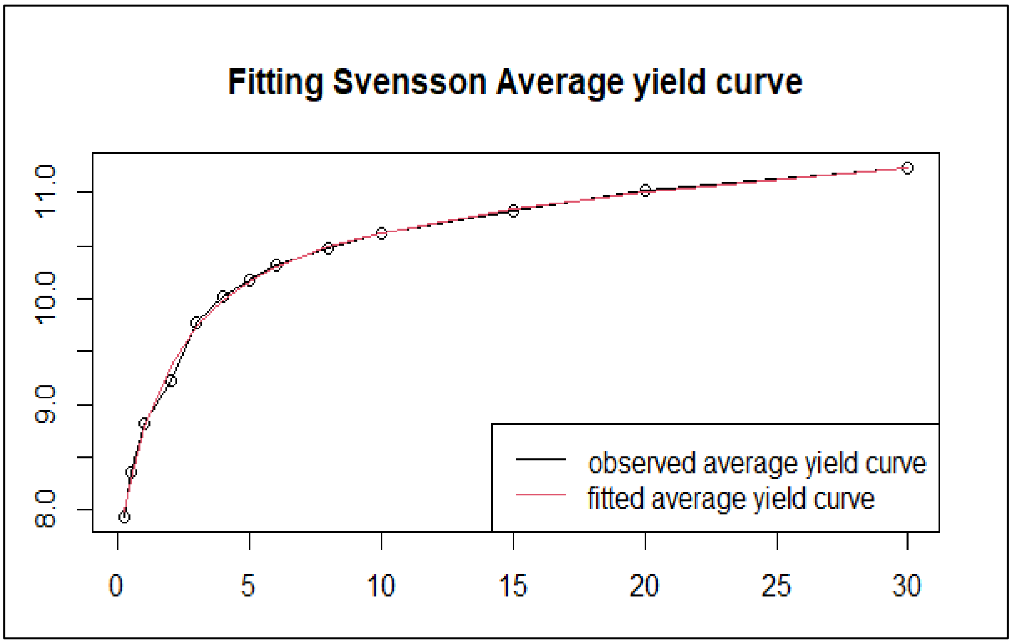


Figure 5.2: Graphical daily average yield curve output obtained using R function for the SV model.

Average yield data is represented by the y-axis and maturity data by the x-axis.

In the above graphical representations, of the two fitted models, it is clear that both yield curves are upward sloping and is therefore, a positive yield curve in which short-term debt securities have a lower yield than long-term debt securities. Looking at the two plots, it is also evident that, the SV model has a better fit (lower deviation between the observed yield curve and the fitted yield curve) compared to the NS model.

5.1.3 R^2 and RMSE

Table 5.1 Results: R^2 and RMSE values obtained for the two models using the R function for the entire daily data set.

	NS model	**SV model**
Coefficient of Determination (R^2)	0.9932533	0.9971331
Root Mean Squared Error (RMSE)	0.13971	0.0910723

Looking at the values of R^2 (rsq) obtained for the two models it is clear that both the Nelson Siegel model and the Svensson model have values close to 1; i.e., 0.9932533 and 0.9971331 respectively. In other words, 99.3% of the variation in the dependent variable (the yield for a given maturity) is explained by the independent variables in the Nelson Siegel model and, 99.7% of the variation in the dependent variable is explained by the independent variables in the Svensson model. Thus, in terms of the goodness of fit, Svensson model's performance is marginally superior.

Observing the figures obtained for RMSE, it is noted that the Svensson model has a lower RMSE compared to the Nelson Siegel Model (i.e., 0.0910723 < 0.13971); therefore, the Svensson model can be considered more accurate than the Nelson Siegel model. In other words, the residuals are less spread out and the data is more concentrated around the line of best fit in the Svensson model thus giving it a better fit.

5.1.4 Robustness Check

Analyzing further, Figures 5.3 to 5.7 show fitted values derived using the two models, on selected days during certain periods of impact due to exogenous factors. This was done to evaluate the robustness of the two models with respect to estimating the yield curve that prevailed during that particular period.

- **Impact of Easter Sunday Attacks – 21.04.2019**

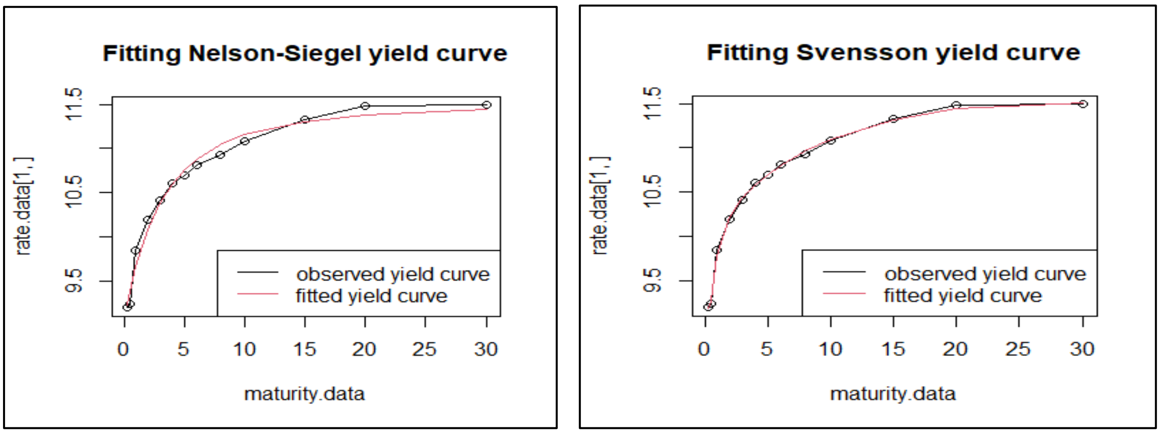


Figure 5.3: actual (data-based) and fitted (model-based) yield curves for NS & SV models as at 18.04.2019.

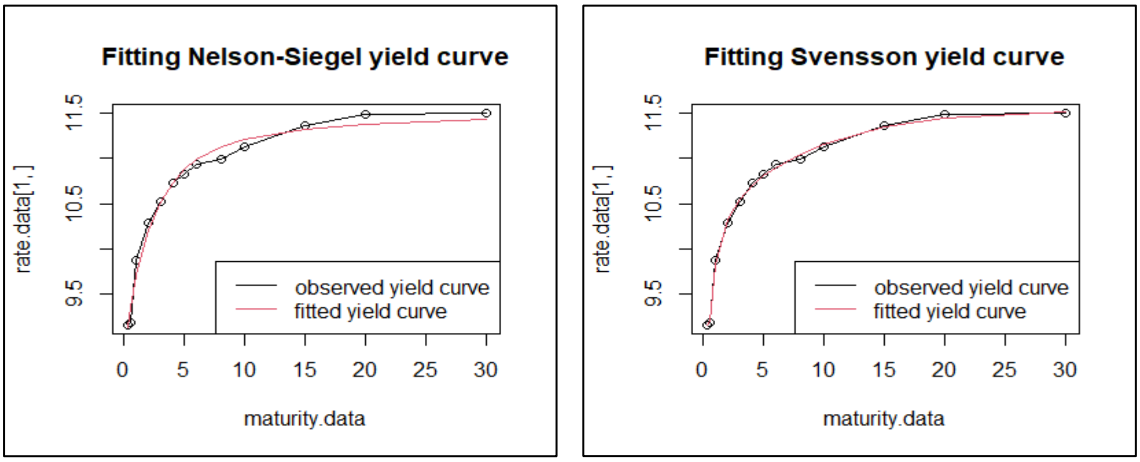
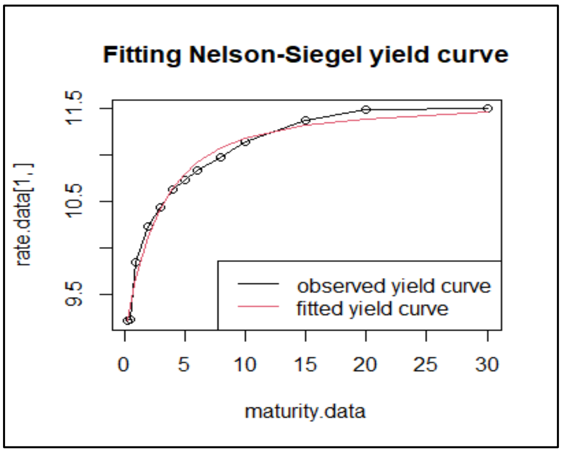


Figure 5.4: actual (data-based) and fitted (model-based) yield curves for NS & SV models as at 22.04.2019.



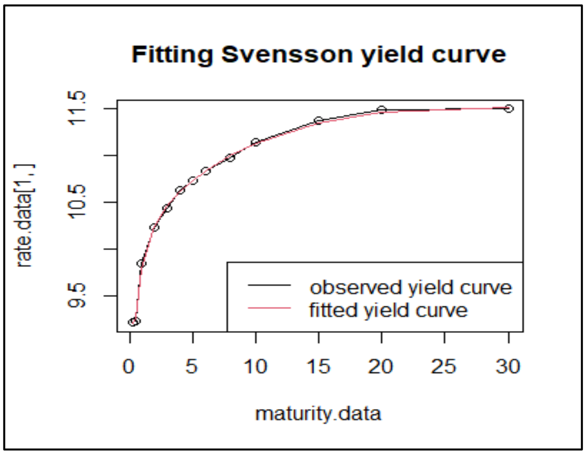


Figure 5.5: actual (data-based) and fitted (model-based) yield curves for NS & SV models as at 30.04.2019.

Table 5.2 Results: R^2 and RMSE values (Impact of Easter Sunday Attacks)

Date	Measure/Statistic	NS model	SV model
18.04.2019.	Coefficient of Determination (R^2)	0.9838381	0.9984745
	Root Mean Squared Error (RMSE)	0.09358107	0.02875067
22.04.2019.	Coefficient of Determination (R^2)	0.9858541	0.9990864
	Root Mean Squared Error (RMSE)	0.0883886	0.0224622
30.04.2019.	Coefficient of Determination (R^2)	0.9853253	0.9983262
	Root Mean Squared Error (RMSE)	0.09199251	0.03106853

There is no evidence of an immediate impact on government security yields as a result of the bomb attacks that happened on the 21st of April 2019. The date 22nd April 2019 was selected to evaluate any immediate impact of the attack on the bond market as 22nd is the first market day after the attack. 30th April 2019 was selected as it is the first month end after the attack and on some occasions more activity can be seen in the market on month end as financial institutions such as banks try to cover their targets for the month. The graphical outputs from 22nd April and 30th April are not significantly different from that of 18th April (before the attacks) output. However, it is apparent from the graphs that the SV model fits the data better compared to the NS model. This is further supported by the higher R^2 and lower RMSE values associated with the SV model for all three dates compared to the NS model.

- **Impact of COVID-19 Pandemic – March 2021 onwards.**

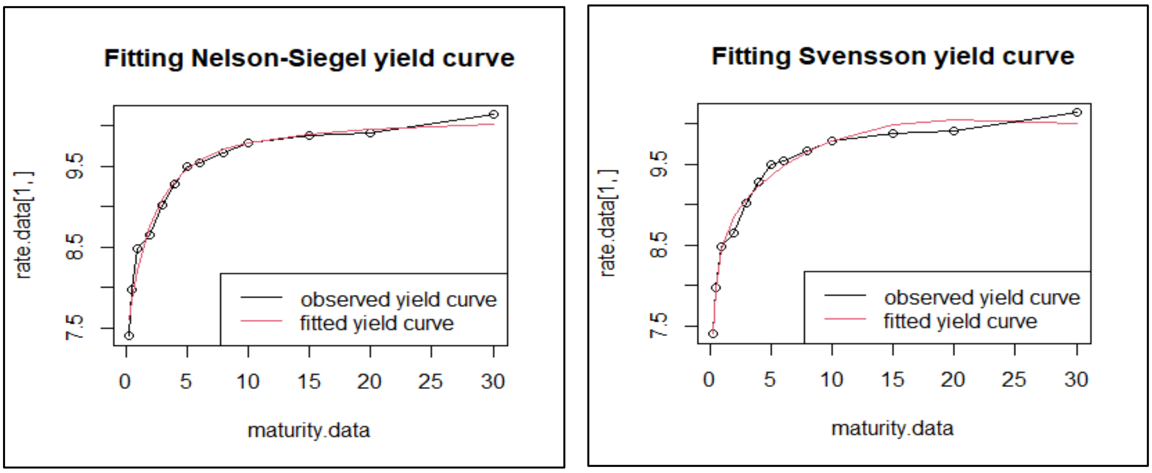


Figure 5.6: actual (data-based) and fitted (model-based) yield curves for NS & SV models as at 13.02.2020.

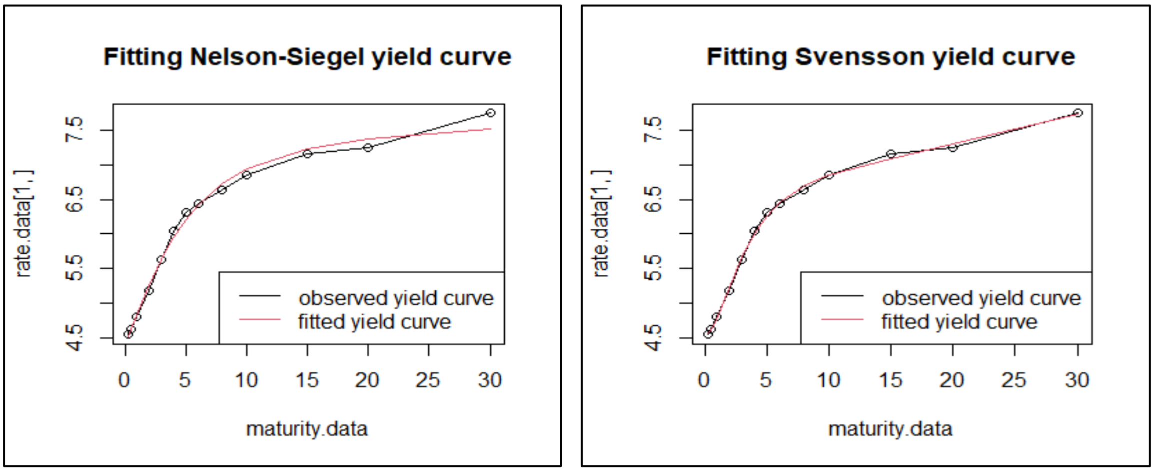


Figure 5.7: actual (data-based) and fitted (model-based) yield curves for NS & SV models as at 22.07.2020.

Table 5.3 Results: R^2 and RMSE values (Impact of COVID-19 Pandemic)

Date	Measure/Statistic	NS model	SV model
13.02.2020.	Coefficient of Determination (R^2)	0.9805898	0.9866292
	Root Mean Squared Error (RMSE)	0.1110062	0.09213199
22.07.2020.	Coefficient of Determination (R^2)	0.9916861	0.9986697
	Root Mean Squared Error (RMSE)	0.09257872	0.03703217

The spread of the COVID-19 pandemic severely affected near term growth prospects in Sri Lanka during the second quarter of 2020. The Monetary Board of the Central Bank of Sri Lanka reduced policy rates by a cumulative of 250 basis points during the year up to mid July 2020 in order to induce reductions in market lending rates and reinforce support to COVID-19 hit businesses as well as to the broader economy. As a result, treasury rates dipped significantly, with the 364-day bill dipping below 5.00% for the first time in history in July 2020. In figures 5.6 to 5.7, a clear parallel shift downwards of the yield curve is visible (i.e., a change in the level of the yield curve) when outputs from Feb 2020 and July 2020 are compared. A date from Feb 2020 was selected as this was before the pandemic started spreading in Sri Lanka (before the lockdown), and a date from July 2020 was selected (after the two-to-three-month lockdown) to assess the medium-term impact of the pandemic on the government securities market. There is also a notable decrease in the slope of the yield curve in the short and medium terms, as the yield curve output from July 2020 depicts a more flatter yield curve in the short to medium terms compared to the steeper yield curve observed in Feb 2020 during the same short to medium term periods. Thus, we can say both models are robust models as both models have highlighted the impact of the COVID-19 pandemic on the government securities market accurately. However, the SV model fits the data better compared to the NS model, as visible from Figure 5.7. This result is reinforced by the higher R^2 and lower RMSE values associated with the SV model for both dates compared to the NS model.

5.1.5 Validity check

An area which questioned the validity of the outputs obtained under the two models, was the difference in the number of data points used for Part 1 (Estimating the current term structure of interest rates) and Part 2 (Forecasting the term structure of interest rates) of the study.

To clear any doubts, the same outputs for Part 1 of the study was obtained, using weekly data (296 weekly data points) instead of daily data (1356 daily data points), so that both Part 1 and Part 2 outputs are based on weekly data.

Figure 5.8 shows the graphical yield curve output of the actual (data-based) and fitted (model-based) weekly average yield curves of the NS model & Figure 5.9 shows the graphical yield curve output of the actual (data-based) and fitted (model-based) weekly average yield curves of the SV model.

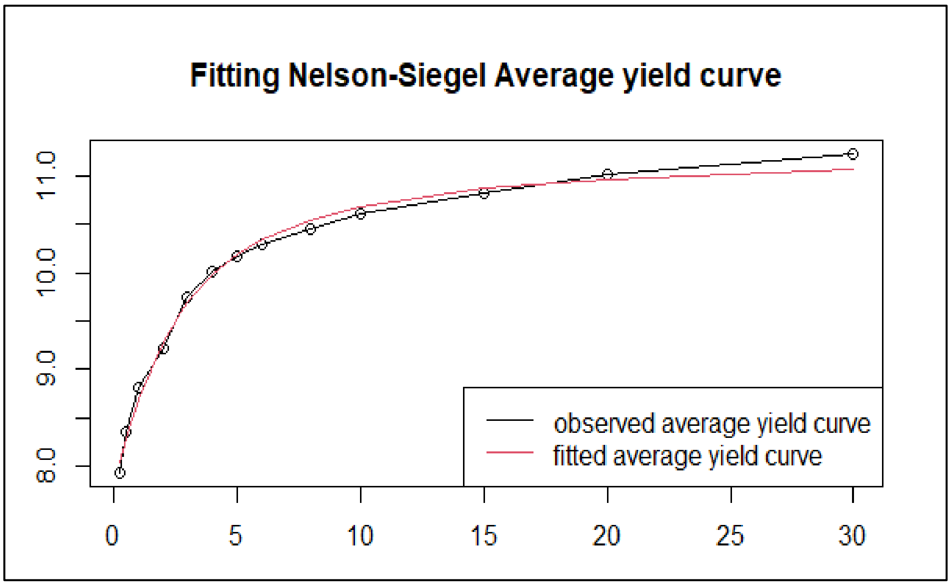


Figure 5.8: Graphical weekly average yield curve output obtained using R function for the NS model.

Average yield data is represented by the y-axis and maturity data by the x-axis.

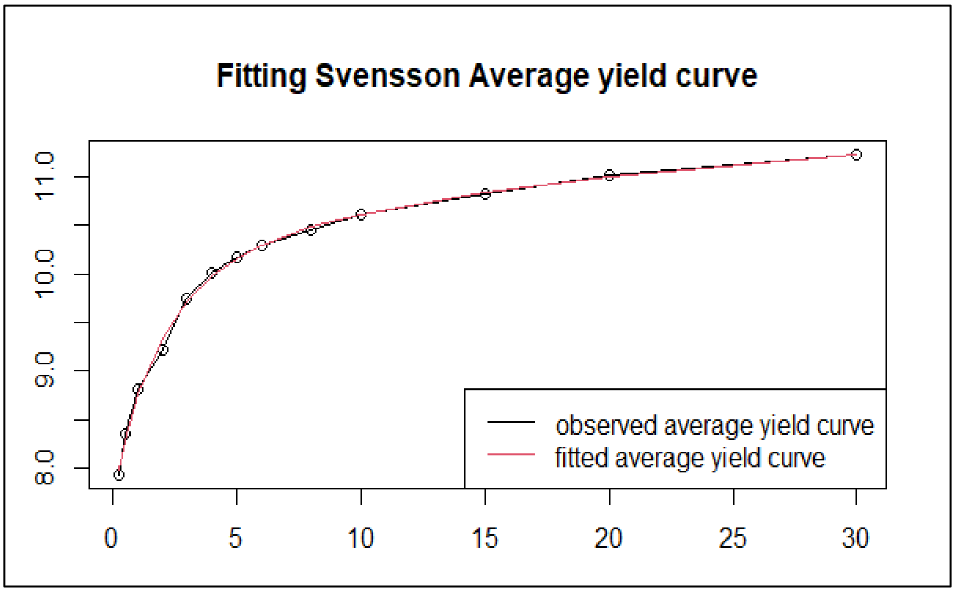


Figure 5.9: Graphical weekly average yield curve output obtained using R function for the SV model.

Average yield data is represented by the y-axis and maturity data by the x-axis.

Table 5.4 Results: R^2 and RMSE values obtained for the two models using the R function for the entire weekly data set.

	NS model	**SV model**
Coefficient of Determination (R^2)	0.9932124	0.9971219
Root Mean Squared Error (RMSE)	0.1404662	0.09146724

Even with weekly data, it can be clearly seen that SV model's graphical output has a better fit compared to the graphical output of the NS model. Despite the reduction in the data points, SV model outperformed the NS model in terms of both R^2 (0.9971219 [SV] > 0.9932124 [NS]) and RMSE (0.09146724 [SV] < 0.1404662 [NS]) as well. Therefore, SV model remains the more applicable model for Part 1 ((Estimating the current term structure of interest rates) of the study, even under weekly data. Weekly data was only used for 5.1.5 Validity check in Part 1. All other outputs obtained in Part 1 are based on daily data.

5.1.6 Parameter Estimation

The figures 5.10 to 5.11 show the behavior of the estimated parameters throughout the sample period for the NS model and SV model, respectively.

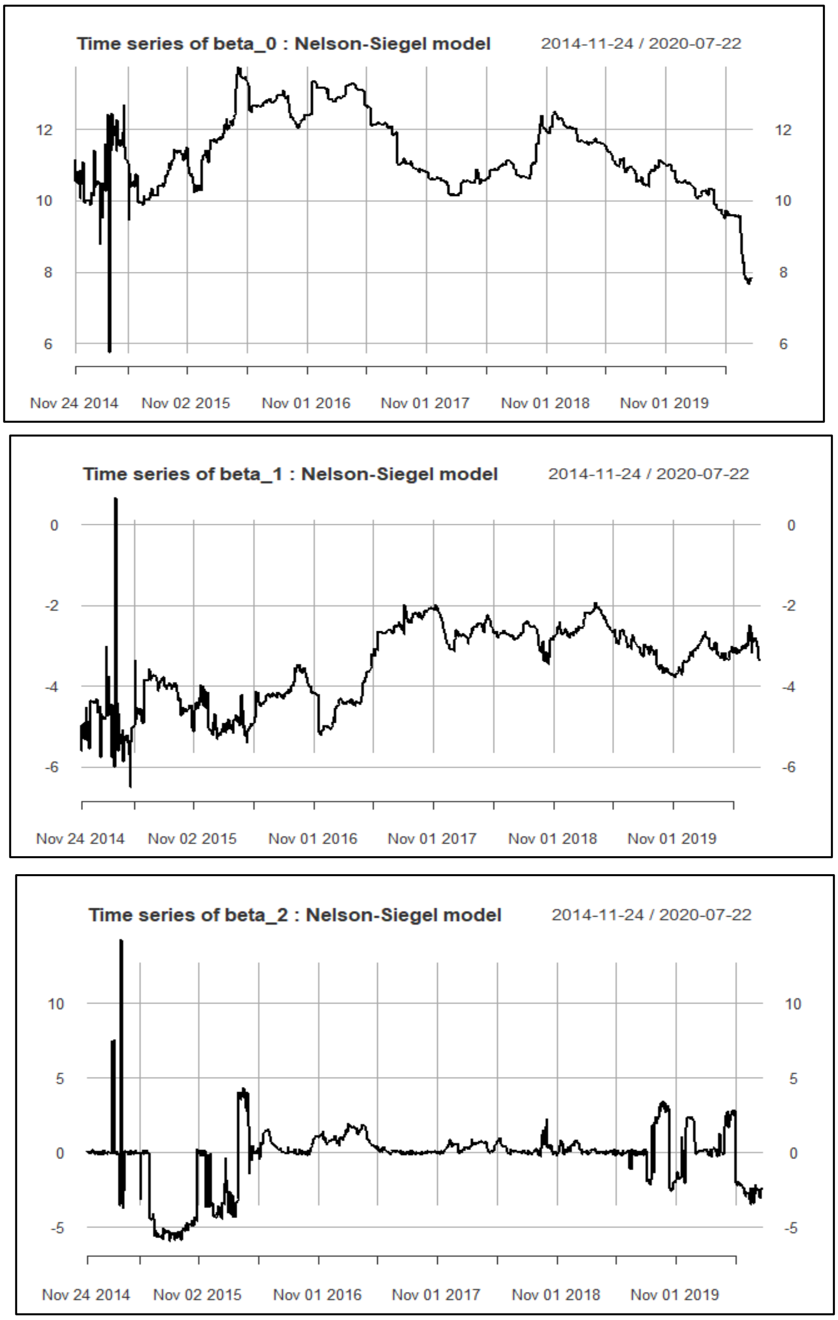


Figure 5.10: Time series of estimated parameters β_0, β_1 & β_2 of the NS model

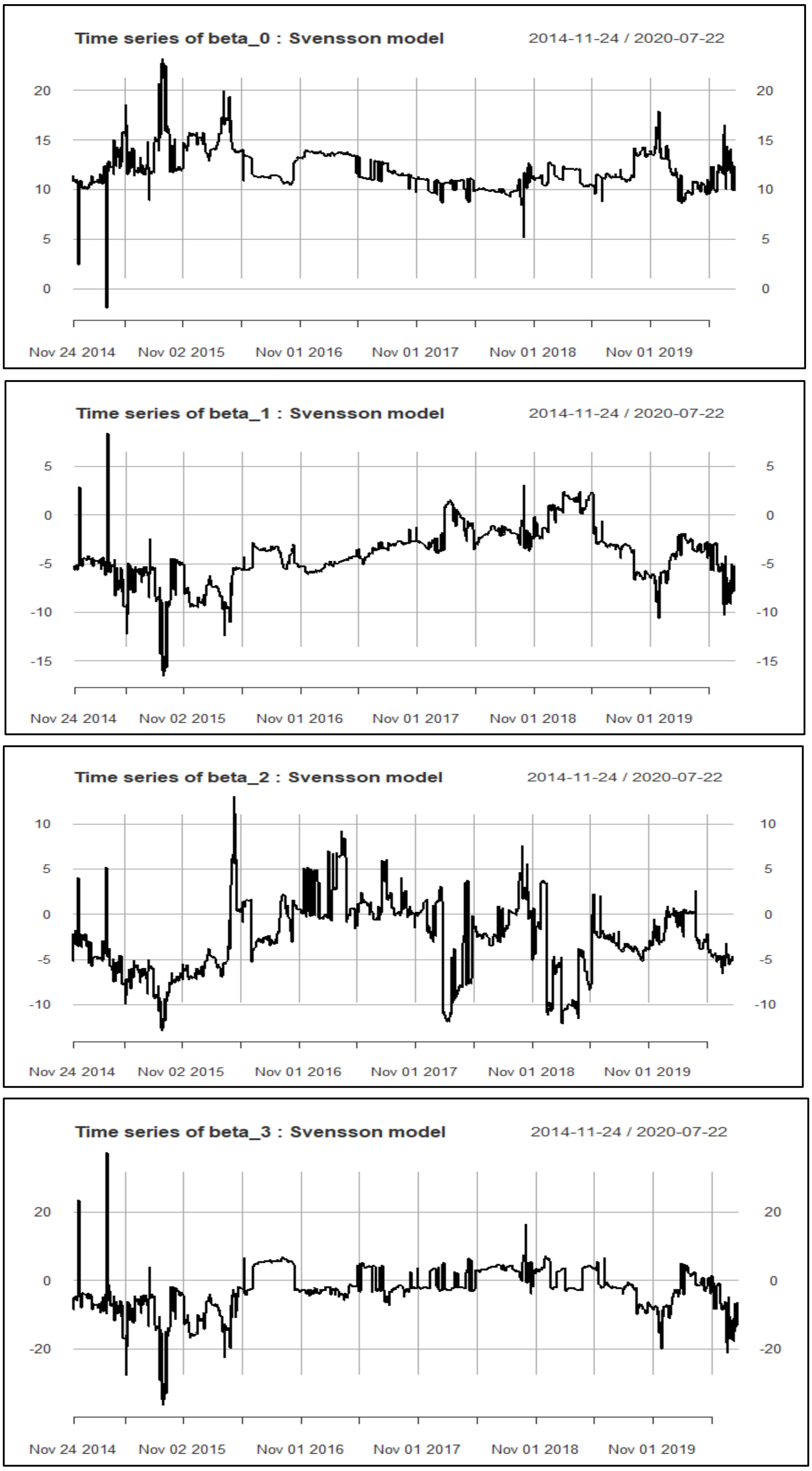


Figure 5.11: Time series of estimated parameters $\beta_0, \beta_1,\ \beta_2$ & β_3 of the SV model

5.2 Part 2: Forecasting the term structure of interest rates (Results)

As mentioned under Section 3.3, the "YieldCurve" R package by Guirreri (2015) along with other functions of R, is used to carry out the forecasting study design (explained above) and evaluate the forecasting performance of the two models; NS model and SV model, respectively.

5.2.1 Nelson-Siegel yield curve- using the methodology presented in Diebold and Li, 2006:

$$y_t(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau}\right) + \beta_{3t}\left(\frac{1-e^{-\lambda_t\tau}}{\lambda_t\tau} - e^{-\lambda_t\tau}\right)$$

5.2.2 Nelson-Siegel-Svensson yield curve.

$$y_t(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1-\exp\left(-\frac{\tau}{\lambda_{1t}}\right)}{\left(\frac{\tau}{\lambda_{1t}}\right)}\right) + \beta_{3t}\left(\frac{1-\exp\left(-\frac{\tau}{\lambda_{1t}}\right)}{\left(\frac{\tau}{\lambda_{1t}}\right)} - \exp\left(-\frac{\tau}{\lambda_{1t}}\right)\right) +$$
$$\beta_{4t}\left(\frac{1-\exp\left(-\frac{\tau}{\lambda_{2t}}\right)}{\left(\frac{\tau}{\lambda_{2t}}\right)} - \exp\left(-\frac{\tau}{\lambda_{2t}}\right)\right)$$

5.2.3 Sample Autocorrelation and Results

The sample autocorrelation of the three factors as estimated by the NS model, and the sample autocorrelation of the four factors as estimated by the SV model, is illustrated in Figures 5.10 & 5.11.

As can be seen, the presence of significant autocorrelation in the first lags of all the series in both the models, validates the proposal to use an autoregressive process to forecast the factors.

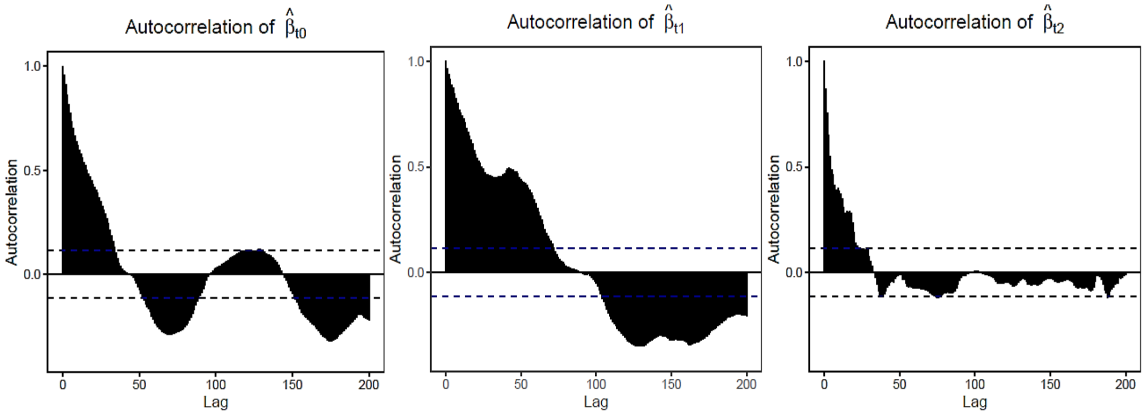


Figure 5.12: Sample autocorrelations of the estimated β-vector of NS Model with lags in weeks, plotted with a 95%-confidence interval.

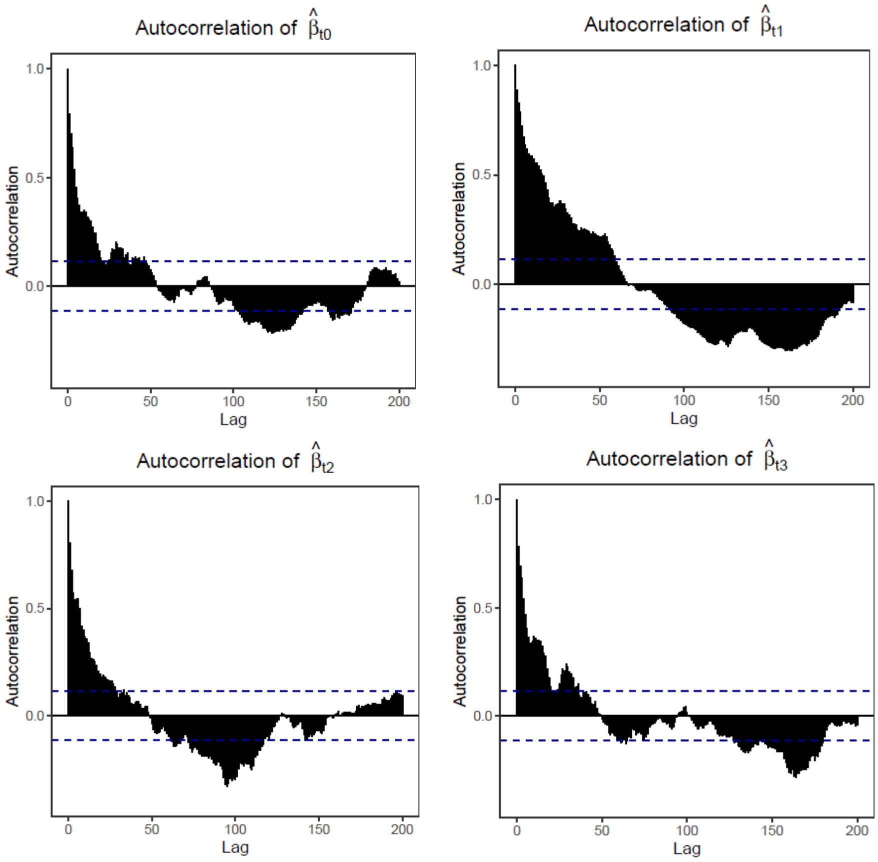


Figure 5.13: Sample autocorrelations of the estimated β-vector of SV Model with lags in weeks, plotted with a 95%-confidence interval.

In order to forecast the yield curves under each model, the factors of each model are forecasted as univariate AR (1) processes. The three factors of the NS model β_{1t} , β_{2t} , β_{3t} & the four factors of the SV model β_{1t} , β_{2t} , β_{3t} and β_{4t} are forecasted applying the univariate AR (1) model.

In order to set a fixed value for λ_t in the forecasting procedure, the mean of all estimated $\lambda_t s$ is calculated (Arbia and Di Marcantonio ,2015; Reinicke,2019).
The forecasts are made iteratively from 1-step to h-steps ahead from the end of the training sample of the available data set. Predictions for different forecast horizons can be conducted, using this setup.

The $\boldsymbol{\beta}$-vector for both the NS model and SV model was forecasted applying the AR (1) process. Forecasting was carried out using forecast horizons of h=4 and h=26 weeks for both models.

Following the forecasting study design of Reinicke (2019), the impact of varying the size of the training sample window, on the forecasting performance was evaluated for both models. Thus, the Figure 5.12 portrays the variation in the RMSE caused by changing the length *l*, of the rolling window of the training sample, for a particular forecast. The figures display the mean RMSE arising from forecasting subsequent models with the relevant fixed window length, *l*.

The variation in the RMSE in the design setup of 50 to 150 periods in the training sample for h=4, is relatively insignificant for both models as the respective RMSE line plots of the NS model as well as the SV model are almost flat throughout the changing number of training datasets.

In the design setup of 50 to 200 periods in the training sample for h=26, significant variation in the RMSE is noted in the SV model compared to the NS model. Thus, the SV model shows more sensitivity to the training sample length as the RMSE of the SV model tends to increase as the length of the training data is increased.
Boxplots representing the mean RMSE of forecasts with rolling windows, is used to evaluate the forecasting performance of the two models, as displayed in Figure 5.13.

For the short forecast horizon of h=4, one can see that yield curves from NS model are predicted more accurately given the comparatively lower RMSE levels. However, on the other hand, the SV model shows less variation in the RMSE (given the lower range of the SV box plot) compared to the NS model.

For the long forecast horizon h=26, RMSE depicts a performance difference between the forecasts of NS model and SV model as the yield curves from the NS model are predicted better (lower RMSE levels of NS model) and also with less variation in RMSE compared to the SV model (given the smaller range of the NS box plot)

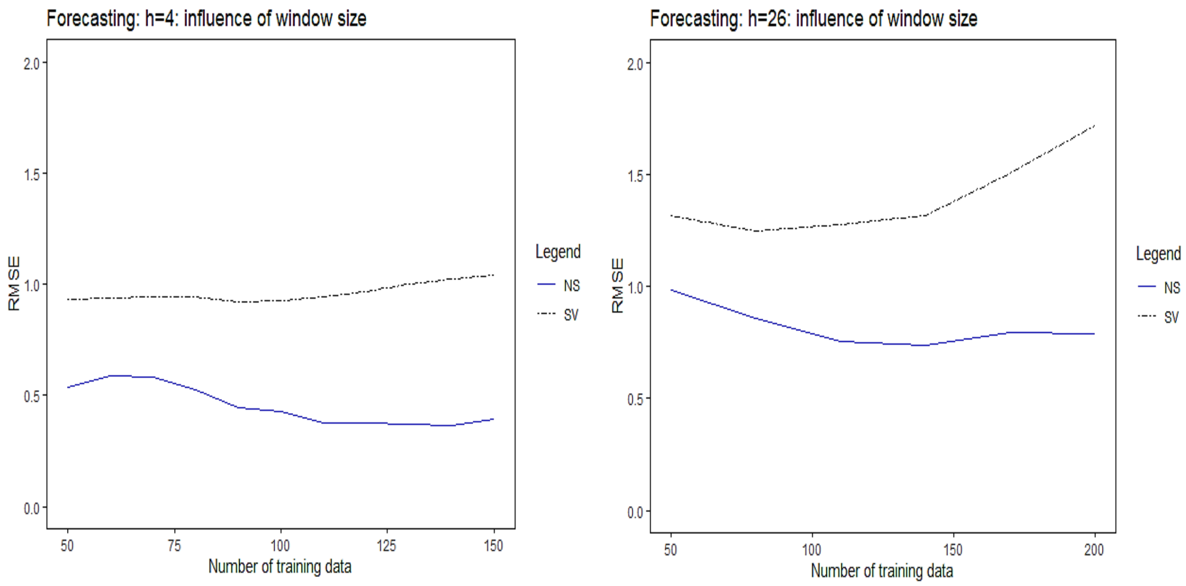


Figure 5.14: Influence of window size on RMSE using the NS model and SV model for multiple steps ahead forecasts of Sri Lankan Treasury securities data.

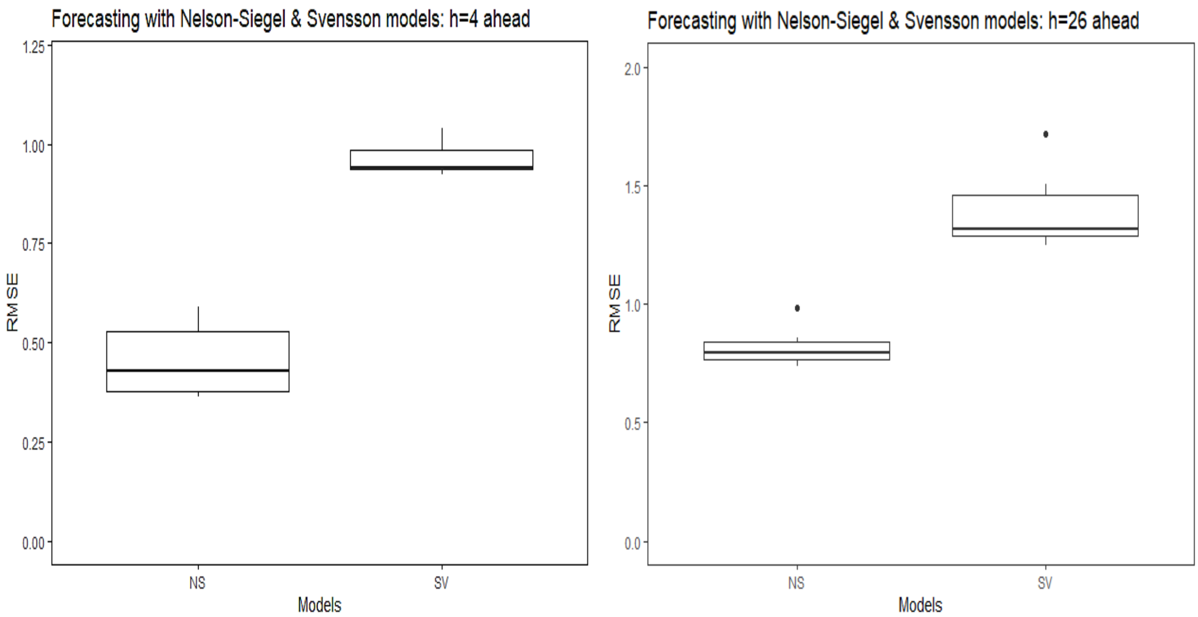


Figure 5.15: Boxplots of RMSE using the NS model and SV model for multiple steps ahead forecast.

Forecasts were conducted with 50 to 150 training periods for h = 4 and 50 to 200 training periods for h = 26.

Summarizing the overall performance of each model under each part of the study, it can be seen from the results, that SV model is the more suitable model for estimating the current term structure of interest rates (Part 1) given the more fitting line visible in the graphical output, higher R^2 value, and lower RMSE value derived from the analysis carried out on the entire data set. This is further supported by the results obtained in the Robustness Check section, where the performance of the two models, under two selected crisis periods (when the country was facing exogenous shocks) is assessed; the finer graphical outputs, higher R^2 values and lower RMSE values of the SV model compared to the NS model, during these critical periods, further marks the SV model as the more robust model. On the other hand, opposite results are derived in the forecasting section of the yield curve (Part 2); that is, the NS model displayed superior forecasting performance compared to the SV model, given the lower RMSE values that were visible in both the short-term forecasting horizon and long-term forecasting horizon. The possible reasons for the contrasting results in the two parts of the study, is addressed in the next section.

CHAPTER 6: CONCLUSION, LIMITATIONS & RECOMMENDATIONS

6.1 Conclusion

This thesis assessed the soundness and validity of two Nelson Siegel class parametric models namely the Nelson-Siegel model, using the methodology presented in Diebold and Li, 2006 (NS model) and the Nelson-Siegel-Svensson model ,1994 (SV model). These two models were tested on directly observed secondary market yields of Sri Lankan government securities. The study was based on two main objectives; First objective was to find out the most applicable model for estimating the current yield curve and the second objective was to choose the more suitable model for forecasting the yield curve.

In the estimation part of the yield curve, it was found that, the SV model fits the data better than the NS model as was visible from the graphical outputs. This was further supported by the higher R^2 and lower RMSE associated with the SV model compared to the NS model.

On the forecasting end of the yield curve, opposite results were noted. In the shorter forecasting horizon (h=4), within the rolling window forecasting design, the NS model performed considerably better with lower overall RMSE values compared to the SV model. However, in terms of variation in RMSE throughout the rolling window movement, SV model showed lower variation compared to the NS model, for the same forecasting horizon. For the longer forecast horizon (h=26) NS model outperformed the SV model in terms of better predictions (lower RMSE) as well as less variation.

The weak prediction ability of the SV model could be due to the existence of confounding effects in the curvature factors of the Svensson model. Confounding effects in the curvature factors of the Svensson is indicated by positive correlations between λ_1 and λ_2 and negative correlations between β_3 and β_4 (Wahlstrom, Paraschiv, and Schurle (2021)).

The higher RMSE levels associated with the SV model's forecasting performance could also be due to fixing λ_1 and λ_2 in the forecasting procedure, as not fixing the value λ_1 and λ_2 generally leads to a better fit of the yield curve since it allows the location of humps or troughs in the curve to change over time (Diebold & Rudebusch, 2013). In the estimation part of the study parameter λ_t is not fixed but is estimated at every step in t, further explaining the relatively better RMSE figures associated with the SV model in the estimation part of the study.

Overall, SV model is the better choice for estimating the current yield curve, while NS model is the more applicable model for forecasting the future yield curve. Thus, going back to the two initial hypothesis scenarios of the research (Chapter 2: Section 2.2 Hypothesis Development), we are rejecting the null hypothesis in both the scenarios, as there is a significant difference in the performance of the two models in terms of estimating the current term structure of interest rates (as SV model is the better choice) and there is also a significant difference in the forecasting performance of the two models (as NS model is the better one).

6.2 Limitations & Recommendations for future work

In the Sri Lankan government securities market, majority of the Treasury bonds fall into the short to medium term maturity buckets. Looking at the entire list of bonds issued since 1997, 94% of them had maturities less than or equal to 10 years (Asian Development Bank Consultant's Report, (2016). Understandably, there have only been a small number of long-term bond issues with maturities of more than 10 years. Thus, due to the limited number of long-term bonds available for trading in the secondary market, liquidity and price discovery for such longer term maturities decreases.

Secondary market yields of Treasury bonds and bills are used in this research. However, due to the lack of transactions in the secondary market specially at longer maturities, most secondary market yields are simply bid and ask quotes from the primary dealers and consequently are not actual transaction yields. Therefore, the secondary market yields are not very reliable and do not provide a sound risk-free yield curve across all maturities.

For the Sri Lankan yield curves, available terms of maturities are less, and they are unevenly spaced specially at longer maturities. This could negatively impact the forecasting performance. For instance, RMSE which is used to measure forecasting performance in this study, is sensitive to the available number of support points and the spacing between them. Hence the estimates of RMSE might not give a true picture of the forecasting performance of the models.

Out of the scope of this thesis, is whether forecasting performance is improved by extending the AR model to a higher order of lags (Reinicke, 2019). Fitting and forecasting the yield curve using other different extensions of the Nelson-Siegel model could also be explored (Michiel De Pooter, 2007). How the two models would perform with respect to different regions of the maturity spectrum, would be another interesting subject to evaluate.

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APPENDICES

Appendix A: Input Files

Directly observed secondary market yields of Sri Lankan government securities.

Full Data File (1356 daily data points)

Date_new	X3M	X6M	X1Y	X2Y	X3Y	X4Y	X5Y	X6Y	X8Y	X10Y	X15Y	X20Y	X30Y
11/24/2014	5.65	5.84	6.04	6.34	6.98	7.22	7.36	7.71	8.12	8.21	8.86	9.54	9.72
11/25/2014	5.65	5.82	6.03	6.32	7.02	7.23	7.4	7.73	8.15	8.24	8.87	9.54	9.72
11/26/2014	5.58	5.77	5.97	6.34	6.98	7.19	7.35	7.66	8.07	8.16	8.95	9.84	9.98
11/27/2014	5.64	5.82	6.04	6.33	7.02	7.23	7.41	7.74	8.16	8.24	8.87	9.54	9.72
11/28/2014	5.71	5.85	6.06	6.33	7.06	7.26	7.44	7.8	8.24	8.32	8.88	9.5	9.77
12/1/2014	5.65	5.95	6.04	6.37	7.03	7.25	7.42	7.8	8.19	8.27	8.87	9.54	9.72
12/2/2014	5.65	5.84	6.06	6.33	7	7.24	7.42	7.82	8.21	8.29	8.9	9.58	9.72
12/3/2014	5.65	5.81	6.05	6.35	7.04	7.25	7.43	7.8	8.2	8.29	8.87	9.54	9.72
12/4/2014	5.57	5.76	5.98	6.43	7.05	7.25	7.41	7.79	8.2	8.28	8.95	9.84	9.87
12/5/2014	5.81	5.93	6.12	6.35	7.06	7.25	7.44	7.79	8.21	8.29	8.86	9.5	9.77
12/8/2014	5.68	5.85	6.08	6.38	7.03	7.25	7.42	7.81	8.2	8.28	8.85	9.55	9.71
12/9/2014	5.67	5.93	6.04	6.35	7.04	7.25	7.43	7.8	8.19	8.28	8.85	9.55	9.71
12/10/2014	5.57	5.76	5.98	6.36	7.06	7.24	7.4	7.78	8.16	8.25	8.78	9.57	9.61
12/11/2014	5.66	5.82	6.04	6.32	7.04	7.24	7.43	7.8	8.17	8.27	8.72	9.23	9.51
12/12/2014	5.53	5.76	5.98	6.43	7.03	7.24	7.38	7.8	8.19	8.27	8.95	9.88	9.87
12/15/2014	5.63	5.84	6.04	6.31	6.99	7.22	7.38	7.8	8.19	8.29	8.88	9.58	9.71
12/16/2014	5.63	5.82	6.03	6.32	7	7.21	7.35	7.75	8.14	8.25	8.85	9.55	9.71
12/17/2014	5.65	5.83	6.05	6.36	7.01	7.22	7.38	7.78	8.16	8.25	8.85	9.55	9.71

12/18/2014	5.68	5.87	6.05	6.32	7.04	7.22	7.42	7.76	8.18	8.26	8.86	9.39	9.72
12/19/2014	5.61	5.78	5.97	6.3	6.94	7.11	7.22	7.59	8.11	8.22	9.01	9.66	9.94
12/22/2014	5.69	5.86	6.04	6.25	6.97	7.19	7.28	7.61	8.08	8.19	8.62	9.06	9.42
12/23/2014	5.67	5.85	6.04	6.24	6.95	7.13	7.23	7.56	7.97	8.07	8.59	9.09	9.28
12/24/2014	5.71	5.86	6.04	6.24	6.94	7.13	7.23	7.56	7.96	8.06	8.59	9.09	9.27
12/26/2014	5.7	5.86	6.04	6.23	6.94	7.13	7.23	7.56	7.95	8.04	8.59	9.15	9.27
12/29/2014	5.73	5.86	6.05	6.22	6.94	7.14	7.24	7.55	7.93	8.02	8.59	9.14	9.27
12/30/2014	5.71	5.85	6.04	6.22	6.94	7.14	7.24	7.54	7.93	8.01	8.58	9.14	9.27
12/31/2014	5.72	5.86	6.04	6.22	6.94	7.14	7.26	7.57	7.91	7.99	8.58	9.15	9.27
1/1/2015	5.72	5.85	6.04	6.21	6.93	7.14	7.25	7.51	7.9	7.99	8.58	9.14	9.27
1/2/2015	5.72	5.85	6.04	6.21	6.93	7.13	7.24	7.5	7.9	7.99	8.58	9.14	9.27
1/6/2015	5.74	5.86	6.05	6.22	6.95	7.14	7.26	7.55	7.92	7.99	8.58	9.14	9.27
1/7/2015	5.74	5.86	6.04	6.22	6.96	7.14	7.27	7.5	7.92	8	8.59	9.1	9.27
1/8/2015	5.73	5.85	6.03	6.22	6.96	7.15	7.29	7.52	7.91	7.99	8.6	9.18	9.27
1/9/2015	5.72	5.85	6.03	6.24	7.02	7.25	7.39	7.63	7.99	8.07	8.6	9.18	9.27
1/12/2015	5.72	5.85	6.03	6.32	7.15	7.39	7.55	7.8	8.18	8.29	8.86	9.42	9.61
1/13/2015	5.74	5.87	6.05	6.33	7.21	7.43	7.61	7.86	8.2	8.32	8.86	9.43	9.61
1/16/2015	5.78	5.91	6.09	6.33	7.21	7.37	7.67	7.87	8.2	8.34	8.94	9.42	9.61
1/19/2015	5.75	5.89	6.07	6.23	7.08	7.25	7.44	7.68	8.01	8.1	8.74	9.32	9.44
1/20/2015	5.76	5.89	6.08	6.19	7.1	7.31	7.47	7.68	7.94	8.01	8.69	9.32	9.44
1/21/2015	5.77	5.89	6.08	6.24	7.13	7.32	7.5	7.67	7.95	8.02	8.71	9.34	9.48
1/22/2015	5.77	5.89	6.08	6.26	7.1	7.3	7.48	7.67	7.92	7.98	8.7	9.35	9.48
1/23/2015	5.74	5.86	6.05	5.95	7.07	7.21	7.38	7.59	7.85	7.95	8.97	9.76	9.98
1/26/2015	5.78	5.9	6.09	6.22	7.04	7.22	7.35	7.53	7.85	7.95	8.7	9.34	9.48
1/27/2015	5.79	5.9	6.08	6.23	7.02	7.2	7.29	7.53	7.82	7.95	8.7	9.33	9.48
1/28/2015	5.79	5.9	6.09	6.22	7	7.18	7.28	7.51	7.8	7.93	8.7	9.33	9.48

1/29/2015	5.79	5.91	6.09	6.22	6.99	7.17	7.28	7.5	7.82	7.93	8.7	9.33	9.48
1/30/2015	5.79	5.91	6.1	6.25	7	7.13	7.25	7.45	7.81	7.94	8.7	9.34	9.48
2/2/2015	5.79	5.91	6.1	6.24	7.01	7.13	7.24	7.46	7.81	7.95	8.7	9.34	9.48
2/5/2015	5.79	5.9	6.09	6.24	7.02	7.14	7.25	7.46	7.82	7.95	8.7	9.33	9.48
2/6/2015	5.79	5.9	6.09	6.27	7.03	7.15	7.26	7.48	7.82	7.95	8.7	9.33	9.48
2/9/2015	5.8	5.92	6.08	6.25	7.04	7.15	7.26	7.47	7.84	7.98	8.83	9.5	9.65
2/10/2015	5.79	5.9	6.08	6.26	7.04	7.14	7.26	7.49	7.85	7.99	8.7	9.33	9.48
2/11/2015	5.79	5.91	6.08	6.29	7.04	7.15	7.27	7.49	7.85	7.97	8.7	9.33	9.48
2/12/2015	5.84	5.94	6.11	6.3	7.06	7.16	7.27	7.49	7.85	7.97	8.7	9.33	9.48
2/13/2015	5.85	5.96	6.12	6.26	7.05	7.14	7.26	7.5	7.86	8	8.7	9.33	9.48
2/16/2015	5.81	5.93	6.08	6.3	7.04	7.15	7.25	7.48	7.84	7.98	8.89	9.77	9.98
2/18/2015	5.86	5.97	6.12	6.29	7.06	7.18	7.27	7.49	7.84	7.99	8.7	9.33	9.48
2/19/2015	5.9	6.03	6.17	6.32	7.09	7.24	7.32	7.55	7.9	8.04	8.7	9.34	9.48
2/20/2015	5.88	6.03	6.17	6.26	7.09	7.2	7.28	7.51	7.89	8.03	8.72	9.34	9.48
2/23/2015	5.9	6.04	6.18	6.32	7.14	7.3	7.38	7.63	7.98	8.1	8.73	9.34	9.48
2/24/2015	5.91	6.05	6.19	6.36	7.16	7.34	7.43	7.66	8	8.13	8.73	9.34	9.48
2/25/2015	5.9	6.02	6.15	6.29	7.08	7.25	7.36	7.56	7.95	8.07	8.91	9.8	10.03
2/26/2015	5.92	6.07	6.21	6.35	7.09	7.32	7.43	7.65	7.97	8.1	8.73	9.34	9.45
2/27/2015	5.88	6.05	6.17	6.33	7.1	7.27	7.4	7.59	7.95	8.09	8.89	9.77	10.03
3/2/2015	6.06	6.19	6.34	6.57	7.36	7.64	7.73	8.05	8.53	8.71	9.25	10.1	10.51
3/3/2015	6.16	6.32	6.5	6.65	7.42	7.65	7.8	8.17	8.63	8.8	9.36	9.8	10.14
3/4/2015	6.47	6.6	6.75	6.77	7.43	7.7	7.76	8.08	8.67	8.94	9.82	10.43	10.99
3/6/2015	6.51	6.6	6.75	6.82	7.48	7.74	7.88	8.05	8.73	9.03	9.76	10.47	10.99
3/9/2015	6.52	6.62	6.79	6.89	7.59	7.81	7.92	8.09	8.75	9.07	9.88	10.55	10.99
3/10/2015	6.61	6.7	6.85	6.94	7.64	7.84	7.97	8.15	8.75	9.04	9.91	10.43	10.14
3/11/2015	6.68	6.78	6.96	6.99	7.77	7.9	8.2	8.36	8.93	9.14	9.68	10.06	10.15

3/12/2015	6.85	6.94	7.14	7.11	7.84	8.09	8.33	8.52	9.04	9.24	9.75	10.04	10.57
3/13/2015	6.83	6.92	7.12	7.34	8.01	8.27	8.47	8.53	9.21	9.47	10.04	10.51	11.07
3/16/2015	7	7.12	7.3	7.34	8.01	8.32	8.33	8.55	9.39	9.56	10.11	10.42	10.8
3/17/2015	6.99	7.11	7.25	7.42	8.13	8.38	8.53	8.65	9.44	9.67	10.08	10.82	11.27
3/18/2015	6.98	7.12	7.25	7.48	8.19	8.52	8.62	8.79	9.58	9.79	10.07	10.64	10.97
3/19/2015	6.91	7.01	7.18	7.47	8.29	8.42	8.65	8.82	9.16	9.71	10.1	10.67	11.21
3/20/2015	6.84	6.94	7.09	7.44	8.23	8.4	8.61	8.8	9.15	9.72	10.12	10.67	11.2
3/23/2015	6.83	6.92	7.05	7.48	8.28	8.39	8.68	8.79	9.16	9.79	10.08	10.66	11.17
3/24/2015	6.81	6.91	7.05	7.47	8.31	8.5	8.71	8.92	9.21	9.8	10.07	10.66	11.17
3/25/2015	6.79	6.88	7.03	7.51	8.31	8.53	8.75	8.93	9.25	9.71	10.14	10.68	11.2
3/26/2015	6.69	6.8	6.96	7.25	8.23	8.42	8.59	8.81	9.14	9.71	10.08	10.66	11.19
3/27/2015	6.7	6.8	6.95	7.27	8.27	8.48	8.66	8.84	9.19	9.82	10.13	10.65	11.19
3/30/2015	6.67	6.78	6.96	7.24	8.25	8.49	8.64	8.84	9.19	9.81	10.14	10.55	11.19
3/31/2015	6.62	6.74	6.89	7.18	8.29	8.53	8.74	8.89	9.21	9.84	10.14	10.54	11.19
4/1/2015	6.6	6.71	6.86	7.14	8.27	8.52	8.67	8.91	9.21	9.82	10.13	10.45	10.85
4/2/2015	6.59	6.71	6.85	7.07	8.25	8.46	8.72	8.93	9.21	9.85	10.18	10.68	11.6
4/6/2015	6.59	6.7	6.84	7.24	8.26	8.5	8.71	8.96	9.24	9.84	10.14	10.55	11.19
4/7/2015	6.59	6.7	6.86	7.18	8.3	8.54	8.76	8.96	9.24	9.84	10.15	10.54	11.19
4/8/2015	6.54	6.64	6.79	7.36	8.32	8.56	8.79	9.12	9.3	9.85	10.14	10.56	11.19
4/9/2015	6.57	6.69	6.85	7.31	8.38	8.63	8.87	9.16	9.36	9.85	10.14	10.56	11.2
4/10/2015	6.63	6.76	6.89	7.32	8.4	8.6	8.88	9.17	9.38	9.88	10.14	10.57	11.21
4/15/2015	6.6	6.73	6.89	7.32	8.26	8.51	8.69	8.97	9.23	9.82	10.11	10.54	11.2
4/16/2015	6.45	6.61	6.77	7.26	8.23	8.43	8.64	8.96	9.21	9.77	10.1	10.53	11.19
4/17/2015	6.43	6.6	6.76	7.24	8.31	8.52	8.77	9.03	9.29	9.76	10.15	10.52	11.19
4/20/2015	6.39	6.55	6.68	7.25	8.22	8.41	8.6	8.95	9.2	9.75	10.1	10.52	11.19
4/21/2015	6.4	6.54	6.68	7.02	8.1	8.21	8.46	8.78	9	9.73	10.1	10.52	11.19

4/22/2015	6.36	6.52	6.66	6.99	8.06	8.19	8.44	8.72	8.91	9.6	10.07	10.5	11.18
4/23/2015	6.26	6.44	6.59	6.82	7.94	8.05	8.37	8.6	8.76	9.39	10.08	10.56	11.56
4/24/2015	6.27	6.43	6.58	6.89	7.91	8.04	8.35	8.56	8.72	9.21	9.81	10.12	10.86
4/27/2015	6.25	6.4	6.56	6.84	7.84	8	8.27	8.44	8.59	9.14	9.8	9.98	10.86
4/28/2015	6.25	6.4	6.55	6.83	7.8	7.97	8.22	8.41	8.53	8.99	9.59	9.91	10.8
4/29/2015	6.22	6.37	6.52	6.82	7.76	7.97	8.2	8.4	8.54	8.89	9.3	9.65	10.79
4/30/2015	6.2	6.35	6.49	6.77	7.79	8.01	8.21	8.42	8.57	8.91	9.31	9.65	10.8
5/5/2015	6.19	6.34	6.49	6.77	7.81	8.01	8.23	8.44	8.59	8.91	9.31	9.65	10.8
5/6/2015	6.17	6.33	6.49	6.83	7.77	7.96	8.19	8.45	8.58	8.92	9.25	9.63	10.78
5/7/2015	6.16	6.32	6.47	6.76	7.87	8.09	8.29	8.46	8.6	8.87	7.65	9.53	9.89
5/8/2015	6.14	6.27	6.41	6.7	7.78	8.03	8.26	8.43	8.53	8.9	9.12	9.66	10.63
5/11/2015	6.14	6.27	6.41	6.69	7.79	8.04	8.28	8.44	8.56	8.9	9.12	9.66	10.6
5/12/2015	6.14	6.27	6.39	6.68	7.79	8.04	8.27	8.45	8.59	8.88	9.14	9.66	10.42
5/13/2015	6.14	6.26	6.38	6.68	7.78	8.02	8.27	8.44	8.58	8.88	9.14	9.66	10.42
5/14/2015	6.1	6.22	6.34	6.73	7.76	8	8.24	8.41	8.55	8.86	9.14	9.65	10.16
5/15/2015	6.09	6.21	6.34	6.72	7.74	8	8.24	8.41	8.53	8.86	9.13	9.65	10.26
5/18/2015	6.07	6.19	6.31	6.66	7.7	7.97	8.22	8.4	8.53	8.86	9.13	9.66	10.26
5/19/2015	6.09	6.21	6.33	6.7	7.7	7.99	8.22	8.39	8.52	8.86	9.13	9.65	10.28
5/20/2015	6.07	6.17	6.3	6.64	7.65	7.94	8.2	8.38	8.51	8.85	9.13	9.66	10.28
5/21/2015	6.07	6.18	6.3	6.63	7.64	7.94	8.2	8.37	8.51	8.85	9.13	9.65	10.28
5/22/2015	6.05	6.17	6.29	6.64	7.67	7.94	8.2	8.37	8.52	8.86	9.13	9.66	10.27
5/25/2015	6.08	6.19	6.33	6.76	7.72	8.09	8.28	8.41	8.56	8.86	9.16	9.56	10.27
5/26/2015	6.06	6.17	6.3	6.56	7.62	7.87	8.16	8.35	8.54	8.87	9.14	9.65	10.39
5/27/2015	6.06	6.17	6.3	6.5	7.58	7.8	8.12	8.33	8.53	8.86	9.14	9.62	10.09
5/28/2015	6.06	6.18	6.31	6.59	7.61	7.89	8.16	8.34	8.52	8.86	9.14	9.65	10.38
5/29/2015	6.06	6.16	6.29	6.49	7.57	7.83	8.13	8.31	8.5	8.82	9.14	9.66	10.39

6/1/2015	6.05	6.16	6.27	6.5	7.56	7.83	8.11	8.33	8.51	8.81	9.14	9.67	10.38
6/3/2015	6.08	6.19	6.32	6.45	7.54	7.76	8.08	8.29	8.52	8.81	9.14	9.59	9.79
6/4/2015	6.07	6.17	6.3	6.43	7.53	7.86	8.14	8.32	8.53	8.8	9.17	9.45	9.79
6/5/2015	6.05	6.16	6.28	6.41	7.52	7.77	8.05	8.28	8.51	8.79	9.11	9.53	9.8
6/8/2015	6.06	6.16	6.29	6.42	7.47	7.75	8	8.27	8.51	8.8	9.11	9.52	9.8
6/9/2015	6.05	6.15	6.27	6.4	7.48	7.75	8.01	8.27	8.5	8.8	9.11	9.52	9.78
6/10/2015	6.06	6.16	6.29	6.43	7.48	7.76	8.02	8.28	8.52	8.82	9.11	9.52	9.8
6/11/2015	6.05	6.14	6.27	6.41	7.49	7.76	8.03	8.27	8.52	8.82	9.11	9.5	9.76
6/12/2015	6.05	6.15	6.27	6.41	7.49	7.76	8.04	8.27	8.52	8.83	9.11	9.49	9.78
6/15/2015	6.07	6.17	6.29	6.42	7.49	7.76	8.03	8.27	8.52	8.83	9.11	9.5	9.76
6/16/2015	6.07	6.17	6.29	6.46	7.52	7.86	8.07	8.29	8.54	8.83	9.13	9.41	9.76
6/17/2015	6.06	6.16	6.29	6.43	7.49	7.76	8.03	8.32	8.57	8.85	9.11	9.5	9.76
6/18/2015	6.05	6.15	6.27	6.41	7.53	7.76	8.08	8.35	8.66	8.91	9.15	9.47	9.75
6/19/2015	6.05	6.15	6.28	6.43	7.53	7.78	8.09	8.35	8.69	8.93	9.15	9.52	9.76
6/22/2015	6.06	6.16	6.28	6.45	7.56	7.77	8.13	8.49	8.78	9	9.15	9.53	9.76
6/23/2015	6.06	6.16	6.28	6.48	7.64	7.93	8.24	8.66	8.98	9.19	9.33	9.68	9.87
6/24/2015	6.06	6.15	6.27	6.51	7.6	7.93	8.2	8.59	8.91	9.08	9.24	9.49	9.77
6/25/2015	6.06	6.16	6.28	6.56	7.55	7.81	8.11	8.51	8.88	9.13	9.32	9.6	9.79
6/26/2015	6.06	6.16	6.29	6.55	7.6	7.88	8.17	8.61	8.95	9.13	9.35	9.53	9.79
6/29/2015	6.06	6.16	6.29	6.55	7.59	7.88	8.17	8.6	8.94	9.1	9.35	9.53	9.79
6/30/2015	6.06	6.16	6.29	6.52	7.57	7.81	8.12	8.52	8.84	9.1	9.32	9.61	9.79
7/2/2015	6.07	6.16	6.29	6.53	7.57	7.81	8.11	8.51	8.83	9.09	9.32	9.61	9.79
7/3/2015	6.06	6.16	6.29	6.53	7.58	7.81	8.12	8.52	8.85	9.1	9.32	9.61	9.79
7/6/2015	6.05	6.14	6.26	6.49	7.58	7.78	8.11	8.53	8.83	9.08	9.28	9.59	9.79
7/7/2015	6.05	6.14	6.26	6.5	7.61	7.79	8.11	8.54	8.87	9.11	9.36	9.62	9.79
7/8/2015	6.07	6.16	6.29	6.57	7.61	7.83	8.12	8.56	8.93	9.15	9.37	9.64	9.79

7/9/2015	6.08	6.19	6.3	6.54	7.61	7.88	8.11	8.51	8.89	9.12	9.37	9.58	9.79
7/10/2015	6.1	6.21	6.32	6.55	7.65	7.91	8.2	8.56	9.01	9.18	9.37	9.62	9.84
7/13/2015	6.11	6.21	6.31	6.55	7.64	7.91	8.22	8.58	9.04	9.21	9.37	9.61	9.83
7/14/2015	6.11	6.21	6.31	6.55	7.67	7.95	8.25	8.67	9.09	9.33	9.47	9.73	9.9
7/15/2015	6.1	6.21	6.31	6.58	7.68	7.97	8.24	8.63	9.1	9.43	9.47	9.76	9.9
7/16/2015	6.16	6.27	6.35	6.79	7.95	8.13	8.54	9.03	9.27	9.53	9.5	9.76	10.11
7/17/2015	6.14	6.24	6.31	6.79	7.9	8.05	8.34	8.85	9.14	9.48	9.59	9.86	10.06
7/20/2015	6.08	6.19	6.28	6.72	7.79	7.96	8.21	8.66	8.96	9.3	9.43	9.73	9.87
7/21/2015	6.08	6.19	6.28	6.73	7.78	7.98	8.21	8.67	8.95	9.28	9.43	9.73	9.87
7/22/2015	6.1	6.2	6.29	6.73	7.8	7.99	8.21	8.69	9	9.32	9.43	9.73	9.87
7/23/2015	6.12	6.23	6.3	6.73	7.81	7.99	8.22	8.69	9.01	9.32	9.43	9.71	9.87
7/24/2015	6.14	6.25	6.32	6.7	7.82	8.02	8.22	8.66	9	9.34	9.43	9.73	9.87
7/27/2015	6.16	6.27	6.35	6.73	7.81	7.99	8.22	8.7	9.01	9.35	9.45	9.75	9.88
7/28/2015	6.17	6.28	6.35	6.71	7.83	8.03	8.23	8.71	9.02	9.36	9.45	9.72	9.87
7/29/2015	6.18	6.29	6.36	6.73	7.81	8.01	8.22	8.72	9.01	9.35	9.45	9.72	9.87
7/30/2015	6.2	6.3	6.37	6.73	7.81	8.01	8.22	8.74	9.01	9.22	9.45	9.73	9.87
8/3/2015	6.21	6.32	6.39	6.71	7.83	8.03	8.23	8.79	9.03	9.35	9.45	9.73	9.84
8/4/2015	6.2	6.31	6.39	6.72	7.81	8.02	8.22	8.74	9.03	9.35	9.45	9.73	9.84
8/5/2015	6.21	6.33	6.42	6.63	7.81	8.13	8.33	8.87	9.26	9.43	9.54	9.75	10.32
8/6/2015	6.2	6.33	6.42	6.7	7.86	8.13	8.41	8.89	9.27	9.42	9.57	9.74	10.32
8/7/2015	6.2	6.35	6.44	6.73	7.9	8.16	8.54	8.95	9.3	9.49	9.54	9.75	10.32
8/10/2015	6.23	6.39	6.48	6.79	7.92	8.16	8.55	8.93	9.31	9.49	9.58	9.76	10.32
8/11/2015	6.2	6.35	6.45	6.78	7.92	8.13	8.58	8.94	9.32	9.5	9.58	9.76	10.33
8/12/2015	6.21	6.37	6.46	6.81	7.92	8.16	8.59	8.96	9.31	9.48	9.59	9.76	10.34
8/13/2015	6.22	6.39	6.48	6.77	7.92	8.17	8.57	8.98	9.31	9.5	9.61	9.77	10.37
8/14/2015	6.26	6.43	6.53	6.8	7.93	8.18	8.61	8.93	9.32	9.48	9.58	9.78	10.34

8/17/2015	6.24	6.41	6.51	6.79	7.93	8.14	8.59	8.93	9.3	9.48	9.59	9.79	10.36
8/18/2015	6.25	6.42	6.51	6.77	7.9	8.11	8.51	8.89	9.27	9.45	9.56	9.82	10.22
8/19/2015	6.27	6.46	6.53	6.74	7.92	8.15	8.57	8.92	9.29	9.51	9.62	9.81	10.48
8/20/2015	6.26	6.45	6.54	6.75	7.92	8.16	8.56	8.93	9.29	9.48	9.59	9.79	10.36
8/21/2015	6.29	6.48	6.57	6.83	7.94	8.24	8.61	8.95	9.34	9.51	9.57	9.77	10.37
8/24/2015	6.27	6.47	6.56	6.8	7.95	8.25	8.6	8.97	9.34	9.53	9.6	9.76	10.39
8/25/2015	6.3	6.49	6.59	6.82	7.97	8.28	8.62	8.97	9.37	9.55	9.59	9.78	10.43
8/26/2015	6.32	6.52	6.61	6.9	8.02	8.35	8.68	9.02	9.48	9.69	9.72	9.95	10.61
8/27/2015	6.52	6.67	6.8	6.99	8.14	8.56	8.87	9.24	9.68	9.81	9.81	9.99	10.64
8/28/2015	6.5	6.63	6.78	6.97	8.09	8.52	8.78	9.17	9.59	9.74	9.79	9.96	10.6
8/31/2015	6.53	6.68	6.82	7.01	8.17	8.6	8.91	9.3	9.69	9.83	9.79	9.97	10.6
9/1/2015	6.56	6.72	6.86	7.01	8.17	8.6	8.91	9.3	9.69	9.83	9.85	9.97	10.61
9/2/2015	6.55	6.7	6.83	7.01	8.21	8.55	8.88	9.3	9.77	9.8	9.89	10	10.64
9/3/2015	6.62	6.8	6.95	7.09	8.26	8.59	8.93	9.35	9.82	9.89	9.99	10.17	10.74
9/4/2015	6.67	6.82	6.97	7.11	8.28	8.57	8.91	9.29	9.8	9.89	9.95	10.17	10.74
9/7/2015	6.73	6.9	7.08	7.22	8.46	8.74	9.03	9.42	9.87	9.98	10.03	10.25	10.81
9/8/2015	6.73	6.92	7.08	7.19	8.46	8.78	9.05	9.47	9.9	9.98	10.06	10.25	10.81
9/9/2015	6.79	6.93	7.11	7.2	8.46	8.77	9.09	9.42	9.93	10.04	10.08	10.36	11.08
9/10/2015	6.72	6.86	7.03	7.13	8.4	8.73	9.03	9.36	9.88	9.92	9.94	10.2	10.83
9/11/2015	6.73	6.88	7.04	7.23	8.48	8.89	9.2	9.49	9.92	10.03	10.08	10.33	10.86
9/14/2015	6.73	6.85	7.01	7.41	8.61	8.98	9.35	9.6	9.94	10.12	10.32	10.49	11.04
9/15/2015	6.78	6.92	7.09	7.32	8.57	8.93	9.31	9.53	9.89	10.04	10.29	10.31	10.95
9/16/2015	6.79	6.92	7.09	7.31	8.55	8.97	9.37	9.59	9.91	10.1	10.33	10.31	10.95
9/17/2015	6.74	6.84	7.02	7.46	8.64	8.97	9.35	9.6	9.93	10.14	10.34	10.49	11.04
9/18/2015	6.74	6.87	7.04	7.39	8.61	9.03	9.42	9.61	9.97	10.15	10.38	10.48	11.04
9/21/2015	6.77	6.89	7.08	7.38	8.59	8.98	9.37	9.55	9.94	10.14	10.37	10.48	11.04

9/22/2015	6.77	6.9	7.07	7.67	8.8	9.35	9.59	9.81	10.14	10.39	10.62	10.9	11.19
9/23/2015	6.77	6.91	7.05	7.67	8.82	9.37	9.63	9.83	10.16	10.43	10.69	10.98	11.19
9/25/2015	6.77	6.93	7.06	7.71	8.83	9.36	9.59	9.83	10.13	10.39	10.65	10.9	11.19
9/28/2015	6.77	6.93	7.06	7.71	8.87	9.42	9.62	9.85	10.17	10.41	10.65	10.9	11.19
9/29/2015	6.75	6.98	7.12	7.58	8.7	9.24	9.53	9.71	10.07	10.34	10.65	10.83	11.16
9/30/2015	6.75	6.98	7.12	7.6	8.75	9.26	9.55	9.74	10.07	10.34	10.65	10.83	11.15
10/1/2015	6.75	6.99	7.13	7.66	8.8	9.23	9.53	9.75	10.06	10.33	10.64	10.83	11.15
10/2/2015	6.76	6.99	7.12	7.64	8.87	9.37	9.57	9.76	10.09	10.37	10.71	10.85	11.2
10/5/2015	6.75	6.99	7.12	7.65	8.88	9.37	9.57	9.77	10.09	10.37	10.7	10.85	11.22
10/6/2015	6.75	6.99	7.12	7.66	8.87	9.37	9.57	9.76	10.09	10.37	10.7	10.85	11.22
10/7/2015	6.8	7.03	7.16	7.66	8.88	9.38	9.57	9.79	10.1	10.35	10.67	10.78	11.22
10/8/2015	6.75	6.97	7.1	7.64	8.86	9.36	9.56	9.77	10.09	10.36	10.7	10.85	11.22
10/9/2015	6.77	7	7.13	7.65	8.87	9.38	9.58	9.79	10.09	10.37	10.7	10.85	11.22
10/12/2015	6.77	6.99	7.13	7.74	8.94	9.35	9.56	9.8	10.09	10.36	10.69	10.86	11.22
10/13/2015	6.77	6.99	7.12	7.66	8.93	9.38	9.56	9.77	10.07	10.35	10.71	10.87	11.29
10/14/2015	6.77	6.99	7.12	7.75	9.02	9.35	9.53	9.75	10.02	10.31	10.67	10.87	11.22
10/15/2015	6.75	6.99	7.11	7.71	8.94	9.29	9.48	9.66	9.93	10.26	10.64	10.86	11.21
10/16/2015	6.74	6.99	7.11	7.68	8.9	9.28	9.46	9.67	9.93	10.23	10.69	10.92	11.2
10/19/2015	6.73	6.98	7.1	7.65	8.91	9.27	9.43	9.63	9.86	10.12	10.53	10.8	11.11
10/20/2015	6.72	6.98	7.12	7.68	8.95	9.29	9.43	9.67	9.88	10.12	10.52	10.81	11.11
10/21/2015	6.66	6.92	7.06	7.63	8.89	9.26	9.38	9.58	9.79	10.05	10.44	10.73	11.07
10/22/2015	6.67	6.94	7.09	7.67	8.9	9.29	9.41	9.61	9.84	10.12	10.52	10.81	11.11
10/23/2015	6.67	6.94	7.07	7.66	8.88	9.3	9.4	9.62	9.84	10.11	10.5	10.8	11.13
10/26/2015	6.67	6.94	7.07	7.65	8.87	9.3	9.4	9.62	9.84	10.11	10.5	10.8	11.13
10/28/2015	6.67	6.94	7.08	7.62	8.85	9.23	9.35	9.54	9.78	10.12	10.51	10.79	11.11
10/29/2015	6.65	6.93	7.05	7.58	8.74	9.18	9.28	9.44	9.7	10.05	10.45	10.78	11.15

10/30/2015	6.64	6.92	7.04	7.57	8.71	9.1	9.27	9.42	9.66	10.03	10.44	10.78	11.14
11/2/2015	6.66	6.95	7.06	7.61	8.75	9.13	9.29	9.45	9.69	10.11	10.51	10.86	11.19
11/3/2015	6.6	6.9	7.01	7.43	8.54	8.86	9.03	9.16	9.36	9.68	10.11	10.55	11
11/4/2015	6.62	6.89	7.02	7.42	8.5	8.79	8.91	9.06	9.32	9.62	10.04	10.42	10.99
11/5/2015	6.53	6.82	6.97	7.35	8.42	8.69	8.87	9.04	9.23	9.56	9.94	10.29	10.91
11/6/2015	6.5	6.77	6.94	7.21	8.25	8.55	8.7	8.9	9.09	9.29	9.7	10.01	10.88
11/9/2015	6.55	6.84	6.99	7.3	8.33	8.69	8.8	8.98	9.25	9.4	9.8	10.01	10.68
11/11/2015	6.52	6.81	6.96	7.19	8.25	8.55	8.74	8.92	9.12	9.34	9.68	9.96	10.61
11/12/2015	6.47	6.73	6.93	7.19	8.23	8.55	8.74	8.92	9.12	9.34	9.68	9.96	10.61
11/13/2015	6.42	6.64	6.91	7.14	8.21	8.54	8.73	8.9	9.13	9.32	9.61	9.95	10.62
11/16/2015	6.46	6.68	6.95	7.25	8.31	8.7	8.83	8.99	9.28	9.47	9.83	10.06	10.66
11/17/2015	6.45	6.67	6.93	7.23	8.29	8.66	8.8	8.96	9.23	9.39	9.74	9.98	10.67
11/18/2015	6.43	6.65	6.92	7.18	8.23	8.6	8.73	8.88	9.18	9.21	9.6	9.75	10.53
11/19/2015	6.41	6.63	6.92	7.19	8.32	8.69	8.78	8.94	9.22	9.29	9.66	9.83	10.57
11/20/2015	6.36	6.58	6.9	7.19	8.33	8.71	8.79	8.95	9.23	9.29	9.65	9.83	10.57
11/23/2015	6.31	6.52	6.87	7.08	8.24	8.66	8.83	8.96	9.2	9.22	9.46	9.72	10.47
11/24/2015	6.31	6.52	6.85	7.13	8.26	8.72	8.89	8.98	9.24	9.28	9.54	9.79	10.51
11/26/2015	6.3	6.49	6.85	7.12	8.24	8.73	8.89	8.98	9.25	9.28	9.54	9.79	10.51
11/27/2015	6.32	6.51	6.88	7.1	8.23	8.71	8.86	8.95	9.22	9.25	9.52	9.77	10.45
11/30/2015	6.27	6.46	6.86	7.11	8.26	8.71	8.88	8.98	9.24	9.29	9.55	9.8	10.51
12/1/2015	6.25	6.45	6.83	7.11	8.25	8.66	8.86	8.98	9.22	9.27	9.55	9.8	10.51
12/2/2015	6.23	6.44	6.87	7.1	8.24	8.64	8.83	8.96	9.2	9.26	9.54	9.79	10.54
12/3/2015	6.25	6.46	6.85	7.11	8.23	8.65	8.85	8.97	9.22	9.27	9.53	9.79	10.51
12/4/2015	6.23	6.45	6.84	7.12	8.24	8.65	8.86	8.97	9.22	9.27	9.54	9.79	10.51
12/7/2015	6.19	6.43	6.85	7.08	8.24	8.62	8.78	8.92	9.17	9.24	9.52	9.79	10.52
12/8/2015	6.18	6.43	6.83	7.08	8.24	8.64	8.82	8.94	9.19	9.26	9.54	9.8	10.52

12/9/2015	6.18	6.43	6.83	7.08	8.24	8.64	8.83	8.94	9.19	9.26	9.54	9.8	10.52
12/10/2015	6.19	6.42	6.83	7.09	8.25	8.68	8.84	8.95	9.2	9.26	9.54	9.83	10.52
12/11/2015	6.19	6.42	6.84	7.11	8.27	8.76	8.87	8.97	9.25	9.27	9.55	9.82	10.48
12/14/2015	6.19	6.45	6.88	7.1	8.28	8.8	8.86	8.97	9.26	9.29	9.56	9.81	10.48
12/15/2015	6.24	6.48	6.87	7.1	8.26	8.83	8.92	8.97	9.29	9.28	9.58	9.84	10.5
12/16/2015	6.2	6.45	6.86	7.17	8.39	8.96	9.13	9.2	9.49	9.61	9.81	10.06	10.62
12/17/2015	6.21	6.46	6.91	7.27	8.56	9.11	9.28	9.45	9.79	9.97	10.18	10.36	10.87
12/18/2015	6.21	6.46	6.91	7.35	8.62	9.18	9.39	9.55	9.87	10.2	10.41	10.63	11.05
12/21/2015	6.24	6.49	6.97	7.37	8.67	9.24	9.42	9.56	9.88	10.21	10.39	10.65	11.11
12/22/2015	6.27	6.52	6.99	7.38	8.76	9.3	9.54	9.64	9.93	10.2	10.49	10.78	11.2
12/23/2015	6.28	6.51	6.97	7.35	8.75	9.25	9.49	9.63	9.91	10.18	10.48	10.78	11.2
12/28/2015	6.34	6.6	7.03	7.55	8.88	9.32	9.57	9.69	10.07	10.37	10.55	10.84	11.34
12/29/2015	6.36	6.62	7.07	7.65	8.92	9.4	9.62	9.76	10.19	10.4	10.61	10.88	11.34
12/30/2015	6.37	6.64	7.09	7.63	8.96	9.37	9.63	9.77	10.15	10.4	10.6	10.88	11.34
12/31/2015	6.39	6.66	7.11	7.65	8.96	9.42	9.63	9.77	10.17	10.41	10.62	10.89	11.34
1/1/2016	6.43	6.72	7.18	7.63	8.88	9.38	9.54	9.69	10.08	10.21	10.45	10.66	11.12
1/4/2016	6.44	6.74	7.19	7.67	8.88	9.39	9.63	9.8	10.17	10.41	10.66	10.89	11.31
1/5/2016	6.45	6.74	7.19	7.67	8.89	9.4	9.64	9.83	10.21	10.43	10.67	10.89	11.31
1/6/2016	6.48	6.79	7.23	7.52	8.76	9.31	9.49	9.71	10.09	10.01	10.35	10.46	11.05
1/7/2016	6.45	6.75	7.21	7.65	8.89	9.4	9.63	9.82	10.23	10.43	10.67	10.89	11.33
1/8/2016	6.48	6.8	7.23	7.62	8.89	9.4	9.62	9.82	10.22	10.41	10.67	10.89	11.33
1/11/2016	6.5	6.79	7.26	7.7	9.01	9.49	9.73	9.95	10.34	10.64	10.87	11.11	11.45
1/12/2016	6.56	6.89	7.35	7.68	9.02	9.43	9.64	9.87	10.23	10.6	10.89	11.11	11.55
1/13/2016	6.62	6.93	7.36	7.67	9	9.42	9.64	9.86	10.22	10.6	10.87	11.1	11.54
1/14/2016	6.6	6.88	7.34	7.67	8.98	9.4	9.61	9.85	10.19	10.58	10.87	11.09	11.5
1/18/2016	6.64	6.94	7.37	7.68	9.01	9.42	9.62	9.84	10.18	10.58	10.87	11.09	11.47

1/19/2016	6.64	6.93	7.36	7.67	8.99	9.4	9.58	9.81	10.13	10.57	10.84	11.09	11.46
1/20/2016	6.64	6.95	7.37	7.68	8.99	9.41	9.6	9.82	10.14	10.57	10.85	11.09	11.46
1/21/2016	6.7	7.05	7.55	7.75	9	9.45	9.64	9.86	10.15	10.57	10.84	11.05	11.46
1/22/2016	6.76	7.12	7.68	7.84	9.05	9.54	9.71	9.89	10.19	10.61	10.88	11.1	11.48
1/25/2016	6.76	7.14	7.69	7.84	9.11	9.58	9.76	9.94	10.21	10.62	10.88	11.1	11.49
1/26/2016	6.76	7.14	7.69	7.87	9.21	9.65	9.83	10	10.24	10.64	10.91	11.1	11.5
1/27/2016	6.76	7.14	7.69	7.88	9.21	9.65	9.83	10	10.24	10.64	10.91	11.1	11.5
1/28/2016	6.76	7.12	7.68	7.9	9.21	9.66	9.83	10.01	10.26	10.65	10.9	11.1	11.5
1/29/2016	6.76	7.12	7.66	7.89	9.27	9.68	9.85	10.05	10.29	10.68	10.94	11.14	11.55
2/1/2016	6.76	7.12	7.63	7.89	9.28	9.71	9.88	10.07	10.32	10.7	10.94	11.15	11.56
2/2/2016	6.77	7.13	7.67	7.88	9.27	9.71	9.86	10.07	10.31	10.7	10.96	11.14	11.56
2/3/2016	6.8	7.19	7.71	7.91	9.28	9.72	9.92	10.1	10.36	10.72	10.99	11.15	11.61
2/5/2016	6.81	7.19	7.7	7.91	9.28	9.72	9.91	10.1	10.36	10.72	10.99	11.15	11.61
2/8/2016	6.81	7.18	7.7	7.91	9.28	9.73	9.95	10.12	10.37	10.73	11.03	11.21	11.63
2/9/2016	6.82	7.19	7.7	7.92	9.29	9.75	9.95	10.14	10.41	10.75	11.04	11.22	11.64
2/10/2016	6.82	7.19	7.7	7.92	9.29	9.74	9.95	10.14	10.42	10.74	11.04	11.22	11.63
2/11/2016	6.82	7.22	7.71	7.92	9.29	9.73	9.95	10.15	10.44	10.74	11.03	11.22	11.63
2/12/2016	6.84	7.31	7.73	7.91	9.29	9.72	9.94	10.15	10.44	10.74	11.02	11.21	11.63
2/15/2016	6.86	7.32	7.74	7.91	9.29	9.72	9.95	10.18	10.47	10.76	11.04	11.23	11.63
2/16/2016	6.88	7.36	7.77	7.93	9.33	9.75	9.99	10.23	10.51	10.8	11.08	11.26	11.66
2/17/2016	6.89	7.35	7.77	7.96	9.34	9.76	10.02	10.24	10.52	10.81	11.09	11.27	11.67
2/18/2016	6.94	7.42	7.81	8.06	9.45	9.86	10.17	10.4	10.68	10.93	11.18	11.38	11.74
2/19/2016	6.93	7.4	7.81	8.02	9.39	9.86	10.17	10.37	10.66	10.93	11.18	11.38	11.75
2/23/2016	6.93	7.4	7.81	8.07	9.45	9.88	10.19	10.4	10.68	10.93	11.19	11.38	11.75
2/24/2016	7.13	7.57	8.01	8.28	9.69	10.12	10.45	10.64	10.92	11.16	11.43	11.6	11.89
2/25/2016	7.2	7.7	8.16	8.47	9.84	10.27	10.67	10.74	11.07	11.2	11.46	11.62	11.97

2/26/2016	7.27	7.81	8.25	8.53	9.84	10.26	10.72	10.81	11.12	11.28	11.47	11.61	11.96
2/29/2016	7.27	7.83	8.27	8.67	9.96	10.39	10.84	10.97	11.27	11.45	11.57	11.72	12.11
3/1/2016	7.35	7.9	8.33	8.76	10.04	10.54	10.93	11.08	11.39	11.46	11.58	11.72	12.12
3/2/2016	7.38	7.93	8.36	8.78	10.07	10.57	11	11.08	11.44	11.5	11.6	11.72	12.13
3/3/2016	7.45	8.02	8.5	8.85	10.12	10.64	11.07	11.15	11.5	11.53	11.6	11.73	12.13
3/4/2016	7.55	8.08	8.57	8.94	10.19	10.66	11.14	11.22	11.58	11.59	11.67	11.8	12.17
3/8/2016	7.63	8.25	8.74	9.02	10.24	10.7	11.18	11.26	11.61	11.61	11.74	11.81	12.17
3/9/2016	7.63	8.27	8.75	9.06	10.34	10.79	11.2	11.27	11.63	11.61	11.75	11.82	12.19
3/10/2016	7.64	8.29	8.78	9.18	10.37	10.84	11.27	11.28	11.65	11.62	11.76	11.82	12.2
3/11/2016	7.64	8.29	8.78	9.16	10.37	10.84	11.27	11.28	11.65	11.62	11.76	11.82	12.2
3/14/2016	7.68	8.34	8.85	9.27	10.52	11.01	11.38	11.41	11.78	11.75	11.86	11.92	12.28
3/15/2016	7.73	8.42	8.93	9.44	10.74	11.2	11.53	11.6	11.9	11.9	11.96	12	12.34
3/16/2016	7.68	8.34	8.86	9.29	10.57	11.03	11.4	11.45	11.8	11.76	11.86	11.93	12.27
3/17/2016	7.58	8.28	8.82	9.24	10.46	10.97	11.33	11.34	11.76	11.65	11.76	11.78	12.2
3/18/2016	7.64	8.33	8.85	9.31	10.58	11.06	11.41	11.45	11.83	11.78	11.86	11.93	12.27
3/21/2016	7.69	8.36	8.89	9.4	10.67	11.18	11.5	11.54	11.88	11.88	11.95	12.04	12.36
3/23/2016	7.99	8.76	9.32	9.51	10.74	11.24	11.57	11.56	11.94	11.91	11.96	12.04	12.39
3/24/2016	8.31	9.08	9.71	9.66	10.99	11.36	11.7	11.61	12.08	11.96	11.99	12.1	12.52
3/28/2016	8.42	9.21	9.84	9.93	11.17	11.5	11.78	11.74	12.21	12.04	12.04	12.16	12.58
3/29/2016	8.83	9.59	10.23	10.3	11.74	12.1	12.29	12.33	12.57	12.65	12.76	12.95	13.11
3/30/2016	8.82	9.63	10.24	10.4	11.86	12.34	12.56	12.58	12.83	12.93	12.92	13.03	13.2
3/31/2016	8.77	9.59	10.31	10.4	11.88	12.37	12.56	12.61	12.87	13.07	13.13	13.27	13.49
4/1/2016	8.8	9.63	10.34	10.39	11.85	12.25	12.45	12.52	12.71	12.88	13.05	13.22	13.44
4/4/2016	8.85	9.65	10.35	10.47	11.97	12.38	12.52	12.67	12.75	13	13.24	13.46	13.58
4/5/2016	8.85	9.65	10.35	10.39	11.91	12.34	12.42	12.63	12.65	12.95	13.19	13.44	13.53
4/6/2016	8.85	9.65	10.36	10.35	11.85	12.24	12.28	12.49	12.53	12.88	13.15	13.42	13.53

4/7/2016	8.71	9.53	10.32	10.28	11.85	12.25	12.33	12.54	12.57	12.95	13.18	13.45	13.54
4/8/2016	8.65	9.5	10.27	10.27	11.82	12.22	12.22	12.49	12.48	12.9	13.16	13.44	13.53
4/11/2016	8.54	9.45	10.17	10.25	11.83	12.2	12.25	12.54	12.48	12.93	13.2	13.5	13.51
4/12/2016	8.52	9.41	10.08	10.14	11.57	11.96	12.06	12.34	12.34	12.66	12.94	13.2	13.25
4/15/2016	8.49	9.44	10.06	10.13	11.55	11.99	12	12.3	12.3	12.67	12.94	13.19	13.25
4/18/2016	8.48	9.43	10.04	10.09	11.45	11.87	11.95	12.18	12.22	12.6	12.89	13.13	13.33
4/19/2016	8.49	9.43	10.05	10.09	11.44	11.87	11.94	12.18	12.21	12.59	12.89	13.13	13.28
4/20/2016	8.5	9.44	10.08	10.09	11.44	11.87	11.92	12.18	12.22	12.59	12.89	13.13	13.28
4/22/2016	8.5	9.47	10.1	10.18	11.47	11.88	11.93	12.15	12.27	12.59	12.9	13.14	13.29
4/25/2016	8.51	9.51	10.13	10.17	11.47	11.85	11.91	12.1	12.24	12.57	12.89	13.12	13.31
4/26/2016	8.52	9.51	10.12	10.2	11.48	11.85	11.9	12.09	12.24	12.57	12.89	13.12	13.31
4/27/2016	8.55	9.53	10.15	10.25	11.54	11.9	11.97	12.16	12.31	12.65	12.95	13.19	13.36
4/28/2016	8.52	9.5	10.11	10.25	11.49	11.87	11.95	12.12	12.25	12.59	12.89	13.12	13.31
4/29/2016	8.51	9.5	10.11	10.26	11.5	11.88	11.97	12.13	12.27	12.59	12.88	13.12	13.31
5/3/2016	8.5	9.5	10.12	10.27	11.54	11.86	11.91	12.11	12.23	12.52	12.8	13.07	13.29
5/4/2016	8.5	9.51	10.13	10.28	11.55	11.85	11.9	12.12	12.24	12.5	12.78	13.05	13.23
5/5/2016	8.56	9.57	10.22	10.27	11.58	11.86	11.93	12.12	12.22	12.47	12.77	13.04	13.23
5/6/2016	8.55	9.55	10.21	10.27	11.58	11.86	12.01	12.09	12.22	12.47	12.77	13.04	13.23
5/9/2016	8.56	9.56	10.2	10.2	11.44	11.72	11.84	11.93	12.05	12.22	12.47	12.67	12.96
5/10/2016	8.57	9.63	10.28	10.19	11.32	11.56	11.65	11.78	11.88	12.01	12.28	12.48	12.86
5/11/2016	8.6	9.61	10.26	11.1	11.38	11.54	11.63	11.76	11.84	12	12.25	12.48	12.86
5/12/2016	8.56	9.59	10.3	11.03	11.32	11.49	11.58	11.73	11.8	11.97	12.22	12.48	12.86
5/13/2016	8.55	9.57	10.28	11.03	11.31	11.49	11.59	11.74	11.81	11.97	12.23	12.48	12.86
5/16/2016	8.66	9.59	10.37	11.16	11.39	11.61	11.71	11.84	11.91	12.02	12.21	12.4	12.83
5/17/2016	8.65	9.62	10.4	11.17	11.39	11.64	11.75	11.91	11.94	12.05	12.23	12.41	12.85
5/18/2016	8.65	9.6	10.4	11.27	11.55	11.78	11.89	12.04	12.09	12.2	12.41	12.59	12.92

5/19/2016	8.65	9.61	10.42	11.27	11.55	11.78	11.89	12.04	12.08	12.2	12.41	12.59	12.92
5/20/2016	8.59	9.6	10.43	11.28	11.57	11.79	11.89	12.03	12.09	12.24	12.44	12.6	12.92
5/24/2016	8.6	9.62	10.43	11.27	11.58	11.84	11.92	12.07	12.13	12.28	12.46	12.61	12.93
5/25/2016	8.6	9.62	10.44	11.27	11.58	11.84	11.93	12.08	12.14	12.29	12.47	12.61	12.93
5/26/2016	8.62	9.62	10.45	11.23	11.58	11.84	11.9	12.04	12.13	12.26	12.44	12.56	12.91
5/27/2016	8.63	9.63	10.45	11.27	11.58	11.84	11.93	12.05	12.15	12.26	12.42	12.56	12.91
5/30/2016	8.63	9.63	10.44	11.27	11.57	11.82	11.94	12.05	12.14	12.25	12.4	12.56	12.9
5/31/2016	8.63	9.64	10.44	11.28	11.58	11.83	11.95	12.05	12.15	12.26	12.41	12.55	12.87
6/1/2016	8.63	9.64	10.44	11.27	11.58	11.83	11.96	12.05	12.16	12.27	12.41	12.55	12.87
6/2/2016	8.64	9.64	10.46	11.26	11.57	11.82	11.94	12.05	12.15	12.26	12.41	12.55	12.87
6/3/2016	8.65	9.64	10.46	11.24	11.56	11.81	11.93	12.04	12.14	12.26	12.4	12.55	12.87
6/6/2016	8.66	9.6	10.44	11.17	11.53	11.76	11.89	12.02	12.15	12.26	12.41	12.56	12.81
6/7/2016	8.65	9.61	10.43	11.16	11.51	11.74	11.86	12.02	12.15	12.26	12.41	12.56	12.83
6/8/2016	8.67	9.63	10.45	11.07	11.42	11.68	11.8	11.97	12.12	12.26	12.39	12.54	12.81
6/9/2016	8.67	9.63	10.44	11.07	11.42	11.68	11.8	11.96	12.11	12.26	12.39	12.54	12.81
6/10/2016	8.68	9.63	10.45	11.05	11.41	11.64	11.77	11.94	12.09	12.24	12.38	12.53	12.8
6/13/2016	8.69	9.62	10.45	11.02	11.4	11.62	11.74	11.91	12.07	12.24	12.37	12.53	12.78
6/14/2016	8.69	9.63	10.45	11.03	11.38	11.62	11.75	11.93	12.1	12.26	12.4	12.53	12.78
6/15/2016	8.7	9.64	10.46	11.03	11.37	11.62	11.75	11.92	12.09	12.26	12.4	12.53	12.78
6/16/2016	8.7	9.65	10.45	11.03	11.37	11.62	11.75	11.93	12.1	12.26	12.41	12.53	12.78
6/17/2016	8.7	9.64	10.45	11.04	11.38	11.63	11.77	11.94	12.12	12.28	12.42	12.53	12.79
6/20/2016	8.71	9.65	10.45	11.02	11.38	11.63	11.77	11.95	12.14	12.29	12.43	12.53	12.8
6/21/2016	8.7	9.66	10.46	11.05	11.39	11.64	11.79	11.97	12.17	12.32	12.45	12.54	12.81
6/22/2016	8.7	9.66	10.46	11.06	11.39	11.65	11.82	12.02	12.2	12.36	12.51	12.6	12.8
6/23/2016	8.73	9.67	10.47	11.06	11.4	11.65	11.8	12.01	12.19	12.35	12.5	12.6	12.8
6/24/2016	8.74	9.69	10.47	11.07	11.39	11.66	11.8	12	12.2	12.35	12.51	12.6	12.8

6/27/2016	8.75	9.7	10.49	11.1	11.42	11.67	11.84	12.02	12.25	12.41	12.57	12.67	12.83
6/28/2016	8.75	9.7	10.48	11.07	11.41	11.66	11.8	11.99	12.18	12.35	12.5	12.62	12.8
6/29/2016	8.77	9.71	10.47	11.06	11.4	11.65	11.82	11.97	12.18	12.35	12.5	12.62	12.8
6/30/2016	8.77	9.71	10.46	11.05	11.38	11.65	11.82	11.96	12.19	12.36	12.5	12.62	12.8
7/1/2016	8.77	9.7	10.45	11.05	11.39	11.65	11.81	11.96	12.18	12.35	12.5	12.62	12.8
7/4/2016	8.79	9.76	10.48	11.12	11.5	11.72	11.84	11.96	12.17	12.45	12.6	12.75	12.96
7/5/2016	8.77	9.74	10.47	11.12	11.47	11.7	11.83	11.96	12.18	12.42	12.55	12.7	12.87
7/7/2016	8.79	9.76	10.48	11.12	11.48	11.71	11.83	11.96	12.19	12.42	12.56	12.71	12.86
7/8/2016	8.78	9.75	10.48	11.11	11.5	11.7	11.84	11.98	12.26	12.43	12.57	12.7	12.89
7/11/2016	8.78	9.74	10.45	11.09	11.52	11.71	11.84	11.97	12.23	12.42	12.61	12.75	12.96
7/12/2016	8.77	9.73	10.45	11.04	11.43	11.64	11.75	11.93	12.15	12.32	12.51	12.71	12.91
7/13/2016	8.78	9.74	10.46	11.04	11.43	11.63	11.75	11.93	12.15	12.32	12.5	12.71	12.91
7/14/2016	8.75	9.7	10.43	11.04	11.43	11.62	11.78	11.93	12.14	12.29	12.49	12.71	12.91
7/15/2016	8.74	9.7	10.42	11.02	11.4	11.61	11.76	11.91	12.11	12.28	12.47	12.71	12.91
7/18/2016	8.74	9.7	10.43	11.01	11.39	11.6	11.76	11.9	12.09	12.26	12.46	12.71	12.91
7/20/2016	8.72	9.68	10.41	11.01	11.39	11.6	11.76	11.91	12.1	12.26	12.46	12.71	12.91
7/21/2016	8.74	9.7	10.42	11.01	11.39	11.6	11.76	11.92	12.12	12.29	12.46	12.71	12.91
7/22/2016	8.73	9.69	10.43	11.01	11.39	11.6	11.76	11.92	12.12	12.29	12.46	12.71	12.91
7/25/2016	8.73	9.68	10.42	10.99	11.38	11.59	11.75	11.91	12.11	12.29	12.46	12.71	12.91
7/26/2016	8.72	9.68	10.42	10.99	11.38	11.59	11.76	11.93	12.14	12.32	12.48	12.71	12.92
7/27/2016	8.7	9.66	10.41	11	11.39	11.59	11.76	11.93	12.15	12.35	12.5	12.72	12.92
7/28/2016	8.69	9.65	10.4	11.01	11.39	11.61	11.78	11.96	12.19	12.36	12.54	12.72	12.89
7/29/2016	8.72	9.68	10.42	11.03	11.4	11.63	11.81	11.99	12.23	12.4	12.57	12.73	12.9
8/1/2016	8.85	9.78	10.54	11.08	11.48	11.67	11.89	12.07	12.26	12.44	12.61	12.77	12.94
8/2/2016	8.86	9.81	10.58	11.17	11.58	11.75	11.9	12.13	12.31	12.44	12.61	12.76	12.93
8/3/2016	8.89	9.82	10.56	11.17	11.58	11.77	11.97	12.13	12.33	12.5	12.69	12.85	13.05

8/4/2016	8.95	9.87	10.64	11.18	11.59	11.78	11.96	12.14	12.33	12.5	12.69	12.85	13.05
8/5/2016	8.95	9.88	10.66	11.19	11.59	11.78	11.96	12.14	12.33	12.5	12.69	12.85	13.04
8/8/2016	8.96	9.85	10.66	11.19	11.56	11.77	11.97	12.13	12.3	12.48	12.68	12.87	13.06
8/9/2016	8.96	9.85	10.67	11.19	11.56	11.77	11.97	12.13	12.3	12.48	12.68	12.87	13.06
8/10/2016	8.96	9.85	10.67	11.18	11.56	11.77	11.97	12.14	12.3	12.48	12.68	12.87	13.06
8/11/2016	8.96	9.87	10.67	11.18	11.56	11.77	11.97	12.13	12.29	12.47	12.67	12.87	13.06
8/12/2016	8.96	9.87	10.66	11.18	11.58	11.81	11.97	12.13	12.29	12.47	12.67	12.87	13.06
8/15/2016	8.95	9.85	10.66	11.18	11.58	11.82	11.97	12.13	12.29	12.47	12.67	12.88	13.07
8/16/2016	9.04	9.91	10.7	11.18	11.58	11.82	11.97	12.13	12.29	12.47	12.67	12.88	13.07
8/18/2016	8.98	9.87	10.68	11.18	11.58	11.81	11.97	12.12	12.29	12.48	12.67	12.88	13.07
8/19/2016	9.01	9.88	10.7	11.18	11.58	11.81	11.98	12.13	12.29	12.49	12.67	12.88	13.07
8/22/2016	9.03	9.89	10.72	11.21	11.6	11.83	12	12.14	12.32	12.55	12.76	13.02	13.2
8/23/2016	9.01	9.88	10.7	11.18	11.58	11.81	11.98	12.12	12.29	12.5	12.67	12.88	13.07
8/24/2016	9.01	9.88	10.7	11.18	11.58	11.81	11.98	12.12	12.29	12.5	12.67	12.88	13.07
8/25/2016	9.02	9.89	10.71	11.18	11.58	11.81	11.98	12.12	12.29	12.5	12.67	12.88	13.07
8/26/2016	9.01	9.89	10.71	11.15	11.5	11.71	11.88	12.1	12.23	12.43	12.61	12.85	12.98
8/29/2016	9	9.89	10.72	11.15	11.49	11.7	11.85	12.07	12.21	12.38	12.59	12.84	12.96
8/30/2016	9	9.89	10.71	11.15	11.48	11.7	11.86	12.08	12.21	12.39	12.59	12.84	12.96
8/31/2016	9	9.89	10.71	11.14	11.48	11.7	11.86	12.08	12.2	12.39	12.59	12.84	12.96
9/1/2016	9	9.9	10.71	11.14	11.47	11.68	11.86	12.09	12.19	12.38	12.58	12.84	12.96
9/2/2016	9.01	9.89	10.72	11.08	11.4	11.61	11.79	11.95	12.15	12.35	12.61	12.85	13
9/5/2016	9	9.9	10.7	11.04	11.35	11.55	11.72	11.87	12.09	12.27	12.58	12.83	12.99
9/6/2016	9	9.88	10.69	10.98	11.29	11.5	11.66	11.76	11.98	12.19	12.54	12.82	12.95
9/7/2016	8.98	9.84	10.65	10.92	11.19	11.37	11.56	11.65	11.85	12.04	12.36	12.62	12.78
9/8/2016	8.85	9.76	10.53	10.88	11.12	11.32	11.51	11.52	11.8	12.01	12.34	12.62	12.78
9/9/2016	8.74	9.67	10.39	10.77	10.99	11.17	11.33	11.4	11.63	11.81	12.11	12.4	12.6

9/13/2016	8.72	9.65	10.36	10.73	10.94	11.11	11.25	11.35	11.56	11.75	12.01	12.29	12.51
9/14/2016	8.73	9.68	10.38	10.74	10.97	11.12	11.27	11.39	11.57	11.75	12.01	12.29	12.51
9/15/2016	8.72	9.67	10.39	10.74	10.98	11.15	11.28	11.4	11.58	11.76	12.02	12.3	12.51
9/19/2016	8.72	9.68	10.39	10.73	10.99	11.15	11.27	11.42	11.57	11.74	12	12.27	12.48
9/20/2016	8.69	9.65	10.36	10.76	10.98	11.17	11.33	11.46	11.6	11.75	11.99	12.27	12.48
9/21/2016	8.69	9.65	10.36	10.76	10.99	11.18	11.33	11.46	11.6	11.75	11.99	12.27	12.48
9/22/2016	8.68	9.64	10.35	10.78	11.04	11.21	11.35	11.48	11.63	11.76	11.99	12.27	12.48
9/23/2016	8.66	9.6	10.31	10.78	11.03	11.21	11.35	11.48	11.63	11.75	11.99	12.26	12.48
9/26/2016	8.64	9.57	10.28	10.75	10.99	11.15	11.34	11.42	11.56	11.68	11.97	12.26	12.48
9/27/2016	8.62	9.56	10.27	10.7	10.99	11.13	11.3	11.38	11.52	11.64	11.92	12.23	12.46
9/28/2016	8.63	9.56	10.26	10.69	10.93	11.11	11.27	11.36	11.5	11.62	11.91	12.23	12.46
9/29/2016	8.58	9.45	10.17	10.67	10.89	11.09	11.26	11.33	11.48	11.6	11.91	12.23	12.42
9/30/2016	8.54	9.37	10.09	10.54	10.8	10.96	11.19	11.23	11.39	11.51	11.8	12.13	12.34
10/3/2016	8.51	9.33	10.06	10.5	10.74	10.93	11.12	11.2	11.34	11.47	11.73	12.06	12.26
10/4/2016	8.56	9.37	10.11	10.52	10.81	11.02	11.18	11.23	11.38	11.5	11.75	12.05	12.26
10/5/2016	8.55	9.38	10.12	10.54	10.84	11.04	11.19	11.27	11.42	11.54	11.77	12.05	12.27
10/6/2016	8.53	9.37	10.04	10.53	10.84	11.07	11.21	11.31	11.45	11.57	11.79	12.06	12.27
10/7/2016	8.53	9.37	10.05	10.55	10.88	11.08	11.22	11.25	11.45	11.59	11.81	12.06	12.27
10/10/2016	8.55	9.39	10.06	10.57	10.93	11.1	11.23	11.36	11.48	11.59	11.8	12.04	12.26
10/11/2016	8.55	9.39	10.06	10.65	11.01	11.16	11.3	11.4	11.56	11.67	11.88	12.11	12.32
10/12/2016	8.59	9.43	10.08	10.8	11.13	11.26	11.38	11.48	11.61	11.73	11.96	12.22	12.4
10/13/2016	8.59	9.43	10.09	10.83	11.15	11.28	11.44	11.51	11.66	11.76	11.98	12.22	12.41
10/14/2016	8.59	9.43	10.1	10.83	11.14	11.28	11.44	11.51	11.66	11.77	11.98	12.22	12.41
10/17/2016	8.6	9.44	10.1	10.87	11.2	11.32	11.48	11.58	11.72	11.81	12.02	12.26	12.44
10/18/2016	8.6	9.44	10.11	10.89	11.25	11.42	11.54	11.59	11.73	11.82	12.03	12.26	12.44
10/19/2016	8.6	9.46	10.12	10.9	11.27	11.45	11.55	11.6	11.74	11.83	12.03	12.27	12.46

10/20/2016	8.6	9.47	10.14	10.9	11.28	11.45	11.55	11.6	11.72	11.82	12.02	12.27	12.46
10/21/2016	8.63	9.48	10.15	10.9	11.28	11.45	11.56	11.61	11.72	11.82	12.01	12.27	12.46
10/24/2016	8.62	9.5	10.15	10.92	11.33	11.49	11.6	11.63	11.73	11.82	12.02	12.28	12.47
10/25/2016	8.63	9.49	10.15	10.91	11.33	11.49	11.6	11.63	11.73	11.81	12.01	12.28	12.47
10/26/2016	8.63	9.5	10.16	11.01	11.42	11.59	11.69	11.72	11.81	11.92	12.14	12.43	12.63
10/27/2016	8.63	9.5	10.16	11.04	11.43	11.61	11.68	11.71	11.81	11.91	12.15	12.43	12.63
10/28/2016	8.62	9.49	10.13	11	11.35	11.57	11.69	11.73	11.79	11.89	12.1	12.41	12.59
10/31/2016	8.62	9.49	10.15	11	11.35	11.57	11.7	11.74	11.79	11.89	12.1	12.41	12.59
11/1/2016	8.62	9.49	10.14	11	11.35	11.56	11.68	11.74	11.79	11.89	12.1	12.41	12.58
11/2/2016	8.62	9.49	10.14	10.99	11.35	11.56	11.68	11.73	11.79	11.89	12.1	12.42	12.58
11/3/2016	8.61	9.49	10.14	11	11.37	11.58	11.69	11.77	11.84	11.93	12.11	12.41	12.59
11/4/2016	8.61	9.48	10.14	11.01	11.37	11.58	11.7	11.77	11.84	11.93	12.1	12.41	12.59
11/7/2016	8.61	9.49	10.15	11.01	11.37	11.58	11.7	11.77	11.83	11.93	12.1	12.41	12.58
11/8/2016	8.62	9.49	10.15	11.01	11.38	11.58	11.7	11.77	11.84	11.93	12.1	12.41	12.58
11/9/2016	8.62	9.5	10.15	11.01	11.37	11.59	11.7	11.77	11.83	11.93	12.1	12.41	12.58
11/10/2016	8.62	9.5	10.15	11.02	11.41	11.6	11.72	11.85	11.88	11.97	12.12	12.42	12.6
11/11/2016	8.62	9.52	10.14	11.02	11.41	11.61	11.73	11.85	11.88	11.97	12.12	12.41	12.59
11/15/2016	8.63	9.54	10.16	11.03	11.43	11.64	11.74	11.89	11.9	11.99	12.13	12.41	12.62
11/16/2016	8.65	9.54	10.17	11.11	11.46	11.68	11.77	11.92	11.93	12.01	12.14	12.42	12.64
11/17/2016	8.65	9.55	10.16	11.36	11.79	12.04	12.13	12.15	12.28	12.37	12.53	12.86	13.06
11/18/2016	8.68	9.6	10.21	11.56	11.94	12.21	12.36	12.32	12.67	12.76	12.96	13.3	13.42
11/21/2016	8.69	9.6	10.21	11.55	11.96	12.22	12.36	12.41	12.69	12.77	12.97	13.3	13.43
11/22/2016	8.69	9.6	10.21	11.63	11.94	12.25	12.42	12.43	12.74	12.79	12.99	13.3	13.43
11/23/2016	8.69	9.6	10.22	11.63	11.92	12.24	12.42	12.41	12.74	12.78	12.98	13.28	13.43
11/24/2016	8.69	9.62	10.22	11.6	11.88	12.17	12.41	12.39	12.67	12.76	12.98	13.27	13.43
11/25/2016	8.69	9.62	10.22	11.58	11.84	12.13	12.37	12.35	12.63	12.72	12.98	13.27	13.44

11/28/2016	8.69	9.63	10.23	11.58	11.83	12.11	12.34	12.27	12.62	12.72	12.99	13.3	13.44
11/29/2016	8.69	9.62	10.22	11.59	11.86	12.13	12.35	12.3	12.67	12.76	12.99	13.31	13.44
11/30/2016	8.68	9.61	10.23	11.56	11.83	12.12	12.33	12.25	12.62	12.7	12.96	13.28	13.43
12/1/2016	8.66	9.59	10.21	11.46	11.8	12.04	12.23	12.22	12.53	12.61	12.84	13.09	13.28
12/2/2016	8.66	9.59	10.2	11.45	11.81	12.05	12.23	12.22	12.53	12.6	12.84	13.09	13.28
12/5/2016	8.65	9.58	10.19	11.46	11.82	12.05	12.23	12.26	12.53	12.61	12.85	13.09	13.28
12/6/2016	8.65	9.58	10.19	11.45	11.82	12.05	12.23	12.26	12.53	12.61	12.85	13.09	13.28
12/7/2016	8.65	9.58	10.19	11.42	11.82	12.05	12.22	12.25	12.53	12.61	12.85	13.09	13.28
12/8/2016	8.65	9.58	10.18	11.45	11.85	12.06	12.22	12.25	12.53	12.6	12.85	13.09	13.28
12/9/2016	8.65	9.58	10.19	11.45	11.84	12.05	12.22	12.26	12.53	12.6	12.84	13.09	13.28
12/14/2016	8.65	9.58	10.19	11.46	11.86	12.06	12.22	12.28	12.56	12.66	12.85	13.09	13.28
12/15/2016	8.66	9.58	10.19	11.46	11.86	12.05	12.22	12.28	12.56	12.66	12.85	13.09	13.26
12/16/2016	8.66	9.59	10.19	11.46	11.87	12.05	12.22	12.28	12.56	12.66	12.86	13.09	13.26
12/19/2016	8.64	9.58	10.18	11.46	11.88	12.05	12.22	12.29	12.56	12.66	12.87	13.09	13.26
12/20/2016	8.64	9.58	10.18	11.45	11.89	12.05	12.22	12.29	12.56	12.66	12.86	13.09	13.26
12/21/2016	8.64	9.58	10.18	11.45	11.89	12.05	12.24	12.29	12.56	12.66	12.86	13.09	13.26
12/22/2016	8.64	9.59	10.18	11.45	11.86	12.08	12.25	12.3	12.55	12.64	12.86	13.09	13.26
12/23/2016	8.65	9.58	10.18	11.5	11.92	12.12	12.29	12.32	12.57	12.65	12.87	13.09	13.26
12/27/2016	8.64	9.57	10.16	11.38	11.82	12	12.13	12.24	12.46	12.6	12.83	13.09	13.26
12/28/2016	8.64	9.57	10.16	11.38	11.81	12.02	12.2	12.26	12.43	12.55	12.81	13.08	13.26
12/29/2016	8.69	9.6	10.18	11.37	11.8	12.04	12.17	12.22	12.42	12.53	12.8	13.07	13.28
12/30/2016	8.69	9.6	10.17	11.38	11.8	12.04	12.18	12.25	12.44	12.55	12.82	13.07	13.27
1/2/2017	8.67	9.58	10.16	11.21	11.73	11.95	12.1	12.19	12.32	12.43	12.7	12.9	13.14
1/3/2017	8.7	9.6	10.17	11.33	11.78	12.03	12.21	12.24	12.43	12.54	12.81	13.07	13.26
1/4/2017	8.7	9.6	10.17	11.31	11.76	12.02	12.21	12.24	12.42	12.52	12.8	13.07	13.26
1/5/2017	8.7	9.62	10.18	11.28	11.74	11.98	12.16	12.23	12.38	12.47	12.73	12.98	13.19

1/6/2017	8.72	9.68	10.2	11.26	11.71	11.9	12.05	12.15	12.22	12.33	12.54	12.75	12.98
1/9/2017	8.71	9.68	10.19	11.26	11.73	11.89	12.05	12.15	12.23	12.33	12.54	12.75	12.98
1/10/2017	8.7	9.68	10.19	11.25	11.72	11.89	12.04	12.15	12.23	12.33	12.53	12.75	12.97
1/11/2017	8.76	9.72	10.22	11.26	11.72	11.9	12.04	12.16	12.23	12.34	12.53	12.75	12.97
1/13/2017	8.77	9.73	10.21	11.26	11.73	11.9	12.04	12.16	12.25	12.35	12.53	12.75	12.97
1/16/2017	8.82	9.77	10.22	11.28	11.73	11.9	12.06	12.18	12.27	12.39	12.54	12.76	12.96
1/17/2017	8.9	9.82	10.24	11.32	11.74	11.91	12.07	12.17	12.28	12.39	12.55	12.75	12.97
1/18/2017	8.91	9.83	10.24	11.35	11.75	11.94	12.08	12.18	12.29	12.39	12.54	12.66	12.88
1/19/2017	8.91	9.85	10.25	11.36	11.76	11.94	12.09	12.17	12.28	12.38	12.53	12.67	12.87
1/20/2017	8.91	9.88	10.26	11.39	11.78	11.95	12.11	12.17	12.29	12.38	12.53	12.67	12.87
1/23/2017	8.92	9.89	10.27	11.4	11.78	11.95	12.11	12.18	12.29	12.38	12.53	12.67	12.87
1/24/2017	8.9	9.88	10.27	11.41	11.79	11.95	12.12	12.18	12.3	12.38	12.53	12.67	12.87
1/25/2017	8.9	9.88	10.27	11.42	11.79	11.96	12.13	12.18	12.3	12.38	12.53	12.67	12.87
1/26/2017	8.92	9.9	10.28	11.46	11.81	12.02	12.17	12.24	12.33	12.4	12.54	12.67	12.87
1/27/2017	8.94	9.93	10.32	11.5	11.84	12.05	12.24	12.29	12.4	12.46	12.61	12.77	12.94
1/30/2017	8.95	9.95	10.33	11.53	11.89	12.14	12.27	12.35	12.44	12.48	12.62	12.77	12.94
1/31/2017	8.96	9.95	10.33	11.51	11.88	12.08	12.24	12.37	12.46	12.49	12.63	12.77	12.94
2/1/2017	9.02	9.99	10.38	11.59	11.93	12.23	12.43	12.42	12.49	12.52	12.65	12.77	12.94
2/2/2017	9.08	10	10.39	11.6	11.93	12.25	12.42	12.43	12.5	12.52	12.64	12.77	12.94
2/3/2017	9.07	9.97	10.39	11.63	12.01	12.29	12.42	12.44	12.49	12.52	12.65	12.77	12.94
2/6/2017	9.08	9.99	10.39	11.61	11.98	12.25	12.4	12.43	12.5	12.52	12.64	12.77	12.94
2/7/2017	9.04	9.98	10.38	11.6	11.97	12.25	12.42	12.43	12.5	12.52	12.65	12.77	12.94
2/8/2017	9.03	9.98	10.39	11.57	11.95	12.21	12.37	12.4	12.46	12.51	12.64	12.77	12.94
2/9/2017	9.04	9.99	10.38	11.56	11.94	12.2	12.36	12.4	12.46	12.51	12.64	12.77	12.94
2/13/2017	9.04	9.99	10.37	11.57	11.95	12.17	12.33	12.39	12.46	12.5	12.62	12.77	12.94
2/14/2017	9.06	9.99	10.37	11.57	11.94	12.18	12.32	12.38	12.44	12.49	12.62	12.77	12.94

2/15/2017	9.07	9.99	10.37	11.59	11.98	12.22	12.4	12.43	12.48	12.52	12.65	12.83	12.97
2/16/2017	9.12	10.02	10.42	11.61	11.99	12.25	12.41	12.45	12.49	12.52	12.66	12.83	12.97
2/17/2017	9.07	10	10.41	11.61	11.99	12.24	12.4	12.45	12.49	12.51	12.66	12.83	12.97
2/20/2017	9.13	10.03	10.45	11.62	12	12.25	12.4	12.45	12.49	12.52	12.66	12.83	12.97
2/21/2017	9.12	10.02	10.45	11.62	11.99	12.26	12.42	12.45	12.49	12.52	12.67	12.83	12.97
2/22/2017	9.14	10.05	10.48	11.62	12.02	12.26	12.37	12.43	12.49	12.52	12.66	12.88	13.02
2/23/2017	9.17	10.07	10.49	11.63	12.05	12.28	12.42	12.43	12.5	12.54	12.67	12.88	13.02
2/27/2017	9.27	10.15	10.53	11.72	12.14	12.38	12.51	12.54	12.63	12.66	12.81	13.05	13.17
2/28/2017	9.29	10.16	10.54	11.76	12.17	12.43	12.64	12.62	12.73	12.76	12.93	13.13	13.25
3/1/2017	9.31	10.17	10.55	11.75	12.16	12.43	12.64	12.62	12.73	12.76	12.93	13.13	13.25
3/2/2017	9.29	10.17	10.55	11.75	12.16	12.43	12.64	12.62	12.73	12.76	12.93	13.13	13.25
3/3/2017	9.3	10.19	10.56	11.77	12.18	12.44	12.65	12.62	12.73	12.77	12.93	13.13	13.26
3/6/2017	9.31	10.19	10.57	11.78	12.19	12.45	12.65	12.66	12.76	12.78	12.94	13.13	13.26
3/7/2017	9.31	10.19	10.57	11.78	12.19	12.46	12.67	12.66	12.75	12.77	12.95	13.13	13.26
3/8/2017	9.31	10.2	10.57	11.79	12.2	12.46	12.69	12.69	12.79	12.79	12.98	13.13	13.26
3/9/2017	9.42	10.33	10.66	11.88	12.3	12.6	12.66	12.8	12.79	12.88	12.98	13.13	13.31
3/10/2017	9.43	10.34	10.68	11.89	12.32	12.62	12.68	12.83	12.8	12.9	13	13.14	13.33
3/13/2017	9.46	10.37	10.7	11.9	12.33	12.63	12.68	12.83	12.81	12.9	13	13.14	13.33
3/14/2017	9.46	10.37	10.71	11.98	12.43	12.68	12.69	12.83	12.81	12.9	13.04	13.14	13.33
3/15/2017	9.46	10.37	10.71	11.98	12.44	12.68	12.7	12.83	12.81	12.9	13.05	13.14	13.29
3/16/2017	9.46	10.37	10.71	11.93	12.4	12.69	12.72	12.82	12.83	12.9	13.05	13.14	13.29
3/17/2017	9.46	10.37	10.71	11.93	12.4	12.69	12.73	12.82	12.84	12.91	13.05	13.15	13.29
3/20/2017	9.46	10.37	10.71	11.93	12.4	12.69	12.73	12.83	12.84	12.91	13.06	13.15	13.29
3/21/2017	9.46	10.37	10.71	11.93	12.4	12.69	12.73	12.83	12.84	12.91	13.06	13.15	13.29
3/22/2017	9.46	10.36	10.71	11.94	12.41	12.69	12.72	12.83	12.87	12.94	13.07	13.14	13.28
3/23/2017	9.47	10.37	10.71	11.94	12.42	12.69	12.72	12.83	12.86	12.94	13.07	13.14	13.28

3/24/2017	9.48	10.38	10.73	11.94	12.43	12.67	12.7	12.84	12.85	12.94	13.06	13.14	13.28
3/27/2017	9.51	10.41	10.75	11.88	12.4	12.65	12.68	12.82	12.79	12.87	13.04	13.13	13.28
3/28/2017	9.51	10.42	10.75	11.85	12.37	12.59	12.65	12.79	12.76	12.85	13.03	13.12	13.28
3/29/2017	9.51	10.42	10.75	11.74	12.19	12.44	12.53	12.69	12.71	12.79	12.89	13.01	13.19
3/30/2017	9.52	10.44	10.76	11.69	12.15	12.39	12.5	12.66	12.68	12.76	12.86	13	13.2
3/31/2017	9.57	10.5	10.87	11.69	12.14	12.41	12.51	12.65	12.69	12.77	12.87	13	13.2
4/3/2017	9.6	10.49	10.9	11.7	12.02	12.42	12.5	12.63	12.7	12.8	12.88	13	13.19
4/4/2017	9.6	10.5	10.91	11.67	12.17	12.4	12.49	12.63	12.82	12.78	12.88	13	13.21
4/5/2017	9.6	10.5	10.91	11.74	12.16	12.34	12.49	12.6	12.68	12.76	12.87	13	13.2
4/6/2017	9.53	10.44	10.83	11.65	12.07	12.32	12.43	12.48	12.62	12.68	12.83	13	13.16
4/7/2017	9.61	10.53	10.89	11.67	12.09	12.3	12.41	12.5	12.62	12.7	12.84	13	13.21
4/11/2017	9.63	10.6	10.93	11.69	12.09	12.31	12.39	12.49	12.63	12.72	12.84	13	13.21
4/12/2017	9.66	10.63	10.98	11.68	12.06	12.29	12.37	12.51	12.63	12.72	12.84	12.98	13.2
4/17/2017	9.66	10.64	10.98	11.68	12.06	12.29	12.37	12.5	12.63	12.71	12.83	12.99	13.2
4/18/2017	9.66	10.64	10.98	11.66	12.04	12.28	12.36	12.49	12.65	12.72	12.86	12.99	13.2
4/19/2017	9.66	10.64	10.98	11.69	12.05	12.28	12.35	12.5	12.65	12.73	12.86	12.99	13.2
4/20/2017	9.67	10.64	10.98	11.69	12.05	12.27	12.35	12.49	12.65	12.73	12.86	12.99	13.2
4/21/2017	9.68	10.65	10.99	11.66	12.03	12.25	12.33	12.44	12.6	12.67	12.82	12.98	13.19
4/24/2017	9.68	10.65	10.99	11.65	12.04	12.26	12.33	12.47	12.58	12.67	12.81	12.98	13.19
4/25/2017	9.69	10.68	11.02	11.61	12.02	12.19	12.33	12.47	12.58	12.66	12.81	12.98	13.19
4/26/2017	9.7	10.68	11.03	11.58	11.96	12.14	12.26	12.39	12.51	12.59	12.75	12.9	13.11
4/27/2017	9.61	10.61	10.95	11.53	11.9	12.08	12.21	12.3	12.39	12.49	12.7	12.82	13.05
4/28/2017	9.58	10.55	10.89	11.4	11.8	11.95	12.04	12.11	12.16	12.22	12.41	12.66	12.88
5/2/2017	9.57	10.49	10.86	11.39	11.79	11.96	12	12.08	12.17	12.22	12.42	12.66	12.88
5/3/2017	9.55	10.46	10.83	11.36	11.78	11.89	12.01	12.07	12.18	12.23	12.42	12.66	12.86
5/4/2017	9.51	10.47	10.79	11.33	11.71	11.79	11.91	11.98	12.03	12.09	12.34	12.66	12.86

5/5/2017	9.48	10.41	10.75	11.18	11.59	11.71	11.81	11.86	11.94	12.03	12.29	12.63	12.85
5/8/2017	9.49	10.4	10.71	11.21	11.71	11.88	11.94	11.91	12.09	12.19	12.41	12.63	12.85
5/9/2017	9.48	10.44	10.72	11.17	11.59	11.76	11.82	11.84	11.98	12.06	12.3	12.63	12.85
5/12/2017	9.48	10.44	10.72	11.18	11.59	11.74	11.82	11.84	11.99	12.03	12.29	12.63	12.83
5/15/2017	9.46	10.45	10.76	11.21	11.63	11.8	11.87	11.84	11.99	12.03	12.27	12.63	12.83
5/16/2017	9.46	10.42	10.69	11.06	11.35	11.51	11.52	11.59	11.67	11.71	11.86	12.1	12.41
5/17/2017	9.45	10.42	10.7	11.06	11.35	11.51	11.52	11.61	11.67	11.72	11.87	12.1	12.4
5/18/2017	9.5	10.4	10.69	11.09	11.34	11.52	11.54	11.62	11.7	11.74	11.88	12.1	12.4
5/19/2017	9.49	10.41	10.71	11.1	11.34	11.53	11.55	11.63	11.72	11.76	11.89	12.1	12.39
5/22/2017	9.49	10.36	10.67	11.07	11.33	11.44	11.54	11.65	11.69	11.74	11.9	12.11	12.4
5/23/2017	9.49	10.36	10.67	11.07	11.33	11.44	11.55	11.64	11.69	11.74	11.9	12.11	12.4
5/24/2017	9.49	10.36	10.67	11.07	11.33	11.44	11.54	11.64	11.69	11.74	11.9	12.11	12.4
5/25/2017	9.48	10.37	10.67	11.07	11.33	11.44	11.54	11.64	11.69	11.74	11.9	12.11	12.4
5/26/2017	9.49	10.36	10.67	11.07	11.33	11.44	11.54	11.63	11.68	11.73	11.9	12.11	12.4
6/1/2017	9.49	10.35	10.66	11.05	11.32	11.44	11.54	11.64	11.7	11.75	11.91	12.11	12.46
6/2/2017	9.5	10.35	10.66	11.05	11.32	11.44	11.54	11.64	11.7	11.75	11.91	12.11	12.46
6/5/2017	9.51	10.33	10.66	11.04	11.32	11.44	11.55	11.64	11.71	11.75	11.91	12.11	12.46
6/6/2017	9.51	10.33	10.66	11.03	11.32	11.44	11.55	11.64	11.71	11.75	11.91	12.11	12.46
6/7/2017	9.51	10.33	10.65	11.02	11.32	11.44	11.55	11.64	11.7	11.75	11.9	12.11	12.46
6/9/2017	9.5	10.33	10.63	11	11.3	11.43	11.51	11.62	11.68	11.73	11.9	12.11	12.46
6/12/2017	9.51	10.31	10.62	10.99	11.3	11.43	11.49	11.61	11.66	11.71	11.89	12.1	12.46
6/13/2017	9.51	10.31	10.62	10.98	11.29	11.42	11.49	11.61	11.66	11.71	11.89	12.1	12.4
6/14/2017	9.49	10.3	10.6	10.93	11.26	11.36	11.45	11.56	11.61	11.67	11.85	12.1	12.39
6/15/2017	9.49	10.25	10.53	10.9	11.21	11.34	11.44	11.55	11.6	11.66	11.82	12.07	12.34
6/16/2017	9.49	10.26	10.52	10.9	11.21	11.34	11.45	11.56	11.61	11.66	11.81	12.07	12.31
6/19/2017	9.48	10.25	10.5	10.9	11.21	11.34	11.46	11.56	11.61	11.67	11.82	12.07	12.33

6/20/2017	9.48	10.25	10.5	10.9	11.21	11.35	11.46	11.56	11.6	11.66	11.82	12.07	12.33
6/21/2017	9.49	10.24	10.47	10.88	11.21	11.35	11.45	11.55	11.6	11.66	11.82	12.07	12.33
6/22/2017	9.49	10.25	10.48	10.89	11.21	11.35	11.45	11.55	11.6	11.65	11.82	12.07	12.33
6/23/2017	9.5	10.24	10.46	10.88	11.21	11.34	11.44	11.55	11.6	11.65	11.82	12.07	12.33
6/27/2017	9.5	10.24	10.46	10.86	11.21	11.35	11.47	11.56	11.63	11.69	11.85	12.07	12.35
6/28/2017	9.5	10.22	10.43	10.9	11.25	11.37	11.53	11.58	11.66	11.73	11.9	12.08	12.33
6/29/2017	9.51	10.22	10.43	10.89	11.23	11.36	11.49	11.55	11.63	11.69	11.88	12.08	12.32
6/30/2017	9.5	10.22	10.43	10.89	11.23	11.35	11.49	11.54	11.6	11.67	11.87	12.08	12.32
7/3/2017	9.51	10.22	10.44	10.88	11.24	11.35	11.48	11.54	11.6	11.66	11.87	12.09	12.32
7/4/2017	9.52	10.22	10.44	10.85	11.21	11.32	11.45	11.52	11.56	11.61	11.83	12.04	12.23
7/5/2017	9.51	10.21	10.44	10.81	11.17	11.27	11.42	11.48	11.51	11.58	11.73	12.02	12.17
7/6/2017	9.5	10.2	10.42	10.78	11.12	11.25	11.39	11.47	11.5	11.57	11.7	12.01	12.14
7/7/2017	9.5	10.2	10.41	10.78	11.14	11.26	11.4	11.47	11.51	11.56	11.67	12.02	12.17
7/10/2017	9.5	10.2	10.41	10.79	11.14	11.27	11.4	11.47	11.52	11.57	11.72	12.01	12.19
7/11/2017	9.5	10.19	10.41	10.77	11.07	11.27	11.37	11.46	11.51	11.58	11.75	12.01	12.19
7/12/2017	9.5	10.2	10.41	10.75	11.04	11.27	11.37	11.45	11.51	11.58	11.75	12.01	12.19
7/13/2017	9.51	10.18	10.4	10.71	11.04	11.25	11.36	11.44	11.5	11.55	11.75	12.01	12.19
7/14/2017	9.51	10.14	10.34	10.65	10.96	11.21	11.32	11.39	11.45	11.5	11.71	11.96	12.14
7/17/2017	9.5	10.12	10.31	10.65	10.97	11.21	11.31	11.36	11.44	11.49	11.7	11.96	12.14
7/18/2017	9.5	10.11	10.3	10.64	10.96	11.19	11.29	11.35	11.43	11.48	11.69	11.96	12.14
7/19/2017	9.5	10.06	10.26	10.64	10.98	11.16	11.21	11.29	11.45	11.46	11.71	11.97	12.14
7/20/2017	9.47	9.94	10.16	10.53	10.8	10.95	11.12	11.15	11.21	11.27	11.51	11.78	12.01
7/21/2017	9.41	9.73	9.94	10.46	10.71	10.88	11.01	11.07	11.12	11.19	11.42	11.71	11.9
7/24/2017	9.41	9.76	10.01	10.43	10.7	10.88	11.02	11.09	11.12	11.19	11.42	11.73	11.94
7/25/2017	9.42	9.77	10.01	10.43	10.7	10.87	11.04	11.08	11.13	11.19	11.42	11.73	11.94
7/26/2017	9.4	9.74	10	10.41	10.7	10.9	11.03	11.09	11.19	11.23	11.46	11.73	11.94

7/27/2017	9.38	9.69	9.96	10.39	10.68	10.88	11.03	11.08	11.18	11.23	11.46	11.73	11.94
7/28/2017	9.36	9.65	9.94	10.39	10.67	10.87	11.02	11.07	11.16	11.21	11.45	11.73	11.94
7/31/2017	9.33	9.57	9.84	10.35	10.66	10.85	10.86	11.02	11.12	11.17	11.42	11.73	11.94
8/1/2017	9.31	9.56	9.83	10.29	10.62	10.8	10.81	10.99	11.11	11.13	11.4	11.7	11.94
8/2/2017	9.28	9.49	9.79	10.27	10.55	10.78	10.8	10.94	11.03	11.07	11.39	11.71	11.94
8/3/2017	9.11	9.3	9.6	10.1	10.35	10.64	10.64	10.78	10.86	10.92	11.19	11.6	11.76
8/4/2017	9.1	9.28	9.58	9.78	10	10.29	10.36	10.39	10.45	10.51	10.66	10.88	11.05
8/8/2017	9.01	9.16	9.48	9.79	10.02	10.28	10.38	10.4	10.46	10.52	10.64	10.88	11.05
8/9/2017	9	9.16	9.49	9.78	10.02	10.28	10.4	10.46	10.5	10.53	10.64	10.88	11.05
8/10/2017	8.91	9.07	9.41	9.75	10.01	10.27	10.4	10.48	10.5	10.53	10.65	10.88	11.05
8/11/2017	8.9	9.05	9.41	9.84	10.03	10.31	10.42	10.52	10.57	10.6	10.74	10.9	11.07
8/14/2017	8.83	9	9.36	9.83	10.05	10.31	10.4	10.52	10.58	10.61	10.74	10.9	11.07
8/15/2017	8.83	9.01	9.37	9.83	10.06	10.32	10.4	10.55	10.58	10.62	10.73	10.9	11.06
8/16/2017	8.83	9.02	9.38	9.85	10.09	10.34	10.44	10.58	10.63	10.66	10.76	10.9	11.06
8/17/2017	8.86	9.07	9.44	9.87	10.11	10.39	10.49	10.62	10.67	10.69	10.79	10.92	11.07
8/18/2017	8.86	9.07	9.44	9.87	10.11	10.38	10.47	10.61	10.66	10.69	10.79	10.92	11.07
8/21/2017	8.88	9.12	9.49	9.89	10.11	10.37	10.47	10.62	10.67	10.7	10.79	10.92	11.08
8/22/2017	8.89	9.14	9.51	9.86	10.11	10.38	10.48	10.62	10.68	10.71	10.8	10.92	11.07
8/23/2017	8.9	9.18	9.5	9.9	10.17	10.43	10.51	10.66	10.74	10.8	10.88	11.01	11.16
8/24/2017	8.9	9.2	9.53	9.9	10.18	10.44	10.52	10.66	10.75	10.81	10.88	11.01	11.16
8/25/2017	8.9	9.21	9.53	9.9	10.18	10.43	10.55	10.66	10.74	10.8	10.88	11.01	11.16
8/28/2017	8.9	9.22	9.54	9.87	10.09	10.34	10.48	10.54	10.65	10.66	10.82	10.99	11.16
8/29/2017	8.9	9.21	9.54	9.82	10.04	10.28	10.45	10.49	10.58	10.61	10.76	10.9	11.06
8/30/2017	8.9	9.21	9.54	9.81	10.02	10.26	10.43	10.47	10.56	10.6	10.75	10.9	11.06
8/31/2017	8.89	9.2	9.55	9.8	10.01	10.26	10.42	10.46	10.53	10.59	10.75	10.9	11.05
9/4/2017	8.88	9.19	9.55	9.8	10.01	10.26	10.42	10.47	10.53	10.6	10.75	10.9	11.05

9/6/2017	8.9	9.25	9.58	9.8	10.01	10.26	10.42	10.44	10.52	10.59	10.75	10.91	11.05
9/7/2017	8.88	9.23	9.55	9.8	10.01	10.27	10.42	10.44	10.53	10.59	10.75	10.9	11.04
9/8/2017	8.88	9.22	9.54	9.8	10.01	10.27	10.39	10.45	10.53	10.59	10.75	10.9	11.04
9/11/2017	8.87	9.2	9.51	9.8	10.01	10.28	10.4	10.45	10.52	10.59	10.75	10.9	11.04
9/12/2017	8.85	9.19	9.51	9.76	10.01	10.22	10.35	10.4	10.47	10.52	10.73	10.89	11.04
9/13/2017	8.84	9.17	9.47	9.61	9.86	10.15	10.24	10.32	10.4	10.46	10.7	10.91	11.07
9/14/2017	8.74	9.11	9.37	9.6	9.81	10.1	10.2	10.25	10.32	10.41	10.66	10.9	11.07
9/15/2017	8.74	9.1	9.36	9.57	9.78	10.07	10.18	10.22	10.3	10.38	10.62	10.85	11.01
9/18/2017	8.7	9.05	9.27	9.55	9.77	10.06	10.13	10.19	10.25	10.36	10.63	10.84	11.01
9/19/2017	8.68	9.03	9.26	9.44	9.63	9.96	10.05	10.06	10.19	10.29	10.53	10.75	11
9/20/2017	8.68	9.03	9.25	9.4	9.61	9.91	10.02	10.03	10.15	10.23	10.49	10.65	10.88
9/21/2017	8.6	8.91	9.12	9.39	9.6	9.89	10.01	10.02	10.14	10.22	10.49	10.65	10.88
9/22/2017	8.6	8.91	9.12	9.38	9.6	9.88	10	10.02	10.14	10.23	10.49	10.65	10.88
9/25/2017	8.54	8.87	9.08	9.37	9.59	9.87	10	10.03	10.14	10.24	10.49	10.65	10.88
9/26/2017	8.54	8.87	9.09	9.37	9.61	9.87	10.01	10.03	10.15	10.25	10.49	10.66	10.88
9/27/2017	8.54	8.88	9.09	9.38	9.66	9.89	10.01	10.03	10.16	10.28	10.5	10.66	10.88
9/28/2017	8.61	8.92	9.1	9.43	9.72	9.94	10.03	10.04	10.18	10.3	10.51	10.66	10.88
9/29/2017	8.61	8.92	9.11	9.42	9.71	9.94	10.04	10.05	10.2	10.28	10.51	10.66	10.88
10/2/2017	8.64	8.96	9.12	9.47	9.77	9.97	10.06	10.07	10.21	10.3	10.51	10.66	10.88
10/3/2017	8.65	8.96	9.12	9.48	9.78	9.97	10.07	10.08	10.22	10.31	10.52	10.66	10.88
10/4/2017	8.73	9.05	9.28	9.52	9.86	10.07	10.13	10.15	10.3	10.36	10.54	10.66	10.88
10/6/2017	8.73	9.09	9.32	9.55	9.9	10.1	10.16	10.18	10.34	10.4	10.57	10.71	10.93
10/9/2017	8.75	9.09	9.33	9.58	9.93	10.08	10.17	10.21	10.35	10.4	10.58	10.71	10.75
10/10/2017	8.75	9.09	9.33	9.58	9.92	10.07	10.17	10.21	10.35	10.41	10.58	10.71	10.93
10/11/2017	8.75	9.09	9.33	9.58	9.89	10.07	10.17	10.2	10.35	10.4	10.58	10.71	10.93
10/12/2017	8.73	9.07	9.34	9.59	9.91	10.07	10.16	10.21	10.34	10.38	10.57	10.7	10.93

10/13/2017	8.73	9.07	9.35	9.6	9.9	10.04	10.14	10.21	10.33	10.38	10.57	10.7	10.93
10/16/2017	8.75	9.09	9.39	9.68	9.89	10.02	10.13	10.2	10.34	10.38	10.54	10.68	10.9
10/17/2017	8.75	9.09	9.39	9.68	9.89	10.02	10.13	10.2	10.34	10.37	10.54	10.68	10.9
10/19/2017	8.73	9.09	9.4	9.67	9.88	10.01	10.12	10.18	10.32	10.36	10.54	10.68	10.9
10/20/2017	8.72	9.09	9.4	9.67	9.87	10.01	10.12	10.18	10.32	10.35	10.54	10.68	10.9
10/23/2017	8.72	9.09	9.44	9.67	9.87	10.01	10.12	10.17	10.31	10.34	10.53	10.68	10.9
10/24/2017	8.72	9.09	9.44	9.67	9.88	10.01	10.12	10.18	10.31	10.34	10.53	10.68	10.9
10/25/2017	8.73	9.09	9.44	9.68	9.88	10.02	10.13	10.18	10.32	10.38	10.53	10.68	10.9
10/26/2017	8.73	9.09	9.44	9.68	9.88	10.02	10.12	10.18	10.32	10.38	10.54	10.68	10.9
10/27/2017	8.72	9.08	9.45	9.68	9.88	10.06	10.14	10.19	10.32	10.38	10.54	10.68	10.9
10/30/2017	8.72	9.08	9.45	9.68	9.88	10.05	10.14	10.19	10.32	10.38	10.54	10.68	10.85
10/31/2017	8.72	9.09	9.46	9.68	9.89	10.06	10.14	10.19	10.32	10.38	10.54	10.68	10.85
11/1/2017	8.69	9.06	9.43	9.68	9.88	10.06	10.14	10.2	10.32	10.38	10.54	10.68	10.85
11/2/2017	8.69	9.06	9.43	9.71	9.88	10.05	10.14	10.2	10.32	10.38	10.54	10.68	10.85
11/6/2017	8.68	9.04	9.41	9.7	9.88	10.04	10.12	10.18	10.3	10.34	10.54	10.7	10.87
11/7/2017	8.68	9.03	9.41	9.67	9.83	9.98	10.1	10.14	10.22	10.26	10.5	10.7	10.87
11/8/2017	8.68	9.02	9.4	9.65	9.82	9.97	10.09	10.12	10.19	10.21	10.4	10.56	10.74
11/9/2017	8.64	8.99	9.4	9.64	9.82	9.96	10.08	10.11	10.18	10.21	10.4	10.56	10.74
11/10/2017	8.61	8.98	9.4	9.64	9.81	9.96	10.07	10.1	10.18	10.2	10.4	10.56	10.74
11/13/2017	8.59	8.96	9.38	9.66	9.84	9.96	10.07	10.1	10.17	10.19	10.39	10.56	10.74
11/14/2017	8.59	8.96	9.38	9.67	9.84	9.96	10.07	10.1	10.17	10.2	10.4	10.57	10.74
11/15/2017	8.59	8.95	9.38	9.68	9.85	9.97	10.07	10.12	10.18	10.24	10.42	10.58	10.75
11/16/2017	8.56	8.93	9.4	9.72	9.87	9.99	10.11	10.18	10.2	10.27	10.45	10.6	10.75
11/17/2017	8.55	8.93	9.41	9.73	9.88	10.01	10.11	10.17	10.2	10.27	10.45	10.59	10.75
11/20/2017	8.51	8.93	9.41	9.74	9.89	10.02	10.12	10.18	10.19	10.28	10.46	10.6	10.75
11/21/2017	8.51	8.93	9.41	9.74	9.89	10.02	10.12	10.18	10.19	10.28	10.46	10.59	10.75

11/22/2017	8.49	8.92	9.41	9.74	9.89	10.01	10.12	10.17	10.19	10.26	10.45	10.59	10.75
11/24/2017	8.43	8.88	9.38	9.71	9.88	10	10.11	10.15	10.19	10.25	10.45	10.59	10.75
11/27/2017	8.34	8.85	9.38	9.7	9.88	10	10.11	10.15	10.19	10.26	10.45	10.58	10.75
11/28/2017	8.34	8.85	9.38	9.7	9.88	10	10.11	10.15	10.19	10.26	10.45	10.59	10.75
11/29/2017	8.24	8.82	9.37	9.71	9.91	10.04	10.12	10.18	10.23	10.29	10.5	10.65	10.82
11/30/2017	8.24	8.81	9.37	9.72	9.91	10.04	10.12	10.18	10.23	10.31	10.5	10.65	10.82
12/4/2017	8.19	8.75	9.37	9.7	9.91	10.04	10.12	10.18	10.24	10.31	10.5	10.65	10.82
12/5/2017	8.19	8.75	9.36	9.7	9.9	10.04	10.12	10.18	10.24	10.32	10.5	10.65	10.82
12/6/2017	8.15	8.75	9.34	9.7	9.91	10.04	10.12	10.18	10.24	10.31	10.5	10.65	10.82
12/7/2017	8.1	8.7	9.32	9.69	9.89	10.02	10.11	10.18	10.22	10.31	10.49	10.63	10.8
12/8/2017	7.98	8.64	9.29	9.68	9.89	10.02	10.11	10.18	10.23	10.32	10.49	10.63	10.8
12/11/2017	7.96	8.63	9.27	9.67	9.89	10.02	10.11	10.17	10.23	10.31	10.49	10.63	10.8
12/12/2017	7.9	8.65	9.25	9.65	9.88	10.01	10.1	10.16	10.22	10.3	10.49	10.63	10.8
12/13/2017	7.86	8.62	9.22	9.59	9.9	10	10.11	10.15	10.23	10.32	10.5	10.63	10.8
12/14/2017	7.77	8.48	9.09	9.38	9.71	9.83	10.01	10.07	10.16	10.24	10.38	10.52	10.71
12/15/2017	7.77	8.48	9.09	9.38	9.72	9.85	10.02	10.06	10.16	10.24	10.38	10.52	10.71
12/18/2017	7.68	8.39	8.99	9.34	9.7	9.86	9.99	10.03	10.15	10.25	10.39	10.52	10.69
12/19/2017	7.68	8.39	8.99	9.35	9.72	9.86	10	10.03	10.15	10.25	10.39	10.52	10.69
12/20/2017	7.68	8.39	8.99	9.35	9.72	9.85	10	10.06	10.15	10.25	10.39	10.52	10.69
12/21/2017	7.67	8.39	8.98	9.35	9.71	9.84	10	10.06	10.14	10.22	10.37	10.52	10.69
12/22/2017	7.67	8.4	8.98	9.35	9.71	9.84	10	10.06	10.14	10.22	10.37	10.52	10.69
12/26/2017	7.67	8.4	8.96	9.35	9.71	9.84	10	10.07	10.15	10.21	10.37	10.51	10.69
12/27/2017	7.65	8.35	8.93	9.33	9.69	9.81	9.96	10.02	10.1	10.16	10.32	10.45	10.62
12/28/2017	7.65	8.32	8.89	9.34	9.68	9.81	9.96	10.02	10.1	10.14	10.32	10.45	10.62
12/29/2017	7.68	8.3	8.89	9.37	9.68	9.81	9.96	10.01	10.09	10.15	10.34	10.49	10.68
1/2/2018	7.66	8.26	8.89	9.39	9.68	9.83	9.97	10.01	10.11	10.18	10.34	10.49	10.67

1/3/2018	7.65	8.27	8.87	9.28	9.55	9.64	9.84	9.89	10.01	10.07	10.28	10.46	10.63
1/4/2018	7.64	8.25	8.89	9.28	9.54	9.63	9.83	9.88	10.01	10.06	10.26	10.45	10.63
1/5/2018	7.66	8.22	8.87	9.2	9.47	9.58	9.73	9.77	9.89	9.95	10.17	10.42	10.62
1/8/2018	7.66	8.19	8.86	9.17	9.45	9.55	9.63	9.72	9.88	9.92	10.16	10.42	10.62
1/9/2018	7.67	8.18	8.86	9.09	9.36	9.41	9.55	9.57	9.74	9.81	10.01	10.17	10.36
1/10/2018	7.67	8.18	8.85	9.09	9.35	9.41	9.54	9.57	9.74	9.79	10.01	10.17	10.36
1/11/2018	7.63	8.1	8.82	9.09	9.35	9.4	9.53	9.57	9.7	9.72	9.98	10.16	10.32
1/12/2018	7.63	8.09	8.8	9.07	9.33	9.37	9.49	9.53	9.67	9.72	9.97	10.16	10.35
1/16/2018	7.61	8.04	8.78	9.05	9.32	9.37	9.46	9.53	9.67	9.73	9.97	10.16	10.32
1/17/2018	7.62	8.05	8.81	9.11	9.38	9.44	9.53	9.61	9.79	9.89	10.04	10.17	10.33
1/18/2018	7.63	8.04	8.84	9.1	9.36	9.41	9.52	9.57	9.74	9.86	10.04	10.16	10.33
1/19/2018	7.62	8.03	8.84	9.09	9.35	9.4	9.5	9.56	9.73	9.83	10.02	10.16	10.32
1/22/2018	7.63	8.03	8.84	9.1	9.35	9.41	9.5	9.56	9.72	9.83	10.02	10.15	10.32
1/23/2018	7.63	8.02	8.85	9.14	9.4	9.45	9.55	9.63	9.77	9.86	10.02	10.16	10.33
1/24/2018	7.63	8.02	8.85	9.14	9.38	9.43	9.54	9.62	9.76	9.85	10.02	10.15	10.32
1/25/2018	7.63	8	8.85	9.14	9.38	9.43	9.53	9.6	9.76	9.85	10.02	10.15	10.32
1/26/2018	7.63	8.01	8.86	9.14	9.38	9.43	9.52	9.6	9.76	9.85	10.02	10.15	10.32
1/29/2018	7.65	8	8.87	9.15	9.39	9.42	9.51	9.59	9.76	9.85	10.02	10.18	10.32
1/30/2018	7.65	8	8.87	9.14	9.38	9.4	9.48	9.56	9.74	9.8	9.99	10.16	10.33
2/1/2018	7.64	7.95	8.87	9.13	9.37	9.4	9.46	9.56	9.73	9.8	9.99	10.17	10.29
2/2/2018	7.64	7.94	8.86	9.12	9.36	9.42	9.45	9.56	9.73	9.82	10.01	10.17	10.34
2/6/2018	7.66	7.94	8.87	9.17	9.37	9.42	9.45	9.57	9.74	9.84	10.03	10.17	10.34
2/7/2018	7.66	7.93	8.88	9.21	9.4	9.45	9.49	9.6	9.77	9.88	10.08	10.2	10.36
2/8/2018	7.67	7.94	8.89	9.22	9.41	9.47	9.51	9.62	9.8	9.9	10.09	10.2	10.36
2/9/2018	7.67	7.94	8.9	9.22	9.41	9.47	9.51	9.62	9.8	9.9	10.09	10.2	10.36
2/12/2018	7.71	7.96	8.93	9.23	9.43	9.5	9.55	9.63	9.83	9.92	10.11	10.2	10.36

2/14/2018	7.8	8.04	9.01	9.38	9.58	9.64	9.72	9.77	9.92	10.05	10.17	10.21	10.36
2/15/2018	7.94	8.21	9.21	9.56	9.79	9.89	9.96	10.01	10.16	10.27	10.4	10.5	10.62
2/16/2018	7.98	8.26	9.24	9.5	9.73	9.83	9.9	9.97	10.11	10.23	10.38	10.5	10.62
2/19/2018	8.05	8.35	9.33	9.54	9.77	9.88	9.99	10.04	10.19	10.3	10.41	10.5	10.64
2/20/2018	8.05	8.35	9.33	9.54	9.78	9.89	10	10.07	10.17	10.29	10.4	10.52	10.65
2/21/2018	8.06	8.35	9.34	9.53	9.77	9.9	10.01	10.08	10.18	10.31	10.42	10.52	10.65
2/22/2018	8.15	8.44	9.42	9.54	9.79	9.94	10.05	10.1	10.25	10.36	10.44	10.54	10.66
2/23/2018	8.15	8.44	9.42	9.58	9.83	9.95	10.06	10.12	10.25	10.36	10.44	10.53	10.64
2/26/2018	8.2	8.5	9.45	9.54	9.81	9.92	10.04	10.08	10.18	10.27	10.4	10.49	10.64
2/27/2018	8.2	8.5	9.46	9.57	9.84	9.92	10.05	10.1	10.21	10.33	10.42	10.51	10.64
2/28/2018	8.21	8.5	9.51	9.59	9.86	9.93	10.08	10.11	10.23	10.34	10.43	10.51	10.65
3/2/2018	8.26	8.58	9.51	9.59	9.87	9.93	10.09	10.11	10.23	10.35	10.43	10.51	10.65
3/5/2018	8.28	8.57	9.54	9.6	9.89	9.93	10.09	10.13	10.25	10.37	10.44	10.51	10.65
3/6/2018	8.27	8.57	9.54	9.61	9.88	9.95	10.08	10.13	10.24	10.36	10.43	10.51	10.65
3/7/2018	8.27	8.58	9.53	9.61	9.89	9.94	10.08	10.12	10.24	10.36	10.43	10.51	10.65
3/8/2018	8.27	8.6	9.55	9.61	9.89	9.94	10.08	10.13	10.24	10.36	10.44	10.51	10.65
3/9/2018	8.26	8.59	9.56	9.62	9.89	9.94	10.08	10.13	10.25	10.37	10.44	10.51	10.64
3/12/2018	8.31	8.63	9.6	9.64	9.89	9.96	10.08	10.13	10.24	10.36	10.44	10.52	10.64
3/13/2018	8.3	8.63	9.6	9.64	9.9	9.98	10.08	10.13	10.24	10.36	10.44	10.52	10.64
3/14/2018	8.3	8.63	9.6	9.64	9.89	9.98	10.08	10.12	10.24	10.35	10.44	10.52	10.64
3/15/2018	8.28	8.61	9.6	9.64	9.89	9.98	10.07	10.11	10.24	10.35	10.44	10.52	10.64
3/16/2018	8.27	8.62	9.59	9.63	9.88	9.97	10.06	10.09	10.18	10.3	10.42	10.52	10.64
3/19/2018	8.27	8.64	9.59	9.62	9.86	9.96	10.04	10.07	10.17	10.3	10.42	10.52	10.64
3/20/2018	8.27	8.64	9.59	9.62	9.86	9.96	10.04	10.08	10.17	10.3	10.42	10.52	10.64
3/21/2018	8.27	8.65	9.59	9.62	9.85	9.94	10.03	10.07	10.17	10.3	10.41	10.52	10.64
3/22/2018	8.25	8.63	9.57	9.62	9.84	9.94	10.03	10.07	10.17	10.29	10.41	10.52	10.64

3/23/2018	8.26	8.63	9.58	9.62	9.84	9.94	10.03	10.07	10.17	10.29	10.41	10.52	10.64
3/26/2018	8.25	8.63	9.56	9.61	9.84	9.93	10.01	10.06	10.17	10.29	10.41	10.52	10.64
3/27/2018	8.24	8.63	9.56	9.61	9.85	9.93	10.02	10.07	10.18	10.3	10.41	10.52	10.64
3/28/2018	8.25	8.65	9.61	9.63	9.87	9.95	10.06	10.11	10.2	10.33	10.42	10.52	10.61
3/29/2018	8.28	8.67	9.61	9.65	9.95	10	10.17	10.19	10.29	10.42	10.54	10.53	10.65
4/2/2018	8.34	8.78	9.7	9.71	9.99	10.12	10.34	10.34	10.41	10.59	10.74	10.8	10.87
4/3/2018	8.35	8.8	9.72	9.71	10	10.12	10.38	10.43	10.46	10.6	10.76	10.82	10.94
4/4/2018	8.35	8.8	9.73	9.71	9.97	10.1	10.36	10.41	10.44	10.58	10.73	10.82	10.94
4/5/2018	8.38	8.86	9.74	9.71	9.95	10.1	10.33	10.39	10.43	10.56	10.71	10.82	10.94
4/6/2018	8.35	8.81	9.65	9.67	9.84	10.02	10.14	10.17	10.28	10.43	10.61	10.8	10.93
4/9/2018	8.33	8.79	9.62	9.66	9.83	9.99	10.1	10.14	10.24	10.36	10.58	10.74	10.9
4/10/2018	8.33	8.78	9.59	9.62	9.8	9.94	10.05	10.08	10.17	10.32	10.48	10.61	10.78
4/11/2018	8.31	8.78	9.61	9.61	9.78	9.88	10.03	10.07	10.17	10.32	10.49	10.61	10.78
4/12/2018	8.31	8.76	9.58	9.58	9.73	9.85	9.93	9.99	10.1	10.26	10.46	10.45	10.61
4/16/2018	8.31	8.76	9.58	9.58	9.73	9.86	9.95	10.01	10.11	10.25	10.45	10.59	10.77
4/17/2018	8.31	8.76	9.6	9.59	9.77	9.88	10	10.03	10.12	10.28	10.48	10.6	10.72
4/18/2018	8.3	8.76	9.6	9.6	9.77	9.88	9.99	10.03	10.12	10.27	10.47	10.6	10.72
4/19/2018	8.28	8.74	9.59	9.59	9.77	9.88	9.99	10.02	10.12	10.27	10.47	10.59	10.72
4/20/2018	8.26	8.73	9.57	9.59	9.78	9.91	10	10.04	10.13	10.28	10.47	10.59	10.72
4/23/2018	8.25	8.75	9.57	9.59	9.79	9.92	10.02	10.04	10.13	10.28	10.47	10.59	10.73
4/24/2018	8.26	8.73	9.57	9.59	9.8	9.92	10.02	10.05	10.13	10.28	10.47	10.59	10.73
4/25/2018	8.26	8.75	9.57	9.6	9.8	9.92	10.04	10.06	10.14	10.29	10.48	10.61	10.74
4/26/2018	8.15	8.72	9.56	9.6	9.82	9.95	10.06	10.07	10.14	10.3	10.48	10.61	10.72
4/27/2018	8.14	8.74	9.57	9.61	9.83	9.98	10.12	10.14	10.21	10.33	10.49	10.61	10.72
5/1/2018	8.13	8.67	9.55	9.61	9.84	9.99	10.11	10.18	10.21	10.33	10.49	10.61	10.72
5/2/2018	8.13	8.68	9.56	9.61	9.85	9.99	10.12	10.18	10.21	10.33	10.49	10.61	10.72

5/3/2018	8.13	8.69	9.56	9.63	9.86	10	10.13	10.19	10.24	10.38	10.49	10.62	10.73
5/4/2018	8.13	8.69	9.56	9.65	9.88	10.03	10.15	10.27	10.27	10.41	10.52	10.64	10.73
5/8/2018	8.16	8.75	9.58	9.68	9.92	10.03	10.18	10.29	10.28	10.44	10.53	10.65	10.74
5/9/2018	8.16	8.75	9.58	9.72	9.96	10.08	10.23	10.35	10.33	10.48	10.55	10.65	10.74
5/10/2018	8.16	8.76	9.61	9.71	9.95	10.08	10.24	10.38	10.39	10.54	10.56	10.65	10.74
5/11/2018	8.16	8.76	9.61	9.71	9.97	10.09	10.24	10.38	10.39	10.55	10.56	10.65	10.74
5/14/2018	8.27	8.78	9.62	9.72	9.97	10.11	10.26	10.38	10.39	10.55	10.58	10.65	10.74
5/15/2018	8.24	8.81	9.61	9.78	10.04	10.17	10.34	10.44	10.48	10.64	10.72	10.85	10.93
5/16/2018	8.24	8.81	9.61	9.78	10.05	10.17	10.34	10.43	10.48	10.64	10.72	10.85	10.93
5/17/2018	8.3	8.83	9.63	9.78	10.05	10.17	10.34	10.44	10.48	10.64	10.72	10.85	10.93
5/18/2018	8.3	8.82	9.63	9.72	10.05	10.17	10.34	10.44	10.49	10.64	10.72	10.85	10.93
5/21/2018	8.33	8.86	9.64	9.78	10.05	10.17	10.34	10.43	10.48	10.64	10.72	10.85	10.93
5/22/2018	8.34	8.86	9.64	9.77	10.05	10.17	10.34	10.43	10.48	10.64	10.72	10.85	10.93
5/23/2018	8.34	8.86	9.64	9.78	10.05	10.17	10.34	10.43	10.48	10.64	10.72	10.85	10.93
5/24/2018	8.35	8.86	9.65	9.82	10.05	10.17	10.34	10.43	10.48	10.64	10.73	10.85	10.93
5/25/2018	8.35	8.86	9.64	9.82	10.05	10.17	10.35	10.44	10.49	10.64	10.74	10.85	10.93
5/28/2018	8.36	8.85	9.63	9.82	10.05	10.17	10.35	10.44	10.49	10.65	10.74	10.85	10.93
5/30/2018	8.36	8.85	9.63	9.82	10.04	10.16	10.36	10.44	10.49	10.64	10.74	10.85	10.93
5/31/2018	8.35	8.85	9.58	9.77	9.98	10.13	10.33	10.41	10.47	10.62	10.71	10.82	10.92
6/1/2018	8.36	8.85	9.54	9.73	9.93	10.08	10.31	10.4	10.43	10.56	10.7	10.81	10.93
6/4/2018	8.36	8.84	9.53	9.73	9.91	10.08	10.32	10.44	10.45	10.56	10.7	10.86	10.93
6/5/2018	8.36	8.84	9.53	9.72	9.92	10.09	10.32	10.44	10.45	10.57	10.7	10.86	10.94
6/6/2018	8.36	8.84	9.53	9.71	9.92	10.08	10.33	10.44	10.45	10.57	10.7	10.86	10.94
6/7/2018	8.36	8.84	9.52	9.71	9.92	10.09	10.33	10.44	10.45	10.57	10.7	10.86	10.94
6/8/2018	8.34	8.84	9.52	9.71	9.92	10.09	10.32	10.43	10.45	10.56	10.7	10.86	10.94
6/11/2018	8.34	8.84	9.48	9.71	9.93	10.12	10.36	10.46	10.48	10.6	10.71	10.92	10.94

6/12/2018	8.34	8.84	9.48	9.71	9.93	10.13	10.37	10.47	10.49	10.6	10.71	10.92	10.94
6/13/2018	8.34	8.83	9.44	9.67	9.91	10.11	10.35	10.47	10.48	10.61	10.71	10.92	10.94
6/14/2018	8.34	8.83	9.43	9.65	9.92	10.11	10.35	10.46	10.47	10.6	10.71	10.92	10.99
6/18/2018	8.34	8.82	9.41	9.63	9.91	10.11	10.35	10.46	10.48	10.6	10.71	10.92	10.99
6/19/2018	8.34	8.82	9.41	9.63	9.91	10.11	10.35	10.46	10.47	10.6	10.71	10.89	10.99
6/20/2018	8.34	8.82	9.41	9.63	9.91	10.11	10.35	10.47	10.48	10.61	10.71	10.89	11
6/21/2018	8.34	8.81	9.39	9.63	9.91	10.12	10.36	10.48	10.49	10.61	10.72	10.89	11.07
6/22/2018	8.34	8.81	9.38	9.63	9.92	10.13	10.36	10.49	10.49	10.61	10.72	10.89	11.07
6/25/2018	8.35	8.82	9.38	9.64	9.93	10.13	10.36	10.48	10.49	10.62	10.72	10.89	11.07
6/26/2018	8.35	8.82	9.38	9.64	9.94	10.14	10.36	10.48	10.49	10.62	10.72	10.89	11.07
6/28/2018	8.36	8.83	9.38	9.64	9.94	10.14	10.36	10.48	10.49	10.62	10.72	10.89	11.07
6/29/2018	8.36	8.83	9.38	9.64	9.94	10.14	10.37	10.45	10.51	10.62	10.72	10.89	11.07
7/2/2018	8.36	8.83	9.39	9.64	9.95	10.15	10.37	10.45	10.51	10.63	10.72	10.89	11.07
7/3/2018	8.35	8.83	9.39	9.65	9.95	10.15	10.37	10.45	10.51	10.63	10.72	10.89	11.07
7/4/2018	8.35	8.84	9.39	9.67	9.98	10.18	10.43	10.5	10.59	10.7	10.88	10.98	11.08
7/5/2018	8.37	8.87	9.41	9.68	9.99	10.19	10.43	10.5	10.59	10.71	10.89	10.98	11.08
7/6/2018	8.37	8.87	9.41	9.68	9.99	10.19	10.43	10.5	10.59	10.71	10.89	10.98	11.08
7/9/2018	8.37	8.86	9.41	9.68	9.99	10.19	10.44	10.51	10.59	10.71	10.89	10.98	11.08
7/10/2018	8.37	8.86	9.41	9.68	9.97	10.18	10.44	10.51	10.59	10.71	10.89	10.98	11.08
7/11/2018	8.36	8.86	9.42	9.68	9.99	10.19	10.44	10.51	10.59	10.71	10.89	10.98	11.08
7/12/2018	8.37	8.85	9.41	9.68	9.99	10.19	10.44	10.51	10.59	10.71	10.89	10.98	11.08
7/13/2018	8.38	8.84	9.38	9.67	9.97	10.18	10.42	10.49	10.58	10.71	10.89	10.98	11.08
7/16/2018	8.37	8.85	9.39	9.71	9.99	10.2	10.37	10.44	10.53	10.67	10.87	10.94	11.05
7/17/2018	8.37	8.85	9.37	9.68	9.99	10.22	10.37	10.45	10.53	10.67	10.84	10.94	11.05
7/18/2018	8.37	8.85	9.37	9.6	9.95	10.14	10.36	10.43	10.51	10.64	10.82	10.91	11.01
7/19/2018	8.37	8.84	9.35	9.66	9.98	10.22	10.36	10.42	10.51	10.64	10.82	10.91	11.03

7/20/2018	8.35	8.79	9.3	9.53	9.91	10.13	10.24	10.32	10.42	10.55	10.77	10.88	11.01
7/23/2018	8.33	8.78	9.29	9.51	9.89	10.1	10.24	10.3	10.42	10.56	10.79	10.88	11.01
7/24/2018	8.33	8.76	9.28	9.56	9.88	10.1	10.24	10.32	10.42	10.56	10.79	10.88	11.01
7/25/2018	8.32	8.74	9.26	9.48	9.84	10.07	10.23	10.28	10.4	10.51	10.68	10.75	10.87
7/26/2018	8.32	8.74	9.26	9.47	9.84	10.06	10.23	10.28	10.4	10.51	10.68	10.75	10.87
7/30/2018	8.32	8.72	9.25	9.46	9.87	10.06	10.23	10.28	10.4	10.51	10.68	10.75	10.87
7/31/2018	8.32	8.72	9.25	9.45	9.87	10.05	10.23	10.28	10.39	10.5	10.68	10.75	10.87
8/1/2018	8.31	8.71	9.23	9.42	9.81	9.98	10.11	10.15	10.29	10.39	10.55	10.62	10.76
8/2/2018	8.3	8.72	9.22	9.39	9.75	9.95	10.06	10.1	10.22	10.32	10.53	10.62	10.76
8/3/2018	8.3	8.72	9.22	9.39	9.73	9.94	10.06	10.1	10.2	10.32	10.49	10.58	10.76
8/6/2018	8.29	8.73	9.2	9.38	9.72	9.9	10.04	10.08	10.19	10.32	10.5	10.58	10.76
8/7/2018	8.29	8.73	9.19	9.38	9.69	9.88	9.99	10.06	10.18	10.31	10.49	10.58	10.73
8/8/2018	8.29	8.73	9.19	9.38	9.7	9.87	10	10.06	10.16	10.3	10.49	10.57	10.73
8/9/2018	8.25	8.71	9.14	9.35	9.67	9.84	9.96	10	10.14	10.28	10.49	10.57	10.73
8/10/2018	8.25	8.7	9.12	9.34	9.65	9.83	9.93	9.98	10.11	10.23	10.47	10.55	10.72
8/13/2018	8.25	8.7	9.11	9.34	9.69	9.82	9.92	9.99	10.11	10.23	10.47	10.55	10.72
8/14/2018	8.25	8.7	9.09	9.3	9.62	9.79	9.88	9.95	10.08	10.2	10.44	10.48	10.64
8/15/2018	8.25	8.7	9.08	9.28	9.59	9.78	9.87	9.96	10.08	10.19	10.45	10.46	10.64
8/16/2018	8.21	8.65	9.04	9.26	9.59	9.78	9.84	9.96	10.08	10.19	10.45	10.46	10.64
8/17/2018	8.22	8.66	9.04	9.25	9.59	9.77	9.91	10	10.1	10.22	10.47	10.46	10.64
8/20/2018	8.19	8.61	9	9.26	9.6	9.78	9.92	10.01	10.11	10.23	10.47	10.46	10.64
8/21/2018	8.19	8.61	9.01	9.26	9.6	9.78	9.93	10.01	10.11	10.24	10.47	10.46	10.64
8/23/2018	8.18	8.6	9	9.25	9.6	9.79	9.95	10.02	10.13	10.24	10.47	10.46	10.64
8/24/2018	8.19	8.6	9.01	9.26	9.61	9.81	9.96	10.03	10.13	10.25	10.48	10.46	10.64
8/27/2018	8.19	8.6	9.01	9.26	9.62	9.81	9.95	10.03	10.13	10.25	10.48	10.46	10.64
8/28/2018	8.2	8.62	9.01	9.26	9.62	9.81	9.96	10.03	10.13	10.25	10.48	10.46	10.64

8/29/2018	8.2	8.61	9	9.24	9.61	9.81	9.95	10.03	10.13	10.24	10.48	10.46	10.64
8/30/2018	8.18	8.61	8.98	9.24	9.61	9.8	9.95	10.05	10.13	10.24	10.43	10.45	10.61
8/31/2018	8.18	8.61	8.98	9.24	9.61	9.8	9.95	10.05	10.13	10.24	10.43	10.45	10.61
9/3/2018	8.18	8.61	8.98	9.24	9.6	9.8	9.94	10.03	10.13	10.23	10.43	10.44	10.61
9/4/2018	8.18	8.61	8.98	9.24	9.59	9.8	9.95	10.03	10.13	10.23	10.43	10.44	10.61
9/5/2018	8.18	8.61	8.98	9.24	9.59	9.8	9.95	10.04	10.13	10.23	10.43	10.44	10.61
9/6/2018	8.16	8.6	8.96	9.24	9.59	9.8	9.96	10.05	10.13	10.23	10.43	10.44	10.61
9/7/2018	8.15	8.6	8.96	9.24	9.6	9.8	9.95	10.05	10.13	10.24	10.43	10.44	10.61
9/10/2018	8.14	8.59	8.94	9.24	9.6	9.8	9.95	10.05	10.13	10.24	10.43	10.44	10.61
9/11/2018	8.14	8.59	8.95	9.24	9.61	9.82	9.96	10.06	10.14	10.25	10.43	10.44	10.61
9/12/2018	8.16	8.61	8.96	9.25	9.66	9.86	9.99	10.09	10.19	10.31	10.5	10.44	10.61
9/13/2018	8.16	8.62	9.04	9.33	9.74	9.94	10.13	10.2	10.3	10.4	10.53	10.49	10.61
9/14/2018	8.18	8.64	9.01	9.35	9.79	9.99	10.14	10.22	10.34	10.42	10.53	10.58	10.63
9/17/2018	8.19	8.66	9.08	9.23	9.85	10.05	10.16	10.23	10.34	10.42	10.54	10.58	10.63
9/18/2018	8.21	8.67	9.11	9.5	10.08	10.26	10.44	10.52	10.6	10.69	10.84	10.84	10.9
9/19/2018	8.22	8.7	9.13	9.52	10.13	10.35	10.5	10.56	10.65	10.73	10.85	10.85	10.92
9/20/2018	8.23	8.74	9.17	9.56	10.22	10.44	10.54	10.58	10.68	10.77	10.91	10.96	10.93
9/21/2018	8.23	8.74	9.2	9.57	10.24	10.44	10.54	10.55	10.67	10.76	10.9	10.96	10.93
9/25/2018	8.24	8.76	9.22	9.66	10.33	10.46	10.53	10.58	10.67	10.78	10.92	10.96	10.93
9/26/2018	8.25	8.76	9.23	9.66	10.33	10.46	10.53	10.59	10.68	10.78	10.92	10.96	10.93
9/27/2018	8.4	8.85	9.36	9.76	10.37	10.49	10.58	10.67	10.73	10.8	10.92	10.96	10.93
9/28/2018	8.45	8.88	9.41	9.77	10.41	10.55	10.67	10.74	10.81	10.86	11	11.06	10.96
10/1/2018	8.58	8.96	9.5	9.94	10.57	10.7	10.76	10.86	10.93	10.99	11.08	11.11	10.97
10/2/2018	8.6	8.98	9.52	10.04	10.6	10.74	10.81	10.87	10.99	11.03	11.11	11.11	10.97
10/3/2018	8.67	9.03	9.56	10.31	10.77	10.88	10.98	11.1	11.2	11.32	11.44	11.43	11.53
10/4/2018	8.65	9.05	9.56	10.24	10.71	10.82	10.93	11.08	11.16	11.28	11.43	11.43	11.53

10/5/2018	8.65	9.05	9.56	10.28	10.72	10.83	10.94	11.08	11.16	11.28	11.43	11.43	11.53
10/8/2018	8.65	9.06	9.58	10.28	10.74	10.83	10.95	11.09	11.17	11.29	11.43	11.46	11.54
10/9/2018	8.65	9.08	9.59	10.31	10.76	10.85	10.97	11.1	11.19	11.3	11.44	11.51	11.54
10/10/2018	8.66	9.09	9.62	10.34	10.79	10.89	11.01	11.12	11.23	11.33	11.45	11.56	11.55
10/11/2018	9.06	9.41	10.04	10.57	10.96	11.06	11.23	11.32	11.42	11.54	11.7	11.81	11.73
10/12/2018	9.2	9.61	10.18	10.82	11.23	11.4	11.59	11.56	11.72	11.85	12.03	12.01	12.12
10/15/2018	9.3	9.66	10.26	10.81	11.28	11.49	11.58	11.61	11.73	11.86	11.99	11.99	12.11
10/16/2018	9.32	9.68	10.28	10.83	11.32	11.51	11.58	11.67	11.76	11.87	12	12.04	12.12
10/17/2018	9.31	9.67	10.28	10.93	11.4	11.57	11.66	11.76	11.85	11.98	12.14	12.27	12.35
10/18/2018	9.33	9.63	10.28	10.85	11.21	11.42	11.54	11.65	11.73	11.94	12.13	12.27	12.35
10/19/2018	9.33	9.63	10.26	10.8	11.2	11.4	11.53	11.63	11.71	11.92	12.12	12.27	12.35
10/22/2018	9.4	9.7	10.31	10.74	11.08	11.31	11.45	11.55	11.64	11.82	12.02	12.16	12.28
10/23/2018	9.39	9.69	10.3	10.57	10.93	11.23	11.32	11.39	11.48	11.6	11.81	11.96	12.08
10/25/2018	9.37	9.7	10.31	10.56	10.95	11.24	11.31	11.38	11.47	11.58	11.78	11.91	12.03
10/26/2018	9.37	9.7	10.31	10.53	10.9	11.21	11.3	11.37	11.45	11.57	11.77	11.91	11.98
10/29/2018	9.37	9.7	10.31	10.54	10.94	11.25	11.36	11.41	11.46	11.57	11.78	11.91	11.98
10/30/2018	9.4	9.73	10.36	10.66	11.03	11.28	11.4	11.49	11.54	11.67	11.82	11.91	11.98
10/31/2018	9.4	9.73	10.36	10.67	11.03	11.25	11.38	11.48	11.53	11.65	11.82	11.91	11.98
11/1/2018	9.39	9.74	10.39	10.73	11.01	11.23	11.35	11.42	11.48	11.61	11.81	11.91	11.98
11/2/2018	9.38	9.73	10.38	10.68	10.96	11.21	11.31	11.38	11.47	11.59	11.77	11.82	11.88
11/5/2018	9.37	9.71	10.36	10.69	10.96	11.22	11.33	11.4	11.47	11.59	11.77	11.82	11.88
11/7/2018	9.39	9.73	10.36	10.69	10.97	11.23	11.33	11.4	11.47	11.59	11.77	11.82	11.88
11/8/2018	9.45	9.81	10.57	10.81	11.05	11.28	11.39	11.48	11.53	11.65	11.79	11.82	11.88
11/9/2018	9.46	9.82	10.62	10.8	11.08	11.31	11.4	11.51	11.55	11.65	11.79	11.82	11.88
11/12/2018	9.58	9.98	10.79	10.84	11.15	11.35	11.47	11.59	11.63	11.74	11.86	11.82	11.89
11/13/2018	9.59	10.01	10.8	10.91	11.19	11.43	11.52	11.65	11.69	11.77	11.88	11.86	11.88

11/14/2018	9.62	10.08	10.87	10.99	11.25	11.59	11.63	11.67	11.78	11.91	12.02	11.95	11.9
11/15/2018	9.78	10.24	10.96	11.06	11.35	11.66	11.68	11.75	11.85	11.97	12.07	12.01	11.92
11/16/2018	9.79	10.24	10.98	11.06	11.36	11.63	11.65	11.77	11.84	11.98	12.08	12.07	11.93
11/19/2018	9.82	10.3	11	11.03	11.33	11.61	11.61	11.71	11.79	11.89	12	12.07	11.93
11/21/2018	9.89	10.38	11.05	11.25	11.47	11.66	11.7	11.82	11.92	12.11	12.23	12.51	12.38
11/23/2018	9.9	10.4	11.11	11.3	11.55	11.72	11.81	11.93	12	12.2	12.3	12.54	12.38
11/26/2018	9.93	10.43	11.15	11.36	11.61	11.81	11.87	11.97	12.06	12.25	12.36	12.6	12.39
11/27/2018	9.92	10.44	11.14	11.36	11.6	11.81	11.87	11.97	12.09	12.25	12.37	12.64	12.39
11/28/2018	9.92	10.43	11.13	11.35	11.56	11.77	11.81	11.91	12.03	12.19	12.35	12.61	12.39
11/29/2018	9.91	10.39	11.14	11.36	11.61	11.82	11.82	11.89	12	12.17	12.35	12.61	12.39
11/30/2018	9.91	10.4	11.12	11.33	11.59	11.78	11.78	11.88	11.99	12.16	12.34	12.61	12.39
12/3/2018	9.89	10.39	11.11	11.31	11.55	11.71	11.73	11.87	11.95	12.15	12.32	12.6	12.39
12/4/2018	9.89	10.39	11.12	11.31	11.55	11.73	11.75	11.87	11.97	12.15	12.34	12.53	12.38
12/5/2018	9.87	10.37	11.11	11.35	11.56	11.67	11.75	11.86	11.98	12.12	12.3	12.45	12.3
12/6/2018	9.86	10.33	11.1	11.35	11.55	11.68	11.73	11.84	11.94	12.11	12.3	12.43	12.3
12/7/2018	9.82	10.29	11.07	11.24	11.48	11.6	11.65	11.73	11.83	12.02	12.17	12.4	12.3
12/10/2018	9.81	10.27	11.04	11.22	11.46	11.55	11.62	11.73	11.81	12.01	12.17	12.4	12.3
12/11/2018	9.81	10.21	11.03	11.22	11.46	11.56	11.62	11.74	11.82	12.01	12.17	12.4	12.3
12/12/2018	9.81	10.21	11.03	11.22	11.47	11.58	11.64	11.75	11.83	12.02	12.17	12.45	12.3
12/13/2018	9.78	10.16	11.06	11.25	11.54	11.64	11.71	11.79	11.86	12.05	12.19	12.45	12.3
12/14/2018	9.78	10.16	11.06	11.26	11.54	11.66	11.71	11.79	11.88	12.04	12.18	12.45	12.3
12/17/2018	9.76	10.16	11.07	11.26	11.54	11.66	11.7	11.79	11.86	12.03	12.17	12.45	12.3
12/18/2018	9.76	10.16	11.07	11.24	11.55	11.67	11.7	11.79	11.87	12.03	12.17	12.45	12.3
12/19/2018	9.78	10.1	11.08	11.25	11.55	11.67	11.7	11.77	11.85	12.02	12.17	12.45	12.3
12/20/2018	9.77	10.07	11.07	11.25	11.55	11.67	11.69	11.76	11.85	12.04	12.17	12.45	12.3
12/21/2018	9.76	10.07	11.06	11.2	11.47	11.59	11.62	11.68	11.76	11.95	12.08	12.35	12.29

12/24/2018	9.73	10.06	11.03	11.16	11.44	11.54	11.59	11.66	11.72	11.94	12.07	12.27	12.27
12/26/2018	9.69	10.02	11	11.15	11.43	11.52	11.56	11.62	11.67	11.87	12.01	12.16	12.16
12/27/2018	9.69	10.01	10.99	11.15	11.42	11.52	11.56	11.62	11.68	11.86	12.01	12.15	12.16
12/28/2018	9.69	10.01	11.01	11.16	11.44	11.55	11.58	11.66	11.7	11.88	12.01	12.15	12.16
12/31/2018	9.67	9.96	10.91	11.16	11.42	11.54	11.58	11.65	11.69	11.87	12.01	12.15	12.16
1/1/2019	9.67	9.96	10.91	11.16	11.42	11.53	11.58	11.64	11.69	11.87	12.01	12.12	12.15
1/2/2019	9.66	9.96	10.9	11.16	11.42	11.52	11.57	11.63	11.68	11.86	12.01	12.12	12.15
1/3/2019	9.66	9.95	10.89	11.07	11.33	11.44	11.49	11.57	11.61	11.79	11.95	12.06	12.09
1/4/2019	9.65	9.94	10.87	11.07	11.32	11.43	11.5	11.58	11.61	11.79	11.95	12.06	12.09
1/7/2019	9.64	9.93	10.84	11.05	11.31	11.43	11.51	11.58	11.62	11.8	11.95	12.05	12.08
1/8/2019	9.62	9.93	10.84	11.03	11.29	11.41	11.49	11.58	11.61	11.79	11.95	12.02	12.08
1/9/2019	9.62	9.92	10.84	11.03	11.29	11.41	11.49	11.6	11.63	11.79	11.96	12.03	12.08
1/10/2019	9.79	9.92	10.79	11.01	11.29	11.42	11.49	11.61	11.64	11.8	11.96	12.03	12.08
1/11/2019	9.78	9.92	10.79	11.01	11.3	11.42	11.51	11.61	11.64	11.8	11.95	12.03	12.08
1/14/2019	9.73	9.88	10.75	10.98	11.26	11.41	11.49	11.58	11.64	11.78	11.95	12.05	12.08
1/16/2019	9.72	9.82	10.72	10.79	11.1	11.28	11.39	11.5	11.58	11.69	11.87	11.95	11.98
1/17/2019	9.69	9.79	10.67	10.87	11.08	11.29	11.35	11.51	11.55	11.7	11.88	11.96	12.01
1/18/2019	9.67	9.79	10.66	10.84	11.05	11.26	11.34	11.46	11.48	11.64	11.88	11.96	12.01
1/21/2019	9.67	9.78	10.61	10.82	11.01	11.22	11.32	11.44	11.46	11.64	11.89	11.96	12.01
1/22/2019	9.65	9.78	10.6	10.81	11.02	11.24	11.33	11.44	11.47	11.65	11.88	11.96	12.01
1/23/2019	9.65	9.79	10.6	10.81	11.02	11.27	11.36	11.47	11.5	11.66	11.87	11.96	12.01
1/24/2019	9.66	9.79	10.61	10.81	11	11.24	11.33	11.44	11.48	11.66	11.87	11.96	12.01
1/25/2019	9.66	9.79	10.61	10.81	11.01	11.24	11.33	11.37	11.45	11.66	11.87	11.96	12.01
1/28/2019	9.66	9.79	10.62	10.81	11.02	11.26	11.36	11.47	11.53	11.67	11.87	11.96	12.01
1/29/2019	9.66	9.79	10.62	10.8	11.03	11.26	11.34	11.44	11.52	11.67	11.87	11.96	12.01
1/30/2019	9.65	9.77	10.61	10.78	11.02	11.22	11.28	11.39	11.47	11.65	11.86	11.96	12

1/31/2019	9.64	9.76	10.6	10.77	10.98	11.18	11.23	11.34	11.4	11.59	11.86	11.96	12
2/1/2019	9.63	9.75	10.57	10.75	10.95	11.08	11.11	11.22	11.26	11.49	11.77	11.83	11.88
2/5/2019	9.65	9.74	10.58	10.73	10.94	11.03	11.1	11.2	11.22	11.45	11.72	11.83	11.85
2/6/2019	9.65	9.74	10.6	10.74	10.94	11.03	11.1	11.21	11.22	11.42	11.7	11.63	11.84
2/7/2019	9.68	9.76	10.62	10.73	10.95	11.03	11.09	11.13	11.2	11.36	11.63	11.65	11.73
2/8/2019	9.68	9.76	10.62	10.73	10.95	11.03	11.1	11.14	11.2	11.37	11.63	11.65	11.73
2/11/2019	9.7	9.78	10.62	10.75	10.96	11.07	11.1	11.14	11.21	11.38	11.63	11.65	11.73
2/12/2019	9.7	9.78	10.62	10.79	10.98	11.09	11.11	11.17	11.24	11.4	11.63	11.65	11.73
2/13/2019	9.72	9.8	10.63	10.83	11	11.1	11.12	11.2	11.28	11.41	11.64	11.69	11.73
2/14/2019	9.74	9.82	10.67	10.85	11.04	11.12	11.14	11.2	11.27	11.44	11.64	11.71	11.74
2/15/2019	9.74	9.81	10.65	10.86	11.04	11.12	11.14	11.2	11.28	11.43	11.64	11.72	11.75
2/18/2019	9.73	9.82	10.66	10.85	11.04	11.12	11.15	11.2	11.28	11.43	11.63	11.73	11.76
2/20/2019	9.73	9.82	10.66	10.86	11.04	11.13	11.16	11.2	11.28	11.43	11.64	11.73	11.76
2/21/2019	9.73	9.83	10.66	10.87	11.04	11.13	11.16	11.2	11.29	11.43	11.64	11.73	11.76
2/22/2019	9.72	9.83	10.66	10.86	11.01	11.12	11.14	11.18	11.26	11.41	11.57	11.73	11.76
2/25/2019	9.69	9.81	10.63	10.82	10.97	11.09	11.12	11.17	11.22	11.37	11.57	11.65	11.73
2/26/2019	9.69	9.81	10.61	10.84	10.97	11.08	11.11	11.17	11.21	11.36	11.57	11.65	11.73
2/27/2019	9.69	9.81	10.61	10.84	10.97	11.08	11.11	11.16	11.21	11.36	11.57	11.65	11.73
2/28/2019	9.69	9.81	10.61	10.78	10.94	11.06	11.09	11.15	11.2	11.35	11.57	11.65	11.73
3/1/2019	9.69	9.81	10.6	10.79	10.94	11.06	11.09	11.15	11.2	11.35	11.57	11.65	11.73
3/5/2019	9.68	9.81	10.59	10.76	10.9	11.02	11.05	11.12	11.17	11.33	11.56	11.6	11.73
3/6/2019	9.68	9.8	10.58	10.74	10.87	10.99	11.04	11.12	11.17	11.33	11.56	11.6	11.73
3/7/2019	9.68	9.8	10.59	10.73	10.86	10.98	11.02	11.12	11.17	11.33	11.56	11.6	11.73
3/8/2019	9.66	9.78	10.54	10.65	10.72	10.85	10.86	10.96	11.04	11.2	11.44	11.48	11.64
3/11/2019	9.65	9.78	10.52	10.65	10.73	10.85	10.88	10.98	11.05	11.23	11.45	11.48	11.64
3/12/2019	9.64	9.77	10.5	10.65	10.74	10.87	10.89	10.99	11.05	11.23	11.45	11.5	11.65

3/13/2019	9.64	9.77	10.5	10.64	10.75	10.89	10.93	11.03	11.09	11.27	11.53	11.53	11.65
3/14/2019	9.65	9.77	10.52	10.66	10.78	10.91	10.95	11.05	11.12	11.3	11.54	11.59	11.66
3/15/2019	9.65	9.77	10.52	10.67	10.79	10.91	10.96	11.06	11.13	11.32	11.54	11.59	11.66
3/18/2019	9.64	9.76	10.61	10.67	10.79	10.92	10.97	11.04	11.1	11.29	11.52	11.58	11.63
3/19/2019	9.64	9.76	10.51	10.68	10.8	10.93	10.98	11.04	11.11	11.3	11.52	11.58	11.63
3/21/2019	9.62	9.74	10.49	10.68	10.8	10.93	10.98	11.04	11.11	11.3	11.52	11.58	11.64
3/22/2019	9.61	9.7	10.45	10.64	10.76	10.91	10.95	11.04	11.1	11.28	11.51	11.58	11.64
3/25/2019	9.62	9.71	10.44	10.65	10.77	10.92	10.96	11.04	11.09	11.28	11.51	11.58	11.64
3/26/2019	9.6	9.69	10.41	10.59	10.74	10.86	10.93	11.03	11.09	11.28	11.52	11.6	11.66
3/27/2019	9.59	9.68	10.4	10.59	10.73	10.86	10.93	11.03	11.09	11.28	11.52	11.6	11.66
3/28/2019	9.57	9.67	10.34	10.54	10.71	10.84	10.91	11.02	11.08	11.28	11.52	11.6	11.66
3/29/2019	9.53	9.65	10.31	10.5	10.71	10.83	10.91	11.06	11.1	11.31	11.51	11.6	11.66
4/1/2019	9.52	9.64	10.28	10.48	10.69	10.83	10.9	11.04	11.09	11.31	11.51	11.6	11.66
4/2/2019	9.52	9.63	10.33	10.48	10.68	10.83	10.9	11.04	11.09	11.31	11.51	11.6	11.66
4/3/2019	9.52	9.63	10.28	10.47	10.67	10.82	10.9	11.03	11.08	11.3	11.5	11.6	11.66
4/4/2019	9.46	9.54	10.12	10.39	10.56	10.77	10.85	10.98	11.04	11.24	11.47	11.58	11.64
4/5/2019	9.43	9.52	10.09	10.31	10.49	10.69	10.8	10.91	11	11.16	11.38	11.5	11.52
4/8/2019	9.42	9.49	10.03	10.27	10.44	10.64	10.75	10.86	10.98	11.13	11.36	11.5	11.51
4/9/2019	9.37	9.49	10.03	10.28	10.47	10.66	10.77	10.88	10.99	11.15	11.37	11.5	11.52
4/10/2019	9.37	9.49	10.03	10.31	10.49	10.72	10.8	10.92	11.02	11.17	11.38	11.5	11.53
4/11/2019	9.31	9.43	9.99	10.27	10.46	10.69	10.76	10.86	10.97	11.13	11.36	11.5	11.52
4/12/2019	9.29	9.4	9.96	10.24	10.44	10.68	10.76	10.84	10.96	11.11	11.35	11.5	11.52
4/16/2019	9.25	9.33	9.9	10.24	10.44	10.66	10.75	10.84	10.95	11.1	11.34	11.5	11.52
4/17/2019	9.22	9.27	9.86	10.24	10.44	10.64	10.74	10.84	10.97	11.11	11.35	11.5	11.52
4/18/2019	9.2	9.24	9.85	10.2	10.41	10.61	10.7	10.81	10.93	11.08	11.33	11.48	11.49
4/22/2019	9.21	9.23	9.84	10.23	10.43	10.62	10.73	10.83	10.97	11.13	11.36	11.48	11.49

4/23/2019	9.21	9.25	9.85	10.28	10.48	10.68	10.77	10.93	11.03	11.2	11.4	11.49	11.51
4/24/2019	9.22	9.25	9.87	10.28	10.51	10.71	10.81	10.94	11.04	11.17	11.39	11.48	11.51
4/25/2019	9.2	9.22	9.86	10.29	10.52	10.7	10.8	10.94	11.03	11.16	11.38	11.48	11.51
4/26/2019	9.19	9.22	9.86	10.28	10.51	10.72	10.82	10.92	11.02	11.15	11.38	11.48	11.51
4/29/2019	9.17	9.19	9.88	10.31	10.55	10.74	10.84	10.95	11	11.16	11.38	11.48	11.51
4/30/2019	9.16	9.18	9.87	10.29	10.52	10.73	10.83	10.93	10.99	11.13	11.36	11.48	11.5
5/2/2019	9.12	9.13	9.78	10.17	10.39	10.64	10.75	10.87	10.94	11.06	11.26	11.43	11.48
5/3/2019	9.08	9.09	9.74	10.13	10.4	10.62	10.71	10.82	10.89	11.02	11.21	11.34	11.38
5/6/2019	9.06	9.08	9.73	10.09	10.34	10.58	10.68	10.8	10.86	11	11.2	11.34	11.37
5/7/2019	9.06	9.08	9.72	10.09	10.3	10.55	10.66	10.78	10.85	10.99	11.2	11.34	11.37
5/8/2019	9.05	9.08	9.72	10.06	10.26	10.53	10.64	10.76	10.85	10.92	11.19	11.3	11.36
5/9/2019	8.78	8.98	9.46	9.9	10.12	10.42	10.5	10.67	10.76	10.91	11.1	11.22	11.25
5/10/2019	8.78	8.98	9.43	9.89	10.11	10.42	10.5	10.67	10.76	10.9	11.1	11.22	11.25
5/13/2019	8.66	8.81	9.18	9.78	10.04	10.34	10.43	10.59	10.68	10.85	11.07	11.2	11.24
5/14/2019	8.66	8.82	9.18	9.8	10.03	10.34	10.45	10.6	10.69	10.88	11.08	11.2	11.24
5/15/2019	8.66	8.82	9.17	9.83	10.07	10.38	10.48	10.6	10.69	10.89	11.09	11.2	11.24
5/16/2019	8.65	8.79	9.14	9.78	10.04	10.36	10.46	10.59	10.69	10.85	11.05	11.15	11.23
5/17/2019	8.65	8.78	9.13	9.76	10.05	10.35	10.45	10.58	10.68	10.84	11.04	11.15	11.22
5/21/2019	8.66	8.77	9.11	9.71	10.02	10.26	10.36	10.5	10.59	10.74	10.99	11.09	11.21
5/22/2019	8.65	8.74	9.07	9.64	9.95	10.14	10.23	10.35	10.45	10.61	10.86	10.97	11.05
5/23/2019	8.65	8.68	8.91	9.4	9.68	9.88	9.94	10.1	10.23	10.42	10.69	10.84	10.94
5/24/2019	8.65	8.66	8.91	9.4	9.69	9.88	9.94	10.1	10.23	10.42	10.69	10.84	10.94
5/27/2019	8.64	8.64	8.89	9.38	9.72	9.88	9.97	10.11	10.24	10.43	10.68	10.84	10.95
5/28/2019	8.64	8.64	8.89	9.38	9.74	9.89	9.98	10.12	10.24	10.44	10.68	10.84	10.95
5/29/2019	8.64	8.64	8.89	9.38	9.74	9.89	9.98	10.12	10.24	10.44	10.68	10.84	10.95
5/30/2019	8.64	8.63	8.86	9.32	9.66	9.84	9.93	10.06	10.19	10.4	10.63	10.78	10.85

5/31/2019	8.64	8.63	8.86	9.33	9.66	9.85	9.94	10.07	10.2	10.4	10.63	10.78	10.85
6/3/2019	8.39	8.59	8.83	9.31	9.65	9.87	9.92	10.09	10.21	10.39	10.63	10.78	10.84
6/4/2019	8.39	8.59	8.84	9.37	9.71	9.92	9.99	10.15	10.3	10.46	10.64	10.78	10.84
6/6/2019	8.39	8.61	8.84	9.37	9.71	9.91	10	10.16	10.3	10.46	10.64	10.78	10.84
6/7/2019	8.39	8.61	8.84	9.38	9.73	9.94	10.04	10.18	10.31	10.47	10.65	10.78	10.84
6/10/2019	8.38	8.61	8.84	9.42	9.8	10.01	10.08	10.24	10.35	10.5	10.66	10.78	10.86
6/11/2019	8.38	8.61	8.84	9.44	9.85	10.1	10.12	10.28	10.41	10.56	10.69	10.78	10.86
6/12/2019	8.38	8.61	8.85	9.5	10.06	10.15	10.2	10.37	10.48	10.62	10.78	10.82	10.89
6/13/2019	8.39	8.61	8.85	9.5	10.06	10.17	10.22	10.37	10.48	10.63	10.79	10.83	10.89
6/14/2019	8.39	8.62	8.86	9.54	9.95	10.21	10.28	10.44	10.54	10.65	10.86	10.95	11.1
6/17/2019	8.39	8.61	8.84	9.55	9.96	10.22	10.28	10.43	10.53	10.64	10.84	10.95	11.09
6/18/2019	8.39	8.61	8.84	9.55	9.98	10.22	10.28	10.43	10.53	10.64	10.8	10.95	11.09
6/19/2019	8.39	8.61	8.83	9.55	9.97	10.2	10.26	10.4	10.5	10.64	10.8	10.95	11.09
6/20/2019	8.37	8.59	8.8	9.52	9.88	10.1	10.17	10.32	10.45	10.6	10.79	10.95	11.07
6/21/2019	8.37	8.59	8.8	9.5	9.88	10.09	10.17	10.32	10.45	10.6	10.79	10.95	11.07
6/24/2019	8.37	8.58	8.79	9.4	9.78	9.96	10.05	10.23	10.33	10.5	10.74	10.95	11.07
6/25/2019	8.37	8.58	8.79	9.37	9.72	9.91	10.01	10.18	10.3	10.47	10.73	10.95	11.06
6/26/2019	8.37	8.58	8.78	9.34	9.72	9.89	10	10.18	10.3	10.46	10.72	10.95	11.06
6/27/2019	8.29	8.44	8.65	9.2	9.64	9.83	9.94	10.12	10.22	10.4	10.71	10.95	11.05
6/28/2019	8.28	8.43	8.64	9.16	9.58	9.79	9.88	10.03	10.12	10.33	10.51	10.63	10.84
7/1/2019	8.27	8.42	8.62	9.17	9.57	9.79	9.86	9.91	10.08	10.24	10.45	10.58	10.69
7/2/2019	8.22	8.39	8.59	9.27	9.63	9.79	9.85	9.95	10.08	10.26	10.47	10.59	10.75
7/3/2019	8.22	8.39	8.59	9.27	9.65	9.79	9.85	9.95	10.08	10.26	10.47	10.59	10.75
7/4/2019	8.2	8.36	8.56	9.25	9.62	9.78	9.86	9.95	10.08	10.25	10.47	10.59	10.75
7/5/2019	8.2	8.35	8.55	9.24	9.62	9.78	9.86	9.98	10.09	10.29	10.49	10.63	10.83
7/8/2019	8.18	8.3	8.53	9.15	9.57	9.73	9.82	9.97	10.08	10.27	10.49	10.63	10.83

7/9/2019	8.18	8.3	8.52	9.08	9.45	9.67	9.79	9.97	10.08	10.26	10.48	10.63	10.82
7/10/2019	8.18	8.3	8.52	9.08	9.44	9.67	9.79	9.97	10.08	10.22	10.48	10.63	10.82
7/11/2019	8.13	8.23	8.49	8.97	9.32	9.61	9.72	9.89	10.02	10.17	10.43	10.6	10.8
7/12/2019	8.12	8.22	8.47	8.9	9.27	9.55	9.7	9.85	9.96	10.1	10.41	10.6	10.79
7/15/2019	8.11	8.2	8.45	8.8	9.21	9.54	9.68	9.85	9.94	10.1	10.41	10.6	10.79
7/17/2019	8.11	8.2	8.44	8.81	9.22	9.54	9.69	9.84	9.94	10.1	10.41	10.6	10.79
7/18/2019	8.08	8.17	8.43	8.82	9.23	9.55	9.7	9.85	9.95	10.11	10.41	10.6	10.79
7/19/2019	8.06	8.16	8.41	8.85	9.25	9.57	9.71	9.87	9.97	10.12	10.41	10.58	10.78
7/22/2019	8.05	8.13	8.39	8.86	9.26	9.56	9.71	9.86	9.95	10.1	10.4	10.58	10.78
7/23/2019	8.03	8.12	8.39	8.85	9.26	9.56	9.71	9.86	9.95	10.1	10.4	10.58	10.77
7/24/2019	8.03	8.12	8.39	8.86	9.27	9.57	9.72	9.87	9.95	10.1	10.4	10.58	10.78
7/25/2019	7.9	7.98	8.33	8.84	9.24	9.55	9.72	9.86	9.94	10.09	10.39	10.58	10.76
7/26/2019	7.9	7.98	8.34	8.84	9.23	9.55	9.72	9.86	9.94	10.09	10.39	10.54	10.75
7/29/2019	7.84	7.91	8.31	8.82	9.19	9.55	9.72	9.87	9.94	10.08	10.38	10.54	10.75
7/30/2019	7.81	7.9	8.3	8.81	9.19	9.55	9.71	9.87	9.94	10.06	10.31	10.48	10.73
7/31/2019	7.81	7.9	8.31	8.8	9.17	9.54	9.71	9.87	9.9	10.05	10.31	10.48	10.73
8/1/2019	7.78	7.85	8.21	8.76	9.12	9.49	9.68	9.85	9.88	10.02	10.3	10.48	10.73
8/2/2019	7.77	7.83	8.19	8.73	9.11	9.47	9.67	9.84	9.87	10.02	10.3	10.48	10.71
8/5/2019	7.75	7.81	8.08	8.66	9.04	9.42	9.62	9.79	9.85	9.94	10.11	10.23	10.46
8/6/2019	7.74	7.81	8.08	8.67	9.07	9.42	9.63	9.79	9.86	9.95	10.12	10.23	10.46
8/7/2019	7.74	7.81	8.08	8.7	9.08	9.44	9.64	9.81	9.89	9.98	10.12	10.23	10.47
8/8/2019	7.75	7.81	8.08	8.68	9.06	9.44	9.63	9.81	9.89	9.97	10.12	10.23	10.46
8/9/2019	7.75	7.81	8.08	8.68	9.06	9.43	9.63	9.82	9.89	9.99	10.16	10.28	10.48
8/13/2019	7.73	7.78	8.04	8.64	9.04	9.41	9.61	9.81	9.89	9.99	10.16	10.28	10.48
8/15/2019	7.76	7.81	8.11	8.64	9.05	9.44	9.64	9.83	9.9	10.01	10.19	10.34	10.5
8/16/2019	7.76	7.81	8.13	8.7	9.1	9.56	9.74	9.91	9.96	10.12	10.24	10.35	10.43

8/19/2019	7.78	7.82	8.15	8.79	9.21	9.6	9.78	9.93	9.99	10.15	10.27	10.38	10.45
8/20/2019	7.78	7.85	8.18	8.96	9.31	9.66	9.83	9.96	10.03	10.19	10.33	10.47	10.51
8/21/2019	7.78	7.85	8.18	8.91	9.28	9.6	9.79	9.94	10.02	10.15	10.26	10.35	10.44
8/22/2019	7.8	7.86	8.21	8.92	9.29	9.64	9.84	9.97	10.04	10.17	10.29	10.42	10.47
8/23/2019	7.78	7.84	8.18	8.84	9.27	9.61	9.76	9.89	9.98	10.09	10.2	10.3	10.38
8/26/2019	7.81	7.83	8.14	8.79	9.23	9.56	9.7	9.85	9.92	10.05	10.18	10.27	10.36
8/27/2019	7.7	7.83	8.15	8.8	9.27	9.6	9.74	9.9	9.98	10.1	10.22	10.33	10.39
8/28/2019	7.68	7.83	8.16	8.8	9.29	9.65	9.78	9.95	10	10.11	10.24	10.33	10.38
8/29/2019	7.66	7.79	8.16	8.81	9.29	9.65	9.79	9.95	10	10.12	10.24	10.34	10.38
8/30/2019	7.67	7.8	8.16	8.82	9.36	9.75	9.85	10.01	10.05	10.15	10.27	10.35	10.39
9/2/2019	7.65	7.78	8.17	8.84	9.38	9.75	9.83	10.01	10.05	10.16	10.27	10.36	10.42
9/3/2019	7.65	7.78	8.15	8.85	9.38	9.76	9.87	9.99	10.03	10.14	10.26	10.36	10.42
9/4/2019	7.65	7.78	8.15	8.86	9.38	9.77	9.88	10.02	10.05	10.15	10.27	10.36	10.42
9/5/2019	7.66	7.78	8.25	8.93	9.44	9.83	9.94	10.04	10.08	10.17	10.28	10.36	10.43
9/6/2019	7.65	7.78	8.25	8.94	9.38	9.82	9.96	10.05	10.07	10.16	10.28	10.39	10.44
9/9/2019	7.7	7.78	8.26	8.83	9.33	9.78	9.94	10.07	10.1	10.17	10.29	10.4	10.43
9/10/2019	7.7	7.78	8.25	8.85	9.33	9.78	9.95	10.07	10.11	10.17	10.29	10.4	10.44
9/11/2019	7.68	7.75	8.28	8.86	9.34	9.82	10.02	10.14	10.17	10.24	10.33	10.38	10.46
9/12/2019	7.68	7.75	8.28	8.83	9.29	9.93	10.22	10.29	10.37	10.4	10.51	10.7	10.79
9/16/2019	7.68	7.75	8.28	8.85	9.3	9.95	10.25	10.32	10.4	10.44	10.51	10.72	10.8
9/17/2019	7.67	7.75	8.27	8.88	9.31	9.98	10.31	10.4	10.48	10.54	10.62	10.9	10.82
9/18/2019	7.67	7.75	8.27	8.88	9.33	9.98	10.31	10.4	10.48	10.54	10.62	10.9	10.84
9/19/2019	7.67	7.76	8.3	8.87	9.31	9.96	10.28	10.38	10.48	10.57	10.66	10.91	10.86
9/20/2019	7.67	7.76	8.3	8.87	9.3	9.95	10.25	10.36	10.44	10.51	10.6	10.85	10.83
9/23/2019	7.67	7.78	8.32	8.82	9.27	9.91	10.24	10.36	10.44	10.51	10.62	10.86	10.84
9/24/2019	7.67	7.79	8.33	8.81	9.27	9.91	10.24	10.37	10.46	10.55	10.64	10.87	10.84

9/25/2019	7.67	7.79	8.32	8.79	9.25	9.9	10.24	10.36	10.43	10.51	10.62	10.86	10.84
9/26/2019	7.67	7.77	8.33	8.75	9.24	9.91	10.24	10.36	10.43	10.51	10.62	10.86	10.84
9/27/2019	7.67	7.77	8.32	8.74	9.24	9.91	10.23	10.36	10.42	10.51	10.62	10.85	10.84
9/30/2019	7.66	7.76	8.36	8.71	9.21	9.9	10.22	10.37	10.44	10.54	10.68	10.83	10.96
10/1/2019	7.66	7.76	8.36	8.7	9.21	9.9	10.22	10.36	10.44	10.54	10.69	10.83	10.96
10/2/2019	7.66	7.75	8.36	8.7	9.22	9.9	10.22	10.36	10.44	10.54	10.69	10.84	10.96
10/3/2019	7.7	7.75	8.36	8.7	9.22	9.9	10.22	10.36	10.45	10.54	10.69	10.83	10.96
10/4/2019	7.71	7.75	8.36	8.7	9.22	9.89	10.22	10.36	10.45	10.54	10.69	10.83	10.96
10/7/2019	7.7	7.75	8.37	8.69	9.21	9.9	10.22	10.36	10.44	10.54	10.69	10.82	10.96
10/8/2019	7.7	7.75	8.37	8.69	9.21	9.9	10.22	10.36	10.44	10.54	10.69	10.79	10.95
10/9/2019	7.7	7.75	8.37	8.66	9.17	9.87	10.19	10.36	10.43	10.53	10.66	10.74	10.97
10/10/2019	7.72	7.75	8.36	8.66	9.15	9.83	10.17	10.33	10.42	10.52	10.63	10.74	10.95
10/11/2019	7.72	7.75	8.36	8.66	9.16	9.83	10.17	10.33	10.43	10.52	10.62	10.74	10.97
10/14/2019	7.72	7.74	8.36	8.65	9.14	9.79	10.12	10.3	10.38	10.49	10.62	10.73	10.95
10/15/2019	7.72	7.73	8.35	8.64	9.13	9.75	10.08	10.23	10.33	10.47	10.61	10.73	10.95
10/16/2019	7.71	7.73	8.34	8.65	9.13	9.75	10.06	10.22	10.32	10.47	10.61	10.73	10.95
10/17/2019	7.62	7.69	8.33	8.64	9.11	9.72	10.03	10.21	10.31	10.45	10.61	10.72	10.95
10/18/2019	7.62	7.69	8.33	8.64	9.11	9.71	10.03	10.22	10.3	10.45	10.61	10.72	10.95
10/21/2019	7.61	7.68	8.28	8.64	9.1	9.7	10.03	10.21	10.29	10.45	10.61	10.72	10.95
10/22/2019	7.61	7.68	8.26	8.69	9.26	9.76	10.05	10.22	10.3	10.45	10.61	10.72	10.95
10/23/2019	7.61	7.68	8.27	8.69	9.26	9.76	10.06	10.21	10.3	10.44	10.61	10.72	10.95
10/24/2019	7.6	7.66	8.28	8.69	9.26	9.76	10.06	10.21	10.3	10.44	10.6	10.72	10.95
10/25/2019	7.6	7.66	8.28	8.69	9.25	9.75	10.03	10.2	10.26	10.4	10.55	10.67	10.94
10/28/2019	7.58	7.66	8.28	8.69	9.25	9.75	10.03	10.2	10.27	10.39	10.55	10.67	10.94
10/29/2019	7.58	7.65	8.28	8.69	9.24	9.74	10.02	10.2	10.26	10.39	10.55	10.67	10.94
10/30/2019	7.58	7.65	8.29	8.69	9.24	9.75	10.02	10.2	10.26	10.39	10.55	10.63	10.95

10/31/2019	7.58	7.64	8.29	8.69	9.24	9.74	10.02	10.21	10.26	10.39	10.55	10.63	10.95
11/1/2019	7.58	7.64	8.29	8.7	9.26	9.77	10.06	10.21	10.27	10.38	10.54	10.64	10.95
11/4/2019	7.57	7.65	8.36	8.79	9.42	9.83	10.1	10.22	10.3	10.4	10.54	10.63	10.95
11/5/2019	7.57	7.65	8.36	8.79	9.42	9.83	10.1	10.23	10.3	10.4	10.54	10.64	10.95
11/6/2019	7.57	7.65	8.36	8.79	9.42	9.83	10.1	10.22	10.3	10.4	10.54	10.63	10.95
11/7/2019	7.57	7.67	8.38	8.7	9.28	9.78	10.07	10.22	10.29	10.4	10.54	10.65	10.94
11/8/2019	7.57	7.67	8.39	8.7	9.27	9.79	10.07	10.22	10.29	10.4	10.55	10.66	10.94
11/13/2019	7.57	7.67	8.4	8.7	9.27	9.79	10.07	10.22	10.29	10.4	10.54	10.65	10.94
11/14/2019	7.59	7.74	8.5	8.72	9.28	9.8	10.08	10.22	10.3	10.41	10.55	10.67	10.95
11/15/2019	7.6	7.76	8.53	8.72	9.28	9.81	10.08	10.22	10.3	10.41	10.55	10.67	10.95
11/18/2019	7.65	7.81	8.56	8.73	9.28	9.81	10.06	10.2	10.3	10.41	10.55	10.67	10.95
11/19/2019	7.63	7.78	8.5	8.67	9.16	9.64	9.89	10.06	10.12	10.29	10.5	10.57	10.93
11/20/2019	7.49	7.69	8.32	8.5	8.98	9.46	9.64	9.84	9.9	10.06	10.35	10.33	10.85
11/21/2019	7.46	7.61	8.26	8.46	8.86	9.37	9.56	9.84	9.85	10.05	10.34	10.3	10.85
11/22/2019	7.45	7.59	8.26	8.56	8.9	9.43	9.62	9.89	9.89	10.08	10.37	10.3	10.85
11/25/2019	7.42	7.55	8.18	8.54	8.93	9.42	9.62	9.84	9.89	10.07	10.34	10.31	10.85
11/26/2019	7.41	7.56	8.19	8.58	8.97	9.47	9.73	9.94	9.99	10.19	10.37	10.35	10.86
11/27/2019	7.42	7.56	8.19	8.6	9.01	9.54	9.84	10.05	10.1	10.29	10.4	10.4	10.86
11/28/2019	7.42	7.56	8.19	8.6	9.01	9.54	9.84	10.05	10.1	10.29	10.4	10.4	10.86
11/29/2019	7.41	7.6	8.23	8.59	8.99	9.5	9.78	9.96	10.01	10.21	10.32	10.32	10.86
12/2/2019	7.5	7.71	8.33	8.74	9.17	9.66	9.88	10.07	10.1	10.2	10.3	10.39	10.59
12/3/2019	7.41	7.64	8.3	8.64	9.13	9.66	9.9	10.09	10.08	10.17	10.24	10.37	10.55
12/4/2019	7.41	7.64	8.32	8.64	9.13	9.67	9.9	10.09	10.08	10.17	10.24	10.37	10.55
12/5/2019	7.5	7.72	8.26	8.63	9.12	9.67	9.9	10.09	10.08	10.16	10.25	10.37	10.55
12/6/2019	7.4	7.63	8.26	8.63	9.11	9.67	9.9	10.09	10.08	10.17	10.25	10.36	10.55
12/9/2019	7.4	7.64	8.24	8.64	9.11	9.67	9.89	10.09	10.07	10.16	10.24	10.34	10.54

12/10/2019	7.4	7.64	8.24	8.64	9.1	9.66	9.9	10.09	10.09	10.17	10.25	10.35	10.54
12/12/2019	7.4	7.67	8.24	8.64	9.1	9.66	9.89	10.09	10.09	10.17	10.25	10.34	10.54
12/13/2019	7.4	7.73	8.26	8.64	9.11	9.68	9.9	10.09	10.08	10.15	10.27	10.34	10.54
12/16/2019	7.43	7.75	8.27	8.64	9.2	9.71	9.91	10.09	10.09	10.19	10.28	10.35	10.54
12/17/2019	7.42	7.76	8.27	8.64	9.2	9.71	9.91	10.09	10.09	10.19	10.28	10.34	10.54
12/18/2019	7.43	7.78	8.28	8.64	9.2	9.71	9.91	10.09	10.09	10.19	10.28	10.34	10.54
12/19/2019	7.46	7.83	8.35	8.67	9.23	9.74	9.95	10.12	10.1	10.2	10.28	10.34	10.54
12/20/2019	7.5	7.85	8.39	8.68	9.23	9.75	9.95	10.12	10.13	10.22	10.28	10.34	10.54
12/23/2019	7.53	7.94	8.47	8.69	9.23	9.74	9.94	10.12	10.12	10.22	10.28	10.36	10.54
12/24/2019	7.55	7.95	8.47	8.7	9.24	9.74	9.94	10.11	10.12	10.21	10.26	10.36	10.54
12/26/2019	7.53	7.93	8.43	8.66	9.18	9.6	9.84	9.96	10.05	10.14	10.21	10.33	10.54
12/27/2019	7.53	7.88	8.39	8.66	9.16	9.56	9.77	9.89	9.95	10.08	10.21	10.27	10.52
12/30/2019	7.5	7.88	8.39	8.65	9.15	9.55	9.77	9.88	9.95	10.09	10.21	10.29	10.53
12/31/2019	7.52	7.88	8.38	8.62	9.11	9.5	9.72	9.84	9.93	10.07	10.18	10.27	10.52
1/1/2020	7.52	7.88	8.36	8.6	9.08	9.46	9.67	9.8	9.9	10.05	10.18	10.25	10.52
1/2/2020	7.51	7.91	8.38	8.57	9.05	9.42	9.62	9.74	9.86	10.01	10.13	10.2	10.41
1/3/2020	7.51	7.9	8.37	8.6	9.06	9.43	9.62	9.74	9.86	10.01	10.13	10.2	10.41
1/6/2020	7.51	7.91	8.39	8.63	9.06	9.41	9.61	9.74	9.85	10.01	10.12	10.19	10.41
1/7/2020	7.51	7.9	8.38	8.63	9.06	9.43	9.65	9.75	9.87	10.02	10.14	10.21	10.41
1/8/2020	7.53	7.99	8.45	8.67	9.09	9.45	9.67	9.77	9.89	10.03	10.14	10.22	10.42
1/9/2020	7.52	7.98	8.44	8.64	9.08	9.47	9.68	9.76	9.88	10.03	10.14	10.21	10.41
1/13/2020	7.51	8.01	8.46	8.65	9.08	9.47	9.67	9.76	9.88	10.02	10.14	10.22	10.41
1/14/2020	7.51	8	8.47	8.64	9.07	9.46	9.66	9.76	9.87	10	10.13	10.19	10.4
1/16/2020	7.51	8.02	8.48	8.64	9.07	9.45	9.65	9.76	9.85	9.98	10.12	10.15	10.4
1/17/2020	7.51	8.02	8.47	8.64	9.07	9.45	9.63	9.75	9.85	9.98	10.1	10.13	10.4
1/20/2020	7.52	8.02	8.48	8.64	9.07	9.45	9.65	9.76	9.86	9.99	10.11	10.14	10.4

1/21/2020	7.52	8.05	8.49	8.64	9.06	9.44	9.63	9.74	9.84	9.96	10.09	10.12	10.4
1/22/2020	7.52	8.08	8.5	8.64	9.06	9.42	9.62	9.73	9.82	9.94	10.08	10.11	10.38
1/23/2020	7.54	8.09	8.53	8.67	9.13	9.42	9.62	9.73	9.81	9.94	10.08	10.09	10.37
1/24/2020	7.53	8.11	8.54	8.67	9.13	9.42	9.62	9.73	9.81	9.94	10.08	10.09	10.37
1/27/2020	7.53	8.12	8.55	8.69	9.14	9.41	9.6	9.71	9.81	9.94	10.08	10.07	10.37
1/28/2020	7.53	8.12	8.55	8.69	9.14	9.41	9.6	9.7	9.8	9.93	10.08	10.07	10.36
1/29/2020	7.53	8.12	8.54	8.7	9.13	9.37	9.57	9.67	9.75	9.89	10.05	10.05	10.36
1/30/2020	7.47	8.04	8.45	8.64	9.04	9.26	9.45	9.55	9.66	9.77	9.92	9.95	10.25
1/31/2020	7.38	7.93	8.33	8.54	8.92	9.16	9.35	9.45	9.54	9.65	9.8	9.83	10.17
2/3/2020	7.35	7.9	8.3	8.54	8.92	9.16	9.35	9.45	9.54	9.63	9.8	9.79	10.16
2/5/2020	7.39	7.9	8.27	8.54	8.91	9.16	9.34	9.45	9.55	9.61	9.8	9.8	10.16
2/6/2020	7.41	7.95	8.34	8.5	8.88	9.12	9.33	9.39	9.49	9.6	9.76	9.8	10.08
2/7/2020	7.38	7.94	8.36	8.6	8.96	9.18	9.39	9.48	9.58	9.7	9.84	9.9	10.11
2/10/2020	7.39	7.94	8.38	8.63	9	9.24	9.47	9.53	9.63	9.75	9.89	9.92	10.18
2/11/2020	7.39	7.94	8.4	8.64	9.01	9.25	9.48	9.54	9.63	9.75	9.89	9.91	10.17
2/12/2020	7.39	7.94	8.4	8.64	9.01	9.25	9.48	9.54	9.63	9.75	9.89	9.91	10.17
2/13/2020	7.4	7.97	8.48	8.66	9.02	9.28	9.5	9.55	9.67	9.79	9.89	9.92	10.14
2/14/2020	7.41	7.97	8.49	8.72	9.04	9.29	9.5	9.57	9.68	9.8	9.89	9.93	10.13
2/17/2020	7.41	7.98	8.52	8.74	9.1	9.38	9.59	9.65	9.73	9.83	9.93	10.02	10.22
2/18/2020	7.41	8.02	8.55	8.82	9.2	9.45	9.67	9.74	9.79	9.91	10.03	10.05	10.26
2/19/2020	7.43	8.03	8.56	8.84	9.2	9.44	9.61	9.66	9.77	9.88	9.98	10.01	10.21
2/20/2020	7.43	8.03	8.56	8.89	9.26	9.49	9.72	9.77	9.88	9.99	10.06	10.06	10.23
2/24/2020	7.44	8.04	8.57	8.93	9.34	9.56	9.75	9.8	9.92	10.02	10.1	10.11	10.23
2/25/2020	7.45	8.04	8.57	8.94	9.38	9.59	9.78	9.85	9.96	10.03	10.11	10.13	10.28
2/26/2020	7.45	8.04	8.56	8.9	9.33	9.54	9.73	9.79	9.9	9.99	10.07	10.1	10.22
2/27/2020	7.45	8.03	8.54	8.9	9.35	9.55	9.76	9.84	9.94	10.02	10.11	10.13	10.26

2/28/2020	7.43	8.01	8.49	8.9	9.29	9.5	9.7	9.78	9.87	9.96	10.06	10.09	10.24
3/2/2020	7.41	8.01	8.47	8.89	9.28	9.49	9.71	9.79	9.88	9.96	10.06	10.09	10.24
3/3/2020	7.42	8.03	8.48	8.89	9.28	9.5	9.73	9.81	9.9	9.99	10.09	10.1	10.23
3/4/2020	7.4	8.02	8.46	8.82	9.26	9.47	9.71	9.79	9.89	9.98	10.09	10.09	10.23
3/5/2020	7.4	7.99	8.41	8.76	9.19	9.38	9.6	9.69	9.79	9.91	10.02	10.04	10.21
3/6/2020	7.39	7.99	8.41	8.74	9.18	9.34	9.56	9.65	9.75	9.86	9.97	10.02	10.21
3/10/2020	7.37	7.99	8.41	8.72	9.16	9.33	9.52	9.61	9.7	9.82	9.93	9.98	10.17
3/11/2020	7.38	7.98	8.4	8.79	9.27	9.5	9.75	9.87	9.94	10.03	10.12	10.15	10.26
3/12/2020	7.39	7.98	8.41	8.8	9.28	9.5	9.76	9.88	9.97	10.05	10.12	10.15	10.26
3/13/2020	7.39	7.97	8.41	8.8	9.31	9.53	9.8	9.88	9.99	10.05	10.12	10.14	10.25
3/17/2020	7.39	7.98	8.43	8.84	9.33	9.55	9.81	9.89	9.97	10.05	10.13	10.14	10.26
3/18/2020	7.37	7.95	8.39	8.84	9.33	9.56	9.8	9.89	9.97	10.04	10.14	10.13	10.28
3/19/2020	7.3	7.85	8.32	8.76	9.22	9.48	9.71	9.79	9.87	9.97	10.06	10.09	10.24
3/20/2020	7.3	7.84	8.31	8.76	9.22	9.48	9.72	9.8	9.89	9.99	10.06	10.1	10.24
3/24/2020	7.27	7.8	8.28	8.71	9.19	9.45	9.7	9.79	9.87	9.96	10.06	10.08	10.24
3/27/2020	7.15	7.57	7.95	8.44	8.99	9.25	9.53	9.6	9.69	9.83	9.98	10.03	10.12
3/30/2020	7.01	7.27	7.6	8.25	8.78	8.98	9.23	9.33	9.42	9.56	9.65	9.76	9.8
3/31/2020	7	7.21	7.53	8.21	8.84	9.01	9.27	9.39	9.49	9.63	9.75	9.81	9.8
4/1/2020	7	7.23	7.54	8.21	8.84	9.02	9.29	9.41	9.49	9.63	9.75	9.81	9.8
4/2/2020	6.96	7.2	7.52	8.2	8.85	9.04	9.29	9.43	9.5	9.64	9.75	9.8	9.8
4/3/2020	6.95	7.19	7.51	8.27	8.94	9.13	9.32	9.44	9.53	9.65	9.74	9.85	9.81
4/6/2020	6.94	7.2	7.49	8.21	8.89	9.08	9.26	9.37	9.48	9.6	9.66	9.79	9.69
4/8/2020	6.9	7.12	7.39	8.15	8.85	9.05	9.24	9.36	9.46	9.57	9.66	9.77	9.69
4/9/2020	6.83	7.02	7.3	8.09	8.74	8.95	9.07	9.15	9.26	9.39	9.45	9.59	9.67
4/15/2020	6.78	6.99	7.29	7.99	8.74	8.95	9.12	9.26	9.38	9.48	9.63	9.65	9.69
4/16/2020	6.78	6.99	7.27	7.99	8.75	8.97	9.13	9.26	9.38	9.49	9.63	9.69	9.69

4/17/2020	6.78	6.99	7.27	7.98	8.74	8.96	9.13	9.26	9.38	9.48	9.63	9.69	9.7
4/20/2020	6.76	6.96	7.27	7.93	8.63	8.87	9.1	9.24	9.36	9.47	9.63	9.66	9.69
4/21/2020	6.75	6.95	7.25	7.83	8.49	8.71	8.97	9.1	9.24	9.35	9.51	9.58	9.57
4/22/2020	6.75	6.96	7.26	7.83	8.49	8.71	8.97	9.1	9.23	9.35	9.51	9.57	9.57
4/23/2020	6.73	6.94	7.3	7.81	8.43	8.7	8.95	9.09	9.22	9.34	9.51	9.57	9.57
4/24/2020	6.73	6.93	7.24	7.76	8.4	8.68	8.91	9.05	9.18	9.3	9.47	9.52	9.56
4/27/2020	6.73	6.91	7.21	7.75	8.34	8.63	8.87	9	9.15	9.28	9.48	9.44	9.53
4/28/2020	6.74	6.91	7.2	7.69	8.29	8.58	8.86	8.99	9.12	9.27	9.48	9.43	9.52
4/29/2020	6.72	6.89	7.18	7.66	8.23	8.52	8.81	8.96	9.08	9.23	9.48	9.4	9.52
4/30/2020	6.72	6.89	7.18	7.66	8.2	8.52	8.8	8.93	9.05	9.21	9.4	9.43	9.49
5/4/2020	6.71	6.87	7.17	7.66	8.16	8.44	8.75	8.85	8.99	9.12	9.28	9.37	9.47
5/5/2020	6.75	6.9	7.16	7.61	8.18	8.43	8.72	8.81	9.01	9.15	9.33	9.36	9.51
5/6/2020	6.75	6.9	7.16	7.59	8.26	8.62	8.78	8.86	9.06	9.2	9.34	9.38	9.53
5/11/2020	6.71	6.86	7.08	7.45	8.18	8.55	8.7	8.74	8.95	9.1	9.18	9.22	9.45
5/12/2020	6.59	6.75	7.01	7.4	8.13	8.49	8.65	8.75	8.93	9.08	9.19	9.26	9.45
5/13/2020	6.61	6.79	7	7.39	8.13	8.48	8.64	8.76	8.93	9.07	9.18	9.26	9.45
5/14/2020	6.65	6.8	6.99	7.39	8.13	8.48	8.64	8.75	8.93	9.07	9.18	9.26	9.45
5/15/2020	6.64	6.79	6.99	7.4	8.14	8.49	8.66	8.79	8.93	9.07	9.18	9.26	9.45
5/18/2020	6.65	6.79	6.97	7.38	8.12	8.48	8.64	8.77	8.91	9.05	9.16	9.24	9.4
5/19/2020	6.63	6.77	6.93	7.38	8.11	8.48	8.68	8.79	8.95	9.09	9.18	9.24	9.4
5/20/2020	6.64	6.77	6.93	7.38	8.1	8.46	8.65	8.76	8.93	9.08	9.18	9.23	9.4
5/21/2020	6.63	6.77	6.92	7.43	8.1	8.45	8.65	8.76	8.92	9.08	9.18	9.23	9.4
5/22/2020	6.64	6.76	6.92	7.4	8.09	8.42	8.62	8.73	8.91	9.08	9.17	9.23	9.4
5/26/2020	6.64	6.76	6.92	7.39	8.06	8.39	8.58	8.69	8.89	9.06	9.17	9.23	9.4
5/27/2020	6.64	6.75	6.91	7.35	8	8.36	8.56	8.67	8.88	9.04	9.17	9.22	9.4
5/28/2020	6.64	6.75	6.91	7.3	7.95	8.34	8.54	8.67	8.88	9.04	9.17	9.22	9.4

5/29/2020	6.64	6.74	6.88	7.28	7.9	8.32	8.52	8.66	8.85	9.01	9.15	9.2	9.34
6/1/2020	6.63	6.75	6.88	7.24	7.88	8.31	8.51	8.67	8.85	9	9.13	9.2	9.34
6/2/2020	6.63	6.75	6.88	7.24	7.89	8.36	8.53	8.66	8.84	9.03	9.14	9.2	9.45
6/3/2020	6.63	6.75	6.89	7.33	7.97	8.4	8.55	8.68	8.87	9.05	9.14	9.2	9.45
6/4/2020	6.63	6.75	6.88	7.3	7.95	8.39	8.54	8.67	8.87	9.03	9.13	9.2	9.45
6/8/2020	6.63	6.75	6.89	7.33	7.89	8.3	8.49	8.61	8.83	8.98	9.12	9.13	9.39
6/9/2020	6.63	6.75	6.89	7.33	7.9	8.3	8.52	8.67	8.87	9.03	9.13	9.17	9.45
6/10/2020	6.63	6.75	6.89	7.33	7.9	8.28	8.51	8.66	8.87	9.03	9.14	9.16	9.45
6/11/2020	6.63	6.75	6.89	7.32	7.89	8.27	8.49	8.65	8.86	9.03	9.14	9.16	9.45
6/12/2020	6.62	6.75	6.88	7.3	7.81	8.15	8.42	8.58	8.81	8.98	9.11	9.14	9.45
6/15/2020	6.62	6.74	6.88	7.25	7.72	8.1	8.4	8.56	8.79	8.97	9.11	9.13	9.45
6/16/2020	6.62	6.74	6.88	7.23	7.7	8.08	8.38	8.54	8.79	8.98	9.11	9.13	9.45
6/17/2020	6.61	6.73	6.86	7.14	7.6	7.97	8.25	8.38	8.67	8.89	9.06	9.09	9.45
6/18/2020	6.43	6.49	6.71	6.81	7.12	7.51	7.75	7.9	8.16	8.32	8.54	8.59	8.89
6/19/2020	6.22	6.28	6.55	6.64	7.05	7.36	7.65	7.82	8.11	8.28	8.46	8.52	8.89
6/22/2020	5.9	5.98	6.18	6.22	6.52	7	7.2	7.36	7.63	7.76	7.99	8.1	8.3
6/23/2020	5.62	5.73	5.93	6.03	6.39	6.83	7.1	7.26	7.44	7.61	7.82	8.04	8.3
6/24/2020	5.6	5.73	5.93	5.96	6.38	6.82	7.12	7.25	7.43	7.57	7.81	8.01	8.3
6/25/2020	5.47	5.57	5.72	5.81	6.2	6.58	6.85	7.04	7.23	7.47	7.71	7.75	8.09
6/26/2020	5.23	5.24	5.4	5.66	6.05	6.36	6.63	6.77	7.06	7.31	7.62	7.63	8.09
6/29/2020	5.03	5.13	5.27	5.61	6.01	6.38	6.63	6.75	7	7.21	7.4	7.43	7.82
6/30/2020	5.03	5.12	5.27	5.62	6.03	6.38	6.62	6.75	7	7.2	7.4	7.39	7.82
7/1/2020	5.04	5.13	5.28	5.62	6.03	6.38	6.61	6.73	7.01	7.2	7.4	7.39	7.82
7/2/2020	4.98	5.09	5.28	5.61	6.24	6.35	6.58	6.7	6.97	7.17	7.38	7.33	7.7
7/3/2020	4.99	5.11	5.32	5.63	6.01	6.35	6.57	6.69	6.96	7.16	7.38	7.33	7.7
7/6/2020	5	5.11	5.31	5.62	5.99	6.37	6.57	6.7	6.97	7.14	7.38	7.32	7.7

7/7/2020	5	5.11	5.3	5.62	6	6.36	6.58	6.73	6.97	7.14	7.38	7.32	7.7
7/8/2020	5.02	5.11	5.3	5.62	6	6.36	6.58	6.73	6.98	7.15	7.38	7.33	7.7
7/9/2020	4.97	5.07	5.26	5.54	5.98	6.31	6.53	6.7	6.89	7.04	7.31	7.27	7.69
7/10/2020	4.82	4.92	5.09	5.38	5.79	6.22	6.47	6.62	6.78	6.92	7.16	7.15	7.61
7/13/2020	4.79	4.89	5.05	5.34	5.78	6.22	6.42	6.58	6.77	6.96	7.17	7.33	7.74
7/14/2020	4.79	4.88	5.04	5.33	5.75	6.2	6.42	6.59	6.77	6.97	7.18	7.33	7.74
7/15/2020	4.74	4.85	5	5.33	5.73	6.17	6.4	6.58	6.74	6.96	7.17	7.3	7.74
7/16/2020	4.65	4.75	4.91	5.26	5.66	6.11	6.37	6.53	6.7	6.93	7.17	7.24	7.74
7/17/2020	4.59	4.68	4.86	5.2	5.59	6.05	6.33	6.48	6.68	6.9	7.16	7.24	7.74
7/20/2020	4.55	4.64	4.8	5.19	5.6	6.03	6.3	6.44	6.63	6.84	7.16	7.24	7.74
7/21/2020	4.55	4.64	4.8	5.2	5.61	6.04	6.31	6.44	6.63	6.85	7.15	7.24	7.74
7/22/2020	4.55	4.63	4.8	5.19	5.64	6.04	6.31	6.44	6.64	6.85	7.15	7.24	7.74

Robustness check – Input data - date wise

Date_new	R_3M	R_6M	R_1Y	R_2Y	R_3Y	R_4Y	R_5Y	R_6Y	R_8Y	R_10Y	R_15Y	R_20Y	R_30Y
4/18/2019	9.2	9.24	9.85	10.2	10.41	10.61	10.7	10.81	10.93	11.08	11.33	11.48	11.49

Date_new	R_3M	R_6M	R_1Y	R_2Y	R_3Y	R_4Y	R_5Y	R_6Y	R_8Y	R_10Y	R_15Y	R_20Y	R_30Y
4/22/2019	9.21	9.23	9.84	10.23	10.43	10.62	10.73	10.83	10.97	11.13	11.36	11.48	11.49

Date_new	R_3M	R_6M	R_1Y	R_2Y	R_3Y	R_4Y	R_5Y	R_6Y	R_8Y	R_10Y	R_15Y	R_20Y	R_30Y
4/30/2019	9.16	9.18	9.87	10.29	10.52	10.73	10.83	10.93	10.99	11.13	11.36	11.48	11.5

Date_new	R_3M	R_6M	R_1Y	R_2Y	R_3Y	R_4Y	R_5Y	R_6Y	R_8Y	R_10Y	R_15Y	R_20Y	R_30Y
2/13/2020	7.4	7.97	8.48	8.66	9.02	9.28	9.5	9.55	9.67	9.79	9.89	9.92	10.14

Date_new	R_3M	R_6M	R_1Y	R_2Y	R_3Y	R_4Y	R_5Y	R_6Y	R_8Y	R_10Y	R_15Y	R_20Y	R_30Y
7/22/2020	4.55	4.63	4.8	5.19	5.64	6.04	6.31	6.44	6.64	6.85	7.15	7.24	7.74

Forecasting Results – Plots -Input File

```
res_DL_h26_p1;0.78915;0.79606;0.73749;0.75654;0.85578;0.98097;;;;;
res_SV_h26_p1;1.71776;1.50344;1.31359;1.27687;1.24576;1.31371;;;;;
res_DL_h4_p1;0.39263;0.36261;0.37202;0.37292;0.37693;0.4266;0.44146;0.52207;0.58219;0.5894;0.53457
res_SV_h4_p1;1.03969;1.02219;0.99871;0.96843;0.94063;0.9234;0.92283;0.94397;0.94144;0.9394;0.932
```

Appendix B

R files

Packages

```
## Packages (alphabetically) ##
# install.packages("forecast")
# install.packages("ftsa")
# install.packages("ggplot2")
# install.packages("vars")
# install.packages("xts")
# install.packages("YieldCurve")


## Libraries ##
library(xts)

# Input-Data and NelsonSiegel #
library(YieldCurve)
library(forecast)

# Functional approaches #
library(ftsa)
library(rainbow)

# Plots #
library(ggplot2)
```

Fitting the yield curve

```
#Import Data file in to R#
Ratef <- read.csv("C:\\Users\\Desktop\\folder\\Ratef.csv")

#Call required Packages#
require(xts)
require(YieldCurve)

#Convert data file to "xts" format#
Ratef$Date_new <- as.Date.factor(Ratef$Date_new, format="%m/%d/%Y")
Ratef_xts <- xts(Ratef[,2:14], order.by = Ratef$Date_new)

# Vector with maturities #
mat.Ratef <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)


# fts-object from CBSL data #

# Naming of columns #
column_names <- index(Ratef_xts)
column_names <- toString(column_names)
column_names <- strsplit(column_names, ", ")[[1]]

Ratef_daily_core <- t(coredata(Ratef_xts))                 # Matrix with
CBSL data.
colnames(Ratef_daily_core) <- column_names

# Create Functional time series object (by 'fts') #
```

```
CBSL_fts <- fts(x = mat.Ratef, y= Ratef_daily_core, start = 1, xname =
"Maturities", yname = "Yields")


# Nelson.Siegel function for our data-set #
rate.data = Ratef_xts[1:1356]
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
NSParameters <- Nelson.Siegel( rate= rate.data, maturity=maturity.data )
Nelson.rate <- NSrates(NSParameters[1:1356,], maturity.data)


# fts-object from Nelson data #

# Naming of columns #
NS_column_names <- index(Nelson.rate)
NS_column_names <- toString(NS_column_names)
NS_column_names <- strsplit(NS_column_names, ", ")[[1]]

NS_daily_core <- t(coredata(Nelson.rate))                # Matrix with
Nelson data.
colnames(NS_daily_core) <- NS_column_names

# Create Functional time series object (by 'fts') #
NS_fts <- fts(x = mat.Ratef, y= NS_daily_core, start = 1, xname =
"Maturities", yname = "Yields")

# Descriptive #
avgdaily <- centre(CBSL_fts$y, type = "mean")
avgnelson <- centre(NS_fts$y, type = "mean")

#Nelson.SiegelEstimation - Observed vs fitted #
plot(x=mat.Ratef, y=avgdaily, main="Fitting Nelson-Siegel Average yield
curve", type="o")
lines(x=mat.Ratef,y=avgnelson, col=2)
legend("bottomright",legend=c("observed average yield curve","fitted
average yield curve"),
       col=c(1,2),lty=1)


# Svensson function for our data-set #
rate.data = Ratef_xts[1:1356]
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
SvenssonParameters <- Svensson(rate.data, maturity.data)
Svensson.rate <- Srates( SvenssonParameters ,maturity.data,"Spot")

# fts-object from Svensson data #

# Naming of columns #
SV_column_names <- index(Svensson.rate)
SV_column_names <- toString(SV_column_names)
SV_column_names <- strsplit(SV_column_names, ", ")[[1]]

SV_daily_core <- t(coredata(Svensson.rate))                # Matrix with
Svensson data.
colnames(SV_daily_core) <- SV_column_names

# Create Functional time series object (by 'fts') #
SV_fts <- fts(x = mat.Ratef, y= SV_daily_core, start = 1, xname =
"Maturities", yname = "Yields")
```

```
# Descriptive #
avgdaily <- centre(CBSL_fts$y, type = "mean")
avgsvensson <- centre(SV_fts$y, type = "mean")


#Svensson function Estimation - Observed vs fitted #
plot(x=mat.Ratef, y=avgdaily, main="Fitting Svensson Average yield curve",
type="o")
lines(x=mat.Ratef, y=avgsvensson, col=2)
legend("bottomright",legend=c("observed average yield curve","fitted
average yield curve"),
       col=c(1,2),lty=1)


#Nelson.SiegelEstimation - Estimated Parameters #
NSParameters[1:1356,]

#Svensson Model Parameter Estimation
SvenssonParameters[1:1356,]

#Observation Data
obs<- as.vector(Ratef_xts[1:1356,])

#Nelson.Siegel Model Estimation
mod<-as.vector(Nelson.rate)

#Svensson Model Estimation
mod1<-as.vector(Svensson.rate[1:1356,])

rsq <- function (x, y) cor(x, y) ^ 2
RMSE = function(m, o){
  sqrt(mean((m - o)^2))
}
rsq(obs,mod)
RMSE(mod,obs)
rsq(obs,mod1)
RMSE(mod1,obs)
```

Robustness Check

Impact of Easter Sunday Attacks -20190418

```
#Import Data file in to R#
rate20190418<-
read.csv("C:\\Users\\Desktop\\folder\\segr\\excel\\2019.04.18.csv")

#Call required Packages#
require(xts)
require(YieldCurve)

#Convert data file to "xts" format#
rate20190418$Date_new <- as.Date.factor(rate20190418$Date_new,
format="%m/%d/%Y")
rate20190418_xts <- xts(rate20190418[,2:14], order.by =
rate20190418$Date_new)
```

```
# Nelson.Siegel function for our data-set #
rate.data = first(rate20190418_xts,5)
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
NSParameters <- Nelson.Siegel( rate= rate.data, maturity= maturity.data )
y <- NSrates(NSParameters[1,], maturity.data)

#Nelson.SiegelEstimation - Observed vs fitted #
plot(maturity.data,rate.data[1,],main="Fitting Nelson-Siegel yield curve",
type="o")
lines(maturity.data,y, col=2)
legend("bottomright",legend=c("observed yield curve","fitted yield curve"),
       col=c(1,2),lty=1)

# Svensson function for our data-set #
rate.data = first(rate20190418_xts,5)
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
SvenssonParameters <- Svensson(rate.data, maturity.data)
Svensson.rate <- Srates( SvenssonParameters ,maturity.data,"Spot")

#Svensson function Estimation - Observed vs fitted #
plot(maturity.data, rate.data[1,],main="Fitting Svensson yield curve",
type="o")
lines(maturity.data, Svensson.rate[1,], col=2)
legend("bottomright",legend=c("observed yield curve","fitted yield curve"),
       col=c(1,2),lty=1)

#Observation Data
obs<- as.vector(rate20190418_xts[1,])

#Nelson.Siegel Model Estimation
mod<-as.vector(y)

#Svensson Model Estimation
mod1<-as.vector(Svensson.rate[1,])

rsq <- function (x, y) cor(x, y) ^ 2
RMSE = function(m, o){
  sqrt(mean((m - o)^2))
}
rsq(obs,mod)
RMSE(mod,obs)
rsq(obs,mod1)
RMSE(mod1,obs)

# Clear packages
detach("package:", unload = TRUE)
rm(list = ls())
# Clear plots
dev.off()
cat("\014")
```

Impact of Easter Sunday Attacks -20190422

```
#Import Data file in to R#
rate20190422<-
read.csv("C:\\Users\\Desktop\\folder\\segr\\Excel\\2019.04.22.csv")

#Call required Packages#
require(xts)
require(YieldCurve)

#Convert data file to "xts" format#
rate20190422$Date_new <- as.Date.factor(rate20190422$Date_new,
format="%m/%d/%Y")
rate20190422_xts <- xts(rate20190422[,2:14], order.by =
rate20190422$Date_new)

# Nelson.Siegel function for our data-set #
rate.data = first(rate20190422_xts,5)
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
NSParameters <- Nelson.Siegel( rate= rate.data, maturity= maturity.data )
y <- NSrates(NSParameters[1,], maturity.data)

#Nelson.SiegelEstimation - Observed vs fitted #
plot(maturity.data,rate.data[1,],main="Fitting Nelson-Siegel yield curve",
type="o")
lines(maturity.data,y, col=2)
legend("bottomright",legend=c("observed yield curve","fitted yield curve"),
       col=c(1,2),lty=1)

# Svensson function for our data-set #
rate.data = first(rate20190422_xts,5)
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
SvenssonParameters <- Svensson(rate.data, maturity.data)
Svensson.rate <- Srates( SvenssonParameters ,maturity.data,"Spot")

#Svensson function Estimation - Observed vs fitted #
plot(maturity.data, rate.data[1,],main="Fitting Svensson yield curve",
type="o")
lines(maturity.data, Svensson.rate[1,], col=2)
legend("bottomright",legend=c("observed yield curve","fitted yield curve"),
       col=c(1,2),lty=1)

#Observation Data
obs<- as.vector(rate20190422_xts[1,])

#Nelson.Siegel Model Estimation
mod<-as.vector(y)

#Svensson Model Estimation
mod1<-as.vector(Svensson.rate[1,])

rsq <- function (x, y) cor(x, y) ^ 2
RMSE = function(m, o){
  sqrt(mean((m - o)^2))
}
rsq(obs,mod)
RMSE(mod,obs)
rsq(obs,mod1)
RMSE(mod1,obs)
```

```
# Clear packages
detach("package:", unload = TRUE)
rm(list = ls())
# Clear plots
dev.off()
cat("\014")
Impact of Easter Sunday Attacks-20190430
#Import Data file in to R#
rate20190430<-
read.csv("C:\\Users\\Desktop\\folder\\segr\\Excel\\2019.04.30.csv")
```

Impact of Easter Sunday Attacks -20190430

```
#Call required Packages#
require(xts)
require(YieldCurve)

#Convert data file to "xts" format#
rate20190430$Date_new <- as.Date.factor(rate20190430$Date_new,
format="%m/%d/%Y")
rate20190430_xts <- xts(rate20190430[,2:14], order.by =
rate20190430$Date_new)

# Nelson.Siegel function for our data-set #
rate.data = first(rate20190430_xts,5)
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
NSParameters <- Nelson.Siegel( rate= rate.data, maturity= maturity.data )
y <- NSrates(NSParameters[1,], maturity.data)

#Nelson.SiegelEstimation - Observed vs fitted #
plot(maturity.data,rate.data[1,],main="Fitting Nelson-Siegel yield curve",
type="o")
lines(maturity.data,y, col=2)
legend("bottomright",legend=c("observed yield curve","fitted yield curve"),
       col=c(1,2),lty=1)

# Svensson function for our data-set #
rate.data = first(rate20190430_xts,5)
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
SvenssonParameters <- Svensson(rate.data, maturity.data)
Svensson.rate <- Srates( SvenssonParameters ,maturity.data,"Spot")

#Svensson function Estimation - Observed vs fitted #
plot(maturity.data, rate.data[1,],main="Fitting Svensson yield curve",
type="o")
lines(maturity.data, Svensson.rate[1,], col=2)
legend("bottomright",legend=c("observed yield curve","fitted yield curve"),
       col=c(1,2),lty=1)
#Observation Data
obs<- as.vector(rate20190430_xts[1,])

#Nelson.Siegel Model Estimation
mod<-as.vector(y)

#Svensson Model Estimation
mod1<-as.vector(Svensson.rate[1,])

rsq <- function (x, y) cor(x, y) ^ 2
```

```
RMSE = function(m, o){
  sqrt(mean((m - o)^2))
}
rsq(obs,mod)
RMSE(mod,obs)
rsq(obs,mod1)
RMSE(mod1,obs)

# Clear packages
detach("package:", unload = TRUE)
rm(list = ls())
# Clear plots
dev.off()
cat("\014")
```

Impact of COVID Pandemic -20200213

```
#Import Data file in to R#
rate20200213<-
read.csv("C:\\Users\\Desktop\\folder\\segr\\Excel\\2020.02.13.csv")

#Call required Packages#
require(xts)
require(YieldCurve)

#Convert data file to "xts" format#
rate20200213$Date_new <- as.Date.factor(rate20200213$Date_new,
format="%m/%d/%Y")
rate20200213_xts <- xts(rate20200213[,2:14], order.by =
rate20200213$Date_new)

# Nelson.Siegel function for our data-set #
rate.data = first(rate20200213_xts,5)
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
NSParameters <- Nelson.Siegel( rate= rate.data, maturity= maturity.data )
y <- NSrates(NSParameters[1,], maturity.data)

#Nelson.SiegelEstimation - Observed vs fitted #
plot(maturity.data,rate.data[1,],main="Fitting Nelson-Siegel yield curve",
type="o")
lines(maturity.data,y, col=2)
legend("bottomright",legend=c("observed yield curve","fitted yield curve"),
       col=c(1,2),lty=1)

# Svensson function for our data-set #
rate.data = first(rate20200213_xts,5)
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
SvenssonParameters <- Svensson(rate.data, maturity.data)
Svensson.rate <- Srates( SvenssonParameters ,maturity.data,"Spot")

#Svensson function Estimation - Observed vs fitted #
plot(maturity.data, rate.data[1,],main="Fitting Svensson yield curve",
type="o")
lines(maturity.data, Svensson.rate[1,], col=2)
legend("bottomright",legend=c("observed yield curve","fitted yield curve"),
       col=c(1,2),lty=1)

#Observation Data
obs<- as.vector(rate20200213_xts[1,])
```

```
#Nelson.Siegel Model Estimation
mod<-as.vector(y)

#Svensson Model Estimation
mod1<-as.vector(Svensson.rate[1,])

rsq <- function (x, y) cor(x, y) ^ 2
RMSE = function(m, o){
  sqrt(mean((m - o)^2))
}
rsq(obs,mod)
RMSE(mod,obs)
rsq(obs,mod1)
RMSE(mod1,obs)

# Clear packages
detach("package:", unload = TRUE)
rm(list = ls())
# Clear plots
dev.off()
cat("\014")
```

Impact of COVID Pandemic-20200722

```
#Import Data file in to R#
rate20200722<-
read.csv("C:\\Users\\Desktop\\folder\\segr\\Excel\\2020.07.22.csv")

#Call required Packages#
require(xts)
require(YieldCurve)

#Convert data file to "xts" format#
rate20200722$Date_new <- as.Date.factor(rate20200722$Date_new,
format="%m/%d/%Y")
rate20200722_xts <- xts(rate20200722[,2:14], order.by =
rate20200722$Date_new)

# Nelson.Siegel function for our data-set #
rate.data = first(rate20200722_xts,5)
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
NSParameters <- Nelson.Siegel( rate= rate.data, maturity= maturity.data )
y <- NSrates(NSParameters[1,], maturity.data)

#Nelson.SiegelEstimation - Observed vs fitted #
plot(maturity.data,rate.data[1,],main="Fitting Nelson-Siegel yield curve",
type="o")
lines(maturity.data,y, col=2)
legend("bottomright",legend=c("observed yield curve","fitted yield curve"),
       col=c(1,2),lty=1)

# Svensson function for our data-set #
rate.data = first(rate20200722_xts,5)
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
SvenssonParameters <- Svensson(rate.data, maturity.data)
Svensson.rate <- Srates( SvenssonParameters ,maturity.data,"Spot")

#Svensson function Estimation - Observed vs fitted #
```

```
plot(maturity.data, rate.data[1,],main="Fitting Svensson yield curve",
type="o")
lines(maturity.data, Svensson.rate[1,], col=2)
legend("bottomright",legend=c("observed yield curve","fitted yield curve"),
       col=c(1,2),lty=1)

#Observation Data
obs<- as.vector(rate20200722_xts[1,])

#Nelson.Siegel Model Estimation
mod<-as.vector(y)

#Svensson Model Estimation
mod1<-as.vector(Svensson.rate[1,])

rsq <- function (x, y) cor(x, y) ^ 2
RMSE = function(m, o){
  sqrt(mean((m - o)^2))
}
rsq(obs,mod)
RMSE(mod,obs)
rsq(obs,mod1)
RMSE(mod1,obs)

# Clear packages
detach("package:", unload = TRUE)
rm(list = ls())
# Clear plots
dev.off()
cat("\014")

---------------------------------------------------------------------------
```

Validity Check

```
# Load csv #
Ratef <- read.csv("C:\\Users\\Desktop\\folder\\Ratef.csv")
# 1356 x 14

#Convert data file to "xts" format#
Ratef$Date_new <- as.Date.factor(Ratef$Date_new, format="%m/%d/%Y")
Ratef_xts <- xts(Ratef[,2:14], order.by = Ratef$Date_new)

# Vector with maturities #
mat.Ratef <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)

# Convert to xts #
Ratef_daily <- as.xts(Ratef_xts)

# Sample weekly data from daily data#
Ratef_week_OHLC <- to.weekly(Ratef_daily)        # to.weekly Function
returns OHLC, not the original data.

# Retrieve index for weekly data
index <- index(Ratef_week_OHLC)
Ratef_weekly <- Ratef_daily[index]
```

```
# Checks #
# head(Ratef_weekly)
# y <- weekdays(index(Ratef_weekly))
# table(y)              # TY: always takes Fridays; otherwise different
day.

#########################################
# fts-object from CBSL data #

# Naming of columns #
column_names <- index(Ratef_weekly)
column_names <- toString(column_names)
column_names <- strsplit(column_names, ", ")[[1]]

Ratef_weekly_core <- t(coredata(Ratef_weekly))                # Matrix
with CBSL data.
colnames(Ratef_weekly_core) <- column_names

# Create Functional time series object (by 'fts') #
CBSL_fts <- fts(x = mat.Ratef, y= Ratef_weekly_core, start = 1, xname =
"Maturities", yname = "Yields")


# Nelson.Siegel function for our data-set #
rate.data = Ratef_weekly[1:296,]
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
NSParameters <- Nelson.Siegel( rate= rate.data, maturity=maturity.data )
Nelson.rate <- NSrates(NSParameters[1:296,], maturity.data)

# fts-object from Nelson data #

# Naming of columns #
NS_column_names <- index(Nelson.rate)
NS_column_names <- toString(NS_column_names)
NS_column_names <- strsplit(NS_column_names, ", ")[[1]]

NS_weekly_core <- t(coredata(Nelson.rate))                # Matrix with
Nelson data.
colnames(NS_weekly_core) <- NS_column_names

# Create Functional time series object (by 'fts') #
NS_fts <- fts(x = mat.Ratef, y= NS_weekly_core, start = 1, xname =
"Maturities", yname = "Yields")

# Descriptive #
avgweekly <- centre(CBSL_fts$y, type = "mean")
avgnelson <- centre(NS_fts$y, type = "mean")

#Nelson.SiegelEstimation - Observed vs fitted #
plot(x=mat.Ratef, y=avgweekly, main="Fitting Nelson-Siegel Average yield
curve", type="o")
lines(x=mat.Ratef,y=avgnelson, col=2)
legend("bottomright",legend=c("observed average yield curve","fitted
average yield curve"),
       col=c(1,2),lty=1)

# Svensson function for our data-set #
rate.data = Ratef_weekly[1:296]
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
```

```
SvenssonParameters <- Svensson(rate.data, maturity.data)
Svensson.rate <- Srates( SvenssonParameters ,maturity.data,"Spot")

# fts-object from Svensson data #

# Naming of columns #
SV_column_names <- index(Svensson.rate)
SV_column_names <- toString(SV_column_names)
SV_column_names <- strsplit(SV_column_names, ", ")[[1]]

SV_weekly_core <- t(coredata(Svensson.rate))                 # Matrix with
Svensson data.
colnames(SV_weekly_core) <- SV_column_names

# Create Functional time series object (by 'fts') #
SV_fts <- fts(x = mat.Ratef, y= SV_weekly_core, start = 1, xname =
"Maturities", yname = "Yields")

# Descriptive #
avgweekly <- centre(CBSL_fts$y, type = "mean")
avgsvensson <- centre(SV_fts$y, type = "mean")
#Svensson function Estimation - Observed vs fitted #
plot(x=mat.Ratef, y=avgweekly, main="Fitting Svensson Average yield curve",
type="o")
lines(x=mat.Ratef, y=avgsvensson, col=2)
legend("bottomright",legend=c("observed average yield curve","fitted
average yield curve"),
       col=c(1,2),lty=1)

#Nelson.SiegelEstimation - Estimated Parameters #
NSParameters[1:296,]

#Svensson Model Parameter Estimation
SvenssonParameters[1:296,]

#Observation Data
obs<- as.vector(Ratef_weekly[1:296,])

#Nelson.Siegel Model Estimation
mod<-as.vector(Nelson.rate)

#Svensson Model Estimation
mod1<-as.vector(Svensson.rate[1:296,])

rsq <- function (x, y) cor(x, y) ^ 2
RMSE = function(m, o){
  sqrt(mean((m - o)^2))
}
rsq(obs,mod)
RMSE(mod,obs)
rsq(obs,mod1)
RMSE(mod1,obs)



---------------------------------------------------------------------------
```

Parameter Estimation

```
#Import Data file in to R#
Ratef <-
read.csv("C:\\Tha_files\\MSc_Thesis\\PackagesCodes&Outputs\\Inputs\\Ratef.c
sv")
#Call required Packages#
require(xts)
require(YieldCurve)

#Convert data file to "xts" format#
Ratef$Date_new <- as.Date.factor(Ratef$Date_new, format="%m/%d/%Y")
Ratef_xts <- xts(Ratef[,2:14], order.by = Ratef$Date_new)

# Nelson.Siegel function for our data-set #
rate.data = first(Ratef_xts,1356)
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
NSParameters <- Nelson.Siegel( rate= rate.data, maturity=maturity.data )
y <- NSrates(NSParameters[1356,], maturity.data)
#Nelson.SiegelEstimation - Observed vs fitted #
plot(maturity.data,rate.data[1356,],main="Fitting Nelson-Siegel yield
curve", type="o")
lines(maturity.data,y, col=2)
legend("bottomright",legend=c("observed yield curve","fitted yield
curve"),col=c(1,2),lty=1)

write.csv(NSParameters,file = "NSParametersf.csv")
write.csv(rate.data,file = "Actualf.csv")
write.csv(y,file = "predictedf.csv")

# Svensson function for our data-set #
rate.data = first(Ratef_xts,1356)
maturity.data <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)
SvenssonParameters <- Svensson(rate.data, maturity.data)
Svensson.rate <- Srates( SvenssonParameters ,maturity.data,"Spot")

#Svensson function Estimation - Observed vs fitted #
plot(maturity.data, rate.data[1356,],main="Fitting Svensson yield curve",
type="o")
lines(maturity.data, Svensson.rate[1356,], col=2)
legend("bottomright",legend=c("observed yield curve","fitted yield
curve"),col=c(1,2),lty=1)

write.csv(SvenssonParameters,file = "SvenssonParametersff.csv")
write.csv(rate.data,file = "Actualff.csv")
write.csv(y,file = "predictedff.csv")
```

Forecasting yield curve – Input Data adjustment

```
# source("01_packagest.R")

#########################################
# CBSL data #

# Load csv #
Ratef <- read.csv("C:\\Users\\Desktop\\folder\\Ratef.csv")
# 1356 x 14

#Convert data file to "xts" format#
```

```
Ratef$Date_new <- as.Date.factor(Ratef$Date_new, format="%m/%d/%Y")
Ratef_xts <- xts(Ratef[,2:14], order.by = Ratef$Date_new)

# Vector with maturities #
mat.Ratef <- c(3/12, 0.5, 1,2,3,4,5,6,8,10,15,20,30)

# Convert to xts #
Ratef_daily <- as.xts(Ratef_xts)

# Sample weekly data from daily data#
Ratef_week_OHLC <- to.weekly(Ratef_daily)        # to.weekly Function
returns OHLC, not the original data.

# Retrieve index for weekly data
index <- index(Ratef_week_OHLC)
Ratef_weekly <- Ratef_daily[index]

# Checks #
# head(Ratef_weekly)
# y <- weekdays(index(Ratef_weekly))
# table(y)              # TY: always takes Fridays; otherwise different
day.


########################################
# fts-object from CBSL data #

# Naming of columns #
column_names <- index(Ratef_weekly)
column_names <- toString(column_names)
column_names <- strsplit(column_names, ", ")[[1]]

Ratef_weekly_core <- t(coredata(Ratef_weekly))                 # Matrix
with CBSL data.
colnames(Ratef_weekly_core) <- column_names

# Create Functional time series object (by 'fts') #
CBSL_fts <- fts(x = mat.Ratef, y= Ratef_weekly_core, start = 1, xname =
"Maturities", yname = "Yields")

# Indexed weeks instead of individual dates as colunn names #
yield_data <- Ratef_weekly_core
index_weeks <- c(1:dim(Ratef_weekly_core)[2])                     # ast
change
colnames(yield_data) <- index_weeks

CBSL_indx_fts <- fts(x = mat.Ratef, y= yield_data, xname = "Maturities",
yname = "Yields")

########################################

---------------------------------------------------------------------------
```

Forecasting yield curve– Function

```
# Clear workspace #
#rm(list=ls())

# Set working directory #
setwd("C:\\Users\\Desktop\\folder\\Forecasting")

source("01_packagest.R")
source("02_input_datat.R")


########################################
# Function for evaluating Diebold-Li model #

wrap_DL <- function(trainings_weeks, xts_object, start, h, order_p,
mat_vec) {

  if((start -1 + trainings_weeks + h) > nrow(xts_object)) stop("Too few
curves in test data, reduce trainings_weeks or h")

  max_model <- nrow(xts_object) - trainings_weeks - h +1

  comp_apply <- function(x) {

    end <- x + trainings_weeks -1
    xtssubset <- xts_object[x:end]                    # Subset data

    print(paste("Estimating model:", x))
    est_parameters <- Nelson.Siegel(xtssubset, mat_vec)          # DL_model
estimates parameters, takes most time.

    # AR model and forecast parameters
    arfit0 <- auto.arima(est_parameters$beta_0, max.p = order_p, max.q = 0,
max.order = order_p, max.d = 0, max.D = 0,
                         ic = c("aic"), seasonal = FALSE, stepwise = TRUE)
    arfit1 <- auto.arima(est_parameters$beta_1, max.p = order_p, max.q = 0,
max.order = order_p, max.d = 0, max.D = 0,
                         ic = c("aic"), seasonal = FALSE, stepwise = TRUE)
    arfit2 <- auto.arima(est_parameters$beta_2, max.p = order_p, max.q = 0,
max.order = order_p, max.d = 0, max.D = 0,
                         ic = c("aic"), seasonal = FALSE, stepwise = TRUE)

    for0 <- forecast(arfit0, h = h)
    for1 <- forecast(arfit1, h = h)
    for2 <- forecast(arfit2, h = h)

    # Calculate nelsonsiegel_rates with forecasted parameters
    NSparameter <- est_parameters[1:h]
    NSparameter$beta_0 <- round(as.vector(for0$mean), 6)
    NSparameter$beta_1 <- round(as.vector(for1$mean), 6)
    NSparameter$beta_2 <- round(as.vector(for2$mean), 6)
    NSparameter$lambda <- mean(est_parameters$lambda)

    for_rates <- NSrates(NSparameter, mat_vec)
    error_rates <- t(for_rates)

    # Calculate errors
```

```
    predict_error <- error(forecast = error_rates,
                           true =
t(as.matrix(coredata(xts_object)[(end+1):(end+h),])), method = "rmse")

    result <- c((end+1), (end+h), predict_error)
  }

  table_forecasting <- as.matrix(vapply(start:max_model, comp_apply,
c("First" = 0, "Last" = 0, "RMSE" = 0)))

  res_list <- list("Results_D-L" = t(table_forecasting),
 "Mean_RMSE" = round(mean(table_forecasting["RMSE",]), 5),
Infos = cbind(c("Forecast horizon:", "Number of models:","Training set:"),
c(h, max_model-start+1, trainings_weeks))
  )

  # print(res_list$"Results_D-L")
  # print("##########")
  # print("Mean RMSE:")
  # print(res_list$Mean_RMSE)

  return(res_list)
}

# For rolling study #

roll_DL <- function(trainings_weeks, xts_object, start, h, order_p,
mat_vec) {
  inner <- wrap_DL(trainings_weeks = trainings_weeks, xts_object =
xts_object, start = start, h = h, order_p = order_p, mat_vec = mat_vec)
  print(paste("RMSE:", inner$Mean_RMSE))
  return(list(inner$Mean_RMSE, inner))
}

########################
# Function for evaluating Svensson model #

wrap_SV <- function(trainings_weeks, xts_object, start, h, order_p,
mat_vec) {

  if((start -1 + trainings_weeks + h) > nrow(xts_object)) stop("Too few
curves in test data, reduce trainings_weeks or h")

  max_model <- nrow(xts_object) - trainings_weeks - h +1

  comp_apply <- function(x) {

    end <- x + trainings_weeks -1
    xtssubset <- xts_object[x:end]                   # Subset data

    print(paste("Estimating model:", x))
    est1_parameters <- Svensson(xtssubset, mat_vec)          # SV_model
estimates parameters, takes most time.

    # AR model and forecast parameters
    arfit0 <- auto.arima(est1_parameters$beta_0, max.p = order_p, max.q =
0, max.order = order_p, max.d = 0, max.D = 0,
                         ic = c("aic"), seasonal = FALSE, stepwise = TRUE)
```

```
    arfit1 <- auto.arima(est1_parameters$beta_1, max.p = order_p, max.q =
0, max.order = order_p, max.d = 0, max.D = 0,
                         ic = c("aic"), seasonal = FALSE, stepwise = TRUE)
    arfit2 <- auto.arima(est1_parameters$beta_2, max.p = order_p, max.q =
0, max.order = order_p, max.d = 0, max.D = 0,
                         ic = c("aic"), seasonal = FALSE, stepwise = TRUE)
    arfit3 <- auto.arima(est1_parameters$beta_3, max.p = order_p, max.q =
0, max.order = order_p, max.d = 0, max.D = 0,
                         ic = c("aic"), seasonal = FALSE, stepwise = TRUE)

    for0 <- forecast(arfit0, h = h)
    for1 <- forecast(arfit1, h = h)
    for2 <- forecast(arfit2, h = h)
    for3 <- forecast(arfit3, h = h)

    # Calculate Svensson_rates with forecasted parameters
    Svenssonparameter <- est1_parameters[1:h]
    Svenssonparameter$beta_0 <- round(as.vector(for0$mean), 6)
    Svenssonparameter$beta_1 <- round(as.vector(for1$mean), 6)
    Svenssonparameter$beta_2 <- round(as.vector(for2$mean), 6)
    Svenssonparameter$beta_3 <- round(as.vector(for3$mean), 6)
    Svenssonparameter$tau1 <- mean(est1_parameters$tau1)
    Svenssonparameter$tau2 <- mean(est1_parameters$tau2)

    for_rates1 <- Srates(Svenssonparameter, mat_vec)
    error_rates1 <- t(for_rates1)

    # Calculate errors
    predict_error1 <- error(forecast = error_rates1,
                           true =
t(as.matrix(coredata(xts_object)[(end+1):(end+h),])), method = "rmse")

    result1 <- c((end+1), (end+h), predict_error1)
  }

  table_forecasting1 <- as.matrix(vapply(start:max_model, comp_apply,
c("First" = 0, "Last" = 0, "RMSE" = 0)))

  res_list1 <- list("Results_SV" = t(table_forecasting1),
                   "Mean_RMSE" = round(mean(table_forecasting1["RMSE",]),
5)
                   #                   , Infos = cbind(c("Forecast
horizon:", "Number of models:","Training set:"),
                   #                                 c(h, max_model-
start+1, trainings_weeks))
  )

  # print(res_list1$"Results_SV")
  # print("##########")
  # print("Mean RMSE:")
  # print(res_list1$Mean_RMSE)

  return(res_list1)
}
# For rolling study #

roll_SV <- function(trainings_weeks, xts_object, start, h, order_p,
mat_vec) {
```

```
  inner <- wrap_SV(trainings_weeks = trainings_weeks, xts_object =
xts_object, start = start, h = h, order_p = order_p, mat_vec = mat_vec)
  print(paste("RMSE:", inner$Mean_RMSE))
  return(list(inner$Mean_RMSE, inner))
}

########################
---------------------------------------------------------------------------
```

Forecasting yield curve – Results

```
source("03_function_comparet.R")


# Variables for functions #
horizon <- 4
st <- 1

# Error measurement by method = "rmse".


#########################################
# Diebold-Li models #

# Arguments
#' @param xts_object = An object of class xts.
#' @param start = First week.
#' @param trainings_weeks = Number of weeks of training data.
#' @param h = Forecast horizon.
#' @param order_p = Lag of AR(p) model to fit.

res_DL <- wrap_DL(trainings_weeks = 292, xts_object = Ratef_weekly, start =
st, h = horizon, order_p = 1, mat_vec = mat.Ratef)

res_SV <- wrap_SV(trainings_weeks = 292, xts_object = Ratef_weekly, start =
st, h = horizon, order_p = 1, mat_vec = mat.Ratef)

#########################################
# Rolling functions: Estimating models with decreasing number of trainings
weeks #

range_tw <- seq(150, 50, -10)
range_tw_lg <- seq(200, 50, -30)


# DL Standard model #
# 3h
results_DL_26_1 <- sapply(range_tw_lg, roll_DL, xts_object = Ratef_weekly,
start = st, h = 26, order_p = 1, mat_vec = mat.Ratef)
res_DL_26_1 <- cbind(range_tw_lg, results_DL_26_1[1,])
# results_DL_26_1[2,]
write.csv(res_DL_26_1, file="DL_h26_p1.txt")

results_SV_26_1<- sapply(range_tw_lg, roll_SV, xts_object = Ratef_weekly,
start = st, h = 26, order_p = 1, mat_vec = mat.Ratef)
res_SV_26_1 <- cbind(range_tw_lg, results_SV_26_1[1,])
# results_SV_26_1[2,]
write.csv(res_SV_26_1, file="SV_h26_p1.txt")
```

```
results_DL_4_1 <- sapply(range_tw, roll_DL, xts_object = Ratef_weekly,
start = st, h = 4, order_p = 1, mat_vec = mat.Ratef)
res_DL_4_1 <- cbind(range_tw, results_DL_4_1[1,])
# results_DL_4_1[2,]
write.csv(res_DL_4_1, file="DL_h4_p1.txt")

results_SV_4_1 <- sapply(range_tw, roll_SV, xts_object = Ratef_weekly,
start = st, h = 4, order_p = 1, mat_vec = mat.Ratef)
res_SV_4_1 <- cbind(range_tw, results_SV_4_1[1,])
# results_SV_4_1[2,]
write.csv(res_SV_4_1, file="SV__h4_p1.txt")

---------------------------------------------------------------------------
```

Forecasting Yield curves – Results – plots & illustrations

```
#########################################
results_plots <-
read.table("C:\\Users\\Desktop\\folder\\Forecasting\\TY_results_plots.csv",
sep=";", header = FALSE)

#########################################
# DL model #
#########################################
# range_tw = seq(150, 50, -10) #
NS_4_1_150_50 <- as.numeric(results_plots[3,2:12])
df_NS_4_1_150_50 <- data.frame(Data = "NS", RMSE = NS_4_1_150_50)

SV_4_1_150_50 <- as.numeric(results_plots[4,2:12])
df_SV_4_1_150_50 <- data.frame(Data = "SV", RMSE = SV_4_1_150_50)

plot.data_5 = rbind(df_NS_4_1_150_50, df_SV_4_1_150_50)

# Boxplots: Standard Model #
ggplot(plot.data_5, aes(x=Data, y=RMSE)) + geom_boxplot() +
theme(panel.border = element_rect(colour = "black", fill=NA, size=0.5)) +
  coord_cartesian(ylim = c(0, 1.2)) +
  labs(title = "Forecasting with Nelson-Siegel & Svensson models: h=4
ahead", x = 'Models' , y = 'RMSE') +
  theme(plot.title = element_text(size = '14', face = 'bold', hjust = 0.5))
+
  theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())#+  geom_jitter(width = 0.2)
ggsave("NS_SV_4_mid.pdf", width=6, height=6)

# range_tw = seq(200, 50, -30) #
NS_26_1_200_50 <- as.numeric(results_plots[1,2:7])
df_NS_26_1_200_50 <- data.frame(Data = "NS", RMSE = NS_26_1_200_50)

SV_26_1_200_50 <- as.numeric(results_plots[2,2:7])
df_SV_26_1_200_50 <- data.frame(Data = "SV", RMSE = SV_26_1_200_50)

plot.data_6 = rbind(df_NS_26_1_200_50, df_SV_26_1_200_50)

ggplot(plot.data_6, aes(x=Data, y=RMSE)) + geom_boxplot() +
theme(panel.border = element_rect(colour = "black", fill=NA, size=0.5)) +
  coord_cartesian(ylim = c(0, 2)) +
```

```
  labs(title = "Forecasting with Nelson-Siegel & Svensson models: h=26
ahead", x = 'Models' , y = 'RMSE') +
  theme(plot.title = element_text(size = '14', face = 'bold', hjust = 0.5))
+
  theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())#+  geom_jitter(width = 0.2)
ggsave("NS_SV_26_mid.pdf", width=6, height=6)



####
range_tw_plot = seq(150, 50, -10)

plot.data3 = data.frame(cbind(NS_4_1_150_50, SV_4_1_150_50, range_tw_plot))

ggplot(plot.data3, aes(range_tw_plot)) +
  geom_line(aes(y = NS_4_1_150_50, colour = "NS", linetype = "NS")) +
geom_line(aes(y = SV_4_1_150_50, colour = "SV", linetype = "SV")) +
  scale_colour_manual("Legend", values=c("NS" = "blue", "SV" = "black")) +
  scale_linetype_manual("Legend", values=c("NS"=1, "SV"=6)) +
  theme(panel.border = element_rect(colour = "black", fill=NA, size=0.5)) +
  coord_cartesian(ylim = c(0, 2)) +
  labs(title = "Forecasting: h=4: influence of window size", x = 'Number of
training data' , y = 'RMSE') +
  theme(plot.title = element_text(size = '14', face = 'bold', hjust = 0.5))
+
  theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())
ggsave("NS_SV_tw_4_mid.pdf", width=6, height=6)

##
range_tw_plot_lg = seq(200, 50, -30)

plot.data4 = data.frame(cbind(NS_26_1_200_50, SV_26_1_200_50,
range_tw_plot_lg))

ggplot(plot.data4, aes(range_tw_plot_lg)) +
  geom_line(aes(y = NS_26_1_200_50, colour = "NS", linetype = "NS")) +
geom_line(aes(y = SV_26_1_200_50, colour = "SV", linetype = "SV")) +
  scale_colour_manual("Legend", values=c("NS" = "blue", "SV" = "black")) +
  scale_linetype_manual("Legend", values=c("NS"=1, "SV"=6)) +
  theme(panel.border = element_rect(colour = "black", fill=NA, size=0.5)) +
  coord_cartesian(ylim = c(0, 2)) +
  labs(title = "Forecasting: h=26: influence of window size", x = 'Number
of training data' , y = 'RMSE') +
  theme(plot.title = element_text(size = '14', face = 'bold', hjust = 0.5))
+
  theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())
ggsave("NS_SV_tw_26_mid.pdf", width=6, height=6)
########################################


----------------------------------------------------------------------------
```

General Plots

```
###########################################
# Descriptive plots #
# 3D Plots
# source("02_input_datat.R")

library(plotly)

index <- c(1:1356)                      # For daily data #
Maturities <- mat.Ratef
Yields <- (coredata(Ratef_daily))
plot_ly(z = ~Yields, x = ~Maturities,y = ~index) %>% add_surface()

index <- c(1:296)                       # For weekly data #
Maturities <- mat.Ratef
Yields <- (coredata(Ratef_weekly))
plot_ly(z = ~Yields, x = ~Maturities, y = ~index) %>% add_surface()


# CBSL data #
first(CBSL_fts$y)
plot(CBSL_fts, ylab = "Yield curves", colorchoice = "terrain_hcl",
     plotlegend = TRUE, legend = "bottomright", ylim = c(1,15), main =
"From 11-2014 to 07-2020")

# Descriptive #
avg <- centre(CBSL_fts$y, type = "mean")
plot(x=mat.Ratef, y=avg, type = "p")
plot(x=mat.Ratef, y=avg, type = "o", ylim = c(1,15),
     xlab = "Maturities", ylab = "Average yield curve", main = "Average
Yield Curve from 11-2014 to 07-2020")

# Split means #
split_1 <- extract(CBSL_indx_fts, direction = "time", timeorder = 198:296)
index(Ratef_weekly[198])
plot(x=mat.Ratef, y=centre(split_1$y, type = "mean"), type = "o", ylim =
c(1,12),
     xlab = "Maturities", ylab = "Average yield curve", main = "Average
Yield Curve from 09-2018 to 07-2020")

split_2 <- extract(CBSL_indx_fts, direction = "time", timeorder = 276:296)
index(Ratef_weekly[276])
plot(x=mat.Ratef, y=centre(split_2$y, type = "mean"), type = "o", ylim =
c(1,12),
     xlab = "Maturities", ylab = "Average yield curve", main = "Average
Yield Curve from 03-2020 to 07-2020")


par(mfrow=c(1,2))
plot(CBSL_fts, ylab = "Yield curves", colorchoice = "terrain_hcl",
     plotlegend = TRUE, legend = "bottomright", ylim = c(1,15), main =
"From 11-2014 to 07-2020")
plot(x=mat.Ratef, y=avg, type = "o", ylim = c(1,15),
     xlab = "Maturities", ylab = "Average yield curve", main = "Average
Yield Curve from 11-2014 to 07-2020")


###########################################
```

```
# DL: ACFs #
parameters_plot <- Nelson.Siegel(Ratef_weekly, mat.Ratef)
# beta0_plot <- parameters_plot$beta_0
# beta1_plot <- parameters_plot$beta_1
# beta2_plot <- parameters_plot$beta_2

parameters_plot <- coredata(parameters_plot)
beta0_plot <- parameters_plot[,1]
beta1_plot <- parameters_plot[,2]
beta2_plot <- parameters_plot[,3]

conf.level <- 0.95
ciline <- qnorm((1 - conf.level)/2)/sqrt(length(beta0_plot))

acf_beta0 <- acf(beta0_plot, lag.max = 200, plot = FALSE)
df_acf_beta0 <- with(acf_beta0, data.frame(lag, acf))

p <- ggplot(data = df_acf_beta0, mapping = aes(x = lag, y = acf)) +
  geom_hline(aes(yintercept = 0)) +
  geom_segment(mapping = aes(xend = lag, yend = 0)) +
  geom_hline(aes(yintercept = ciline), linetype = 2, color = 'darkblue') +
  geom_hline(aes(yintercept = -ciline), linetype = 2, color = 'darkblue') +
  coord_cartesian(xlim = c(0, 200), ylim = c(-0.4,1)) +
  labs(title = bquote("Autocorrelation of " ~ hat(beta)[t0]), x = 'Lag' , y
= 'Autocorrelation') +
  theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())
p + theme(plot.title = element_text(size = '14', face = 'bold', hjust =
0.5))
ggsave("CBSL_acf0_DL.pdf", width=4, height=4)


##
acf_beta1 <- acf(beta1_plot, lag.max = 200, plot = FALSE)
df_acf_beta1 <- with(acf_beta1, data.frame(lag, acf))

q <- ggplot(data = df_acf_beta1, mapping = aes(x = lag, y = acf)) +
  geom_hline(aes(yintercept = 0)) +
  geom_segment(mapping = aes(xend = lag, yend = 0)) +
  geom_hline(aes(yintercept = ciline), linetype = 2, color = 'darkblue') +
  geom_hline(aes(yintercept = -ciline), linetype = 2, color = 'darkblue') +
  coord_cartesian(xlim = c(0, 200), ylim = c(-0.4,1)) +
  labs(title = bquote("Autocorrelation of " ~ hat(beta)[t1]), x = 'Lag' , y
= 'Autocorrelation') +
  theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())
q + theme(plot.title = element_text(size = '14', face = 'bold', hjust =
0.5))
ggsave("CBSL_acf1_DL.pdf", width=4, height=4)

##
acf_beta2 <- acf(beta2_plot, lag.max = 200, plot = FALSE)
df_acf_beta2 <- with(acf_beta2, data.frame(lag, acf))

r <- ggplot(data = df_acf_beta2, mapping = aes(x = lag, y = acf)) +
  geom_hline(aes(yintercept = 0)) +
  geom_segment(mapping = aes(xend = lag, yend = 0)) +
  geom_hline(aes(yintercept = ciline), linetype = 2, color = 'darkblue') +
  geom_hline(aes(yintercept = -ciline), linetype = 2, color = 'darkblue') +
```

```
  coord_cartesian(xlim = c(0, 200), ylim = c(-0.4,1)) +
  labs(title = bquote("Autocorrelation of " ~ hat(beta)[t2]), x = 'Lag' , y
= 'Autocorrelation') +
  theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())
r + theme(plot.title = element_text(size = '14', face = 'bold', hjust =
0.5))
ggsave("CBSL_acf2_DL.pdf", width=4, height=4)

# Svensson: ACFs #

parameters_plot_SV <- Svensson(Ratef_weekly, mat.Ratef)
parameters_plot_SV <- coredata(parameters_plot_SV)
beta0_plot_sv <- parameters_plot_SV[,1]
beta1_plot_sv <- parameters_plot_SV[,2]
beta2_plot_sv <- parameters_plot_SV[,3]
beta3_plot_sv <- parameters_plot_SV[,4]

conf.level <- 0.95
ciline_sv <-  qnorm((1 - conf.level)/2)/sqrt(length(beta0_plot_sv))

acf_beta0_sv <- acf(beta0_plot_sv, lag.max = 200, plot = FALSE)
df_acf_beta0_sv <- with(acf_beta0_sv, data.frame(lag, acf))

p <- ggplot(data = df_acf_beta0_sv, mapping = aes(x = lag, y = acf)) +
  geom_hline(aes(yintercept = 0)) +
  geom_segment(mapping = aes(xend = lag, yend = 0)) +
  geom_hline(aes(yintercept = ciline_sv), linetype = 2, color = 'darkblue')
+
  geom_hline(aes(yintercept = -ciline_sv), linetype = 2, color =
'darkblue') +
  coord_cartesian(xlim = c(0, 200), ylim = c(-0.4,1)) +
  labs(title = bquote("Autocorrelation of " ~ hat(beta)[t0]), x = 'Lag' , y
= 'Autocorrelation') +
  theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())
p + theme(plot.title = element_text(size = '14', face = 'bold', hjust =
0.5))
ggsave("CBSL_acf0_SV.pdf", width=4, height=4)
# acf(beta0_plot_sv, lag.max = 200)

acf_beta1_sv <- acf(beta1_plot_sv, lag.max = 200, plot = FALSE)
df_acf_beta1_sv <- with(acf_beta1_sv, data.frame(lag, acf))

q <- ggplot(data = df_acf_beta1_sv, mapping = aes(x = lag, y = acf)) +
  geom_hline(aes(yintercept = 0)) +
  geom_segment(mapping = aes(xend = lag, yend = 0)) +
  geom_hline(aes(yintercept = ciline_sv), linetype = 2, color = 'darkblue')
+
  geom_hline(aes(yintercept = -ciline_sv), linetype = 2, color =
'darkblue') +
  coord_cartesian(xlim = c(0, 200), ylim = c(-0.4,1)) +
  labs(title = bquote("Autocorrelation of " ~ hat(beta)[t1]), x = 'Lag' , y
= 'Autocorrelation') +
  theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())
q + theme(plot.title = element_text(size = '14', face = 'bold', hjust =
0.5))
ggsave("CBSL_acf1_SV.pdf", width=4, height=4)
```

```
# acf(beta1_plot_sv, lag.max = 200)

acf_beta2_sv <- acf(beta2_plot_sv, lag.max = 200, plot = FALSE)
df_acf_beta2_sv <- with(acf_beta2_sv, data.frame(lag, acf))

r <- ggplot(data = df_acf_beta2_sv, mapping = aes(x = lag, y = acf)) +
  geom_hline(aes(yintercept = 0)) +
  geom_segment(mapping = aes(xend = lag, yend = 0)) +
  geom_hline(aes(yintercept = ciline_sv), linetype = 2, color = 'darkblue')
+
  geom_hline(aes(yintercept = -ciline_sv), linetype = 2, color =
'darkblue') +
  coord_cartesian(xlim = c(0, 200), ylim = c(-0.4,1)) +
  labs(title = bquote("Autocorrelation of " ~ hat(beta)[t2]), x = 'Lag' , y
= 'Autocorrelation') +
  theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())
r + theme(plot.title = element_text(size = '14', face = 'bold', hjust =
0.5))
ggsave("CBSL_acf2_SV.pdf", width=4, height=4)
# acf(beta2_plot_sv, lag.max = 200,  ci.type = "ma")


acf_beta3_sv <- acf(beta3_plot_sv, lag.max = 200, plot = FALSE)
df_acf_beta3_sv <- with(acf_beta3_sv, data.frame(lag, acf))

r <- ggplot(data = df_acf_beta3_sv, mapping = aes(x = lag, y = acf)) +
  geom_hline(aes(yintercept = 0)) +
  geom_segment(mapping = aes(xend = lag, yend = 0)) +
  geom_hline(aes(yintercept = ciline_sv), linetype = 2, color = 'darkblue')
+
  geom_hline(aes(yintercept = -ciline_sv), linetype = 2, color =
'darkblue') +
  coord_cartesian(xlim = c(0, 200), ylim = c(-0.4,1)) +
  labs(title = bquote("Autocorrelation of " ~ hat(beta)[t3]), x = 'Lag' , y
= 'Autocorrelation') +
  theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())
r + theme(plot.title = element_text(size = '14', face = 'bold', hjust =
0.5))
ggsave("CBSL_acf3_SV.pdf", width=4, height=4)
# acf(beta3_plot_sv, lag.max = 200,  ci.type = "ma")

#############################################

#########################################
```