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Forecasting the U.S. Treasury Yield Curve using Targeted Diffusion Indices

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Abstract

We investigate possible empirical linkages between variation in the U.S. Treasury yield curve and several measures of economic and financial activity by the methodology targeted diffusion index forecasting. First, we model the entire yield curve with the Nelson-Siegel exponential components framework period-by-period, thereby distilling the yield curve into three, dynamic parameters. We show that these three parameters can be interpreted as yield curve factors corresponding to level, slope and curvature, and that their variation explain almost all yield curve variation. We then use targeted diffusion indices estimated from a set of 1196 different macroeconomic and financial variables to produce both in-sample and out-of-sample forecasts these three parameters, thus obtaining forecasts of the the entire yield curve. While we do find in-sample predictability of the Nelson-Siegel dynamic paramaters by the targeted diffusion indices, we do not find that they are able to produce better out-of-sample forecasts than the competitor models. Additionally, we find that the established Diebold-Li yield curve forecasting model, which has previously been found to produce superior forecasts, is outperformed by a simple random walk model. Our findings on a new, updated sample thus contradict earlier findings.

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Contents

1 Introduction

The objective of our thesis is to investigate the predictability of the US Treasury yield curve and study whether it can be foretasted using so-called targeted diffusion indices estimated from a large set of macroeconomic and financial variables.

Diffusion indices are often referred to as latent factors, or principal components, that explain the majority of the variation in a set of variables, and such factors estimated from macroeconomic variables have previously been shown to predict excess returns on Treasury securities (Ludvigson & Ng, 2009). Our set of explanatory variables, from which we estimate principal components, consists of 1196 monthly different macroeconomic variables such as inflation and industrial production indices, and financial variables such as the dividend-price ratio on the S&P500 index and investor sentiment indices. We test whether the first few principal components estimated from this dataset predicts changes in the U.S. Treasury yield curve. We do so by producing monthly in-sample and out-of-sample forecasts of the Dynamic Nelson-Siegel yield curve model parameters using these principal components from January, 1991 to December, 2019. This topic is interesting for several reasons, both from a financial and macroeconomic perspective. Understanding the dynamic evolution of the yield curve and its predictability is important for tasks such as pricing both financial and real assets, risk management, bond portfolio management, structuring fiscal debt and conducting monetary policy (Diebold & Rudebusch, 2013).

A yield curve is a plot of yields on similar quality securities against their contract lengths, or maturities. This thesis studies the US Treasury Yield Curve which relates yields on Treasury bills, notes and bonds to their respective time to maturity. Forecasting the U.S. Treasury yield curve ultimately amounts to forecasting yields on U.S. Treasury securities. One could view the yields for different maturities as separate time-series and forecast them separately, thereby predicting the yield curve by forecasting the yields that constitute it. In this thesis, however, we forecast the entire yield curve, i.e. yields for a continuum of maturities. As the historical yield curves are nothing more than *graphical representations* of the relationship between observed yields and their respective time to maturity, we need a method to obtain a parsimonious *model representation* of historical Treasury yield curves, comprised of time varying variables which can be forecasted. In other words, we model historical yield curves by assuming a general functional form which we fit to the cross-section of yields, before we forecast this yield curve function.

Many such yield curve models have been produced by researchers whose goal have been to investigate yield curve dynamics, but most of them tend to be either theoretically or empirically disappointing (Diebold & Rudebusch, 2013). We have chosen to employ an extension by Diebold and Rudebusch

(2013) to the Nelson-Siegel (NS) model (1987) called the Dynamic Nelson-Siegel model (DNS), since this model has proven to exhibit both good fit and forecast abilities (Diebold & Rudebusch, 2013). For example, Diebold and Li (2006) use the DNS model to produce out-of-sample yield forecasts superior to that of several benchmark models. They forecast the yield curve by forecasting the DNS model parameters as autoregressive models of order 1.

The original NS model is a parametrically parsimonious functional form (Nelson & Siegel, 1987) which over time has proved to fit well in the cross section of yields (Diebold & Rudebusch, 2013), and it has become one of the most popular and widely used approaches in yield curve modelling (Rebonato, 2018). When moving from the original, cross-sectional NS model to a time-series perspective with the DNS, the time-varying estimates of the three model parameters transmute into variables which capture almost all temporal variation in the yield curve (Diebold & Rudebusch, 2013). We will show that these variables can be interpreted as three latent yield curve factors corresponding to the yield curve *level*, *slope* and *curvature*. Forecasting the yield curve translates into forecasting these factors, which a-priori can be linked to several macroeconomic and financial variables (Diebold & Rudebusch, 2013). If we are able to approximate the historical, unsmoothed yield curves (i.e. the set of "raw" yields) with a smooth yield curve function in an accurate manner with the DNS model, we might be able to explain some of the variation in the yield curve by explaining the variation in the three DNS parameters. Inspired by the methodology of Diebold and Li (2006), we fit the NS model to the set of observed yields period-by-period to obtain the DNS model parameters, resulting in one estimate of the three model parameters for each month in our sample. We find that the model provides a good fit in our sample, explaining 93.42% of the variation in yields across maturities on average.

However, before we can model the historical yield curves with the DNS model we must obtain historical "raw" yields which will be used as input in the model. As "raw" yields in practice are *unobserved*, they have to be estimated using the large set of *observed* bond prices which exist at any given moment in time (Diebold & Li, 2006). In our thesis, we obtain historical "raw" yields from two different sources. In the first part of our sample, from January, 1991 to December, 2014, we estimate "raw yields" using data on historical Treasury bond quotes obtained from CRSP. In the final part of our sample, from January, 2015 to December, 2019, we employ the historical yield estimates of the U.S. Treasury Department. The reason we are using two different sources to obtain historical "raw" yields is because CRSP only offers bond quotes data until December, 2014. Since the data from CRSP enables to obtain "raw" yields for a larger set of maturities than what is offered by the U.S. Treasury Department, and thus gives us more data-points as input into the DNS model, we choose to use this data where possible.

We forecast the estimated DNS parameters, i.e. the three yield curve factors level, slope, and curvature, using targeted diffusion indices inspired by the works of Bai and Ng (2008) and Ludivigson and Ng (2009). We are, to the best of our knowledge, the first to use this forecasting methodology on the U.S. Treasury yield curve. By targeted diffusion indices we mean that we target variables that have been tested to have predictive power for the three factors before we form the principal components. We construct an algorithm which seeks to minimize the Bayesian Information Criterion (BIC) by selecting an optimal (in terms of BIC) forecasting model specification using a combination of autoregressive processes and the targeted diffusion indices. We use this algorithm to produce in-sample forecasts and recursive out-of-sample forecasts of the three DNS yield curve factors. We then use these out-of-sample forecasts to re-construct the Nelson-Siegel yield curves, from which we can extract yield forecasts for different maturities.

We do find in-sample predictability in two of the three DNS yield curve factors by the targeted diffusion indices, specifically the first and the third yield curve factor (i.e. level and curvature). The in-sample results are reported in Section 5. We find that the 10 first principal components estimated from the set of targeted variables explain almost 16% of the variation in the one-month ahead change in the curvature factor (the third DNS model parameter), and 14% of the twelve-month ahead change in the level factor (the first DNS model parameter). For the level factor we find the most predictability, with the 10 first targeted principal components explaining 7% and 9% at the one and six month horizons, respectively. By using the BIC-minimizing algorithm in-sample, we find that the optimal forecasting models for the second DNS model parameter, slope, never include targeted principal components. For the first DNS model parameter, level, it is optimal to include targeted principal components across all forecast horizons, and for the last DNS model parameter, curvature, it is optimal to include targeted principal components at the one and six month forecast horizons. We thus find that the yield curve level and curvature are forecastable by the targeted diffusion indices, while the yield curve slope is not.

Does the in-sample predictability we find in the first and last DNS model parameter translate to superior out-of-sample forecasts? Unfortunately, we find that it does not. We find that our out-of-sample forecasting algorithm using targeted diffusion indices produce forecasts inferior to that of all benchmark models. Not only do we find that our targeted diffusion indices forecasting framework exhibit poor out-of-sample forecasting performance; we also find that the Diebold and Li (2006) model is outperformed by a simple random walk model. This means that the finding of Diebold and Li (2006), i.e. that optimal yield curve forecasts are obtained by forecasting the DNS model parameters as AR(1) processes, does not hold in our sample. In fact, we find that both the random walk model and simple AR(1) models used directly on yield levels, as opposed to forecasting yields through the DNS model, outperform both our targeted diffusion indices model and the model of Diebold and Li (2006).

We proceed as follows. In Section 2, we conduct a literature review in which we look at the literature on both yield curve modelling and yield curve forecasting. We will emphasize why we choose to use the parametric NS function to model the yield curves before forecasting them, and why we use the targeted diffusion indices framework of Bai and Ng (2008) to forecast the yield curves. In Section 3 we cover the methodology we use to forecast the yield curves. First, we look at the method of obtaining "raw" yields from observed bond prices. Second, we review the DNS yield curve modelling methodology we employ in this thesis. Third, we look at the targeted diffusion indices forecasting framework and the algorithm we use to forecast the yield curve. In Section 4, we describe the data and provide descriptive statistics on the "raw" yields we use as input into our yield curve model. In Section 5 we review how well the DNS model perform at replicating the historical yield curves, before we look at the in-sample and out-of-sample forecasting results. In Section 6, we provide some concluding remarks and suggestions for further research.

2 Literature Review

We will now review relevant yield curve literature and theory. We will begin with a review of two fundamental yield curve theories, specifically the expectation hypothesis and liquidity preference theory, before we study whether these theories hold empirically. We will then continue with a review of the different models one can employ to model the yield curve, before assessing the ability of these models to predict changes in the yield curve. We will also review studies that do not model and forecast the yield curve directly, but rather seek to forecast excess bond returns.

2.1 Two Fundamental Yield Curve Theories

The term structure of interest rates, i.e. the yield curve, is the relation between the yield to maturity (YTM) and the time to maturity (TTM) of bonds (Bodie, Kane, & Marcus, 2018). The yields tend to change with the different maturities, which means that the yield curve tends not to be flat. The curve can take on a variety of shapes, from (approximately) linearly increasing to linearly decreasing in maturity, and from humped to U-shaped (Bodie et al., 2018). The shape might dramatically change from one period to another, and it is this time-variation in the shape of the yield curve we seek to forecast. As we will see later, the average yield curve is increasing and concave, meaning that you get a higher yield, or higher compensation, for holding longer maturity bonds, but at a decreasing rate. We present figures showing the different yield curve shapes in Section 5.

Why do investors require different yields for different maturities, i.e. what explains the shape of the yield curve? And how do expectations for future interest rates affect the yield curve today? In a world without uncertainty and hence without risk, and upward sloping yield curve implies that the future short-rate, i.e. the interest rate for a 1-period time interval in the future, will be higher than the short-rate today. This is due to the equalization of returns over different strategies with equal risk and investment horizon; the return of two consecutive one-year investments in zeros must equal an equal-sized investment in a two-year zero. If the yield on the two-year bond is higher than the yield on the one-year bond, it must be because the short rate between year 1 and 2 is higher than the short-rate today. If not, an arbitrage opportunity exists (Bodie et al., 2018).

How can we explain the shape of the yield curve when future interest rates are not certain? There are two fundamental theories explaining the yield curve under the presence of uncertainty, namely the Expectations Hypothesis (EH) and the Liquidity Preference Theory (LPT) (Bodie et al., 2018). Before we look at these models, we introduce the forward interest rate which is the future short-rate you can lock in today. For no arbitrage opportunities to exist, we have that the forward interest rate must be the break-even interest rate that equates the return of an n-period bond investment and an $(n-1)$-period investment rolled over into a one-year bond investment

$$(1 + f_n) = \frac{(1 + y_n)^n}{(1 + y_{n-1})^{n-1}} \tag{1}$$

Both EH and LPT relates the forward interest rate, f_n, to the expected future short-rate, $E(r_n)$. As we will see, the return of different equal-sized investment strategies with the same horizon need not be equalized in presence of risk, meaning that investors might require a premium for investing in strategies with uncertain returns. We now look at a theory which assumes that investors do not require such a premium, namely the expectation hypothesis.

2.1.1 Expectations Hypothesis

The expectations hypothesis is the simplest theory trying to explain the shape of the yield curve. According to this theory, the interest rates for the different maturities are solely determined by current and expected future one-period short-rates; a change in the shape of the yield curve from one period to another can only be attributed to a change in the current and/or expected future short-rates. The hypothesis assumes risk neutral investors and hence no liquidity premiums, which means that an upward sloping yield curve would indicate that investors expect interest rates to increase. In other words, we can infer the expected future short-rates by looking at the yield curve today, i.e. using today's information on yields to make forecasts for future short-rates. A well-recognized version of the hypothesis states that the forward rate is equal to the short-term future interest rate expected by the overall market, i.e. $f_n = E(r_n)$ (Bodie et al., 2018). If we assume that the EH holds and we rewrite Eq. (1), we get

$$(1 + y_n)^n = (1 + y_{n-1})^{n-1} \times (1 + E(r_n)) \tag{2}$$

According to this equation, bonds with different maturities are perfect substitutes due to equalization of expected rates of returns under a no-arbitrage argument, even with uncertainty. As mentioned above, the current and future expected future spot rates are the only variables explaining the interest rates at different maturities.

What implications does the EH have for the research question of our thesis, if it were to hold? Well, if investors are indeed risk neutral and $f_n = E(r_n)$, it means that the optimal forecasts of future short-rates are the prevailing forward rates. For example, we could forecast the short-rate between period 1 and 2 as f_2, and the short-rate between period 2 and 3 as f_3. We could use these short-rate forecasts to find the expected 2-period yield *in one year*, i.e. the yield on bonds issued in period 1 and maturing in period 3. In other words, there is no forecastable variation in yields that is not already incorporated in today's yield curve; remember that the forward rates are found using yields known today (Eq. (1)). This is an important point because, if the theory holds, there is no point in searching for a yield curve forecasting model. However, the theory does not hold. As will be discussed in a later section, several studies find predictability in excess bond returns, which is evidence against the EH (Cochrane & Piazzesi, 2005). Next, we consider the second fundamental yield curve theory and assess its implications for our research question.

2.1.2 Liquidity Preference Theory

As mentioned above, investors might require a risk premium for strategies with uncertain returns. Short-term investors can choose between buying a short-term bond with a certain return, and a longer-term bond sold off before maturity with an uncertain return. Contrarily, long-term investors may choose between long-term bonds held to maturity with certain returns, and rolling their investment over from a short-term bond to another with uncertain returns. In the liquidity preference theory one assumes that investors preferring *liquid* securities dominate the market, such that investors typically require a *liquidity premium* for holding long-term bonds. This means that the prices of long-term bonds under the LPT would have to be lower than under the EH, allowing for a greater expected holding period return for holding a long-term bond and selling it before maturity than holding a short-term bond until maturity

$$\frac{(1+y_n)^n}{1+E(r_n)} > (1+y_{n-1})^{n-1} \tag{3}$$

The above inequality states that the holding period return for holding an n-period bond for $n-1$ periods must exceed the certain return of holding an $n-1$-period bond for $n-1$-periods. We re-write Eq. (3) to see that

$$\frac{(1+y_n)^n}{(1+y_{n-1})^{n-1}} > 1+E(r_n) \tag{4}$$

From Eq. (4) it is easy to see that $f_n > E(r_n)$. The difference $f_n - E(r_n)$ is the liquidity premium for holding long-term bonds, such that $f_n = E(r_n) + LP$.

What are the implications of the LPT on our goal of forecasting the yield curve? The expected future short rates depend only on the prevailing forward rates and the unknown liquidity premium, meaning that we can no longer infer expected future short rates from today's yield curve. If the theory holds, we could try to estimate this liquidity premium. It turns out, however, that neither of the two fundamental yield curve theories hold. The observation by Fama and Bliss (1987) that the ordering of expected returns across maturities changes through time translates to that the ordering of risks changes through time. This is not in line with the LPT which assumes that expected returns always increase with maturity (Fama & Bliss, 1987).

We have to look beyond the two fundamental yield curve theories in order to obtain a good forecasting model of the yield curve. We now proceed to review different models that aim to model and forecast the yield curve as functional forms.

2.2 Yield Curve Modelling

When looking for a suitable yield curve modelling framework from a *forecasting perspective*, we not only have to find a model which describes the yield curve well both theoretically and empirically (i.e. providing a good fit), but also one that is good at predicting its evolution. Finding and choosing *one* such model from the enormous literature that has emerged from the quest for understanding what moves bond yields, is a challenging task (Piazzesi, 2010). In this thesis we will employ a model belonging to the so-called "snapshot"-class of models, that is the Nelson-Siegel (NS) parametric model. A detailed explanation of this model, including its derivation, limitations, and benefits, will be presented in the methodology section. We will now review the most important classes of yield curve models that have been used to model and/or forecast yields, albeit somewhat superficially. We will see if and how we could have used the models to reach the goal of our thesis; to forecast the yield curve. A detailed explanation of *all* the existing yield curve models and their extensions is beyond the scope of this thesis.

The tradition of yield curve fitting originates from Durand's publication from 1942. He studied the shape of the yield curve estimated through observed corporate bond prices in the United States of all maturities for the first quarter of each year between 1900 and 1942. Durand obtained the yield curves by fitting a free-hand trend line to the lowest yield bonds. He concluded that the yield curve generally takes on three different shapes: a horizontal straight line, a smooth curve increasing at a decreasing rate and a smooth curve decreasing at a decreasing rate (Durand, 1942). Today, these shapes of the yield curve are well-recognized as "flat", "normal" and "inverted". Durand‘s method is, for obvious reasons, considered to be statistically disappointing, but the study motivated researchers to develop statistical methods for fitting the yield curves.

2.2.1 Statistical Yield Curve Models

The main models from this class are Vector Autoregresive models (VARs) (Rebonato, 2018). Yield curve movements over time can be described by simple VARs in yields, or simple VARs in yields and other macroeconomic, explanatory variables (Piazzesi, 2010). VARs are often employed to forecast the yield curve because of their relative ease of use, their ability to fit observed yield curves well, and their good predictive power. All of this comes at a cost, however; they lack the theoretical foundation to make the estimated yields arbitrage-free. This lack of a theoretical foundation results in the need for cross-equation restrictions in the VAR systems (Piazzesi, 2010). Additionally, Rebonato (2018) argues that "quasi-unit-root nature of the level of rates" renders the VAR yield estimation procedure difficult, along with making the estimation errors large (Rebonato, 2018).

Piazzesi (2010) argues that several aspects of yields make them different from other variables often used in VARs. First, several bonds with different maturities are traded at the same time, giving a large cross-section of yields across maturities ranging from a few months to several years. As previously discussed, long-term bonds held for short horizons are risky, and investors demand compensation for bearing this risk. This results in the existence of arbitrage opportunities unless the long-term yields are risk-adjusted expectations of future short-rates (Piazzesi, 2010). In other words; the risk-adjusted expected future short-rates drive long-term yields, and movements in the cross-section of yields (i.e. movements in the yield curve) are thus linked across maturities. These links give the rise to the above-mentioned cross-equation restrictions, such that the system do not allow for any free lunches to be had. Furthermore, Piazzesi (2010) argues that yields are generally not normally distributed, rendering the computation of risk-adjusted expected value of future short rates difficult (Piazzesi, 2010).

Because of the limitations of yield-VARs we now move to a popular and frequently employed class of models, namely the class of so-called affine yield curve models.

2.2.2 Affine Yield Curve Models

Here we look at a specific class of structural models; the affine class of yield curve models. Affine term structure models are any type of arbitrage-free model in which bond yields are depended on constant-plus-linear functions of some vector x containing state variables. The general model for yields can be written as

$$y(\tau) = A(\tau) + B(\tau)^T x \tag{5}$$

where both $A(\tau)$ and $B(\tau)$ are coefficients depending on the time to maturity, τ (Piazzesi, 2010). Vasicek (1977) and Cox et al. (1985) introduced the first well-recognized one-factor models where the risk-free interest rate was the only state variable included in their models, resulting in perfectly correlated bond yields. In the following years, a number of extensions to this model appeared both in terms of the number of state variables included and the data-generating processes used for these variables (Piazzesi, 2010). Duffie and Kan (1996) paved the way for a second generation of mixture models, or more precisely the multifactor affine models of the term structure of interest rates. The authors tried to explain bond yields with *latent*, i.e. not observable but rather inferred, factors. The factors of their model are the zero-coupon bond yields $X = (X_1, X_2, ..., X_n)$ of n different fixed maturities $(\tau_1, \tau_2, ..., \tau_n)$, and these yield factors form a Markov process (Duffie & Kan, 1996). Contrarily, the state vector x in the Vasicek-type models follow a Gaussian process. However, are any of these affine models suitable for our objective of forecasting the U.S. Treasury yield curve?

Diebold and Li (2006) argues that the arbitrage-free yield curve literature is mainly about fitting the curve at a certain point in time, rather than focusing on the dynamics or forecasting of the term structure. The affine equilibrium literature discussed above could be linked to forecasting since it looks at dynamics of the term structure driven by the short rate. However, most of the research within the area of affine term structure models focus only on in-sample fit, rather than out-of-sample forecasts. The publications of Dai and Singleton (2000) and de Jong (2000) are well-known examples on the in-sample fitting of the term structure using affine models (Diebold & Li, 2006). Dai and Singleton (2000) studied the relative goodness-of-fit of different affine term structure models, while de Jong (2000) provided an empirical analysis using the multifactor affine models presented by Duffie and Kan. Furthermore, Diebold and Li (2005) mention that those studies that actually do employ the affine models for out-of-sample forecasts, like Duffee (2002), conclude that the models forecast poorly. The affine arbitrage-free models generally exhibit disappointing time-series performance and poor out-of-sample forecasting abilities (Diebold & Rudebusch, 2013). Recall that the objective of this thesis is to forecast the U.S. Treasury yield curve, and we therefore need a model that perform well both in-sample and out-of-sample. Consequently, we move on to the parametric "snapshot"-models due to the limited forecasting ability of the affine models.

2.2.3 'Snapshot' Models

Lastly we look at a class in which the model we use in this thesis belongs; the class of so-called parametric "snapshot"-models. What set these "snapshot" models apart from the affine and statistical models described above? "Snapshot" models are a-theoretical cross-sectional devices used to interpolate unobserved yields (i.e. yields of unobserved maturities) through functional forms using the set of observed yields (Rebonato, 2018). In other words, these models are functions one fit to the cross-section of yields at time t, thereby obtaining a "snapshot" of the yield curve at time t. They seek to obtain as high goodness of fit as possible without overfitting, even if this means allowing for arbitrage opportunities. These models assume a continuum of discount bonds with different maturities, and their output serve as the yield data input in the affine models (Rebonato, 2018).

Early examples of such models are those of Cohen, Kramer, and Waugh (1966), Fisher (1966), Echols and Elliott (1976), Dobson (1978), Heller and Khan (1979), and Chambers, Carleton, and Waldman (1984). In 1987 and 1992, more modern approaches to term structure modelling were introduced by Nelson and Siegel (NS) and Longstaff and Schwartz (LS). Dahlquist and Svensson (1994) are investigating the application of the simple functional NS-model and the highly complex model presented by LS, by comparing estimates of spot (zero-coupon) interest rates and implicit forward interest rates in the Swedish market derived from these models. The authors conclude that the NS is much easier to use, while the LS is more flexible. In addition, their analysis reveal only a marginally better fit for LS. The property of flexibility provided by LS is only needed when studying a country with a highly complex term structure (when the fit of NS is bad). This is certainly not the case for the term structure of interest in our study. Hence, the use of the complex LS model, which would probably contribute with a marginal increase in the goodness of fit, is not necessary in our case (Dahlquist & Svensson, 1994). Because of its parsimony and ability to fit the cross-section of yields well, the

NS model has become the most known and widely adopted "snapshot" model by both academics and practitioners alike. For example, this is the model preferred by the Federal Reserve (Rebonato, 2018).

Given a set of observed yields, y, for different maturities, τ, these models try to find a function, $f(\tau$, that best replicate the observed yield curve; $y = f(\tau)$. As an example, we will here present the NS model which we will use throughout this thesis. The NS model is

$$y(\tau) = \beta_1 + \beta_2 \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} \right) + \beta_3 \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau} \right) \tag{6}$$

This model will be fitted to the observed set of yields, resulting in parameter estimates $\{\hat{\beta}_1,\ \hat{\beta}_2,\ \hat{\beta}_3\}$. Yield curve movements from period to period will result in changes in $\{\hat{\beta}_1,\ \hat{\beta}_2,\ \hat{\beta}_3\}$. By predicting $\{\hat{\beta}_1,\ \hat{\beta}_2,\ \hat{\beta}_3\}$, we predict the yield curve. This will be expanded upon in the methodology section.

This class of models generally lack a theoretical foundation. For example, the models preceding the NS model shared a common problem; they failed to fit extrapolated long term yields outside of the data range. This is due to the fact that at least one linear term (linear in maturity) is included in each of the models. Consequently, as the time to maturity goes to infinity, the yields will become unboundedly large, i.e. $\lim_{\tau\to\infty} y(\tau) = \pm\infty$ (Nelson & Siegel, 1987). This feature does not reason well with neither the theory or observed yield curve behaviour. Newer "snapshot" models do not display this behavior.

Another possible weakness of this class is that because of the lack of a theoretical foundation, these models cannot guarantee arbitrage-free yields; they are often not imposed with a no-arbitrage condition. It is reasonable to assume that the existence of arbitrage opportunities in deep and well-organized bond markets is rare. If the bond markets are virtually arbitrage free, good yield curve models should not allow for arbitrage (Diebold & Rudebusch, 2013). Is it a problem, then, that the model we have chosen for modelling yield curves in our thesis does not exhibit no-arbitrage behavior? Not necessarily. Diebold and Rudebusch (2013) argues that although a model might be internally consistent, meaning free from arbitrage, it might at the same time be misspecified and bear little relationship with the real world. Such a model would forecast poorly. In other words, absence of arbitrage does not necessarily imply a good model, although a model perfectly replicating real world curves would be arbitrage free (Diebold & Rudebusch, 2013). Further, one could argue that if a model provides a very good description of reality, and reality is arbitrage free, then imposing an arbitrage-free condition would have little effect but constraining the flexibility of the model by reducing the degrees of freedom (Diebold & Rudebusch, 2013). We would not gain much by introducing constraints if the model already is approximately free from arbitrage. We believe this to be true for the model we have chosen for this thesis, i.e. the NS model, which is known to provide an accurate description of real world yield curves. Moreover, as our intention is to forecast the yield curve, we are more concerned with replicating reality as accurately as possible than we are with ensuring arbitrage-free yields. If we by imposing arbitrage constraints reduce the model's time-series performance, we are not maximizing our chances of obtaining a good forecasting model. Diebold and Rudebusch (2013) show that it is actually possible to obtain both no-arbitrage behavior and good out-of-sample forecasting abilities by including a yield-adjustment term in the NS model. They call this model the Arbitrage-Free Nelson-Siegel (AFNS). Because of the difficultly we found using this model to produce out-of-sample forecasts with the diffusion index forecasting framework, we refer the interested reader to the chapter on the Arbitrage-Free Nelson-Siegel in Diebold and Rudebusch (2013).

Additionally, it is generally not possible to give any theoretical or economic interpretation of the parameters in the "snapshot"-models. The exception is the NS model, whose parameters can be interpreted as three latent yield curve *factors*, corresponding to the yield curve level, slope and curvature (Diebold & Li, 2006). Furthermore, the seemingly ad-hoc nature of the Nelson-Siegel functional form will later be shown to exhibit some very appealing features that reason well with yield curve theory.

The advantage of using a "snapshot" model to model the yield curves for the purpose of forecasting them, is the goodness of fit these model provide along with the ease of which the model parameters are estimated. The NS model has been shown to generally fit well the cross-section of yields while maintaining parsimony, i.e. to provide a high R^2 for a number of different samples using only a few variables (Diebold & Li, 2006). Nelson and Siegel (1987) report an average R^2 of 96% for their 1981-1983 sample, while we find that the model on average explains 93.42% of the variation in yields across maturities in our 1991-2019 sample. Furthermore, the NS model allows us to distill the entire yield curve into three, dynamic parameters, such that forecasting the yield curve translates to forecasting the model parameters which, as mentioned above, can be interpreted as three latent yield curve factors. The Nelson-Siegel parameters, i.e. the three latent yield curve factors, have previously been shown to be forcastable. Fabozzi et. al. (2005), Diebold and Li (2006), and Diebold and Rudebusch (2013) forecast the yield curve through forecasting these parameters with good results. For example, Diebold and Li (2006) find their yield curve forecasts based on the NS parameters to be superior to that of several established yield curve forecasting models.

We wish to employ the relatively new time-series forecasting methodology of diffusion index forecasting to predict the yield curve. We find the Nelson-Siegel modelling framework to be very suitable for this purpose, as it enables us to distill the entire cross section of yields into to three, time-varying parameters to which the method of diffusion index forecasting can be applied. We now move to a more detailed and in-depth review of the literature on yield curve forecasting.

2.3 Yield Curve Forecasting

Several studies have successfully been able to forecast yields, either through some functional form like the NS model or by forecasting excess bond returns. We will now review the most important findings of these studies, before explaining how our forecasting methodology differs from previous studies on this topic. We begin by looking at the empirical literature on forecasting excess bond returns.

2.3.1 Forecasting Excess Bond Returns

One of the best known early studies using yield-curve based regressors to predict excess bond returns is a study by Fama and Bliss (1987). The authors find that one-year forward rates forecast the one-year short-rate two to four years ahead, with the predictive power increasing in the forecast horizon. They also find that current forward rates explain the one-year expected returns, that is, the expected one-year holding period return on the bonds less the return on a one year zero, on one-to-five year bonds (Fama & Bliss, 1987). Specifically, they find that the spread between the n-year forward rate and the one year yield predicts n-year excess bond returns; i.e. that excess bond returns are forcastable by the same maturity forward spread (Cochrane & Piazzesi, 2005).

They test the information in current forward rates about current expected returns and future interest rates by simple regressions of future returns and changes in interest rates on forward rates. The authors find the term-structure of expected bond returns to be time-varying. As differences in expected returns across maturities often are regarded as rewards for risk, this time-variability implies changes in the ordering of risk over time. This does not resonate well with the liquidity preference theory, as mentioned above. In their sample, they find that the term-structure of expected return can be both positive and negative, while it on average is flat. This means that you on average obtain the same reward for holding bonds of maturities one-to-five years.

Specifically, the authors find that forward rates are poor at forecasting interest rates at short horizons, but obtain a high forecasting power at longer horizon. For example, they find that the one-year forward rate contracted at time t for bonds from time $t + 4$ to the maturity date $t + 5$ explains 48% of the variation of the change in the one-year short-rate four years ahead (Fama & Bliss, 1987). The authors attribute this finding to a slow mean-reverting tendency in short-rates which becomes more apparent as the horizon increases. At the time, these results were novel. Past studies had fail to explain expected return on bonds with longer than one year to maturity. Previous studies had also failed to find evidence that the forward rates can predict future interest rates. For example, a study by Robert Shiller et al. (1983) actually conclude that current forward rates have *no* predictive power over future interest rates. This finding has been refuted by several studies in addition to Fama and Bliss (1987).

In later years, Cochrane and Piazzesi (2005) presented an extended version of the classic regressions by Fama and Bliss (1987). The authors study the time variation in excess bond returns on the Fama and Bliss one through five year discount bonds (obtained from CRSP) and find that the one year excess returns, that is, the holding period return of holding a long-term bond for one year in excess of the return on the one year bond, is forecastable by a single tent-shaped factor; a linear combination of five forward rates (Cochrane & Piazzesi, 2005). By forecasting excess returns both inflation and the level of interest rates are netted out, such that they focus directly on the risk premia in the nominal term structure. This single factor explains time-variation in excess returns at all maturities. This differs from Fama and Bliss (1987), in which different forward spreads is used for different maturities. Their results are encouraging; they find that their *p*-values are much smaller and their forecast R^2 is more than doubled compared to the previous findings of Fama and Bliss (1987) and Campbell and Shiller (1991).

The return-forecasting factor (CP) is a symmetric, tent-shaped linear combination of forward rates which is unrelated to the three standard yield curve factors (i.e. the three first yield principal components), namely the level, slope and curvature factors (Cochrane & Piazzesi, 2005). It is widely accepted that these three factors explain almost all time-variation in the cross-section of yields (Diebold & Rudebusch, 2013), and it is these three factors that the Nelson-Siegel parameters emulate. The authors find that forecasting power of the return-forecasting factors is both statistically and economically significantly higher than that of three-factor forecasts (Cochrane & Piazzesi, 2005). This is an important finding in relation to our thesis, as we construct yield curve forecasts based on the NS model parameters. As the parameters can be interpreted as proxies for the three yield curve factors means that we ultimately form three-factor forecasts.

Both Fama and Bliss (1987) and Cochrane and Piazzesi (2005) use the information in forward rates to forecast excess bond returns. They find that excess bond returns indeed are forcastable (and hence the expectations hypothesis to be false) by pure financial indicators such as yield spreads and forward spreads rather than by macroeconomic variables such as consumption or production variables. In other words, they use yield-based regressors to forecast yields as opposed to using non-yield based explanatory variables. We will review two studies that employ such macroeconomic variables to successfully forecast excess bond returns. The first is a study by Cooper and Priestley (2009) which employs the output gap, a productivity-based macroeconomic variable measuring real-economic activity, to predict U.S. excess bond returns, U.S. excess stock returns, and excess stock returns in other G7 countries (Cooper & Priestley, 2009). The second is a study by Ludvigson and Ng (2009) using so-called diffusion indices based on targeted predictors to forecast U.S. excess bond returns (Ludvigson & Ng, 2009).

Cooper and Priestley (2009) study the economics of time-varying risk premia. As risk premia vary across business cycles, are risk premia on bonds and stocks predictable by business cycle variables? The authors choose to employ the output gap as their business cycle variable because it has several a-priori advantages over other predictors. First, asset return predictability by the output gap is unlikely to arise from asset mispricing, because the output gap does not contain the level of asset prices (Cooper & Priestley, 2009). Second, the output gap is a production based measure as opposed to almost all other known macroeconomic predictor variables, which largely are consumption based measures like consumer price indices. This means that any predictive power of the output gap represents independent evidence on excess returns and the business cycle (Cooper & Priestley, 2009). Since we are concerned with forecasting yields we will focus on the part of the paper regarding the ouput gap's predictive power over excess bond returns.

To the best of the authors' knowledge, they are the first to show that a single macroeconomic variable can predict excess bond returns. This finding is of great interest to us as we are interested in the predictive power of macroeconomic variables for yields. The authors find that the output gap, measured as deviations of the industrial production index from its trend, is negatively correlated with the Cochrane and Piazessi (2005) return-forecasting factor CP; they find a correlation coefficient of -0.46 (Cooper & Priestley, 2009). When the authors include the part of the CP uncorrelated with the output gap they still find the output gap to have predictive power, meaning that their results are robust to the inclusion of CP. The authors argue that this may suggest that a part of the predictive power of the CP stems from its correlation with the output gap (Cooper & Priestley, 2009).

The authors use the same Fama and Bliss discount bonds as Cochrane and Piazzesi (2005) and Fama and Bliss (1987) to estimate monthly excess returns on bonds with two, three, four, and five-year bonds from 1952:6 to 2003:12. They use data obtained from the Federal Reserve to compute the output gap from the Industrial Production index (IPI), an index we also employ as a predictor in this thesis (see Appendix 3). They use several methods to measure the output gap, with the main specification being $y_t = a + bt + ct^2 + v_t$, where y_t is the log of IPI, t is a time trend, and the error term v_t is the output gap at time t. This measure of the output gap is used to predict excess returns on U.S. government bonds.

Cochrane and Piazzesi (2005) suggest that there may be a correlation between excess bond returns and the business cycle, while they do not attempt to establish any relationship between the two. In fact, in seems as if this potential source of bond return predictability has been largely unexplored. Ludvigson and Ng (2009) state that there has been few studies exploring this relationship, before they set out to do just so. Indeed, they find a strong counter-cyclical component in the yield curve (Ludvigson & Ng, 2009). However, as they use macro factors estimated from several macroeconomic variables to predict excess returns, they fail to identify a specific such variable as the source bond return predictability (Cooper & Priestley, 2009). In this regard, Cooper and Priestley (2009) seem to be somewhat unique.

The authors regress excess bond returns on v_t, and on v_t along with an orthogonalized version of CP. They orthogonalize this factor by first regressing CP on the output gap, such that only the uncorrelated part of the factor is included in the final regression (they do so because of the collinearity of the two variables). They find all coefficient estimates to be statistically significant across all maturities, and an adjusted R^2 ranging from 1-4% depending of the choice of output gap measure (Cooper & Priestley, 2009). They also find out-of-sample predictability in the bond risk premia by the output gap and the orthogonalized CP. Their results suggest that the output gap is capturing risk not contained in CP, and that affine yield curve models only employing yield-based predictors such as forward rates are unlikely to fully describe movements in the yield curve (Cooper & Priestley, 2009).

We will now take a more detailed look at the second study involving macroeconomic variables we choose to include in this literature review, namely the Ludvigson and Ng (2009) paper on macro factors and excess bond returns. The authors are trying to ascertain whether there are important cyclical variations in bond risk premia, and if so, whether there are empirical linkages between forecastable variation in excess bond returns and macroeconomic aggregates. They use the method of diffusion index forecasting to predict excess bond returns using a large set of macroeconomic variables, and they find that factors based on real-economic activity and inflation have important predictive power above and beyond what is contained in forward rates and yield spreads such as the regressors used in Fama and Bliss (1987) and Cochrane and Piazzesi (2005) (Ludvigson & Ng, 2009). As mentioned above, the authors find a strong counter-cyclical component in the risk premia of both returns and long-term yields when the macro factors are included, as opposed to an a-cyclical behavior when they are not.

The authors argue that there are three main reasons why it may be difficult to find a direct link between macroeconomic activity and bond risk premia. First, there might exist latent, i.e. unobservable, macroeconomic variables whose information cannot be summarized by just a few observable time series.

Second, observable macroeconomic time-series might be imperfectly measured and thus not correspond to theoretical economic concepts in a satisfactory manner. Third, theoretical models trying to explain macroeconomic concepts do not model reality perfectly, in addition to only being concerned with a small set of variables that fail to incorporate all the information used by financial market participants (Ludvigson & Ng, 2009). The method of diffusion index forecasting offers an elegant way around these problems.

As we will cover the methodology of diffusion index forecasting in great depth later in this thesis, we restrict ourselves to only here include a brief description of their method and results. The macro factors of Ludvigson and Ng (2009) are so-called diffusion indices estimated from a monthly set of 132 macroeconomic variables through the method of principal component analysis. In broad strokes, their method is to form factors (i.e. the first few principal components) from a large set of macroeconomic variables that one a-priori expect to be linked with the business cycle, before using these factors as predictors for excess bond returns and for the risk premia in long-term yields. Indeed, they find that these macro factors predict excess bond returns to both a statistcally and economically significant extent. They also find a strong, countercyclical variation in bond risk premia (Ludvigson & Ng, 2009). This countercyclicality is in line with the findings of Cooper and Priestley (2009), who as mentioned predict excess bond returns with a business-cycle related variable. The factors have the strongest predictive power for the two-year bond excess return with an R^2 of 26%, but they also predict the excess returns on three, four and five-year bonds. They benchmark the macro factor-based forecasts against that of the Cochrane and Piazzesi (2005) return-forecasting factor CP, and find that while they obtain a higher R^2 for the two-year bond using CP, the factors contain important information about future excess bond returns not contained in CP. This is similar to the finding that the output gap contains information not found in CP. Together, the macro factors and CP obtain an R^2 as high as 44% with all coefficient estimates being strongly significant (Ludvigson & Ng, 2009).

The authors find the single most important factor in terms of predictive power to be the factor most highly correlated with measures of the real economy and employment and not highly correlated with measures of prices and financial activity. They also find the factor most correlated with inflation measures to contain important information about future excess bond returns (Ludvigson & Ng, 2009). What is the economic interpretation of these findings? Interpreting the individual factors economically is not possible nor meaningful, as no individual factor correspond precisely to an economic concept like real economic activity. This is due to the factors being linear combinations of *all* the variables in the dataset; hence all variables will to some extent influence the factors. As these variables span across several different economic concepts, so do the factors. However, as the factors loads differently on the different variables, one can find what kind of variables each factor loads the most heavily on. The first factor (first principal component) of Ludvigson and Ng (2009) loads heavily on production and employment variables. This is the factor with the greatest individual predictive power mentioned above. As Cooper and Priestley (2009) also found the production-related variable output gap to contain important information about excess bond returns, it seems that such variables might be important for predicting yields. This finding is of great interest to us, and we include several production based variables in our analysis.

We find the findings and methodology of Ludvigson and Ng (2009) to be highly interesting. In this thesis, we will employ an extension of the original diffusion index forecasting methodology employed in Ludvigson and Ng (2009) to forecast yield curve changes. We will do so not by forecasting the term risk premia, excess bond returns, or yields directly, but rather by forecasting the parameters of the NS yield curve model by using diffusion indices as explanatory variables. To the best of our knowledge, this has not been done before.

We are not, however, the first to use the NS model to forecast the yield curve. We will now briefly review a study by Diebold and Li (2006) who successfully predicts the yield curve by forecasting the model parameters as AR(1) processes.

2.3.2 Forecasting the Nelson-Siegel Yield Curves

The framework of Diebold and Li (2006) has been the greatest source of inspiration for this thesis. The authors model historical yield curves with the NS model using data on end-of-month bond price quotes from January, 1985 to December, 2000 obtained from CRSP. By modelling the historical yield curves with the NS model they distill the curves into three dynamic parameters which can be shown (as we will later) to be proxies for three latent yield curve factors explaining almost all cross-sectional variation in yield (meaning variation across maturities); namely the level, slope an curvature factors. The authors show that the NS model provides a good fit historically, and they obtain superior yield forecasts by forecasting the three parameters as AR(1) processes. They use AR(1) models to independently produce 1, 6, and 12 months ahead out-of-sample forecasts of the change in each of the three NS yield curve parameters $\{\beta_{1t},\ \beta_{2t},\ \beta_{3t}\}$ with a recursive approach, and find that their simple AR(1) models outperform all of the natural benchmark models, including the Fama and Bliss (1987) model and the Cochrane and Piazessi (2005) CP-factor, at both the 6 and 12 months ahead horizons for maturities of 3, 12, 36, 60 and 120 months (Diebold & Li, 2006)

As the methodology of Diebold and Li (2006) will be discussed thoroughly later in this thesis, we keep this review rather brief. We emphasize, however, that our forecasting methodology differs from that of Diebold and Li (2006), as we use diffusion indices rather than autoregressive models to forecast the NS parameters. In this regard, we marry the methodology of Diebold and Li (2006) and Ludvigson and Ng (2009). We will test if we are able to produce forecasts superior to that of the Diebold and Li (2006) forecasting framework by including diffusion indices in addition to autoregressive terms in the forecasting model.

3 Methodology

3.1 Obtaining Historical Yields

When modelling historical Treasury yield curves one needs data one historical Treasury yields. That is, we need to obtain historical data on Treasury zero coupon yields ranging from short to long maturities. As zero coupon bonds with maturities longer than one year are not traded in the market, these zero coupon yields are not observed directly; they have to be estimated using the large set of *observed* bond prices on coupon bonds which exist at any given moment in time (Diebold & Li, 2006). We derive the so-called stripped zero-coupon Treasury securities from the observed bond quotes, which means zero-coupons created by stripping the bond price of the present value of each coupon payment. We call these artificial zero coupon yields the “observed raw yields”. These raw yields will serve as input in the NS modelling framework. We will now consider the method we use to estimate these raw yields from observed Treasury bond quotes.

3.1.1 Yields Estimated with the Bootstrap Method

The raw yield sample from 1991:1 to 2014:12 is estimated from monthly, end-of-month observed price quotes (bid-ask average) for non-callable Treasury bills, notes and bonds. This data is obtained from the CRSP Treasury files through Wharton Research Data Services. We filter the data for securities with liquidity problems, i.e. bonds and notes with less than one year to maturity, and bills with less than one month to maturity. The prices are clean, meaning that they do not include accrued interest. We sort the data after *settle date*. At each settle date, hundreds of transactions of Treasury securities is observed. Each of these observations have a unique time to maturity; we observe trades on bonds ranging from less than one month to maturity to close to 30 years to maturity. The settle dates are the last trading day each month from 1991:1 to 2014:12. We must use the observed trades on each settle date to estimate the raw yields, such that we each settle date have a set of zero coupon yields for maturities ranging from less than one month to 30 years. This set of estimated zero yields for different maturities is the set of raw yields we will use to construct the monthly NS yield curves.

To obtain these raw yields we employ the Matlab algorithm "zbtprice". This algorithm estimates the zero curve, i.e. the set of zero yields, on each settle date with the bootstrap method. This method uses a theoretical par bond arbitrage argument, and linear yield interpolation for determining the interest rates for the cash flows, to derive all zero yields on each settle date (MathWorks, 2020). The arbitrage argument assumes that the value of the whole bond, i.e. the bond including all coupon payments, is equal to the value of the sum of the separate cash flows the bond produces. If this does not hold, an arbitrage opportunity exits. If investors observe that the value of the bond is higher than the sum of it's parts, they could buy the bond, sell of the stripped cash flows, and make an instant, risk-less profit (Bodie et al., 2018). In other words, we assume any discrepancies between the observed bond prices and the prices of the stripped cash flow to be a violation the Law of One Price. The artificial zero coupon yields produced by "zbtprice" will satisfy this no-arbitrage assumption.

We use an actual/actual (ICMA) day-count convention in this algorithm, which is the convention generally used for pricing U.S. Treasury securities. The output of "zbtprice" is a vector containing the set of raw continuously compounded yields with each row corresponding to a maturity date, and a vector containing the maturity date associated with each zero yield. We use the maturity date for each zero yield and the settle date to calculate the time to maturity. By concatenating the zero yields vector and the time to maturity vector on each settle date, we obtain the monthly datasets of raw yields for a range of different maturities we need for the NS model. We choose to only use yields with maturities between three months and 10 years as input in the NS model, as the yields with less than three months to maturity are volatile and as we have most observations on yields with less than 10 years to maturity. The NS curve offers the best fit to our data in this range. The maturities are actual, observed maturities. For example, we observe several maturities of approximately 10 years, but none that are *exactly* 10 years. We want to compare the Nelson-Siegel yield forecasts with observed raw yields at exact maturities, e.g. comparing the 10-year Nelson-Siegel yield forecast with the actual 10-year yield. Hence, we employ a method of interpolation, specifically a piecewise cubic hermite interpolating polynomial, to obtain yields for regularly spaced maturities of 3, 6, 9, 12, 15, 18, 21, 24, 30, 36, 48, 60, 72, 84, 96, 108 and 120 months. This is the method used by the U.S. Treasury to obtain raw yields for exact maturities (U.S. Department of the Treasury, 2020).

Data on observed Treasury bond quotes is only available until 2014:12. In order to extend the sample period with observations until 2019:12 we use data on estimated zero yields obtained from the U.S. Department of the Treasury. Said department publishes end-of-month estimated zero yields for eight selected maturities. The reason for not using this data for the whole sample period is because the selection of maturities are much more narrow than what we obtain by estimating the raw yields from observed bond quotes. This means we get more data-points when modelling the yield curves for the sample 1991:1 to 2014:12 compared to what we would have if we used data from the U.S. Treasury for the whole sample period.

3.1.2 Raw Yields Estimated by The U.S. Department of the Treasury

We download yields for maturities of 3, 6, 12, 24, 36, 60, 84 and 120 months estimated by the U.S. Treasury Department for the final part of our raw yield sample (2015:1 to 2019:12). They use a cubic hermite spline interpolation function to obtain yields at evenly spaced maturities from quotation data on Treasury securities. Ideally, we would prefer to obtain the bond quotes data used by the U.S. Treasury and estimate the yields with the bootstrap method described above. However, we have not been able to obtain this data; the bond price quote data on CRSP ends with 2014:12.

Since we for the latter part of our sample have fewer intermediate maturities (that is, maturities between 3 and 120 months), the NS parameters will be estimated using fewer data-points. The function will interpolate greater distances between the data-points, causing the estimated model parameters to contain less information about the actual, continuous yield curve that were at the time. We consider this to be a weakness with using the data from the U.S. Treasury. However, since the yields we obtain from the U.S. Treasury are estimated using interpolation from observed bond trades, most information about the actual yield curve should be incorporated in the set of eight estimated maturities they provide. The benefits of including this data in our sample is that we are able to greatly extend the sample period. We want to obtain a forecasting model that can be used by investors today, meaning using data they can obtain today. Hence, we choose to extend our sample period with the U.S. Treasury data such that it runs until 2019:12 instead of 2014:12.

3.2 Yield Curve Modelling

We now turn to the task of modelling yield curves from the estimated raw yields. Before we explain the yield curve NS modelling framework we employ in this thesis, we look at some basic yield curve concepts.

3.2.1 The Discount Curve, Forward Rate Curve and Yield Curve

To understand the NS model, we first have to define three important bond market curves and understand the relationship among them, specifically the discount curve, forward rate curve and yield curve. Let $P(\tau)$ denote the price of a discount bond with time to maturity τ and $y(\tau)$ denote its continuously compounded yield to maturity. The discount curve is the present value of receiving \$1 τ-periods ahead:

$$P(\tau) = e^{-\tau y(\tau)} \tag{7}$$

The forward rate curve is defined as

$$f(\tau) = \frac{-P'(\tau)}{P(\tau)} \tag{8}$$

Together, Eq. (7) and (8) lets us express the yield curve in terms of the forward rate curve:

$$f(\tau) = \frac{e^{-\tau y(\tau)}(\tau y'(\tau) + y(\tau))}{e^{-\tau y(\tau)}} \Leftrightarrow f(\tau) = \tau y'(\tau) + y(\tau) \tag{9}$$

The yield curve is the solution to this differential equation (Eq. (9)), solved for $y(\tau)$ and given some initial condition:

$$y(\tau) = \frac{1}{\tau}\int_0^\tau f(u)du \tag{10}$$

Eq. (10) expresses that the yield on a zero-coupon bond is the equally weighted average of the forward rates (Nelson & Siegel, 1987). This relationship will be used later.

3.2.2 The Nelson-Siegel Model

We now turn to the original paper by Nelson and Siegel (1987). The authors state that a class of functions associated with solutions to differential equations are able to generate the typical yield curve shapes. They further motivate an investigation of such functions by the following argument; "... if spot rates are generated by a differential equation, then forward rates, being forecasts, will be the solution to the equations."(Nelson & Siegel, 1987). Hence, they begin with a search among a class of solutions to differential equations for a function that fits the forward rate curve. They find the following solution equation for the case of equal roots to provide a good fit:

$$f(\tau) = \beta_1 + \beta_2 e^{-\lambda\tau} + \beta_3 \lambda\tau e^{-\lambda\tau} \tag{11}$$

where λ is a time constant associated with the equation, while β_0, β_1 and β_2 are determined by initial conditions (Nelson & Siegel, 1987). We are now ready to obtain yields as a function of maturities. This is done by using the relationship expressed in Eq. (10). By integrating Eq. (11) from 0 to τ and dividing by τ we obtain the following functional form to fit the cross-section of yields

$$y(\tau) = \beta_1 + \beta_2 \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} \right) + \beta_3 \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau} \right) \tag{12}$$

where $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ is obtained with ordinary least squares (OLS). In Nelson and Siegel (1987) the parameter $\hat{\lambda}$ is also estimated through non-linear estimation. We choose to fix λ to a constant in the same manner as Diebold and Li (2006) for reasons which will be discussed later.

It is important to mention that we use a different notation and a different factorization than that of the Nelson and Siegel (1987), in a similar manner as Diebold and Rudebusch (2013) (first introduced by Diebold and Li (2006)). The factorization of Diebold and Rudebusch (2013) makes it possible to to interpret the parameters β_1, β_2 and β_3 as *yield curve factors*, specifically level, slope and curvature. Why this is the case will be discussed later.

Although the NS functional form (Eq. (12)) might seem somewhat ad hoc, it exhibits some very appealing features which link it to financial reality and economic theory (Diebold & Rudebusch, 2013). First, it satisfies the two limiting values of bond prices, specifically $\lim_{\tau \to 0} P(\tau) = 1$ and $\lim_{\tau \to \infty} P(\tau) = 0$ for any values of the parameters. Second, NS satisfies $\lim_{\tau \to 0} y(\tau) = \lim_{\tau \to 0} f(\tau) = r$, where r denotes the instantaneous short rate, i.e. the yield on a zero coupon with infinitesimally short time to maturity. This means that the yields of the NS model converge to the instantaneous short rate as the time to maturity approaches zero, which is an economically sound feature (Rebonato, 2018). Finally, the yields produced by the model converge to a constant, β_1, as the time to maturity goes to infinity; $\lim_{\tau \to \infty} y(\tau) = \beta_1$.

In addition, the NS functional form is both parsimonious and flexible. Parsimony inhibits in-sample overfitting, while its flexibility lets it approximate the variety of shapes the yield curve assumes, including the upward sloping, downward sloping, humped and inverted hump shapes (Diebold & Li, 2006). Lastly, the NS functional form is an appropriate yield curve approximation from a mathematical perspective. The forward rate curve (Eq. (11)) can be viewed as a constant plus a Laguerre function, and such functions are common approximating functions on the domain $[0, \infty]$, which is the domain of the yield curve (Diebold & Rudebusch, 2013).

Before introducing dynamics in the model and obtain the DNS, we are going to investigate the principal components, or *factors*, of the yield curve. This analysis will be important when we later show that the DNS model parameters can be used as proxies for these factors.

3.2.3 Yield Curve Factors

The large set of observed bond yields is a high-dimensional object, meaning that the number of features (i.e. the different yields for different maturities) exceed the number of observations. This makes computations difficult. Luckily, financial asset returns like yields are typically driven by an underlying lower-dimensional set of factors (Diebold & Rudebusch, 2013), which make computations more feasible. The three first *bond yield principal components*, or factors, typically explain most yield curve variation, and these three factors can be shown to effectively equal the level, slope and curvature of the yield curve (Diebold & Rudebusch, 2013). Diebold and Rudebusch (2013) show this by plotting time series of the three first principal components (factors) against the standard empirical yield curve measures of level, slope and curvature (the $10Y$ yield, the $10Y - 3M$ spread, and the $2 \times 2Y - (10Y + 3M)$ butterfly spread, respectively). This is an important feature of the yield curve factors, as level, slope, and curvature can be linked economically with different explanatory variables. The yield curve level is for example related to inflation, and the slope is related to the stage of the business cycle (Diebold & Rudebusch, 2013). As we are going to show, the estimated parameters of the DNS can be interpreted as proxies for these three factors. When we are to forecast these parameters, we can use the economic link these factors have with macroeconomic (and possibly financial) variables as the theoretical foundation of our forecasting model.

3.2.4 The Dynamic Nelson-Siegel Model

Eq. (12) above represents the *static* NS yield curve. However, the yield curve is not static, but time varying. Hence, the model parameters must be time varying. Introducing dynamics is uncomplicated; we just let the three parameters of (12) be time-varying.

$$y_t(\tau) = \beta_{1t} + \beta_{2t}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) + \beta_{3t}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right) \tag{13}$$

This factor model explains the yield curve with three, dynamic factors (β_{1t}, β_{2t} and β_{3t}) and three factor loadings (1, $\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right)$, and $\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right)$). We plot the three loadings against τ for $\lambda = 0.0609$ in Figure (1). Why we fix λ to this value will be explained in the next paragraph. The loading on β_{1t} is constant across all maturities and equal to 1. Hence, a change in β_{1t} shifts the entire curve, and β_{1t} thus governs the yield curve level. The loading on β_{2t}, $(1-e^{-\lambda\tau})/\lambda\tau$, is a function of τ that starts at 1 and decreases monotonically and rapidly to zero. A change in β_{2t} thus mainly affect short-term yields, with the effect becoming negligible as τ increases. As a result, β_{2t} governs the yield curve slope. The loading on the last factor, $(1-e^{-\lambda\tau})/\lambda\tau - e^{-\lambda\tau}$, has a humped shape; it starts at zero before increasing, then decreasing toward 0. A change in β_{3t} thus mostly affect medium-term yields, with an insignificant effect on short-term and long-term yields. Hence, β_{3t} governs the yield curve curvature (Diebold & Li, 2006). In their sample period, Diebold and Li (2006) find a very high correlation between their estimated DNS factors and the empirical yield curve (l_t), slope (s_t), and curvature (c_t), specifically $\rho(\hat{\beta}_{1t}, l_t) = 0.97$, $\rho(\hat{\beta}_{2t}, s_t) = -0.99$, and $\rho(\hat{\beta}_{3t}, c_t) = 0.99$ (Diebold & Li, 2006). In the Section 5 on results we presents plots of the three first yield curve principal components against both (l_t, s_t, c_t) and ($\hat{\beta}_{1t}$, $\hat{\beta}_{2t}$, $\hat{\beta}_{3t}$) for our sample period, and report their correlations.

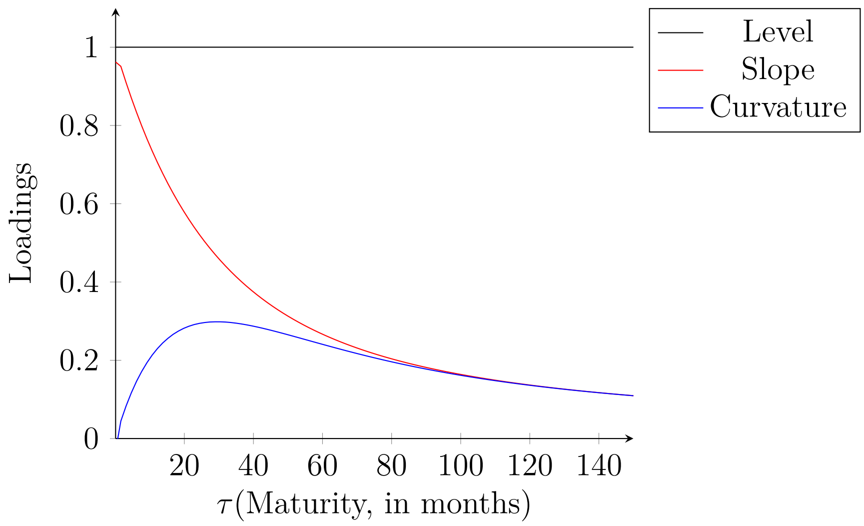


Figure 1: Plot of the factor loadings as a function of maturity for $\lambda = 0.0609$

As one can see from Eq. (13), the model also contains an additional parameter λ. When fitting the model to historical, unsmoothed yields, one can either let λ be time-varying (λ_t), or it can be treated as a known constant. We plan to calibrate λ to a constant in the same manner as Diebold and Li (2006). λ determines where the loading on β_{3t} (the hump-shaped function) is maximized, and this maximum should be at a medium maturity in order for β_{3t} to drive curvature (Diebold & Rudebusch, 2013). The authors argue that maturities in the range of two to three years commonly is considered medium-term maturities, and hence they pick the average of 2.5 years, or 30 months; τ = 30. To make the loading on β_{3t} achieve its maximum at $\tau = 30$, λ is set to 0.0609 (Diebold & Li, 2006). The motivation for fixing λ is that it enables us to employ simple OLS when fitting the yield curve each month, rather than some complex nonlinear least squares estimation method. This should increase the reliability of the estimates as the number of numerical optimizations is drastically reduced (Diebold & Li, 2006). Additionally, as we are going to forecast the Nelson-Siegel yield curve, fixing λ reduces the number of time-series we need to forecast. Furthermore, the fit of the model is typically robust to the exact choice of λ (Diebold & Rudebusch, 2013).

For the DNS to be a good model, the yield curves it produces should accord with historical facts about the yield curve. The average yield curve is increasing and concave, and it assumes different shapes at different times. Yield dynamics are persistent, meaning that shocks to the empirical yield curve level (10-year yield) persist for a long time, while yield spread dynamics are much less persistent, which means that shocks to the the empirical yield curve slope do not persist for a long time. The short-term yields are more volatile than long-term yields, while long-term yields are more persistent than short-term yields (Diebold & Li, 2006). Diebold and Li (2006) argue that the DNS yield curves *in principle* accord with all of these facts. A potential problem with using the NS model for forecasting purposes is that we might loose some important information as we smooth the yields. Cochrane and Piazzesi (2004) argues that the Nelson-Siegel procedure smooths away not just noise, but also information.

We have now investigated the theoretical aspects of the framework we employ to model the yield curves. To summarize, we fit Eq. (13) to the monthly, historical cross-section of yields (i.e. to the observed unsmoothed yields each month from 1991:1 to 2019:12) and obtain monthly DNS parameter estimates $\{\hat{\beta}_{1t},\ \hat{\beta}_{2t},\ \hat{\beta}_{3t}\}$. Most of the temporal yield curve variation will be captured by the time-varying DNS parameter estimates. Hence, if we can explain the variation $\{\hat{\beta}_{1t},\ \hat{\beta}_{2t},\ \hat{\beta}_{3t}\}$ we can explain the variation in the yield curves (given that the model provides a good fit in the cross-section of yields).

3.3 Forecasting the Yield Curve

Forecasting the yield curve translates into forecasting the DNS yield curve factors $\{\hat{\beta}_{1t},\ \hat{\beta}_{2t},\ \hat{\beta}_{3t}\}$, i.e. to forecast the level, slope and curvature of the yield curve. The forecast of the factors will result in a forecasted NS yield curve from which we can extract the forecasted yields for different maturities.

As discussed in the literature review, there exist a range of models one can employ to model and forecast financial and economic time series, from univariate autoregressive processes or simple and multiple linear regression models, to more sophisticated multivariate systems such as vector autoregression processes with exogenous variables. In this thesis, we will employ the method of "diffusion index forecasting" (sometimes called "factor augmented forecasting") to forecast the change in the DNS yield curve factors. With this method we use the information stored in 1196 different economic and financial time-series to construct a parsimonious model producing out-of-sample forecasts 1, 6 and 12 months ahead with a recursive approach.

DI forecasting makes it possible to utilize the information stored in several hundred, or even thousand, economic time series to forecast a few financial or economic variables (Stock & Watson, 2002). This is achieved by replacing the large set of predictors with a smaller set of estimated *factors* which capture most of the time-variation in the predictors. Specifically, we create an algorithm which from a very large set of potential predictors, both financial and macroeconomic in nature, selects the most informative predictors based on some predictive power threshold, and uses these *targeted predictors* to construct *factors* (principal components). These factors are then ultimately used to forecast the changes in the DNS yield curve factors. We call this method "targeted diffusion index forecasting", which is inspired by the works of Bai and Ng (2008).

Stock and Watson (2002) find that their 6, 12, and 24 months ahead DI forecasts of 8 different U.S. macroeconomic variables outperform univariate autoregressions, small vector autoregressions, and leading indicator models (Stock & Watson, 2002). Bai and Ng (2008) refines the methodology of Stock and Watson (2002) by introducing the use of targeted predictors, i.e. to let an algorithm select different predictors for different dependent variables and/or different samples, drawing from a very large pool of economic and financial time series. The authors argue that their set of predictors is suitable for forecasting several different economic variables, including inflation which is the variable they choose to forecast in their study. They find that the use of targeted predictors improve the DI forecasts at all forecasting horizons, in addition to outperforming their AR(4) benchmark model. They find that holding the set of predictors fixed as you would in the original DI forecasting framework, rather than flexible as you would with the use of targeted predictors, is unnecessarily restrictive (Bai & Ng, 2008).

While we do not find that this forecasting procedure has been used to forecast yield curves, we do find that the DI forecasting procedure with targeted predictors has been used to explain and forecast variation in excess bond returns. As mentioned in the literature review, Ludvigson and Ng (2009) find that diffusion indices based on macroeconomic variables have important forecasting power for future excess return on U.S. government bonds. While these findings do not directly translate to the predictability of the U.S. Treasury yield curve (i.e. to forecast the YTM across *all* maturities), these findings indicate a promising relationship between macroeconomic variables and yields generally, and the DI forecasting procedure and yields specifically. We wish to explore this relationship further, and investigate whether such macro factors (or diffusion indices) have any predictive power for future U.S. Treasury yield curves.

Other studies have found predictability in the yield curve by using simpler, univariate models. One of the most cited papers on this topic is Diebold and Li (2006), which find that univariate autoregressive processes of order 1 best predict the yield curve. They do not benchmark the performance of their model against DI forecasts. Hence, we view the AR(1) model as the main benchmark model when we evaluate the performance of our forecasting model.

3.3.1 Introducing the Full Set of Predictors

Consider a very large set of economic and financial time-series contained in the matrix X with elements X_{it}. In this set, there are N predictors and T observations. Each row of X corresponds to an observation $t = 1, 2, ..., T$ and each column corresponds to a variable $i = 1, 2, ..., N$. We call the $N \times 1$ vector $X_t = (X_{1t}, X_{2t}, ..., X_{Nt})$ the *the full set of predictors* at time t. The cross-sectional dimension N can be very large, and possibly much larger than the time dimension T; X can contain observations on several hundred or several thousand variables which capture information about the real-economy and the financial markets. As such, we let X contain time-series on several leading economic indicators and real economic activity measures such as unemployment rates in different industries, inflation measures in different industries, confidence indicators and capacity utilization measures, along with several financial market activity measures such as volatility indices, put vs. call volume indices and stock market returns. An exhaustive list of the time-series contained in X is presented in Appendix 3 and elaborated on in the data-section.

Now consider the three time-series on the estimated DNS yield curve factors $\{\hat{\beta}_{1t},\ \hat{\beta}_{2t},\ \hat{\beta}_{3t}\}$. For simplicity, we will use $\hat{\beta}_{it}$ to denote the factors when explaining the forecasting methodology as all of the three time-series are to be forecast in exactly the same way. Additionally, we will refer to the forecasts as forecasts of $\hat{\beta}_{it}$ (meaning the *level* of the factors) although we in practice are going to forecast the *change* in $\hat{\beta}_{it}$ due to non-stationarity of the estimated factors and persistent NS yield curve residuals (if errors are persistent, they vanish when we take the change of the yield curve. This will be expanded upon in Section 5 on modelling results). Lastly, we will throughout the paper denote the forecasts of the estimated factors as $\hat{\hat{\beta}}_{it}$. The first (lower) hat means that we are looking at the OLS estimate of β_{it} from Eq. (13), and the second (upper) hat means that we are looking at the forecast of this estimate.

When using X_t to forecast $\hat{\beta}_{i,t+h}$ (i.e. $\hat{\beta}_{it}$ h-steps ahead), one could run a multiple linear regression on the form

$$\hat{\beta}_{i,t+h} = (\alpha_0, \alpha_1, \cdots, \alpha_k) \times \begin{pmatrix} 1 \\ \hat{\beta}_{i,t} \\ \hat{\beta}_{i,t-1} \\ \vdots \\ \hat{\beta}_{i,t-k} \end{pmatrix} + (\gamma_1, \gamma_2, \cdots, \gamma_N) \times \begin{pmatrix} X_{1t} \\ X_{2t} \\ \vdots \\ X_{Nt} \end{pmatrix} + \epsilon_{t+h} \quad (14)$$

or in matrix notation (which we will from now on use)

$$\hat{\beta}_{i,t+h} = \alpha^T Z_t + \Gamma^T X_t + \epsilon_{t+h} \tag{15}$$

where Z_t is a vector containing a constant and lags of $\hat{\beta}_{i,t+h}$ and X_t is the full set of predictors at time t. $\hat{\alpha}$ and $\hat{\Gamma}$ could be estimated through OLS and the optimal number of lags and predictors could be chosen by minimizing some information criterion like the Bayesian Information Criterion (BIC). The minimum BIC value BIC^* is found as the optimal trade-off between reduced residuals ($log(\hat{\sigma}_n^2)$) and a penalty term for adding more variables ($n\frac{log(T)}{T}$)

$$BIC^* = min\left(log(\hat{\sigma}_n^2) + n\frac{log(T)}{T}\right) \tag{16}$$

The main problem with this forecasting procedure (Eq. (15)) is that when the number of predictors is large and the predictors have no natural ordering, it is computationally infeasible to obtain the BIC-minimizing set of predictors. This is because there are 2^N possible combinations of predictors, which in our case implies a staggering amount of different potential BIC-minimizing combinations of regressors.

We thus turn to the DI forecasting framework as explained in Stock and Watson (2002). An important concept in this framework is Principal Component Analysis (PCA). By using PCA to obtain the factor scores, or *principal components*, of X, we can greatly reduce the dimensionality of our dataset without loosing much information. That is, important information contained in X in the form of time-variation can be preserved in a much smaller set of factors, which greatly reduces the number of explanatory variables used in the forecasting model (Stock & Watson, 2002). The principal components of X now becomes the explanatory variables instead of the variables in X. Before we look at how DI forecasting models are constructed through the use of principal components, we first take a look at what principal components are, how they are calculated, and why just a few of them are able to preserve the majority of the information in X.

3.3.2 Principal Component Analysis

To understand PCA, we begin by explaining how Matlab finds the principal components of our dataset X. First, we center the data by demeaning each variable (i.e. subtracting its mean) such that the mean of each centered variable is zero. We denote the centered data $\dot{X}$

$$\dot{X} = \begin{pmatrix} X_{11}-\bar{X}_1 & X_{12}-\bar{X}_2 & \cdots & X_{1N}-\bar{X}_N \\ X_{21}-\bar{X}_1 & X_{22}-\bar{X}_2 & \cdots & X_{2N}-\bar{X}_N \\ \vdots & \vdots & \ddots & \vdots \\ X_{T1}-\bar{X}_1 & X_{T2}-\bar{X}_2 & \cdots & X_{TN}-\bar{X}_N \end{pmatrix}$$
$$= \begin{pmatrix} \dot{X}_{11} & \dot{X}_{12} & \cdots & \dot{X}_{1N} \\ \dot{X}_{21} & \dot{X}_{22} & \cdots & \dot{X}_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \dot{X}_{T1} & \dot{X}_{T2} & \cdots & \dot{X}_{TN} \end{pmatrix} \tag{17}$$

We then calculate the $N \times N$ covariance matrix C of $\dot{X}$ as $\dot{X}^T\dot{X}$

$$\dot{X}^T\dot{X} = C = \begin{pmatrix} \sigma^2(\dot{X}_1) & \sigma(\dot{X}_1,\dot{X}_2) & \cdots & \sigma(\dot{X}_1,\dot{X}_N) \\ \sigma(\dot{X}_2,\dot{X}_1) & \sigma^2(\dot{X}_2) & \cdots & \sigma(\dot{X}_2,\dot{X}_N) \\ \vdots & \vdots & \ddots & \vdots \\ \sigma(\dot{X}_N,\dot{X}_1) & \sigma(\dot{X}_N,\dot{X}_2) & \cdots & \sigma^2(\dot{X}_N) \end{pmatrix} \tag{18}$$

We then find the N eigenvalues (λ_i) and N $N \times 1$ orthogonal (perpendicular) eigenvectors ($\mathbf{v}$) of the covariance matrix

$$\lambda = \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_N \end{pmatrix} \text{ and } \mathbf{v} = (\mathbf{v}_1|\mathbf{v}_2|\cdots|\mathbf{v}_N) \tag{19}$$

The N eigenvectors are used to construct the feature vector $\mathbf{v}$ which is a matrix with the eigenvectors as column vectors. Each eigenvector is a unit vector, meaning that they are of length 1. These eigenvectors capture important relationships between the data in X. In fact, the whole data-set X can be explained (i.e. reconstructed) by these eigenvectors and eigenvalues. The eigenvector in $\mathbf{v}$ that explains the largest share of the total variance in X is the eigenvector associated with the largest eigenvalue (in absolute terms). In other words, the eigenvectors associated with the largest eigenvalues capture most of the important relationships between the data in X. Hence, we order the eigenvectors by their eigenvalues from highest to lowest, and identify each eigenvector's degree of significance as the percentage of the total variance in X explained by each eigenvector. The ordered eigenvectors are stored in $\mathbf{v}^*$ with descending importance column-wise

$$\mathbf{v}^* = \begin{pmatrix} v_{11} & v_{12} & \cdots & v_{1N} \\ v_{21} & v_{22} & \cdots & v_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ v_{N1} & v_{N2} & \cdots & v_{NN} \end{pmatrix} \tag{20}$$

Each column in $\mathbf{v}^*$ is an eigenvector, with the first column corresponding to the most important eigenvector in terms of variance explained. We then use these eigenvectors to obtain the factor scores, or prinicipal components (PCs), of X by multiplying the centered data $\dot{X}$ with $\mathbf{v}^*$

$$P = \dot{X} \cdot \mathbf{v}^* = \begin{pmatrix} \dot{X}_{11} & \dot{X}_{12} & \cdots & \dot{X}_{1N} \\ \dot{X}_{21} & \dot{X}_{22} & \cdots & \dot{X}_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \dot{X}_{T1} & \dot{X}_{T2} & \cdots & \dot{X}_{TN} \end{pmatrix} \cdot \begin{pmatrix} v_{11} & v_{12} & \cdots & v_{1N} \\ v_{21} & v_{22} & \cdots & v_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ v_{N1} & v_{N2} & \cdots & v_{NN} \end{pmatrix} \tag{21}$$

The above matrix multiplication yields a transposed matrix of principal components with T rows and N columns. The first observation of the first principal component P_{11} is a linear combination of the first eigenvector in $\mathbf{v}^*$ and all the N variables in $\dot{X}$ at time $t = 1$

$$P_{11} = (\dot{X}_{11}, \dot{X}_{12}, \ldots, \dot{X}_{1N}) \cdot \begin{pmatrix} v_{11} \\ v_{21} \\ \vdots \\ v_{N1} \end{pmatrix} \tag{22}$$

and the first observation of the second principal component P_{12} is a linear combination of the second eigenvector in $\mathbf{v}^*$ and all variables in $\dot{X}$ at time $t = 1$, and so on. Remember that because we ordered the eigenvectors after decending importance, the PCs are also ordered after descending order of importance (in terms of the share of total variance explained). The first column of P is the *first principal component* of X and explains the largest share of total variance. To reduce the dimensionality of our dataset we only keep the most important PCs, say, the N^* first PCs ($N^* << N$). In this way we are able to greatly reduce the number of dimensions without loosing much of the information contained in X.

To see how the original data relates to the PCs, we show how one can reconstruct the original centered data $\dot{X}$ using the eigenvectors in $\mathbf{v}^*$ and the PCs in P

$$P = \dot{X} \cdot \mathbf{v}^* \;\Rightarrow\; P \cdot (\mathbf{v}^*)^{-1} = \dot{X} \;\Rightarrow\; \dot{X} = P \cdot (\mathbf{v}^*)^{-1} \tag{23}$$

How do we find the inverse of $\mathbf{v}^*$? Well, it turns out that as long as we have N unique eigenvalues (no eigenvalues of multiplicity larger than 1), finding $(\mathbf{v}^*)^{-1}$ is easy. Since C is a square and symmetric matrix we can make $\mathbf{v}^*$ to be an *orthonormal basis*, which means that $\mathbf{v}^*$ consists of N orthogonal eigenvectors of length 1. This makes the process of finding $(\mathbf{v}^*)^{-1}$ much easier. When $\mathbf{v}^*$ is an orthonormal basis, we have that $(\mathbf{v}^*)^{-1} = (\mathbf{v}^*)^T$, such that $\dot{X} = P \cdot (\mathbf{v}^*)^T$. The first observation of the first centered variable ($\dot{X}_{11}$) can thus be written as the linear combination

$$\dot{X}_{11} = (P_{11}, P_{12}, \ldots, P_{1N}) \cdot \begin{pmatrix} v_{11} \\ v_{12} \\ \vdots \\ v_{1N} \end{pmatrix} \tag{24}$$

The N^* first PCs, i.e. the most important PCs in terms of total variance explained, will serve as the predictors in our forecasting model. We will now examine how PCs are used in the DI forecasting method.

3.3.3 Diffusion Index Forecasting

Let P be the set of principal components estimated from X, with T rows and N columns. Each column corresponds to a principal component, and each row corresponds to an observation. $P_t = (P_{1t}, P_{2t}, \ldots, P_{Nt})$ is the row-vector of all the PCs at time t. In our data-set we have 1196 predictors ($N = 1196$), and hence we have 1196 PCs at time t. We choose to only use the N^* first PCs ($N^* << N$) because these explain the majority of the total variance in X. We denote these N^* first PCs by P_t^*. Similar to Bai and Ng (2008), we choose to only include the ten first PCs ($N^* = 10$) before estimating the forecasting model because these explain most of the variance in X while rendering the computation feasible. We then specify the forecasting model

$$\hat{\beta}_{i,t+h} = \alpha^T Z_t + \gamma^T p_t + \epsilon_{t+h} \tag{25}$$

where Z_t is a vector containing a constant and lags of $\hat{\beta}_{i,t+h}$, p_t is a subset of P_t^* and contains the optimal PCs to include in the model, and γ are the coefficients pertaining to p_t. The subset p_t of P_t^* and the optimal number of lags of $\hat{\beta}_{i,t+h}$ is obtained by minmizing BIC. The DI forecast of $\hat{\beta}_{i,t+h}$ is $\hat{\hat{\beta}}_{t+h} = \hat{\alpha}^T Z_t + \hat{\gamma}^T p_t$. This model constitutes the DI forecasting framework of Stock and Watson 2002.

Comparing Eq. (15) and Eq. (25), it is clear that Eq. (25) has to be evaluated at much fewer combinations of predictors than Eq. (15). Whereas Eq. (15) is computationally infeasible, Eq. (25) is easily estimated because of the dramatically reduced number of explanatory variables. However, since the PCs can be written as linear combinations of *all* the variables in X, the DI forecasting model (26) uses *all* of the $N = 1196$ predictors (Bai & Ng, 2008). Hence, through the method of DI forecasting, one is able to use a very large set of predictors to forecast economic and financial time series in a computationally feasible and effective manner. In practice, Eq. (25) is estimated by running an algorithm which searches through all the possible combinations of predictors and lags and saves the model specification that minimizes BIC. Not only is this method of forecasting in practice relatively straight forward, it has also been used to produce promising forecasts historically. Stock and Watson (2002), Ludvigson and Ng (2005), and Bai and Ng (2008) find that the DI forecasts often outperform alternative methods of forecasting.

3.3.4 Targeted Diffusion Index Forecasting

In this thesis we will employ an extension to the original DI forecasting model (Eq. (25)) as presented in the section above, namely the method of "targeted diffusion index forecasting" as introduced by Bai and Ng (2008). This method involves two new concepts over the standard DI forecasting framework. First, we take the *predictive ability* of each predictor for $\hat{\beta}_{it}$ in to account *before* estimating the PCs of X, only allowing the most informative predictors to form the set from which we form PCs. In other words, we form PCs from a subset $x \subset X$ consisting of variables that are tested to have predictive power for $\hat{\beta}_{it}$ (Bai & Ng, 2008). Secondly, we allow for a non-linear link function between the predictors and the PCs.

The standard DI forecasting method is comparatively rigid as it always forms the PCs from the same set of predictors regardless of both which dependent variable one is trying to forecast, and of which sample one uses to estimate the forecasting model. Additionally, it only allows for a linear relationship between the predictors and the PCs (Bai & Ng, 2008). The targeted DI forecasting method relaxes these constraints and thus provides a more flexible structure. Bai and Ng (2008) argues that only allowing for linear relationships and holding the set of predictors fixed is unnecessarily restrictive. Furthermore, as shown in Boivin and Ng (2006), expanding the dataset by including variables that have little predictive power for the variable to be forecasted does not necessarily improve the forecasts. These variables constitute noise rather than information, and we are thus better off by discarding them before forming the PCs (Bai & Ng, 2008).

We allow for a non-linear relationship between the predictors and the PCs by using a non-linear link function between the predictors in X_t and the PCs. In practice, this is done by augmenting X_t to include a squared term of each predictor before forming the PCs; $X_t^* = \{X_{it}, X_{it}^2\}$. In other words, we let P (Eq. (22)) be a linear combination of both the linear and the squared terms of X_{it}. Bai and Ng (2008) refers to this procedure as Squared Principal Components (SPC). We will use the SPCs, i.e. the PCs of X_t^*, when forecasting $\hat{\beta}_{it}$. Note that the forecasting equation (Eq. (25)) is still linear in the PCs.

The predictors are targeted through a procedure which employs so-called "hard" thresholding. With this procedure, a statistical test to determine the individual significance of predictor i is used to decide which of the predictors in X make it to the subset of predictors x. We want to use a statistical test which tests the predictive power of the variable X_{it} for $\hat{\beta}_{i,t+h}$. For this purpose we use the same method as Bai and Ng (2008), which is to form a threshold rule based on the t-statistic from regressions of $\hat{\beta}_{i,t+h}$ on each X_{it} after controlling for lags of $\hat{\beta}_{i,t+h}$. Only variables associated with a t-statistic above some threshold significance level α are included in the subset x of predictors. We use an α of 5% as this is the conventional threshold for determining statistical significance, and, as recommended by Bai and Ng (2008), we control for four lags of $\hat{\beta}_{i,t+h}$ since autoregressive forecasts always are available as an alternative to other forecasting models (Bai & Ng, 2008).

3.3.5 The Targeted DI Forecasting Algorithm

We now present the targeted DI forecasting algorithm which we use to construct forecasts of $\{\hat{\beta}_{1t},\ \hat{\beta}_{2t},\ \hat{\beta}_{3t}\}$. Since we use subscript i to denote the variables in X_t, we now denote $\{\hat{\beta}_{1t},\ \hat{\beta}_{2t},\ \hat{\beta}_{3t}\}$ by $\hat{\beta}_{jt}$ for $j = 1, 2, 3$. The algorithm produces out-of-sample forecasts of $\hat{\beta}_{jt}$ recursively (the training period increases with one observation each forecast), with a training period of ($t = 1$ to $t = T^*$) and a holdout period of ($t = T^*+1$ to $t = T$). We choose to use a 10-year training period in our out-of-sample forecasting, such that $T^* = 2001 : 1$ Before initiating the algorithm, we import and transform the dataset X. We use the Augmented Dickey Fuller test to determine whether the time-series are stationary, before transforming the non-stationary variables to $I(0)$ stationary time-series by taking logs, log first differences, or log second differences if possible (i.e. if $X_{it} > 0$ for all t). For time-series with observations for which the logarithm is not defined (i.e. $X_{it} \leq 0$ for all or some t) we take ordinary first or second differences to make the time-series stationary. We report which transformation has been applied to each variable in Appendix 3. The targeted DI forecasting algorithm is as follows

1. Load the training sample, i.e. X_t^* and $\hat{\beta}_{j,t+h}$ for $t = 1$ to $t = T^*$.

2. For each $i = 1, 2, \ldots, N$, run $\hat{\beta}_{j,t+h} = \alpha + \sum_{q=0}^{3} \vartheta_i \beta_{t-q} + \gamma X_{it}^* + \epsilon_{t+h}$. From these N regressions, save the t-statistic associated with each X_{it} as t_i.

3. Sort the t-statistics from highest to lowest in descending order $(|t_1|, |t_2|, \ldots, |t_N|)$.

4. Extract the predictors associated with t-statistics above the threshold significance level $\alpha = 5\%$, and let k_α denote the number of series where $|t_i| \geq 1.65$.

5. Save these targeted predictors in $x_t(\alpha) = (x_{1t}, x_{2t}, \ldots, x_{k_\alpha t})$ and form PCs from $x_t(\alpha)$. We then have k_α PCs.

6. Extract the 10 first PCs ($10 << k_\alpha$) and save them in $P_t^* = (P_{1t}, P_{2t}, \ldots, P_{10t})$. These 10 first PCs explain almost all variation in $x_t(\alpha)$.

7. Estimate $\hat{\beta}_{j,t+h} = \alpha^T Z_t + \gamma^T p_t + \epsilon_{t+h}$ where Z_t contains a constant and lags of $\hat{\beta}_{j,t+h}$, and γ contains coefficients pertaining to $p_t \subset P_t^*$. Use BIC to select lags and p_t. The algorithm searches through all possible model specifications and selects the one minimizing BIC. For computational efficiency and parsimony we restrict the number of lags the algorithm draws from to 4.

8. Save the $\hat{\alpha}$ and $\hat{\gamma}$ estimates of the BIC-minimizing model specification. Load data for the observation succeeding T^* (observation number T^*+1), i.e. the first observation in the hold-out period.

9. The first h period ahead out-of-sample forecast is $\hat{\hat{\beta}}_{j,(T^*+1)+h} = \hat{\alpha}^T Z_{T^*+1} + \hat{\gamma}^T p_{T^*+1}$. We use coefficients estimated from the sample $t = 1$ to $t = T^*$ to predict the h period ahead $\hat{\beta}_{j,t+h}$ at $t = T^* + 1$.

10. Iterate steps 1-9 by including one new observation each iteration until $t = T - h$. This observation will be used to predict the last observation $\hat{\beta}_{jT}$.

We use this algorithm separately to forecast $\hat{\beta}_{jt}$ for $j = 1, 2, 3$ (i.e. we run the algorithm for each DNS yield curve factor separately) and obtain forecasts for the three DNS yield curve factors $\{\hat{\beta}_{1t},\ \hat{\beta}_{2t},\ \hat{\beta}_{3t}\}$ for forecast horizons of one, six and twelve months ($h = 1, 6, 12$). This means that we use the same full set of predictors to forecast all three time-series, i.e. the yield curve level, slope and curvature. However, as the algorithm is designed to *target* the most informative predictors, we expect it to choose a different set of predictors for the three different time-series. Also note that we let the targeted set of predictors change with both the forecast horizon and the sample period. This means that the targeted set of predictors used to forecast the 300$^{\text{th}}$ observation of, say, $\hat{\beta}_{1t}$ (level), might not be same set of predictors used to forecast the 299$^{\text{th}}$ observation of $\hat{\beta}_{1t}$. It also means that the same set of predictors need not be used when forecasting $\hat{\beta}_{1t}$ one month ahead and, say, six months ahead. Bai and Ng (2008) argues that this flexibility is an advancement over the original DI forecasting framework.

There are potential problems with the procedure with which we target the predictors, i.e. the hard thresholding procedure. While the decision rule based on the t-statistic associated with each predictor is both relatively easy to program and execute, it ignores any joint significance of the predictors, leading us to disregard predictors that might be jointly significant. Furthermore, by selecting predictors independently we ignore information in other predictors, resulting in the possibility of selecting too similar predictors (i.e. collinear predictors). This is a problem because the DI forecasting model is most effective when we pool variables that bear distinct information about the time-series to be forecasted (Bai & Ng, 2008). Moreover, as the decision rule is based on statistical significance rather than economic significance, we might not include highly economic significant predictors if their corresponding t-statistics happen to be just below the threshold significance level α. Lastly, such hard thresholding can be very sensitive to small changes is the data. A small change in the sample can cause some t-statistics to change just enough for the corresponding predictor to be either in or out, while the predictive power of that variable is virtually unchanged. That is, the discreteness of the decision rule causes the targeting procedure to be sensitive to small changes in the data (Bai & Ng, 2008).

3.3.6 Benchmarking

To determine the accuracy of our forecasts we will calculate the root mean squared error (RMSE) of the yield forecasts at some selected maturities (i.e. at specific points on the yield curve), and compare this measure to the RMSE of several benchmark models. We denote the targeted DI forecasting model as presented in this thesis by "TDIF" and the benchmarking models by "BM". We will use these benchmark models to produce out-of-sample yield curve forecasts with a recursive approach in the same manner as with the TDIF model of this thesis. To compare the performance of the different models we construct a *relative measure* inspired by Bai and Ng (2008). We call the relative measure the "relative RMSE" (RRMSE)

$$RRMSE = \frac{RMSE(TDIF)}{RMSE(BM)} \tag{26}$$

A value of RRMSE less than 1 implies that the targeted DI forecasts are superior to that of the benchmark model.

The first competitor model we are going to consider is the simple Random Walk model. This model assumes that the yields each period take a random step away from its previous value, and that the steps are IID with a mean of zero (Brooks, 2019). By this assumption, the optimal yield forecast is

$$\hat{y}_{t+h}(\tau) = y_t(\tau) \tag{27}$$

where τ is the time to maturity.

Diebold and Li (2006) find that modelling and forecasting the DNS yield curve factors $\{\hat{\beta}_{1t},\ \hat{\beta}_{2t},\ \hat{\beta}_{3t}\}$ as univariate AR(1) processes generates superior yield curve forecasts. As stated by Diebold and Li (2006): "The AR(1) models can be viewed as natural benchmarks determined a priori: the simplest great workhorse autoregressive models." (Diebold & Li, 2006). Hence, we consider the AR(p)-class of forecasting models to be the main benchmarks when evaluating the performance of the TDIF model. This is similar to how Bai and Ng (2008) choose to evaluate their TDIF model; they benchmark their inflation forecasts against that of an AR(4) model. The Diebold-Li model is as follows

$$\hat{y}_{t+h}(\tau) = \hat{\beta}_{1,t+h} + \hat{\beta}_{2,t+h}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) + \hat{\beta}_{3,t+h}\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right) \tag{28}$$

where

$$\hat{\hat{\beta}}_{i,t+h} = \hat{\alpha}_i + \hat{\gamma}_i\hat{\beta}_{it}, \quad i = 1,2,3 \tag{29}$$

and coefficients $\hat{\alpha}_i$ and $\hat{\gamma}_i$ are obtained by OLS.

We will also extend the Diebold-Li model to allow for more lags, in addition to letting the optimal number of lags change with both the forecast horizon and the sample period, thereby making it more flexible. Eq. (29) then becomes

$$\hat{\hat{\beta}}_{i,t+h} = \hat{\alpha}_i + \sum_{n=0}^{p}\hat{\gamma}_n\hat{\beta}_{i,t-n}, \quad i = 1,2,3 \tag{30}$$

where p is obtained by minimizing BIC and restricted to four. We re-specify the model recursively, meaning that we with each forecast re-evaluate the optimal number of lags p as more observations are added to the training period. The reason why we are altering the Diebold-Li model is both because we wish to examine if this added flexibility improves the forecasts over the original Diebold-Li model, and because we view this added flexibility to render the Diebold-Li model more comparable with the TDIF model. This is because we in the latter model let the optimal number of lags vary with both the forecast horizon and the sample period.

In addition to model and forecast the DNS yield curve factors as univariate AR(p) processes, we will also use AR(1) models to forecast the *yield levels* directly

$$\hat{y}_{t+h}(\tau) = \hat{c}(\tau) + \hat{\gamma}_i y_t(\tau) \tag{31}$$

With this method we do not need to model the yield curve before forecasting the yields, since we are forecasting the observed yields directly. If we are not able to produce superior forecasts over this simple forecasting method, either with the TDIF model or the AR(1) models described above, we are not benefiting from modelling the yield curve by the three DNS yield curve factors.

An alternative to the AR(p)-class of models is to model and forecast the DNS yield curve factors as a *system*, specifically as an Vector Autoregressive model (VAR). However, Diebold and Li (2006) and Diebold and Rudebusch (2013) argue that forecasts of economic variables from unrestricted VARs might perform worse than that of an AR(p) due to the large number of parameters and hence the potential for in-sample overfitting. Additionally, VARs are used to capture important cross-variable interactions. We do not expect such interactions between the factors as they should not be significantly correlated due to their close resemblance to principal components (Diebold & Li, 2006). Hence, we do not employ VAR models when evaluating the performance of our TDIF model.

4 Data and preliminary analysis

4.1 Obtaining Historical Yield Data

Our historical yield data is twofold; the first part, which is spanning from January, 1991 through December, 2014, is calculated through non-callable treasury securities, while the yield data staring from January, 2015 and ending December, 2019 is obtained directly from the U.S. Department of the Treasury.

4.1.1 Historical yield curve data from 1991 to 2014

To estimate the historical yields, we use *end-of-month* price quotes on T-bills, T-notes and T-bonds collected from the The Center of Research in Security Prices (CRSP) through Wharton Research Data Services. For each treasury security, we gathered the following characteristics: settlement date, the maturity date, yearly coupon rate (if any), and both the first price (usually bid) and the second price (usually ask). Finally, we calculated the bid-ask average for each security. This data is then used as input to the bootstrap method of obtaining the theoretical zero curve with the Matlab-algorithm *zbtprice*.

We made two major adjustments to our treasury data during this stage. Originally, we collected data all the way back to the beginning of 1990. However, we decided to remove all treasuries with settlement dates during 1990 due to a serious outlier problem. Secondly, we filtered out all notes and bonds with less than one year to maturity and t-bills with less than one month using the same argument as Diebold and Li (2006); these types of treasury securities with such a short time to maturity have significant liquidity problems. Finally, we removed all treasury securities with more than 10 years to maturity to avoid a missing data problem. Approximately 84% of the bond data observations have a maturity of less than 10 years. Hence, increasing the time to maturity would reduce the statistical power of our model. In addition, using the interpolation technique for such long maturities would diminish the quality of our estimated yield curves.

4.1.2 Historical yield curve data from 2015 to 2019

To obtain the second part of our yield curve data, we started by collecting *daily treasury yield curve rates* from the U.S. Department of the Treasury as of January 2015 through December 2019. To derive these yields, commonly referred to as "Constant Maturity Treasury" rates, the treasury department uses a quasi-cubic hermite spline function calculated from indicative, bid-side market quotations obtained by the Federal Reserve Bank of New York at or near 3:30 PM each trading day. The collected data consists of fixed maturities of 3 and 6 months and 1, 2, 3, 5, 7 and 10 years. Notice that we filtered out yields with maturities of 1 month, 2 months, 20 years og 30 years. Finally, we imported the *daily* data to Excel and extracted the last trading day of each month resulting in 60 *end-of-month* yield curves from January 2015 through December 2019, containing the 8 different maturities mentioned above.

4.2 Obtaining Data on Explanatory Variables

Our dataset consists of 1196 *monthly* explanatory variables for the United States in the period from January 1991 through December 2019. Our choice of explanatory variables is inspired by the works of Stock and Watson (2002), Bai and Ng (2008), and Ludvigson and Ng (2009). We include all variables used in these studies that we have found access to and matches our sample period of 1991:1 to 2019:12. In addition to these variables, we have included new variables that we a-priori believe to affect bond markets. The vast majority of the predictors are retrieved from the Federal Reserve Bank of St.Louis Economic Data (FRED) through their self-developed Excel Add-in, while the remaining variables are retrieved from the following sources: Chicago Board Options Exchange (CBOE), Yale School of Management - International Center of Finance, Bloomberg, Yahoo Finance, and the home page of both Kenneth R. French and Robert Shiller. All variables in our dataset have either a daily, weekly of monthly reporting frequency. Consequently, we needed to convert the daily and weekly data to be monthly. For the variables with daily sampling frequencies, we have extracted the first trading day of each month to obtain monthly series. Further, the weekly data is transformed such that the observation at or closest to the first day of each month is stored. I.e. if a macroeconomic variable is reported at both the 28$^{\text{th}}$ of January and the 4$^{\text{th}}$ of February, we use the observation in January to represent the 1$^{\text{st}}$ of February.

In Table (1) below we have sorted the variables in 14 different classes depending on their nature. We exemplify the type and report number of variables of each class. See Appendix 3 for an exhaustive list of all the variables used in this study.

Categories	**#**	**Types of variables**
Employment & Hours	279	(Un)employment level and rates for various population groups, number of un(employeed) by industry, avearges on overtime, hours and earnings. Job losers, initial claims, etc
Bond Market	164	Corporate bond yields, secondary market rates, constant maturity rates, interest rate spreads, loans outstanding
Housing	131	Home price indices, housing starts and sales, new private housing units authorized
Real Output Measures	126	Industrial production, capacity utilization
Price Indices	102	Consumer price indices, producer price indeces
Personal Income & Expenditures	77	Personal income, (real) disposal personal income, personal current taxes, transfer payments, interest payments, savings and outlays. Personal consumption expenditures and prices
Leading Indicators	72	Leading indicators for each state and for US in total, OECD leading indicators: business situation, confidence, recession indicators etc.
Monetary Measures	61	Money Stock, US government deposits and demand, monetary base
Equity Market	59	Foreign stock indices, US stock market indices, S&P500 level/dividend/earnings etc, Fama-French factors, equity market volatility tracker, volatility indices
Exports & Imports	35	Exports of goods by FAS basis, imports of goos by custom basis, exports/imports of services, export/import prices (commodities and semi-finished products)
Manufacturing Activity	26	Manufacturing and trade, retail sales, unfilled orders and new orders
Sentiment	12	Business expectations, tendency and uncertainty, current and future company outlook and general business activity, consumer opinion survey, consumer sentiment and inflation expectations
Miscellaneous	52	NAPM indices, put/call ratios, fitted instantaneous forward rates, foreign exchange rates, excess reserves, effective federal funds rate

Table 1: Types of explanatory variables

4.3 Descriptive Statistics on Historical Raw Yields

We now present descriptive statistics on the raw yields we use to model the Nelson-Siegel yield curves. As we have two different samples of raw yields, one that is estimated from observed bond price quotes and one that is obtained from the U.S. Treasury, we present descriptive statistics for each sub-sample in addition to statistics for the full sample. The tables for each sub-sample is reported in Appendix 1.

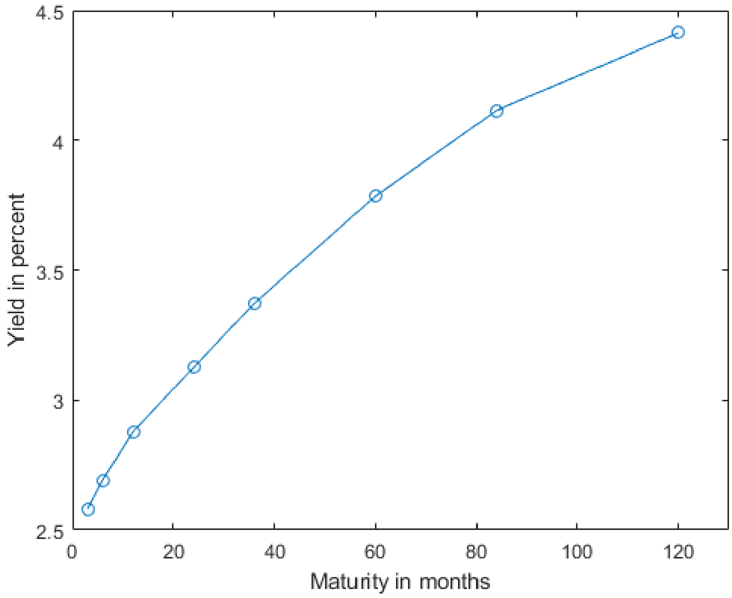


Figure 2: We plot the average actual yields (data-based) for maturities of 3, 6, 12, 24, 36, 60, 84 and 120 months.

Maturity (Months)	Mean	Std.dev.	Min.	Max.	$\hat{p}(1)$	$\hat{p}(12)$	$\hat{p}(30)$
3	2.580	2.107	0.000	6.323	0.991	0.790	0.456
6	2.692	2.126	0.000	6.406	0.990	0.792	0.465
12	2.878	2.171	0.100	7.148	0.990	0.801	0.507
24	3.125	2.154	0.206	7.529	0.988	0.814	0.587
36	3.372	2.115	0.290	7.677	0.987	0.821	0.635
60	3.785	1.999	0.597	7.870	0.984	0.815	0.678
84	4.115	1.893	0.976	8.179	0.980	0.815	0.696
120	4.413	1.802	1.460	8.321	0.980	0.801	0.689

Table 2: Descriptive statistics, yields (full sample)

We begin by looking at the average yield curve for the full sample presented in Figure (2) and observe that the average yield curve in our sample exhibits typical yield curve behavior; it is upward sloping and concave. From Table 2 we see that the longest maturity yield on average is about two percentage points higher than the shortest maturity yield, and that long yields are less volatile than short yields. Shocks in long term yields are more persistent compared to short term yields, although there is a high degree of persistence across all maturities. Looking at Table (12) and (13) in Appendix (1) we see that the average yield curve looks similar across the two samples, although the level of interest rates is lower in the latter. The volatility of the observed yields is also substantially lower in the second sub-sample, meaning that yield curves have become more stable over time.

In Figure (3) we present a 3D-plot of the historical yields. From the figure it becomes evident that the yield curve typically is upward sloping and concave. One can also easily see that the level of interest rates has substantially decreased over time, with a low-point following the financial crisis of 2007-2008. There seems to be a high temporal variation in the level, with less observable (but still apparent) temporal variation in the slope and curvature.

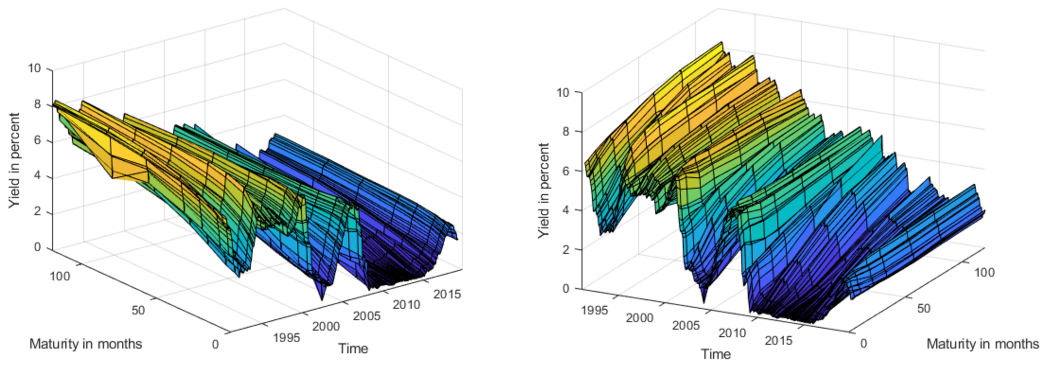


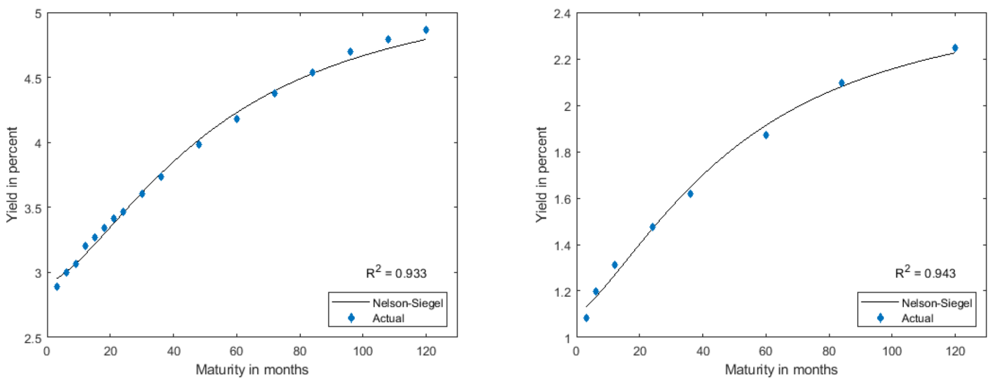
Figure 3: The plane of historical yield curves, 1991:1-2019:12. The sample consists of monthly yield data at maturities of 3, 6, 12, 24, 36, 60, 84 and 120 months.

5 Results and main analysis

In this section we will present our main results. First, we will look at the NS modelled yield curves and how well the model is at replicating the historical yield curves. We will then move to an assessment of the performance of our TDIF model; is our DNS targeted diffusion index forecasting framework able to produce superior forecasts?

5.1 Modelling Results: Is the Dynamic Nelson-Siegel Model Able to Replicate the Yield Curves?

We begin by comparing the average fitted NS yield curve with the actual average yield curve in each sub-sample in Figure (4). As we can see, the NS model is on average very good at replicating the yield curve in both samples, explaining 93.3% and 94.3% of the cross-sectional variation in yields on average, respectively. For the whole sample, the average R^2 is 93.42%.



(a) 1991:1-2014:12

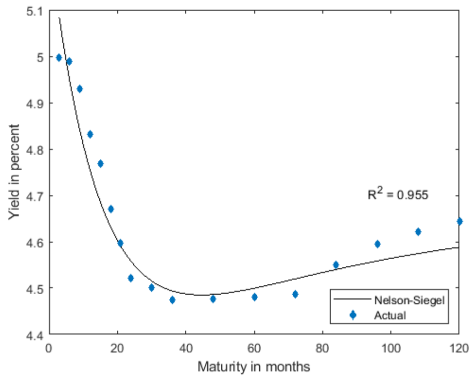
(b) 2015:1-2019:12

Figure 4: We scatter the actual (data-based) and plot the fitted (NS based) average yield curve for each sub-sample. We find the average NS yield curve by evaluating the NS function at the mean values of $\{\hat{\beta}_{1t}, \hat{\beta}_{2t}, \hat{\beta}_{3t}\}$.

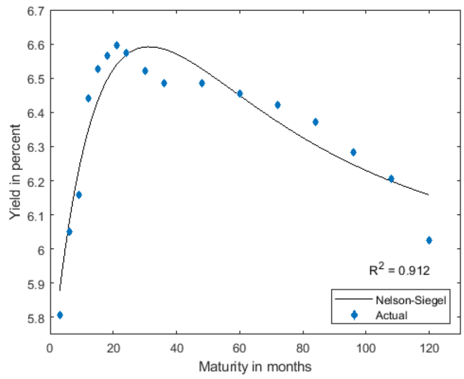
Maturity (Months)	Mean	Std.dev.	Min.	Max.	$\hat{p}(1)$	$\hat{p}(12)$	$\hat{p}(30)$
3	2.637	2.081	-0.049	6.320	0.991	0.784	0.443
6	2.687	2.127	0.007	6.443	0.991	0.795	0.472
12	2.815	2.178	-0.032	6.977	0.990	0.806	0.517
24	3.112	2.173	0.106	7.532	0.988	0.815	0.585
36	3.395	2.112	0.329	7.728	0.986	0.818	0.632
60	3.829	1.986	0.693	7.811	0.984	0.818	0.682
84	4.107	1.907	0.959	8.079	0.983	0.814	0.695
120	4.350	1.851	1.204	8.296	0.982	0.805	0.690

Table 3: Descriptive statistics, NS yields (full sample)

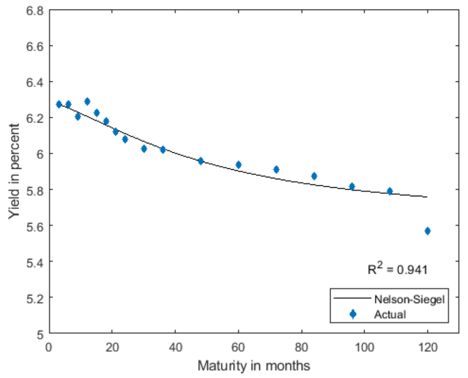
In Table 3 we report descriptive statistics for the NS yields at the same maturities as in Table (2). Comparing Table (2) and (3) we see that the NS yields exhibit very similar behaviour as the actual yields. The average at each maturity is very close, both increasing from about 2.60% at the three-month maturity to around 4.35% at the ten-year maturity. The volatility of the yields are also similar and share the same trend; the standard deviation is decreasing in maturity. While none of the observed yields are negative at any point in time, the minimum values of the shorter-term NS yields are negative. This is a weakness of the NS model; it allows for negative yields. Both yields exhibit the same pattern of persistence; the autocorrelation coefficients are approximately equal at the one, twelve and thirty months displacements. From Figure (4) and Table (3) it becomes clear that the NS model generally provides a good fit in the cross-section of yields, i.e. that the DNS model generally is able to replicate the historical yield curves. In Figure (5) we report four observed yield curves far from the average, and review how the NS model handles a-typical yield curve shapes. One can see how the NS model is able to provide a good fit for the various yield curve shapes present in our sample.



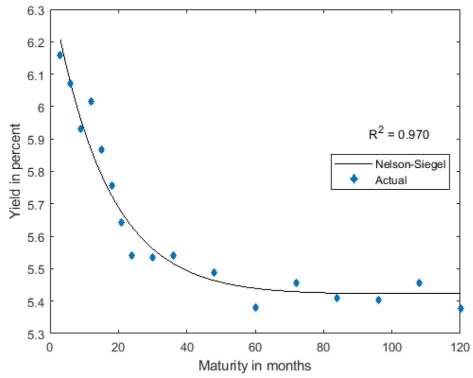
(a) Mar. 2007: U-shape



(b) Apr. 2000: Humped



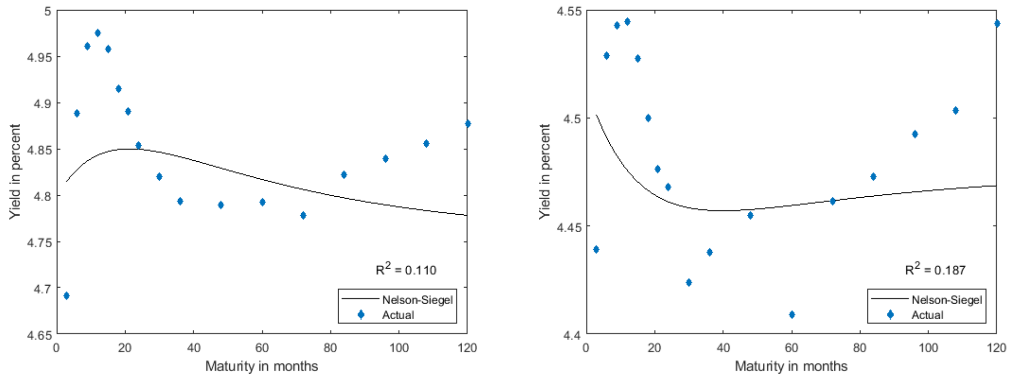
(c) Aug. 2000: Inverted



(d) Nov. 2000: Inverted and convex

Figure 5: Various yield curves with special shapes.

The NS model does not always provide a good fit, however. There are certain yield curves in our sample our model struggles to replicate, explaining only a small proportion of the cross-sectional variation. Two such yield curves are presented in Figure (6). The first is a yield curve increasing rapidly at short maturities, decreasing at medium maturities and slowly increasing again at longer maturities. As one can see, the NS model is largely affected by the steep humped shape in the area between maturities 0 and 40. The second is a curve with yields "all over the place" and no distinct shape. The R^2 is 11% and 19%, respectively.



(a) May 2007

(b) Jan. 2006

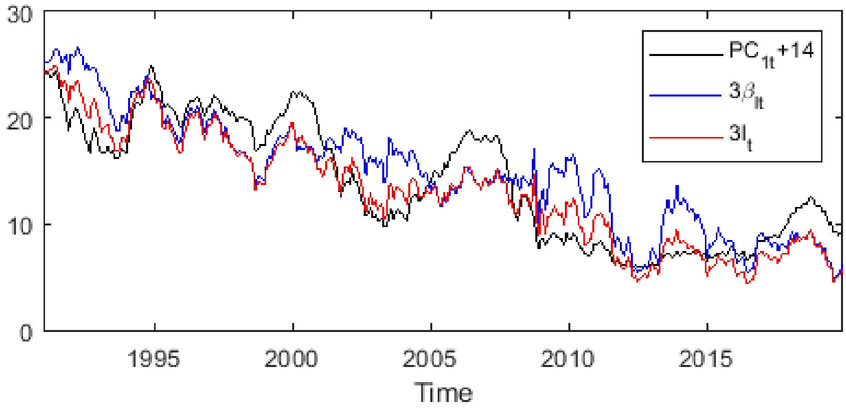
Figure 6: Two observations where the NS model provides a bad fit.

In Table 4 we present statistics on the NS model residual for each maturity, that is, statistics on the difference between the NS yields and the actual yields. From the autocorrelation coefficients we see that the residuals are persistent. This implies that we have persistent pricing errors. Diebold and Li (2006) argue that there is a general discrepancy between actual bonds prices and prices estimated from yield curve models, probably due to persistent tax and/or liquidity effects (Diebold & Li, 2006). They further argue these errors pose no threat; because the errors are persistent they should disappear from fitted yield *changes*, which is ultimately what we are going to forecast.

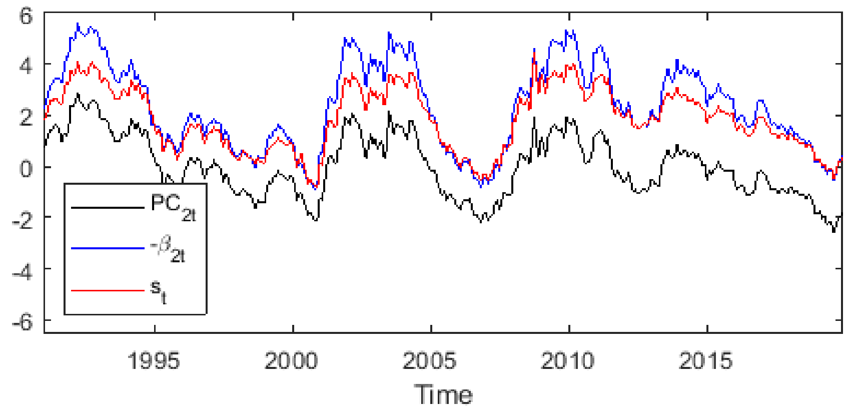
Maturity	Mean	Std.dev.	Min.	Max.	MAE	RMSE	$\hat{p}(1)$	$\hat{p}(12)$	$\hat{p}(30)$
3	-0.058	0.096	-0.538	0.160	0.085	0.112	0.751	0.366	0.168
6	0.004	0.066	-0.907	0.244	0.034	0.066	0.151	0.101	0.019
12	0.062	0.079	-0.213	0.464	0.080	0.101	0.775	0.338	0.154
24	0.013	0.045	-0.163	0.223	0.034	0.047	0.776	0.336	0.201
36	-0.024	0.041	-0.224	0.166	0.036	0.047	0.658	0.084	-0.063
60	-0.045	0.042	-0.171	0.076	0.052	0.062	0.667	0.140	0.009
84	0.008	0.131	-1.870	0.368	0.044	0.131	0.655	0.017	-0.006
120	0.063	0.152	-0.238	0.790	0.114	0.164	0.848	0.545	0.333

Table 4: Descriptive statistics, NS-residuals (full sample)

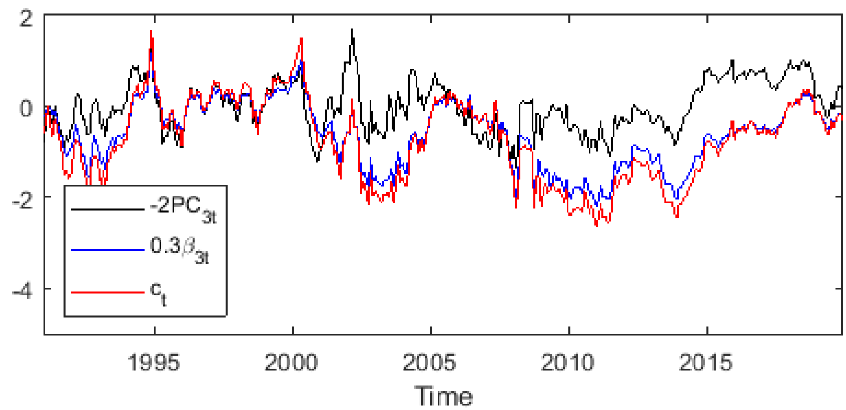
In Figure (7) we plot the DNS yield curve factors $\{\hat{\beta}_{1t}, \hat{\beta}_{2t}, \hat{\beta}_{3t}\}$ along with both the three first yield curve principal components (which together explain almost all cross-sectional variation in yields) and the empirical (data-based) level, slope, and curvature. These measures are defined below Figure (6). The figures display a high observable pairwise correlation between the three; we find that $\rho(\hat{\beta}_{1t}, PC_{1t}) = 0.80$, $\rho(\hat{\beta}_{2t}, PC_{2t}) = -0.95$, and $\rho(\hat{\beta}_{3t}, PC_{3t}) = -0.56$, and that $\rho(\hat{\beta}_{1t}, l_t) = 0.96$, $\rho(\hat{\beta}_{2t}, s_t) = -0.99$, and $\rho(\hat{\beta}_{3t}, c_t) = 0.99$, and finally that $\rho(PC_{1t}, l_t) = 0.92$, $\rho(PC_{2t}, s_t) = 0.94$, and $\rho(PC_{3t}, c_t) = -0.58$.



(a) $\hat{\beta}_{1t}$, first principal component, and empirical level



(b) $\hat{\beta}_{2t}$, second principal component, and empirical slope



(c) $\hat{\beta}_{3t}$, third principal component, and empirical curvature

Figure 7: DNS level, slope, curvature factors (i.e. $\{\hat{\beta}_{1t}, \hat{\beta}_{2t}, \hat{\beta}_{3t}\}$) vs. the three first principal components and empirical level, slope, and curvature. Empirical level is the 10-year yield, empirical slope is the difference between 10-year and 3-month yields, and empirical curvature is two times the 2-year yield less the sum of the 10-year and 3-month yields.

Although Diebold and Li (2006) find the pairwise correlations between $\{\hat{\beta}_{1t},$

$\hat{\beta}_{2t}$, $\hat{\beta}_{3t}\}$ to be negligible and attribute this finding to the fact that their estimated factors resemble the first three principal components (which are orthogonal and therefore uncorrelated), we find that $\rho(\hat{\beta}_{1t}, \hat{\beta}_{2t}) = -0.32$, $\rho(\hat{\beta}_{1t}, \hat{\beta}_{3t}) = 0.17$, and $\rho(\hat{\beta}_{2t}, \hat{\beta}_{3t}) = 0.66$. This might imply that our estimated factors are less correlated with the first three principal components of our yield data compared with what Diebold and Li (2006) find in their sample. This means that the a-priori argument of not using VARs to forecast the factor because of their resemblance with principal components might not be as valid with our sample as for Diebold and Li (2006).

In Table (5) we present descriptive statistics on the estimated DNS yield curve factors level, slope, and curvature, i.e. $\{\hat{\beta}_{1t}, \hat{\beta}_{2t}, \hat{\beta}_{3t}\}$. From the autocorrelations we observe that shocks to all factors are very persistent at the 1 month displacement, with autocorrelations ranging between 0.95 and 0.98. The first factor, $\hat{\beta}_{1t}$, is the most persistent, with the highest autocorrelation at all displacements. This means that shocks to the yield curve level persist for a long time. The second and third factor are about equally persistent. The Augmented Dickey-Fuller (ADF) p-value indicates that $\hat{\beta}_{1t}$ and $\hat{\beta}_{2t}$ may contain unit roots, while the null is rejected for $\hat{\beta}_{3t}$. To avoid working with non-stationary time series we take the first differences of $\hat{\beta}_{1t}$ and $\hat{\beta}_{2t}$, which we find to by stationary by the ADF. Also taking the first difference of $\hat{\beta}_{3t}$ (although the ADF null is rejected) makes it easier to implement the forecasting algorithm and renders the ADF p-value even lower. Hence, we forecast the first difference of each estimated factor.

Factor	Mean	Std.Dev	Min	Max	$\hat{\rho}(1)$	$\hat{\rho}(12)$	$\hat{\rho}(30)$	ADF(p-value)
$\hat{\beta}_{1t}$	4.951	1.798	1.574	8.875	0.977	0.761	0.597	0.096
$\hat{\beta}_{2t}$	-2.349	1.667	-5.565	0.938	0.975	0.502	-0.183	0.182
$\hat{\beta}_{3t}$	-2.057	2.391	-7.312	3.859	0.951	0.596	0.189	0.027

Table 5: Descriptive statistics on DNS factors

Overall, we find the DNS model to generally provide a good fit in the cross-section yields. This is important because we ultimately forecast NS curves; not yields. If the historical NS curves do not provide a good fit, our yield curve forecasts will presumably be bad. Next, we assess the performance of our forecasting framework and finally obtain an answer to our research question; is the U.S. Treasury yield curve as modelled by the NS framework forcastable by diffusion indices?

5.2 Forecasting Results

5.2.1 In-Sample Analysis

We begin with an in-sample analysis of the relationship between the change in the estimated DNS factors $\{\hat{\beta}_{1,t+h}, \hat{\beta}_{2,t+h}, \hat{\beta}_{3,t+h}\}$ and the targeted principal components of X. First, we look at the difference between principal components formed with targeted predictors and with non-targeted predictors; do we gain predictive power by targeting predictors before we form the PCs?

To assess this question, we do as follows. We use the hard thresholding rule based on a t-statistic of 1.65 ($\alpha = 5\%$) to find the targeted predictors from X for $\{\hat{\beta}_{1,t+h}, \hat{\beta}_{2,t+h}, \hat{\beta}_{3,t+h}\}$ with $h = 1$, 6, and 12 months, controlling for four lags of the factors. We obtain the 10 first PCs formed from these targeted predictors, one set for each variable and each horizon, and use them to produce in-sample forecasts of the factors one, six and twelve months ahead. We also form PCs using all the predictors in X (non-targeted PCs) and compare the results. Note that for each factor and each forecast horizon we have a different set of targeted predictors, resulting in a different set of targeted PCs. We report the results in Table (6) and (7).

From the two tables we observe several patterns. First, we find that the R^2 and the RMSE from regressions using targeted PCs are higher for both $\hat{\beta}_{1,t+h}$ and $\hat{\beta}_{2,t+h}$ at all horizons. For $\hat{\beta}_{3,t+h}$, the R^2 and RMSE is higher with targeted PCs only for the one month horizon. This means that the targeted PCs explain more variation in the one, six and twelve months ahead factor changes compared with the non-targeted PCs, with the exception being $\hat{\beta}_{3,t+h}$ at the six and twelve months horizons. Not surprisingly, the targeted F-test p-values are lower (i.e. higher joint significance) for the two first factors at all horizons, and for the third factor at the one month horizon.

Secondly, we find the targeted PCs to generally obtain higher individual statistical significance. This result is the strongest for $\hat{\beta}_{1,t+h}$, lesser for $\hat{\beta}_{2,t+h}$, and the weakest for $\hat{\beta}_{3,t+h}$. For $\hat{\beta}_{1,t+h}$, the targeted PCs have higher t-statistics in seven out of ten cases for the one and six months horizons, and in eight out of ten cases for the twelve months horizon. For $\hat{\beta}_{2,t+h}$, the targeted PCs attain higher t-statistics in six out of ten cases for the one month horizon, and seven of out ten cases for the six and twelve month horizons. For $\hat{\beta}_{3,t+h}$, the numbers are seven, four and five, respectively. Across all factors and horizons, the t-statistics associated with targeted PCs are higher in 64% of the cases.

Thirdly, we find that the targeted PCs attain higher economic significance (i.e. higher coefficient estimates in absolute terms) across all PCs for all factors at all horizons, except for the fourth PC in the $\hat{\beta}_{1,t}$ one month ahead model. This means that we obtain higher economic significance by targeting predictors in 99% of the cases.

In sum, we seem to gain predictive power by targeting predictors before

Threshold t-stat. = 1.65		Targeted Principal Components													
Factor	h	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	R^2	$R^2 adj.$	RMSE	F-test
$\hat{\beta}_{1,t+h}$	1	4.363E-11	2.976E-11	7.075E-11	-7.812E-14	-2.466E-10	7.946E-10	7.266E-10	3.125E-09	3.335E-09	1.260E-08	0.073	0.045	0.075	0.004
		(2.510)	(1.117)	(1.449)	(-0.001)	(-0.880)	(2.698)	(0.447)	(1.539)	(1.151)	(2.184)				
	6	1.545E-10	3.192E-10	7.108E-10	2.488E-08	1.136E-05	7.192E-05	5.280E-05	9.113E-05	3.625E-05	9.784E-05	0.091	0.063	0.177	4.330E-04
		(1.947)	(2.101)	(1.057)	(0.453)	(0.676)	(3.377)	(1.769)	(2.483)	(0.730)	(1.318)				
	12	3.263E-10	9.937E-10	2.610E-05	-5.498E-05	-1.040E-05	-1.352E-04	-5.764E-05	9.600E-05	3.294E-05	-6.168E-06	0.137	0.110	0.237	5.300E-07
		(1.997)	(1.104)	(2.503)	(-4.062)	(-0.469)	(-4.063)	(-1.580)	(2.009)	(0.504)	(-0.062)				
$\hat{\beta}_{2,t+h}$	1	1.110E-12	2.424E-10	-6.102E-11	1.018E-09	5.676E-10	3.335E-09	6.488E-09	1.343E-08	-1.188E-08	1.406E-08	0.025	-0.004	0.839	0.574
		(1.887)	(0.893)	(-0.085)	(1.142)	(0.404)	(1.453)	(0.488)	(0.537)	(-0.209)	(0.235)				
	6	3.161E-12	4.863E-10	2.015E-10	-1.636E-10	2.225E-09	3.442E-09	7.657E-09	3.736E-09	1.140E-08	8.299E-10	0.033	0.004	2.220	0.347
		(2.013)	(0.896)	(0.264)	(-0.084)	(0.948)	(1.015)	(1.287)	(0.564)	(1.529)	(0.089)				
	12	7.557E-08	2.882E-06	1.725E-06	5.762E-05	2.898E-05	-2.694E-05	3.657E-05	-1.887E-05	1.625E-04	3.980E-04	0.035	0.006	4.380	0.295
		(1.719)	(2.135)	(1.185)	(1.203)	(0.427)	(-0.323)	(0.323)	(-0.101)	(0.829)	(0.691)				
$\hat{\beta}_{3,t+h}$	1	-1.869E-06	1.243E-06	-2.480E-05	-2.688E-04	1.489E-05	4.759E-04	2.267E-03	8.765E-04	-5.157E-03	5.195E-05	0.157	0.132	1.420	8.430E-09
		(-6.274)	(1.559)	(-0.854)	(-2.897)	(0.123)	(1.952)	(2.017)	(0.482)	(-1.881)	(0.017)				
	6	4.789E-09	1.841E-08	-1.413E-07	-8.684E-07	4.831E-05	3.063E-05	-1.036E-04	-2.335E-04	-8.287E-05	4.490E-04	0.016	-0.014	4.840	0.857
		(0.830)	(1.171)	(-0.969)	(-0.377)	(0.834)	(0.306)	(-0.749)	(-0.715)	(-0.154)	(0.654)				
	12	4.539E-12	5.077E-10	2.822E-09	-6.093E-11	2.192E-09	4.043E-09	5.291E-09	-2.454E-09	8.686E-09	1.977E-09	0.018	-0.012	4.240	0.814
		(1.500)	(0.421)	(0.989)	(-0.020)	(0.532)	(0.861)	(0.873)	(-0.306)	(0.837)	(0.127)				

Table 6

Threshold t-stat. = 1.65		Non-targeted Principal Components													
Factor	h	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	R^2	$R^2 adj.$	RMSE	F-test
$\hat{\beta}_{1,t+h}$	1	7.807E-14 (1.482)	-2.955E-14 (-0.376)	2.148E-13 (0.582)	-2.229E-13 (-0.469)	2.344E-13 (0.170)	-1.984E-12 (-0.182)	8.543E-12 (0.694)	-2.832E-11 (-1.355)	2.925E-11 (1.192)	1.466E-11 (0.581)	0.021	-0.009	0.077	0.721
	6	2.762E-13 (2.198)	-5.460E-14 (-0.294)	-5.327E-13 (-0.611)	-7.218E-13 (-0.641)	2.397E-12 (0.737)	-4.314E-11 (-1.671)	1.369E-11 (0.469)	-4.203E-11 (-0.850)	1.250E-11 (0.216)	6.891E-11 (1.154)	0.033	0.004	0.183	0.334
	12	1.532E-13 (0.872)	-2.235E-13 (-0.867)	-2.814E-13 (-0.233)	-1.046E-12 (-0.670)	-1.524E-12 (-0.338)	-3.320E-11 (-0.920)	2.340E-11 (0.577)	-3.941E-11 (-0.575)	5.071E-11 (0.630)	9.820E-11 (1.187)	0.017	-0.014	0.253	0.858
$\hat{\beta}_{2,t+h}$	1	9.786E-13 (1.710)	-1.035E-12 (-1.210)	1.938E-12 (0.483)	1.581E-12 (0.306)	3.003E-12 (0.201)	6.880E-11 (0.580)	-1.659E-10 (-1.240)	-1.001E-10 (-0.441)	1.166E-11 (0.044)	-7.073E-11 (-0.258)	0.020	-0.009	0.841	0.735
	6	2.93E-12 (1.914)	-1.54E-12 (-0.678)	2.21E-13 (0.021)	2.16E-11 (1.576)	4.27E-12 (0.108)	2.98E-11 (0.095)	-5.44E-10 (-1.533)	1.04E-10 (0.174)	7.24E-11 (0.103)	-1.80E-10 (-0.248)	0.027	-0.003	2.230	0.526
	12	3.28E-12 (1.069)	-5.38E-12 (-1.198)	-7.45E-12 (-0.354)	6.40E-12 (0.235)	-2.41E-11 (-0.307)	2.39E-10 (0.380)	-1.14E-09 (-1.606)	3.70E-10 (0.310)	4.79E-10 (0.341)	-9.74E-10 (-0.676)	0.019	-0.011	4.420	0.793
$\hat{\beta}_{3,t+h}$	1	4.118E-13 (0.397)	8.903E-14 (0.057)	-1.655E-11 (-2.276)	1.020E-11 (1.089)	3.183E-12 (0.117)	9.021E-11 (0.419)	-3.707E-10 (-1.528)	-2.872E-10 (-0.698)	-8.338E-11 (-0.173)	-5.134E-10 (-1.033)	0.031	0.002	1.520	0.390
	6	4.83E-13 (0.146)	-1.26E-13 (-0.026)	-3.51E-11 (-1.524)	3.95E-11 (1.331)	-1.23E-11 (-0.143)	3.82E-10 (0.560)	-1.52E-11 (-0.020)	-1.67E-09 (-1.280)	-1.31E-09 (-0.855)	-8.10E-10 (-0.514)	0.021	-0.009	4.830	0.717
	12	4.13E-12 (1.410)	-1.81E-12 (-0.422)	-3.51E-11 (-1.743)	2.07E-11 (0.797)	-4.57E-11 (-0.609)	3.77E-10 (0.627)	-2.65E-10 (-0.392)	-9.04E-10 (-0.791)	-9.00E-10 (-0.671)	-6.36E-10 (-0.461)	0.0242	-0.0059	4.230	0.624

Table 7

forming the PCs, as opposed to forming the PCs from all the variables in X. We now turn our focus to only the regressions with targeted PCs. We obtain the highest R^2 in the $\hat{\beta}_{3,t+1}$ model; the targeted PCs explain almost 16% of the variation in the one month ahead curvature factor changes. This number drastically decreases at longer horizons, with R^2s of 1.6% and 1.8% at the six and twelve months horizons, respectively. The second highest R^2 is obtained in the $\hat{\beta}_{1,t+12}$ regression, with about 14% of the variation being explained by the targeted PCs. This number decreases as the horizons decreases. This is an interesting finding; the targeted PCs do better at forecasting $\hat{\beta}_{1,t+h}$ as h increases. The same pattern is observed in the R^2s from the $\hat{\beta}_{1,t+h}$ regressions; here too do the targeted PCs perform better in terms of R^2 at longer horizons. The RMSE, however, tends to increase in the forecasting horizon, meaning that the forecasting errors become larger as we increase h.

In Table (6) and (7), we have simply run multiple linear regressions of the 10 first targeted and non-targeted PCs on the factor changes at different forecasting horizons. What happens if we control for lags of the factors and let an algorithm choose the BIC-minimizing model specifications, i.e., the BIC-minimizing combination of lags and targeted PCs? The answer is found in Table (8). The results presented in Table (8) are from regression specifications chosen by a Matlab algorithm which searches through different combinations of the 10 first targeted PCs and four lags of $\hat{\beta}_{t+h}$ (i.e. $\hat{\beta}_t$, $\hat{\beta}_{t-1}$, $\hat{\beta}_{t-2}$, and $\hat{\beta}_{t-3}$), and selects the combination minimizing BIC. This is the same method we use in the algorithm discussed in the methodology section, only now we produce in-sample forecasts rather than out-of-sample forecasts. In Table (9) we run the same BIC-minimizing algorithm using only lags as predictors, i.e. only using autoregressive models. This is used as an in-sample benchmark against the targeted PCs.

From the results in Table (8) and (9) it becomes clear that we increase the in-sample predictive power for $\hat{\beta}_{1,t+h}$ and $\hat{\beta}_{3,t+h}$ by including targeted PCs in addition to lags of the factors. That is, by extending the forecasting equations to include targeted PCs if this reduces the BIC, we obtain higher predictive power for these two factors. For $\hat{\beta}_{2,t+h}$, it is never optimal to include targeted PCs. At the one month ahead and twelve months ahead regressions only lags of $\hat{\beta}_{2,t+h}$ are included, while at the six month ahead regression the BIC-minimizing specification is to only include an intercept.

We begin with analysis of the $\hat{\beta}_{1,t+h}$ regressions. The BIC-minimizing algorithm chooses to include combinations of targeted PCs and lags at all horizons, and all coefficient estimates are statistically significant, both on the lags and the targeted PCs. The predictors are also jointly significant across all horizons. We slightly improve the predictive power for $\hat{\beta}_{1,t+h}$ by letting the algorithm select from the targeted PCs. This can be seen by higher R^2s, both ordinary and adjusted, lower RMSEs, lower BICs, and lower F-test p-values from

Threshold t-stat. = 1.65

Lags and targeted PCs, BIC-minimzing model specification

Factor	h	Intercept	$\hat{\beta}_t$	$\hat{\beta}_{t-1}$	$\hat{\beta}_{t-2}$	$\hat{\beta}_{t-3}$	P1	P3	P4	P5	P6	P7	P9	P10	R^2	$R^2adj.$	RMSE	BIC	F-test
	1	-0.001		-0.165			4.412E-11				7.291E-10				0.065	0.057	0.075	-781.566	4.590E-05
		(-0.328)		(-3.111)			(2.499)				(2.455)								
$\hat{\beta}_{1,t+h}$	6	-0.003	0.924	-1.361E-01						2.588E-05		5.673E-05			0.678	0.674	0.105	-538.224	1.660E-80
		(-0.440)	(17.442)	(-2.555)						(2.575)		(3.188)							
	12	-0.003	1.112	-0.401	0.388	-0.213						-9.006E-05	9.154E-05	-1.812E-04	0.836	0.833	0.104	-525.2582	3.35E-123
		(-0.516)	(21.919)	(-5.569)	(5.405)	(-4.196)						(-5.613)	(3.201)	(-4.165)					
	1	-0.082	0.140	0.130	-0.240										0.081	0.073	0.811	848.6709	2.490E-06
		(-1.859)	(2.642)	(2.457)	(-4.510)														
$\hat{\beta}_{2,t+h}$	6	-2.24E-01													0.000	0.000	2.240	1.508E+03	0.000
		(-1.840)																	
	12	-4.88E-01	-1.62E-01												0.026	0.023	4.37	1.930E+03	0.003
		(-2.027)	(-2.987)																
	1	-0.125					-1.881E-06		-2.716E-04						0.128	0.123	1.400	1.220E+03	7.940E-11
		(-1.658)					(-6.398)		(-2.953)										
$\hat{\beta}_{3,t+h}$	6	-2.33E-01			-9.946E-02			-1.955E-07							0.058	0.0525	2.460	1.58E+03	4.380E-05
		(-1.738)			(-3.585)			(-2.629)											
	12	-0.388	0.192												0.039	0.036	3.260	1.74E+03	2.990E-04
		(-2.151)	(3.655)																

Table 8

Threshold t-stat. = 1.65 — Lags only, BIC-minimzing model specification

Factor	h	Intercept	$\hat{\beta}_t$	$\hat{\beta}_{t-1}$	$\hat{\beta}_{t-2}$	$\hat{\beta}_{t-3}$	R^2	$R^2 adj.$	RMSE	BIC	F-test
$\hat{\beta}_{1,t+h}$	1	-0.001 (-0.351)		-0.176 (-3.295)			0.031	0.028	0.0764	-781.025	0.001
	6	-2.491E-03 (-0.425)	9.370E-01 (17.351)	-1.601E-01 (-2.960)			0.661	0.659	0.108	-533.350	1.690E-79
	12	-3.031E-03 (-0.492)	1.067E+00 (19.615)	-0.376 (-4.847)	0.371 (4.784)	-0.185 (-3.384)	0.807	8.043E-01	0.112	-487.582	2.70E-115
$\hat{\beta}_{2,t+h}$	1	-0.082 (-1.859)	0.140 (2.642)	0.130 (2.457)	-0.240 (-4.510)		0.081	0.073	0.811	848.671	2.49E-06
	6	-2.24E-01 (-1.840)					0.000	0.000	2.240	1.508E+03	0.000
	12	-4.88E-01 (-2.027)	-1.62E-01 (-2.987)				0.026	0.0234	4.37	1.930E+03	0.003
$\hat{\beta}_{3,t+h}$	1	-1.258E-01 (-1.557)					0.000	0.000	1.500	1.255E+03	0.000
	6	-2.367E-01 (-1.748)			-1.028E-01 (-3.679)		0.039	0.036	2.480	1.584E+03	2.730E-04
	12	-0.388 (-2.151)	0.192 (3.655)				0.039	0.036	3.260	1.737E+03	2.990E-04

Table 9

the regressions including targeted PCs compared to those only including lags. Taking a closer look at $\hat{\beta}_{1,t+1}$, we observe that by including the first and sixth targeted PC in addition the second lag we obtain almost twice as high R^2 and R^2 adjusted compared to only including the second lag, from 3.1% and 2.8% to 6.5% and 5.87%, respectively. Also note that although the R^2 is slightly lower in Table (8) than in Table (6), the R^2 adjusted has increased. This means that we explain more variance relative to the number of predictors, which means that we have a more parsimonious forecasting equation. The RMSE, BIC (obviously), and F-test p-value are also improved by including targeted PCs for $\hat{\beta}_{1,t+1}$, although the differences are slight. If we compare the coefficient estimates of the targeted PCs and the second lag, we see a huge difference in the economic significance; the coefficient estimate on the second lag is much, much larger than the estimates on the targeted principal components. This is the reason why the differences in the BIC and RMSE between not including targeted PCs and including them are so slight; the model with targeted PCs only slightly outperform the alternative.

The same pattern holds for $\hat{\beta}_{1,t+6}$ and $\hat{\beta}_{1,t+12}$; it is optimal to include targeted PCs (the fifth and seventh, and the seventh, ninth and tenth, respectively), but the improvements in predictive power are only slight due to the low economic significance of the targeted PCs. What's noteworthy about these two horizons is the remarkably high R^2 of 68% and 84%, respectively. This finding is mostly driven by the lags; in the regressions only including lags, we obtain an R^2 of 66% and 81%, which means that $\hat{\beta}_{1,t+h}$ is highly forecastable by autoregressive models of order 2 and 4 at the six and twelve months horizons. We gain a slight improvement of the predictive power by including the targeted PCs.

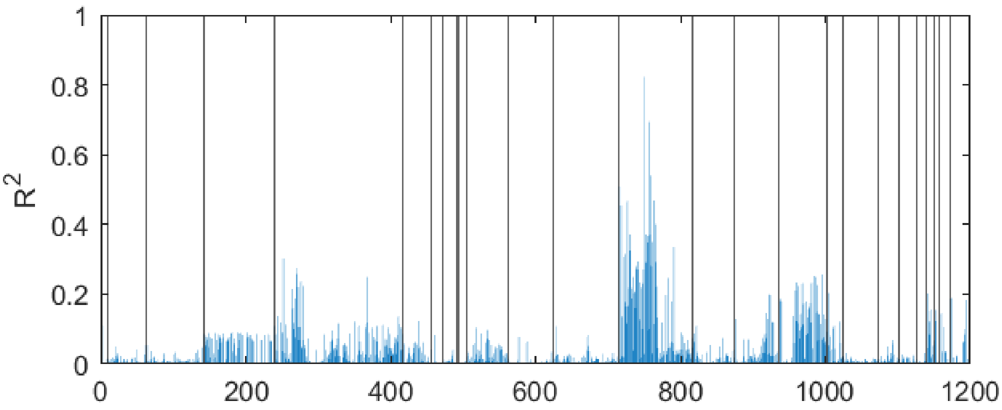
For $\hat{\beta}_{2,t+h}$ it is never optimal to include targeted PCs. At the one month horizon an AR(3) model is chosen by the algorithm which gives an R^2 of 8.1%. At the six months horizon it is optimal to only include an intercept, and we thus obtain an R^2 of 0% for $\hat{\beta}_{2,t+6}$. At the twelve months horizon the minimum BIC is obtained with an AR(1) model, which explains 2.6% of the variation in $\hat{\beta}_{2,t+12}$. We find it quite surprising that $\hat{\beta}_{2,t+h}$ is not forcastable with targeted predictors. As $\hat{\beta}_{2t}$ can be interpreted as the yield curve slope, we expected it to be related to variables measuring real economic activity. Indeed, when we look at the top 100 most important predictors for $\hat{\beta}_{2,t+h}$ (in terms of t-statistics) we find many such variables. Additionally, in Table (6) we see that the first targeted PC for $\hat{\beta}_{2,t+h}$ is statistically significant across all horizons. Nonetheless, we find that the BIC-minimizing in-sample forecasting models do not include any targeted PCs, meaning that we do not find $\hat{\beta}_{2,t+h}$ to be forecastable with the targeted diffusion indices. Note that when we perform out-of-sample forecasting it may for some forecasts be optimal (in terms of BIC) to include targeted PCs, i.e. that targeted PCs might predict $\hat{\beta}_{2,t+h}$ for certain sample periods.

Contrarily, the algorithm chooses to only include targeted PCs, and not any lags, for $\hat{\beta}_{3,t+h}$ at the one month horizon. Here, it is optimal to include the first and fourth targeted PC which together explain 12.8% of the variation in $\hat{\beta}_{3,t+1}$. They are both independently and jointly significant, with an F-test p-value close to zero. Since the algorithm chooses not to include any lags, it seems that we are able to outperform the Diebold and Li model (which forecasts the factors as AR(1) processes) in-sample. We observe that if we only let the algorithm use lags as regressors, it is optimal to only include an intercept for $\hat{\beta}_{3,t+1}$. Comparing Table (6) and Table (8), we see that by using the algorithm to minimize BIC we actually obtain a lower R^2 adjusted than we do by using all of the ten first targeted PCs. We see, however, that the RMSE is lower when using the algorithm and that the difference in the R^2 adjusted is small, while the model chosen by the algorithm is more parsimonious.

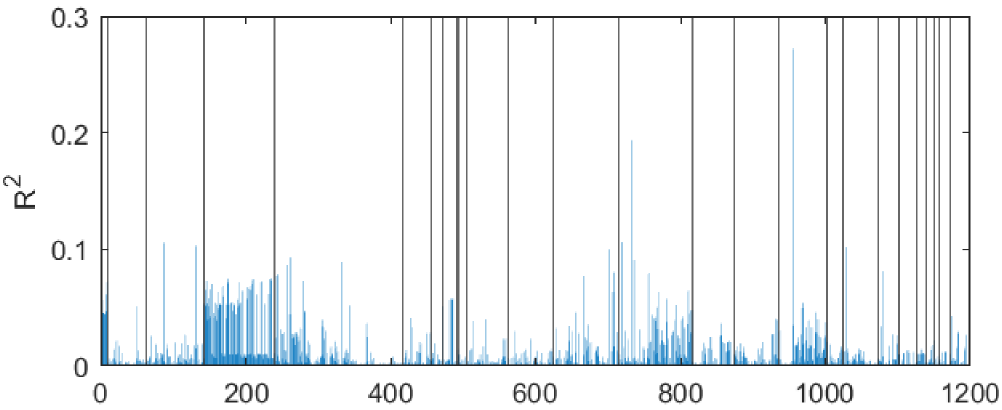
For the six months horizon, it is optimal to include the third lag and the third targeted PC. Both are statistically significant. This model obtains an R^2 of 5.8% and an R^2 adjusted of 5.3% which is higher than what we obtain if we were only to use lags. This is also higher than what we obtain by using all of the ten first PCs, with which we obtain an R^2 of 1.6%. The RMSE is also the lowest when using the algorithm with targeted PCs. At the twelve months horizon an AR(1) model is chosen by the algorithm. With this we obtain an R^2 of 3.9%. This means that we find no in-sample predictive power of the targeted PCs for $\hat{\beta}_{3,t+12}$.

We now move to an analysis of the targeted PCs and the targeted variables for each factor. We begin by looking at which variables the targeted PCs chosen by the algorithm loads the heaviest on. We find this in the same manner as Ludvigson and Ng (2009); we regress each of the targeted PCs on each of the variables in X and report the marginal R^2 using a bar-plot. Each bar corresponds to a variable in X, and we have grouped the variables such that one can see which variable category the targeted PCs load the heaviest on. Because each factor and each forecast horizon use a different set of targeted variables (which gives different targeted PCs), we restrict our analysis to only look at the targeted PCs chosen for the one month horizon. For $\hat{\beta}_{1,t+1}$ this is the first and sixth targeted PC, for $\hat{\beta}_{2,t+1}$ no targeted PCs are chosen, and for $\hat{\beta}_{3,t+1}$ the first and fourth targeted PC are included. Again, we stress that the first targeted PC for $\hat{\beta}_{1,t+1}$ is *not* the same as the first targeted PC for $\hat{\beta}_{3,t+1}$. Hence, we expect the two PCs to load differently on the variables in X. We will examine the two most important variable categories for each of the targeted PCs the algorithm choose to include for $\hat{\beta}_{1,t+1}$ and $\hat{\beta}_{3,t+1}$. For an exhaustive list of all the variables in each category, please see Appendix 3.

First, we look at the first and sixth targeted PC for $\hat{\beta}_{1,t+1}$ in Figure (8). Each vertical line marks the beginning of a new variable category (each cate-



(a) The first targeted PC for $\hat{\beta}_{1,t+1}$ on each variable X_{it} in X



(b) The sixth targeted PC for $\hat{\beta}_{1,t+1}$ on each variable X_{it} in X

Figure 8

gory is reported in Appendix 3). We find that the first targeted PC for $\hat{\beta}_{1,t+1}$ loads the most heavily on the "Jobless Claims"-category, i.e. the range between 716 and 816 on the X-axis. In this category we have variables such as state-level initial claims and continued claims. Initial claims are the claims first to be filed by unemployed individuals to request a determination of eligibility for unemployment insurance benefits, while continued claims are the filed by individuals needing to continue receiving benefits because of continued unemployment. Because they give an indication of the state of employment before the actual unemployment numbers are released, these variables are considered to be important leading indicators of macroeconomic activity (Federal Reserve Bank of St.Louis, 2020). Because the first targeted PC for $\hat{\beta}_{1,t+1}$ load heavily on these variables, it means that these variables have predictive power for the one-month ahead yield curve level.

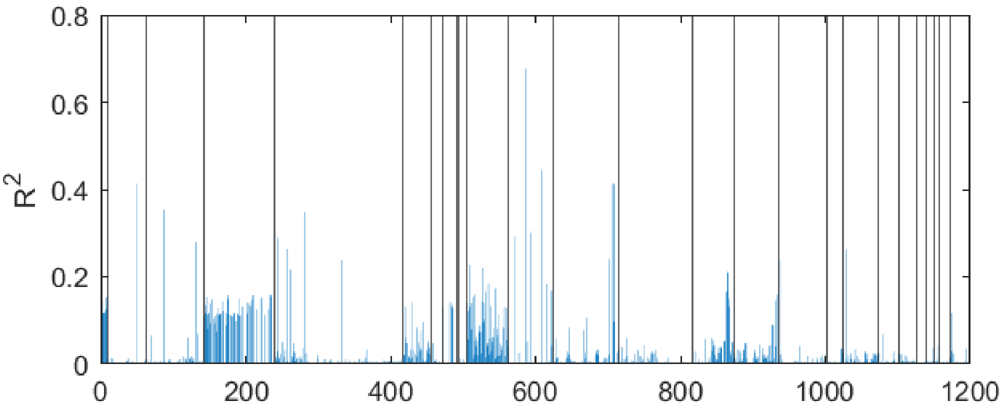
The second group to which the first targeted PC for $\hat{\beta}_{1,t+1}$ loads heavily on is the group of so-called "Leading Index"-variables (the range between 953 and 1003 on the X-axis). A leading index is a state-level prediction of the six-month growth rate of the state's coincident index, which is a measure of the current state of economic activity in that particular state. The leading index is estimated from other, leading variables in addition to the coincident index; state-level housing permits, state initial unemployment insurance claims, delivery times from the Institute for Supply Management manufacturing survey, and the interest rate spread between the 10-year Treasury bond and the 3-month Treasury bill (i.e. the empirical yield curve slope) (Federal Reserve Bank of St.Louis, 2020).

It becomes clear that the first targeted PC for $\hat{\beta}_{1,t+1}$ relates to leading macroeconomic variables such as initial claims and leading indices. Since we find this PC to predict the yield curve level one month ahead, we find a link between these leading variables and $\hat{\beta}_{1,t+1}$.

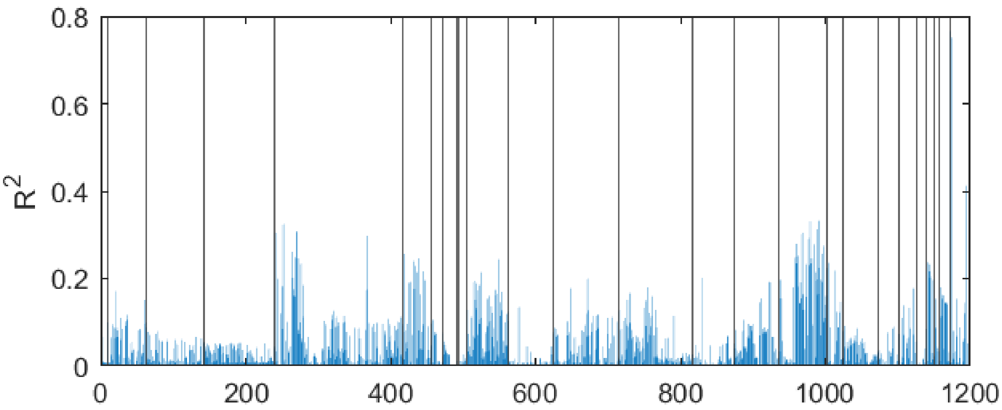
We now move to the sixth targeted PC for $\hat{\beta}_{1,t+1}$. This PC also loads heavily on the "Jobless Claims"-category, albeit weaker than the first targeted PC. The most important variables for this PC are the ones belonging to the group of "High Quality Market (HQM) Corporate Bonds"-variables (the range between 143 and 249 on the X-axis). This category consists of spot rates for HQM Corporate Bonds for different maturities, and can this be viewed as the U.S. HQM Corporate Bond yield curve. The HQM yield curve is constructed from a set of corporate bonds rated AAA, AA or A that accurately represent the high quality U.S. corporate bonds market (Federal Reserve Bank of St.Louis, 2020). Since the sixth targeted PC for $\hat{\beta}_{1,t+1}$ loads heavily on the HQM yield curve, and this PC has predictive power for $\hat{\beta}_{1,t+1}$, we can infer that the HQM yield curve predicts the Treasury yield curve level factor.

In Figure (9) we perform the same analysis on the targeted PCs for $\hat{\beta}_{3,t+1}$ chosen by the algorithm, namely the first and fourth targeted PC. The first targeted PC for $\hat{\beta}_{3,t+1}$ loads very distinctively on both the "High Quality Market (HQM) Corporate Bonds"-category and on the "Home Price Index (HMI)"-category (the range between 506 and 563 on the X-axis). The loading on the first category implies that the HQM yield curve also predicts the US Treasury yield curve curvature factor, in addition to the level factor as discussed above. The second category consists city-level S&P Case-Shiller Home Price Indices, which are the leading measures of U.S. residential real estate prices (Federal Reserve Bank of St.Louis, 2020). Since the first targeted PC for $\hat{\beta}_{3,t+1}$ load heavily on these variables, we can infer a link between current home prices and the one-month ahead yield curve curvature.

Lastly, we look at the fourth targeted PC for $\hat{\beta}_{3,t+1}$. This PC loads very heavily on the already mentioned group of "Leading Index"-variables (the range between 953 and 1003 on the X-axis). This means that the state-level leading indices also predicts the one-month ahead yield curve curvature. Next, the PC loads heavily on the "Home Price Index (HMI)"-category in the same



(a) The first targeted PC for $\hat{\beta}_{3,t+1}$ on each variable X_{it} in X



(b) The fourth targeted PC for $\hat{\beta}_{3,t+1}$ on each variable X_{it} in X

Figure 9

manner as the first targeted PC. Since both the first and sixth targeted PC for $\hat{\beta}_{3,t+1}$ is related to the housing market, and both are chosen by the algorithm to predict $\hat{\beta}_{3,t+1}$, the notion that the home prices predict the yield curve curvature is further strengthened. The last category we will examine is the category we call "Employment and Hours" (the range between 240 and 417 on the X-axis). This group consists of variables on the numbers of employees in different sectors, the number of hours they work, the employment and unemployment rates of different demographical groups, and ratios of unemployed to the labour force (among others). We thus establish a link between the current state of employment and the yield curve curvature factor one month ahead.

The last part of our in-sample analysis will be devoted to further analysing the relationship between the variables in X and the three DNS yield curve factors $\{\hat{\beta}_{1,t+h},\ \hat{\beta}_{2,t+h},\ \hat{\beta}_{3,t+h}\}$. We do so by looking at the variables targeted with our t-statistic threshold of 1.65 ($\alpha = 5\%$); which variables are chosen for the different factors at the different time steps? In other words, we examine the predictive power of each variable in X for $\{\hat{\beta}_{1,t+h}, \hat{\beta}_{2,t+h}, \hat{\beta}_{3,t+h}\}$ at $h = 1$, 6, and 12 months, after controlling for four lags of the factors. This analysis gives insight into which variables are used to form the targeted PCs we employ in the forecasting models reported in Table (6) and Table (8). We present the top 100 most important variables (in terms of t-statistic) for each factor and each forecast horizon in Appendix 2. Note that because for all factors at all horizons the top 100 t-statistics are all greater that 1.65, all top 100 variables make it into the PCs.

For $\hat{\beta}_{1,t+h}$, we see that the HQM Corporate Bonds spot rates are important predictors across all forecast horizons, but especially at the one and twelve months horizons. This is in line with what we found above; the HQM yield curve has predictive power for the Treasury yield curve level. For both $\hat{\beta}_{1,t+6}$ and $\hat{\beta}_{1,t+12}$, but not for $\hat{\beta}_{1,t+1}$, we find that the "Fitted Instantaneous Forward Rate" of various maturities are associated with the highest t-statistics. This implies that forward rates bear important predictive information about the yield curve, which is in line with the findings of Fama and Bliss (1987) and Cochrane and Piazzesi (2005). It is interesting that no forward rates enter the top 100 for $\hat{\beta}_{1,t+h}$ at the one month horizon, since these have been found to have predictive power for excess government bond returns both. Lastly, we find it interesting that different price indices (e.g. inflation) only enters the top 100 at the one month horizon. A priori, we expected the yield curve level to be highly related to inflation. However, our analysis shows that price indices like inflation has decreasing predictive power in the forecast horizon. It is also worth noting that different real-output variables like the industrial production index enters the top 100 at both the six and twelve months horizons, but not at the one month horizon. In sum, we observe more similar variables among the top 100 across the six and twelve months horizons than we do across the one and six months or the one and twelve months horizons.

For $\hat{\beta}_{2,t+h}$ we observe variables from many different groups; the only category that stands out across all three horizons is the "Employment and Hours"-category. Also note that while we for the most part found the *levels* of the variables in the top 100 for $\hat{\beta}_{1,t+h}$, we find several *squared* variables in the top 100 for $\hat{\beta}_{2,t+h}$. This implies that we gain predictive power by allowing for a non-linear link function between the variables and the PCs. We further observe a mix between macroeconomic variables, such as employment and real output measures, and financial variables such as the Fama-French factors across all horizons.

For $\hat{\beta}_{3,t+h}$ we find price indices (e.g. inflation) to be important, especially for the one and six months horizons. For $\hat{\beta}_{3,t+1}$, "Personal Income and Expenditures"-variables are associated with high t-statistics. While some of these variables enter the top 100 at the longer horizons, the relationship is weaker. Furthermore, we observe a lot of real-output measures like industrial production indices for different industries, and also a decent amount of variables related to the state of employment. In sum, we find quite similar variables across all three forecast horizons. Additionally, we find many similar variables to predict both $\hat{\beta}_{2,t+h}$ and $\hat{\beta}_{3,t+h}$. This might imply that the same economic forces are driving the yield curve slope and yield curve curvature (i.e. forecastable by the same economic variables), which might explain why we find a correlation between $\hat{\beta}_2$ and $\hat{\beta}_3$ of 0.66.

We have now seen that the targeted PCs have in-sample predictive power for $\hat{\beta}_{1,t+h}$ and $\hat{\beta}_{3,t+h}$, but not for $\hat{\beta}_{2,t+h}$. This means that we by including targeted PCs in the BIC-minimizing algorithm obtain superior in-sample forecasts to that of an pure autoregressive alternative (see Table (8) vs. Table (9)). This means that we in-sample beat the Diebold and Li (2006) model in terms of BIC; if AR(1) models were optimal, our algorithm would have chosen these models. It is not our ultimate goal, however, to produce in-sample forecast the DNS yield curve factors; we are ultimately going to forecast out-of-sample *yields*, not in-sample *yield curve factors*. We thus turn to the out-of-sample forecasting results.

5.2.2 Out-of-Sample Analysis

Here we employ the algorithm presented in the methodology section. We have an initial training period of 10 years from 1991:1 to 2001:1, and produce out-of-sample forecasts of the changes in $\{\hat{\beta}_{1t}, \hat{\beta}_{2t}, \hat{\beta}_{3t}\}$ 1, 6, and 12 months ahead recursively with a holdout-period from 2001:2 to 2019:12. In Table (10), we report the RMSE of our TDIF model along with the RMSE of the benchmark models outlined in the methodology section, while we in Table (11) report the relative RMSE (RRMSE) measure (Eq. (26)).

As one can see from Table (10) and (11), the TDIF model is systematically outperformed in terms of RMSE by *all* of the benchmark models. It is only for the six months ahead forecast of the three-month yield we are able to outperform the Diebold-Li model, which we considered to be the main benchmark. We find this result to be somewhat surprising given the in-sample predictive power we found the targeted diffusion indexes to have for the DNS model parameters $\{\hat{\beta}_{1t}, \hat{\beta}_{2t}, \hat{\beta}_{3t}\}$. Although we a-priori viewed the Diebold-Li model (Eq. (29)) to be the main benchmark as they were able to beat all benchmarks in their sample, it is with the random walk model (Eq. (27)) we obtain the lowest RMSE. This means that the findings of Diebold and Li (2006) do not hold in our sample. Additionally, we find that the added flexibility of letting an algorithm select the number of lags by minimizing BIC (Eq. (30)) results in lower RMSEs at the six and twelve month horizon compared with the Diebold-Li model. Not only is the Diebold-Li model outperformed by the random walk model; this simple model is superior to all the models we use

Maturity	DNS with AR(1)	DNS with AR(p)	AR(1) on yield levels	Random walk	TDIF
h=1					
3	0.378	0.402	0.195	0.194	0.620
6	0.317	0.353	0.214	0.212	0.622
12	0.285	0.320	0.199	0.197	0.693
24	0.332	0.353	0.231	0.228	0.740
36	0.369	0.379	0.253	0.249	0.680
60	0.356	0.361	0.268	0.264	0.550
84	0.303	0.305	0.279	0.274	0.490
120	0.307	0.311	0.280	0.278	0.484
h=6					
3	1.288	1.116	0.707	0.690	1.250
6	1.273	1.065	0.711	0.687	1.323
12	1.255	1.014	0.713	0.678	1.526
24	1.228	0.971	0.716	0.661	1.727
36	1.153	0.912	0.723	0.662	1.699
60	0.945	0.759	0.702	0.648	1.408
84	0.738	0.604	0.684	0.610	1.117
120	0.574	0.501	0.594	0.579	0.840
h=12					
3	2.096	2.292	1.247	1.162	3.924
6	2.022	2.158	1.249	1.135	3.647
12	1.905	1.959	1.218	1.073	3.206
24	1.734	1.699	1.152	0.970	2.631
36	1.560	1.492	1.094	0.911	2.225
60	1.212	1.142	0.972	0.815	1.642
84	0.920	0.872	0.870	0.749	1.283
120	0.684	0.666	0.752	0.697	0.993

Table 10: RMSE

to produce out-of-sample forecasts of the yield curve. The second lowest RMSEs is obtained with a model also not related to the DNS yield curve model, namely the model in which we forecast the yield levels directly as AR(1) processes (Eq. (31)). This forecasting model along with the random walk model are both not depending on the DNS yield curve modelling procedure, and they are both able to produce superior out-of-sample forecasts to that of any of the DNS based models. This means that the models unrelated to the DNS modelling framework systematically outperform the models which forecast yields by forecasting the DNS model paramaters. From this finding we can infer that we are not benefiting from distilling the yield curve into three dynamic factors with the DNS approach, although we find the DNS model parameters $\{\hat{\beta}_{1t}, \hat{\beta}_{2t}, \hat{\beta}_{3t}\}$ to capture most of the cross-sectional variation in yields. The poor results of the forecasting models on forecasting the DNS model parameters can either be ascribed to poor forecasting of said parameters, or poor estimation of the parameters, or both. We find that the three DNS model parameters explain 93.42% of the variation in the yield curves. This points to the problem being poor out-of-sample forecasts, not poor estimation, of the model parameters.

Maturity	DNS with AR(1)	DNS with AR(p)	AR(1) on yield levels	Random walk
h=1				
3	1.642	1.544	3.184	3.199
6	1.963	1.763	2.902	2.931
12	2.428	2.167	3.472	3.511
24	2.227	2.095	3.198	3.250
36	1.845	1.793	2.684	2.732
60	1.547	1.525	2.053	2.082
84	1.619	1.608	1.757	1.787
120	1.577	1.559	1.731	1.742
h=6				
3	0.970	1.119	1.768	1.812
6	1.039	1.242	1.862	1.927
12	1.216	1.505	2.140	2.249
24	1.407	1.779	2.414	2.612
36	1.473	1.863	2.349	2.568
60	1.489	1.854	2.004	2.174
84	1.514	1.849	1.635	1.832
120	1.462	1.678	1.413	1.451
h=12				
3	1.872	1.712	3.146	3.377
6	1.804	1.690	2.919	3.212
12	1.683	1.636	2.632	2.988
24	1.517	1.548	2.284	2.713
36	1.427	1.491	2.035	2.442
60	1.354	1.438	1.689	2.014
84	1.394	1.471	1.474	1.712
120	1.451	1.492	1.321	1.425

Table 11: RRMSE

5.3 Limitations

Our findings contradict the findings of Diebold and Li (2006). What could be the reason for the inferior out-of-sample forecasts from all the models based on the DNS yield curve modelling framework generally, and the TDIF model specifically? We will now explore the methodological limitations of our study.

First of all, our yield curve modelling methodology involves a lot of estimation which gives room for a lot of measurement errors. First, we estimate “raw” yields from the set of observable bond prices with the bootstrap method. These “raw” yields are not true, observed yields, but rather artificial yields from a theoretical zero coupon Treasury yield curve. Then, we use these estimated “raw” yields to estimate the DNS model parameters by fitting the NS model to the set of “raw” yields period by period. With this, we obtain estimated yields for a continuum of maturities, i.e. smoothed yield curves, but once again we move farther away from the actual yield curves. While this smoothing lets us describe the dynamics of the historical yield curves by just three, dynamic parameters $\{\hat{\beta}_{1t},\ \hat{\beta}_{2t},\ \hat{\beta}_{3t}\}$, we lose some information by doing so. It is clear that the better these parameters explain the variation in the historical yield curves, the better the forecasts based on these parameters.

Second, our yield curve forecasting methodology also involves estimation. We do not use any explanatory variables directly in the forecasting models, but rather the first few principal components estimated from a large set of variables. It is clear that while the first few PCs explain a lot of the variation in X, we also lose potentially important information when reducing the set of 1196 variables to just ten variables. There might also be measurement errors in the PCs. Raykov, Marcoulides and Li (2017) shows that as long as just one variable in the set form which PCs are formed contains error of measurement, so does any estimated PC. When we have as many as 1196 variables it is clearly some risk of measurement error in one or more of the variables.

Additionally, some variables that constitute noise rather than information might make into the PCs; while we test for the predictive power of X_{it} before deciding whether the variable is "in our out" of the set of targeted variables from which we form the targeted PCs, it is not certain that this variable has true predictive power for $\{\hat{\beta}_{1t},\ \hat{\beta}_{2t},\ \hat{\beta}_{3t}\}$. As we use a hard thresholding rule based on a critical t-statstic value of 1.65, we might encounter false rejections; while we can say that if the null hypothesis of no predictive power is true we only get t-statistics larger than 1.65 with a relative frequency of 5%, we almost certainly commit one or more Type I errors since we run the test 1196 times - one time for each of the 1196 variables. In other words, the rate of false rejection is increasing in the number of variables for which we perform the statistical test. We chose a significance level α of 5% because this is the conventional significance threshold level. It would, however, be interesting to use a lower α too see if this yields lower forecast errors.

Furthermore, the choice of using hard thresholding based on t-statics means that we ignore joint significance, as discussed in the methodology section. This means that jointly significant but individually insignificant variables might be dropped. Furthermore, this thresholding is sensitive to small changes in the data because of the discreteness of our threshold rule. For a more detailed discussion regarding this issue we refer to page 38 in the methodology section.

Lastly, a potential weakness of our forecasting methodology might arise from collinear predictors in X. We have, for example, included consumer price indices for several different groups of goods, and we expect these variables to be highly correlated. Since we use PCs in our forecasting model, which are uncorrelated by design, we do not have a problem of collinear predictors directly. However, we rather have an indirect problem of collinearity since the diffusion indices are most effective when the set of variables from which they are estimated contain variables with distinct predictive information (Bai & Ng, 2008). One might thus obtain lower forecast errors by designing a thresholding test which takes into account both (a) the predictive power of X_{it} and (b) the correlation between X_{it} and any other targeted variable(s). For a more detailed discussion on alternative thresholding procedures we refer the interested reader to the section on soft thresholding in Bai and Ng (2008).

6 Conclusion

The objective of this thesis was to investigate the predictability of the U.S. Treasury yield curve and test whether it could be forecasted by targeted diffusion indices. We chose to model the yield curve with the Dynamic Nelson-Siegel model in the same manner as Diebold and Li (2006), both because this model has proven to fit well in the cross-section of yields and because it has successfully been used to forecast the yield curve. Diebold and Li (2006) uses a-theoretical AR(1) processes to forecast the DNS model parameters and extract yields from the forecasted NS yield curves, with which they are able to produce superior out-of-sample forecasting results. We wanted to explore whether we could improve these forecasts by using explanatory variables that might explain the demand for Treasury securities. As Ludvigson and Ng (2009) produce improved forecasts of excess Treasury bond returns using targeted diffusion indices based on macroeconomic variables, we hypothesized that such targeted diffusion indices also might predict the DNS model parameters and thus the entire yield curve.

First of all, we find that the DNS model indeed provides a good fit to the yield curve, with an average R^2 of 93.42%. This means that the three dynamic model parameters $\{\hat{\beta}_{1t},\ \hat{\beta}_{2t},\ \hat{\beta}_{3t}\}$ on average capture most of the variation in the yield curves. We also found that the DNS yield curves largely exhibit the same behavior as the actual yield curves, in terms of the mean values, standard deviation, and persistence. Furthermore, we showed why these three parameters could be interpreted as proxies for three first yield curve factors; level, slope and curvature. These three factors (i.e. the three first principal components of the yield curves) explain almost all cross-sectional variation in yields, and can be a-priori linked with macroeconomic variables such as inflation and real output. This finding helps explain why the DNS model provides such a good fit; it is possible to give its parameters an economic interpretation. Additionally, we show that the NS functional form exhibit some appealing properties that reason well with economic theory, and we presented some stylized facts about the yield curve to which the DNS model in principle should adhere.

Although we find the DNS model to provide a good fit, we do not find that the method of forecasting its parameters gives superior out-of-sample yield curve forecasts. We find that our TDIF model performs the worst in terms of RMSE across all benchmark models. We further find that any of the models based on the DNS model produce inferior results to that of a random walk model, including the Diebold-Li model. This means that the findings of Diebold and Li (2006) do not hold for the yield curves in our sample; we obtain the best out-of-sample forecasts by employing models directly on yield levels rather than on the DNS model parameters.

We do, however, find in-sample predictability of the DNS model parameters by the targeted diffusion indices. This implies that the targeted diffusion indices we have estimated have some predictive power for $\{\hat{\beta}_{1t}, \hat{\beta}_{2t}, \hat{\beta}_{3t}\}$, but that this predictability does not translate into superior out-of-sample yield forecasts. This can either be because the estimated DNS model parameters are sub-optimal for out-of-sample forecasting purposes, or because the targeted diffusion indices have low out-of-sample predictive power.

For further research, we suggest the following. First, it would be interesting to see if the forecasts improved by using a different thresholding procedure to obtain targeted predictors, e.g. the soft thresholding procedures presented in Bai and Ng (2008). The authors find that these procedures, which do not depend on individual t-statistics, generally produce better diffusion indices. Second, we suggest that targeted diffusion indices can be used with alternative yield curve models, such as the affine yield curve model of Vasicek (1977), or on models on the term premium directly. Third, it would be interesting to test whether other financial variables, such as stock market returns, are forecastable by targeted diffusion indices.

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7 Appendixes

7.1 Appendix 1: Descriptive Statistics on Historical Raw Yields

Maturity (Months)	Mean	Std.dev.	Min.	Max.	$\hat{p}(1)$	$\hat{p}(12)$	$\hat{p}(30)$
3	2.891	2.155	0.000	6.323	0.988	0.739	0.331
6	3.003	2.179	0.000	6.406	0.987	0.742	0.339
9	3.064	2.191	0.045	6.858	0.982	0.745	0.371
12	3.204	2.222	0.100	7.148	0.987	0.753	0.382
15	3.271	2.237	0.122	7.366	0.987	0.758	0.404
18	3.341	2.230	0.161	7.418	0.986	0.762	0.426
21	3.412	2.216	0.188	7.480	0.986	0.767	0.445
24	3.469	2.194	0.206	7.529	0.986	0.770	0.465
30	3.603	2.173	0.253	7.646	0.985	0.776	0.493
36	3.737	2.132	0.290	7.677	0.984	0.782	0.515
48	3.987	2.053	0.428	7.700	0.983	0.786	0.546
60	4.183	1.961	0.597	7.870	0.982	0.778	0.558
72	4.378	1.889	0.801	8.038	0.980	0.775	0.568
84	4.536	1.804	0.976	8.179	0.976	0.776	0.575
96	4.695	1.769	1.176	8.295	0.978	0.770	0.578
108	4.796	1.715	1.382	8.367	0.977	0.762	0.574
120	4.864	1.644	1.547	8.321	0.974	0.751	0.568

Table 12: Descriptive statistics, yield curves 1991 to 2014

Maturity (Months)	Mean	Std.dev.	Min.	Max.	$\hat{p}(1)$	$\hat{p}(12)$	$\hat{p}(30)$
3	1.084	0.871	0.000	2.450	0.978	0.444	-0.382
6	1.198	0.855	0.060	2.560	0.976	0.438	-0.378
12	1.313	0.826	0.180	2.700	0.974	0.418	-0.388
24	1.475	0.729	0.470	2.870	0.964	0.366	-0.389
36	1.618	0.655	0.710	2.930	0.955	0.307	-0.393
60	1.873	0.544	1.010	2.980	0.930	0.174	-0.371
84	2.094	0.475	1.290	3.070	0.905	0.054	-0.330
120	2.247	0.437	1.460	3.150	0.892	-0.040	-0.296

Table 13: Descriptive statistics, yield curves 2015 to 2019

7.2 Appendix 2: Top Variables in terms of t-statistics (In-Sample)

$\hat{\beta}_1$: 1 month ahead		
Variable name	Category	t-stat
LI OECD: Component series: Interest rate spread: Original series, US (%, sa)	Leading indicators	11.464
10-Year Treasury Constant Maturity Minus Federal Funds Rate (%, nsa)	Bond market	11.439
10Y Treasury const. mat. minus 3M Treasury const. mat. (%, nsa)	Bond market	11.427
10Y Treasury const. mat. minus 2Y Treasury const. mat. (%, nsa)	Bond market	10.606
37-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	8.057
38.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	7.943
38-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	7.898
39-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	7.841
39.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	7.823
40-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	7.702
41-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	7.659
41.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	7.601
43-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	7.485
45-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	7.290
46-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	7.267
50-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.985
51.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.913
52-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.867
54.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.760
55-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.746
59-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.558
60-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.516
66-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.300
LI OECD: Component series: Interest rate spread: Normalised, US (Index, nsa)	Leading indicators	6.244
69.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.194
70-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.177
71-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.167
75-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.116
73-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.107
74.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.091
76-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	6.008
79-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.995
79.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.979
80-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.971
76.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.960
81-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.934
90-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.833
85.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.815
90.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.803
86.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.784
88-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.724
96-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.703
95.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.694
92-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.685
Moody's Seasoned Baa Corporate Bond Minus Federal Funds Rate (%, nsa)	Bond market	5.651
99-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.649
98-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.646
100-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	5.620
CPI-U: Gasoline (All Types) (1982-1984=100, sa)	Price indices	5.357
CPI-U: Motor Fuel (1982-1984=100, sa)	Price indices	5.304
CPI-U: Energy Commodities (1982-1984=100, sa)	Price indices	5.290
CPI-U: Transportation (1982-1984=100, sa)	Price indices	5.194
CPI-U: Commodities Less Food (1982-1984=100, sa)	Price indices	5.138
CPI-U: Energy (1982-1984=100, sa)	Price indices	4.973

PCE: Energy goods and services (chain-type price index) (2012=100, sa)	Personal income and expenditures	4.909
Business tendency - manuf.: Confidence Indic.: Composite Indic. (Normal=100, sa)	Sentiment	4.889
CPI-U: Nondurables (1982-1984=100, sa)	Price indices	4.814
Prices for PCE: Chained Price Index: energy goods&ser. (%change from prec.period, sa)	Personal income and expenditures	4.811
CPI-U: Commodities (1982-1984=100, sa)	Price indices	4.796
Moody's Seasoned Baa Corp Bond Yield Relative to Yield on 10Y-T cont mat. (%, nsa)	Bond market	4.731
Moody's Seasoned Aaa Corp Bond Yield Relative to Yield on 10Y-T const mat. (%, nsa)	Bond market	4.706
Prices for PCE: Chained Price Index: Goods (% Change from Preceding Period, sa)	Personal income and expenditures	4.670
PCE: Goods (chain-type price index) (2012=100, sa)	Personal income and expenditures	4.646
PCE: Nondurable goods (chain-type price index) (2012=100, sa)	Personal income and expenditures	4.627
CPI-U: All Items Less Food (1982-1984=100, sa)	Price indices	4.577
PPI-C: Fuels & Related Products & Power: Petroleum Products, Refined (1982=100, sa)	Price indices	4.566
Prices for PCE: Chained Price Index: Market-based PCE (%change from prec.period, sa)	Personal income and expenditures	4.541
LI OECD: Component series: BTS - Business situation: Normalised, US (Index, sa)	Leading indicators	4.517
Prices for PCE: Chained Price Index: Nondur.goods (% Change from preced.period, sa)	Personal income and expenditures	4.501
CPI-U: All Items Less Medical Care (1982-1984=100, sa)	Price indices	4.463
PCE:: Market-based (chain-type price index) (2012=100, sa)	Personal income and expenditures	4.448
Experimental CPI: Transportation(1982=100, sa)	Price indices	4.447
CPI-U & clerical workers: All Items (1982-1984=100, sa)	Price indices	4.433
CPI-U: All Items (1982-1984=100, sa)	Price indices	4.376
CPI-U: All Items Less Shelter (1982-1984=100, sa)	Price indices	4.349
PPI-C: Intermed. Demand,C-Type: Processed Materials ex foods&feeds (1982=100, sa)	Price indices	4.109
PPI-C: Final Demand: Personal Consump.goods (Finished con.goods)(1982=100, sa)	Price indices	4.099
PPI-C: Fuels & Related Products & Power: Home heating oil & distillates (1982=100, sa)	Price indices	4.022
PPI-C: Intermediate Demand by Commodity Type: Processed Goods (1982=100, sa)	Price indices	4.008
PCE: Nondurable Goods (bn of usd, sa)	Personal income and expenditures	3.948
PPI-C: Final Demand: Finished Goods (1982=100, sa)	Price indices	3.942
PPI-C: Final Demand: Finished Consumer Energy Goods (1982=100, sa)	Price indices	3.921
Prices for PCE: Chained Price Index (% Change from Preceding Period, sa)	Personal income and expenditures	3.866
CPI-U: Gasoline (All Types) (1982-1984=100, sa), Squared	Price indices	3.815
Leading Index for Georgia (%, sa)	Leading indicators	3.814
PPI-C: Fuels & Related Products & Power: Home heating oil & distillates (1982=100, sa), Squared	Price indices	3.808
CPI-U: Motor Fuel (1982-1984=100, sa), Squared	Price indices	3.770
PCE: Chain-type Price Index (2012=100, sa)	Personal income and expenditures	3.768
CPI-U: Energy Commodities (1982-1984=100, sa), Squared	Price indices	3.753
Real M2 Money Stock (bn of 1982-84 usd, sa), Squared	Monetary measures	3.726
Unemployment Level - Job Losers on Layoff (thous of pers., sa)	Employment and hours	3.681
PPI-C: Fuels and Related Products and Power: No. 2 Diesel Fuel (1982=100, sa)	Price indices	3.671
Real M1 Money Stock (bn of 1982-84 usd, sa), Squared	Monetary measures	3.651
LI OECD: Leading indicators: CLI: Normalised, US (Index, sa)	Leading indicators	3.650
LI OECD: Leading indicators: CLI: Amplitude adjusted, US (Index, sa)	Leading indicators	3.649
Job Losers on Layoff as a % of Total Unemployed (%, sa)	Employment and hours	3.622
Global price of Rubber (U.S. Cents per Pound, nsa)	Miscellaneous	3.621
PPI-C: Fuels & Related Products & Power: Petroleum Products, Refined (1982=100, sa), Squared	Price indices	3.619
LI OECD: Component series: Share prices: Original series, US (2015=100, nsa)	Leading indicators	3.588
Equity Market Volatility Tracker: Macro: Business Investment & Sentiment (Index, nsa), Squared	Sentiment	3.450

$\hat{\beta}_1$: 6 months ahead		
Variable name	Category	t-stat
Fitted Instantaneous Forward Rate 6 Years Hence (%, nsa)	Bond market	15.927
Fitted Instantaneous Forward Rate 7 Years Hence (%, nsa)	Bond market	15.914
Fitted Instantaneous Forward Rate 8 Years Hence (%, nsa)	Bond market	15.821
Fitted Instantaneous Forward Rate 9 Years Hence (%, nsa)	Bond market	15.707
Fitted Instantaneous Forward Rate 5 Years Hence (%, nsa)	Bond market	15.704
Fitted Instantaneous Forward Rate 10 Years Hence (%, nsa)	Bond market	15.598
Fitted Instantaneous Forward Rate 4 Years Hence (%, nsa)	Bond market	14.942
Fitted Instantaneous Forward Rate 3 Years Hence (%, nsa)	Bond market	13.212
Fitted Instantaneous Forward Rate 2 Years Hence (%, nsa)	Bond market	10.152
HPI (Low Tier) for Minneapolis, Minnesota (Jan 2000=100, sa), Squared	Housing	4.318

37-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.819
S&P/Case-Shiller WA-Seattle HPI (Jan 2000=100, sa), Squared	Housing	3.816
38-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.801
39-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.769
Leading Index for Nebraska (%, sa)	Leading indicators	3.767
38.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.758
39.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.720
Leading Index for Nebraska (%, sa), Squared	Leading indicators	3.707
40-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.706
IP: Durable Goods: Truck trailer (2012=100, sa), Squared	Real output measures	3.695
41.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.671
HPI (High Tier) for Seattle, Washington (Jan 2000=100, sa), Squared	Housing	3.668
41-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.664
43-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.627
NYSE Composite Monthly Close 1989-01-01 to 2020-02-01 (Index, nsa)	Equity market	3.591
45-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.585
46-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.567
50-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.550
51.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.505
52-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.505
U.S. Exports of Goods by F.A.S. Basis to World (MM of usd, sa)	Exports and imports	3.499
54.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.457
S&P500 Level (Index, nsa)	Equity market	3.441
55-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.440
Instantaneous Forward Term Premium 10 Years Hence (%, nsa)	Bond market	3.418
Leading Index for Texas (%, sa), Squared	Leading indicators	3.406
All Employees, Clothing and Clothing Accessories Stores (thous of pers., sa)	Employment and hours	3.397
59-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.394
60-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.365
66-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.362
HPI (Middle Tier) for Minneapolis, Minnesota (Jan 2000=100, sa), Squared	Housing	3.321
Exports: Value Goods for the United States (US usd Monthly Level, sa)	Exports and imports	3.312
Exports: Value Goods for the United States (National currency, Monthly Level, sa)	Exports and imports	3.312
69.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.297
CU: Nonmetallic mineral mining and quarrying (% of capacity, sa)	Real output measures	3.284
70-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.282
76-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.273
Exports: Value Goods for the United States (Growth Rate Previous Period, sa)	Exports and imports	3.267
71-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.262
74.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.260
75-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.241
73-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.240
76.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.234
Leading Index for Texas (%, sa)	Leading indicators	3.233
81-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.231
CU: Manufacturing (SIC) (% of capacity, sa), Squared	Real output measures	3.225
79-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.211
10Y Treasury const. mat. minus 3M Treasury const. mat. (%, nsa)	Bond market	3.209
IP: Durable Goods: Automobile (2012=100, sa)	Real output measures	3.209
Business tendency - manuf.: Orders Inflow: Tendency (Net %, sa)	Sentiment	3.203
80-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.201
79.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.199
IP: Durable manufacturing: Furniture and related product (2012=100, sa), Squared	Real output measures	3.196
85.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.194
88-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.191
86.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.180
LI OECD: Component series: Share prices: Original series, US (2015=100, nsa)	Leading indicators	3.174
NPHUA by Building Permits in the Northeast Census Region (thous of units, sa), Squared	Housing	3.173
IP: Manufacturing (SIC)(2012=100, sa), Squared	Real output measures	3.160
IP: Materials (2012=100, sa)	Real output measures	3.154

98-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.153
92-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.146
90.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.146
CU: Manufacturing (NAICS) (% of capacity, sa), Squared	Real output measures	3.144
99-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.132
96-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.131
CU: Manuf. ex. comp., communications equip., & semiconductors (% of capacity, sa), Squared	Real output measures	3.130
CU: Durable Manufacturing (% of capacity, sa), Squared	Real output measures	3.129
HPI (Low Tier) for Tampa, Florida (Jan 2000=100, sa), Squared	Housing	3.129
95.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.122
S&P500 Real Prices (Index, nsa)	Equity market	3.119
90-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.116
100-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.111
S&P500 Real Total Return Price (Index, nsa)	Equity market	3.109
IP: Manufacturing (NAICS)(2012=100, sa), Squared	Real output measures	3.099
S&P500 Shiller's CAPE (Index, nsa)	Equity market	3.074
S&P500 Shiller's TRCAPE (Index, nsa)	Equity market	3.062
S&P/Case-Shiller OR-Portland HPI (Jan 2000=100, sa), Squared	Housing	3.061
10-Year Treasury Constant Maturity Minus Federal Funds Rate (%, nsa)	Bond market	3.048
LI OECD: Leading indicators: CLI: Trend restored, US (Index, sa)	Leading indicators	3.042
LI OECD: Component series: Interest rate spread: Original series, US (%, sa)	Leading indicators	3.040
Business tendency - manufacturing: Production: Tendency (Net %, sa)	Sentiment	3.019
CU: Durable Manufacturing: Furniture and related product (% of capacity, sa), Squared	Real output measures	2.997
Pers. cur. transfer receipts (bn of usd, sa)	Personal income and expenditures	2.959
Pers. cur. transf. receipts: Gov. social benefits to persons (bn of usd, sa)	Personal income and expenditures	2.956
CU: Total ex. Comp., communications equip., and semiconductors (% of capacity, sa)	Real output measures	2.954
Indexes of agg. wkly hrs of prod&nonsup. employees, mining&logging (2002=100, sa)	Employment and hours	2.950
Continued Claims (Insured Unemployment) in New Jersey (number, nsa), Squared	Employment and hours	2.949
Capacity Utilization: Total Industry (% of capacity, sa)	Real output measures	2.916
Production of Total Industry in United States (2015=100, sa)	Real output measures	2.907

$\hat{\beta}_1$: 12 months ahead

Variable name	Category	t-stat
Fitted Instantaneous Forward Rate 6 Years Hence (%, nsa)	Bond market	15.329
Fitted Instantaneous Forward Rate 7 Years Hence (%, nsa)	Bond market	15.273
Fitted Instantaneous Forward Rate 5 Years Hence (%, nsa)	Bond market	15.161
Fitted Instantaneous Forward Rate 8 Years Hence (%, nsa)	Bond market	15.136
Fitted Instantaneous Forward Rate 9 Years Hence (%, nsa)	Bond market	14.980
Fitted Instantaneous Forward Rate 10 Years Hence (%, nsa)	Bond market	14.825
Fitted Instantaneous Forward Rate 4 Years Hence (%, nsa)	Bond market	14.488
Fitted Instantaneous Forward Rate 3 Years Hence (%, nsa)	Bond market	12.881
Fitted Instantaneous Forward Rate 2 Years Hence (%, nsa)	Bond market	9.939
Instantaneous Forward Term Premium 7 Years Hence (%, nsa), Squared	Bond market	4.935
San Francisco Tech Pulse (% Change from Year Ago, sa), Squared	Miscellaneous	4.693
37-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.488
38-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.486
38.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.443
39-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.436
40-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.426
39.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.422
43-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.407
41.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.385
41-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.373
45-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.366
51.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.306
46-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.300
50-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.287
52-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.256
54.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.237

Leading Index for Texas (%, sa), Squared	Leading indicators	4.211
55-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.191
59-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.180
San Francisco Tech Pulse (% Change from Year Ago, sa)	Miscellaneous	4.171
HPI (High Tier) for Seattle, Washington (Jan 2000=100, sa), Squared	Housing	4.159
Leading Index for Texas (%, sa)	Leading indicators	4.151
60-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.145
66-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.143
Business tendency - manufacturing: Production: Tendency (Net %, sa)	Sentiment	4.121
IP: Durable Goods: Truck trailer (2012=100, sa), Squared	Real output measures	4.100
76-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.081
69.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.069
70-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.054
79.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.051
79-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.048
71-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.043
74.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.042
76.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.041
73-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.040
75-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.008
81-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	4.006
85.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.999
80-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.994
88-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.993
92-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.983
96-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.982
Business tendency - manuf.: Orders Inflow: Tendency (Net %, sa)	Sentiment	3.964
95.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.963
90.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.961
86.5-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.955
98-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.952
90-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.941
99-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.937
Instantaneous Forward Term Premium 8 Years Hence (%, nsa), Squared	Bond market	3.917
100-Year HQM Corporate Bond Spot Rate (%, nsa)	Bond market	3.915
10-Year Treasury Constant Maturity Minus Federal Funds Rate (%, nsa)	Bond market	3.815
LI OECD: Component series: Interest rate spread: Original series, US (%, sa)	Leading indicators	3.815
S&P/Case-Shiller WA-Seattle HPI (Jan 2000=100, sa), Squared	Housing	3.808
IP: Durable Goods: Automobile (2012=100, sa), Squared	Real output measures	3.676
CPI-U: Women's and Girls' Apparel (1982-1984=100, sa)	Price indices	3.668
10Y Treasury const. mat. minus 3M Treasury const. mat. (%, nsa)	Bond market	3.606
Instantaneous Forward Term Premium 7 Years Hence (%, nsa)	Bond market	3.581
IP: Durable Goods: Automobile (2012=100, sa)	Real output measures	3.573
HPI (Middle Tier) for Minneapolis, Minnesota (Jan 2000=100, sa), Squared	Housing	3.501
HPI (Low Tier) for Minneapolis, Minnesota (Jan 2000=100, sa), Squared	Housing	3.478
S&P/Case-Shiller IL-Chicago HPI (Jan 2000=100, sa), Squared	Housing	3.310
Business tendency - manuf.: Confidence Indicators: Composite Indicators (Net %, sa)	Sentiment	3.301
LI OECD: Component series: BTS - Business situation: Original series, US (%, sa)	Leading indicators	3.301
Leading Index for Nebraska (%, sa)	Leading indicators	3.294
CU: Total ex. Comp., communications equip., and semiconductors (% of capacity, sa)	Real output measures	3.263
10Y Treasury const. mat. minus 2Y Treasury const. mat. (%, nsa)	Bond market	3.254
CPI-U: Apparel Less Footwear (1982-1984=100, sa)	Price indices	3.252
IP: Durable manufacturing: Furniture and related product (2012=100, sa), Squared	Real output measures	3.234
Pers. cur. transf. receipts: Gov.social benefits to persons: Social security (bn of usd, sa), Squared	Personal income and expenditures	3.233
Capacity Utilization: Total Industry (% of capacity, sa)	Real output measures	3.227
CU: Durable Manufacturing: Motor vehicles and parts (% of capacity, sa)	Real output measures	3.217
CU: Durable Manufacturing: Furniture and related product (% of capacity, sa), Squared	Real output measures	3.161
IP: Durable manufacturing: Motor vehicles and parts (2012=100, sa)	Real output measures	3.154
Motor Vehicle Assemblies: Total motor vehicle assemblies (MM of units, sa)	Real output measures	3.148
CPI-U: Apparel (1982-1984=100, sa)	Price indices	3.109

Motor Vehicle Assemblies: Autos and light truck assemblies (MM of units, sa)	Miscellaneous	3.101
Pers. cur. transf. receipts: Gov.social benefits to persons: Social security (bn of usd, sa)	Personal income and expenditures	3.073
S&P/Case-Shiller MN-Minneapolis HPI (Jan 2000=100, sa), Squared	Housing	3.073
HPI (Middle Tier) for Phoenix, Arizona (Jan 2000=100, sa), Squared	Housing	3.068
CU: Durable Manufacturing (% of capacity, sa)	Real output measures	3.060
Instantaneous Forward Term Premium 4 Years Hence (%, nsa)	Bond market	3.043
Industrial Production Index (2012=100, sa)	Real output measures	3.032
Production of Total Industry in United States (2015=100, sa)	Real output measures	3.032
CU: Manuf. ex. comp., communications equip., & semiconductors (% of capacity, sa)	Real output measures	3.030
CU: Durable Manuf.: Automobile and light duty motor vehicle (% of capacity, sa)	Real output measures	3.021
Real M2 Money Stock (bn of 1982-84 usd, sa)	Monetary measures	3.006
CU: Manufacturing (SIC) (% of capacity, sa)	Real output measures	2.994
IP: Materials (2012=100, sa)	Real output measures	2.980
M2 Money Stock (bn of usd, sa)	Monetary measures	2.944

$\hat{\beta}_2$: 1 month ahead		
Variable name	Category	t-stat
U.S. Imports of Goods by Customs Basis from Venezuela (MM of usd, nsa), Squared	Exports and imports	7.205
Unemployment Rate - Married Women (%, sa), Squared	Employment and hours	6.984
EMVT: Competition Matters(Index, nsa), Squared	Equity market	6.051
IP: Durable Goods: Auto parts and allied goods (2012=100, sa), Squared	Real output measures	5.057
EMVT: Competition Matters(Index, nsa)	Equity market	4.717
Japan / U.S. Foreign Exchange Rate (Ratio, nsa), Squared	Exchange rates	4.367
Moody's Seasoned Aaa Corp Bond Yield Relative to Yield on 10Y-T const mat. (%, nsa)	Bond market	4.353
EMVT: Macroeconomic News and Outlook: Interest Rates(Index, nsa), Squared	Equity market	4.207
Moody's Seasoned Baa Corp Bond Yield Relative to Yield on 10Y-T cont mat. (%, nsa)	Bond market	3.844
CU: Communications equipment (% of capacity, sa), Squared	Real output measures	3.822
Future UOs; % Reporting No Change for FRB - Philadelphia District (%, sa), Squared	Manufacturing activity	3.609
Unemployment Rate - 20 Yrs. & Over, Black or African American Men (%, sa)	Employment and hours	3.586
Moody's Seasoned Baa Corporate Bond Minus Federal Funds Rate (%, nsa), Squared	Bond market	3.551
EMVT: Macroeconomic News and Outlook: Interest Rates(Index, nsa)	Equity market	3.512
Japan / U.S. Foreign Exchange Rate (Ratio, nsa)	Exchange rates	3.298
Unemployment Rate - 18-19 Yrs., Women (%, sa), Squared	Employment and hours	3.243
Avg.wkly.hrs. of prod.&nonsup. Emplys, Professional and Business Services (Hours, sa), Squared	Employment and hours	3.207
Moody's Seasoned Aaa Corp Bond Yield Relative to Yield on 10Y-T const mat. (%, nsa), Squared	Bond market	3.151
Singapore / U.S. Foreign Exchange Rate (Ratio, nsa), Squared	Exchange rates	3.134
Continued Claims (Insured Unemployment) in Arizona (number, nsa), Squared	Employment and hours	3.087
EMVT: Overall(Index, nsa)	Equity market	3.086
Fama-French Small-minus-Big (%, nsa)	Equity market	3.055
CPI-U: Dairy and Related Products (1982-1984=100, sa)	Price indices	3.028
Indexes of agg. wkly payrolls of prod.&nonsup.emp., pro&business ser. (2002=100, sa), Squared	Employment and hours	2.939
Unemployment Rate - 20-24 Yrs. (%, sa), Squared	Employment and hours	2.932
EMVT: Overall(Index, nsa), Squared	Equity market	2.921
EMVT: Monetary Policy(Index, nsa)	Equity market	2.905
Continued Claims (Insured Unemployment) in Illinois (number, nsa)	Employment and hours	2.881
CU: Communications equipment (% of capacity, sa)	Real output measures	2.868
LI OECD: Component series: Interest rate spread: Normalised, US (Index, nsa)	Leading indicators	2.836
EMVT: Monetary Policy(Index, nsa), Squared	Equity market	2.834
Continued Claims (Insured Unemployment) in Colorado (number, nsa)	Employment and hours	2.833
Continued Claims (Insured Unemployment) in New Jersey (number, nsa)	Employment and hours	2.805
Continued Claims (Insured Unemployment) in Massachusetts (number, nsa)	Employment and hours	2.773
Continued Claims (Insured Unemployment) in Pennsylvania (number, nsa)	Employment and hours	2.737
Unemployment Rate - Married Women (%, sa)	Employment and hours	2.722
3-Month Treasury Bill Minus Federal Funds Rate (%, nsa), Squared	Bond market	2.722
IP: Durable manufacturing: Electrical equip., appliance, and component (2012=100, sa)	Real output measures	2.687
EMVT: Macroeconomic News and Outlook: Other Financial Indicators(Index, nsa)	Equity market	2.655
Median Weeks Unemployed (Weeks, sa)	Employment and hours	2.638
CPI-U: Services by Other Medical Professionals (Dec 1986=100, sa), Squared	Price indices	2.625
Initial Claims in Virginia (number, nsa)	Employment and hours	2.621

CPI-U: Women's and Girls' Apparel (1982-1984=100, sa), Squared	Price indices	2.580
EMVT: Policy Related(Index, nsa)	Equity market	2.570
EMVT: Macroeconomic News And Outlook(Index, nsa)	Equity market	2.559
Continued Claims (Insured Unemployment) in Minnesota (number, nsa)	Employment and hours	2.530
CU: Durable Manuf.: Electrical equip., appliance, and component (% of capacity, sa)	Real output measures	2.528
Non-M1 Components of M2 (bn of usd, sa), Squared	Monetary measures	2.521
Initial Claims in West Virginia (number, nsa)	Employment and hours	2.516
Fama-French Small-minus-Big (%, nsa), Squared	Equity market	2.512
AEWT: Merc. wholesalers, dur.goods in Riverside-San BO, CA (thous of pers., sa)	Employment and hours	2.490
Indexes of agg. wkly payrolls of prod.&nonsup.emp., pro&business ser. (2002=100, sa)	Employment and hours	2.476
EMVT: Macroeconomic News and Outlook: Other Financial Indicators(Index, nsa), Squared	Equity market	2.466
IP: Defense and space equipment (2012=100, sa), Squared	Real output measures	2.447
Continued Claims (Insured Unemployment) in Montana (number, nsa)	Employment and hours	2.445
Number Unemployed for 15 Weeks & Over (thous of pers., sa)	Employment and hours	2.441
Initial Claims in Georgia (number, nsa)	Employment and hours	2.417
Initial Claims in Colorado (number, nsa)	Employment and hours	2.404
10-Year Treasury Constant Maturity Minus Federal Funds Rate (%, nsa)	Bond market	2.402
Unemployment Level - Black or African American (thous of pers., sa)	Employment and hours	2.401
LI OECD: Component series: Interest rate spread: Original series, US (%, sa)	Leading indicators	2.397
Continued Claims (Insured Unemployment) (number, nsa)	Employment and hours	2.385
Retail Money Funds (bn of usd, sa)	Manufacturing activity	2.382
Continued Claims (Insured Unemployment) in Massachusetts (number, nsa), Squared	Employment and hours	2.380
CPI-U: Alcoholic Beverages Away From Home (1982-1984=100, sa)	Price indices	2.367
EMVT: Labor Regulations(Index, nsa), Squared	Equity market	2.358
3-Month Treasury Bill Minus Federal Funds Rate (%, nsa)	Bond market	2.356
CPI-U: Women's and Girls' Apparel (1982-1984=100, sa)	Price indices	2.354
Initial Claims in Illinois (number, nsa)	Employment and hours	2.324
EMVT: Macroeconomic News and Outlook: Inflation(Index, nsa)	Equity market	2.319
Non-M1 Components of M2 (bn of usd, sa)	Monetary measures	2.318
Unemployment Rate - Black or African American (%, sa)	Employment and hours	2.318
U.S. Exports of Goods by F.A.S. Basis to Japan (MM of usd, nsa), Squared	Exports and imports	2.317
Continued Claims (Insured Unemployment) in Indiana (number, nsa), Squared	Employment and hours	2.312
Continued Claims (Insured Unemployment) in West Virginia (number, nsa)	Employment and hours	2.290
3M Treasury Constant Maturity Minus Federal Funds Rate (%, nsa), Squared	Bond market	2.281
EMVT: Macroeconomic News and Outlook: Inflation(Index, nsa), Squared	Equity market	2.277
Of Total Unemployed, % Unemployed 15 Weeks & Over (%, sa)	Employment and hours	2.270
New priv.hous. units auth. by buil.per.: 1-unit struc.: Louisville-Jeff., KY-IN (units, sa)	Housing	2.265
EMVT: Macroeconomic News And Outlook(Index, nsa), Squared	Equity market	2.248
New Entrants as a % of Total Unemployed (%, sa), Squared	Employment and hours	2.247
Unemployment Level - New Entrants (thous of pers., sa), Squared	Employment and hours	2.245
U.S. Imports of Goods by Customs Basis from Venezuela (MM of usd, nsa)	Exports and imports	2.243
Continued Claims (Insured Unemployment) in Wyoming (number, nsa)	Employment and hours	2.239
Initial Claims (number, nsa)	Employment and hours	2.236
Unemployment Rate - 25-54 Yrs., Men (%, sa)	Employment and hours	2.234
Continued Claims (Insured Unemployment) in Alabama (number, nsa), Squared	Employment and hours	2.232
Of Total Unemployed, % Unemployed 5-14 Weeks (%, sa), Squared	Employment and hours	2.223
AEWT: Merc. wholesalers, nondur.goods in Newark, NJ-PA (MD) (thous of pers., sa)	Employment and hours	2.214
U.S. Imports of Goods by Customs Basis from China (MM of usd, nsa)	Exports and imports	2.214
Of Total Unemployed, % Unemployed Less Than 5 Weeks (%, sa)	Employment and hours	2.212
EMVT: Policy Related(Index, nsa), Squared	Equity market	2.203
Continued Claims (Insured Unemployment) in California (number, nsa)	Employment and hours	2.201
CPI-U: Motor Vehicle Maintenance and Repair (1982-1984=100, sa), Squared	Price indices	2.191
AEWT: Merc. wholesalers, nondur.goods in Newark, NJ-PA (MD) (thous of pers., sa), Squared	Employment and hours	2.190
Initial Claims in Utah (number, nsa)	Employment and hours	2.188
Continued Claims (Insured Unemployment) in Nebraska (number, nsa)	Employment and hours	2.180
3M Treasury Constant Maturity Minus Federal Funds Rate (%, nsa)	Bond market	2.174
Employment-Population Ratio - Black or African American (%, sa)	Employment and hours	2.170
CPI-U: Apparel (1982-1984=100, sa), Squared	Price indices	2.159

$\hat{\beta}_2$: 6 months ahead		
Variable name	Category	t-stat
CU: Communications equipment (% of capacity, sa), Squared	Real output measures	6.529
Moody's Seasoned Baa Corporate Bond Minus Federal Funds Rate (%, nsa), Squared	Bond market	6.084
IP: Defense and space equipment (2012=100, sa)	Real output measures	4.425
IP: Defense and space equipment (2012=100, sa), Squared	Real output measures	4.387
Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate (%, nsa), Squared	Bond market	3.867
New Entrants as a % of Total Unemployed (%, sa), Squared	Employment and hours	3.648
LI OECD: Component series: Interest rate spread: Normalised, US (Index, nsa)	Leading indicators	3.622
Unemployment Level - New Entrants (thous of pers., sa), Squared	Employment and hours	3.564
CPI-U: Other Goods and Services (1982-1984=100, sa), Squared	Price indices	3.533
Japan / U.S. Foreign Exchange Rate (Ratio, nsa), Squared	Exchange rates	3.411
CPI-U: Other Goods and Services (1982-1984=100, sa)	Price indices	3.334
Median Weeks Unemployed (Weeks, sa)	Employment and hours	3.302
CPI-U: Housing (1982-1984=100, sa), Squared	Price indices	3.302
CPI-U: Housing (1982-1984=100, sa)	Price indices	3.255
Experimental Consumer Price Index: Housing(1982=100, sa), Squared	Price indices	3.250
EMVT: Macroeconomic News and Outlook: Interest Rates(Index, nsa), Squared	Equity market	3.198
CPI-U: Tobacco and Smoking Products (1982-1984=100, sa), Squared	Price indices	3.185
Of Total Unemployed, % Unemployed 15 Weeks & Over (%, sa)	Employment and hours	3.184
Initial Claims in Colorado (number, nsa)	Employment and hours	3.161
CPI-U: Tobacco and Smoking Products (1982-1984=100, sa)	Price indices	3.158
Continued Claims (Insured Unemployment) in Oklahoma (number, nsa), Squared	Employment and hours	3.145
Indexes of agg. wkly payrolls of prod.&nonsup.emp., pro&business ser. (2002=100, sa), Squared	Employment and hours	3.115
EMVT: Macroeconomic News and Outlook: Interest Rates(Index, nsa)	Equity market	3.098
EMVT: Macroeconomic News and Outlook: Other Financial Indicators(Index, nsa), Squared	Equity market	3.063
Prices for PCE: Chained Price Index: Services (% Change from Preceding Period, sa)	Personal income and expenditures	3.032
EMVT: Other Regulation(Index, nsa)	Equity market	3.013
Initial Claims in Washington (number, nsa)	Employment and hours	2.993
Future UOs; % Reporting Increases for FRB - Philadelphia District (%, sa), Squared	Manufacturing activity	2.935
EMVT: Other Regulation(Index, nsa), Squared	Equity market	2.925
Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate (%, nsa)	Bond market	2.910
Avg weekly earnings of prod.&nonsupervisory Employees, tot.priv (usd per Week, sa)	Employment and hours	2.899
Avg weekly earnings of prod.&nonsupervisory Employees, tot.priv (usd per Week, sa), Squared	Employment and hours	2.874
Housing Starts: 2-4 units (thous of units, sa), Squared	Housing	2.873
Of Total Unemployed, % Unemployed 27 Weeks & Over (%, sa)	Employment and hours	2.870
PPI-C: Intermediate Demand by Commodity Type: Unprocessed Goods (1982=100, sa)	Price indices	2.860
CU: Communications equipment (% of capacity, sa)	Real output measures	2.839
CPI-U & clerical workers: Housing (1982-1984=100, sa)	Price indices	2.836
All Employees, Government (thous of pers., sa), Squared	Employment and hours	2.821
Equity Market-related Economic Uncertainty (Index, nsa), Squared	Equity market	2.798
EMVT: Competition Matters(Index, nsa), Squared	Equity market	2.789
Avg.wkly.hrs. of prod.&nonsup. Emplys, Professional and Business Services (Hours, sa), Squared	Employment and hours	2.775
AEWT: Merc. wholesalers, nondur.goods in Newark, NJ-PA (MD) (thous of pers., sa), Squared	Employment and hours	2.771
PPI-C: Farm Products: Slaughter Hogs (1982=100, sa), Squared	Price indices	2.760
CPI-U & clerical workers: Housing (1982-1984=100, sa), Squared	Price indices	2.723
Fama-French Small-minus-Big (%, nsa), Squared	Equity market	2.721
Initial Claims in Maine (number, nsa)	Employment and hours	2.709
Indexes of agg. wkly payrolls of prod&nonsup. Employees, tot. priv (2002=100, sa)	Employment and hours	2.708
Initial Claims in Wyoming (number, nsa)	Employment and hours	2.691
Initial Claims in Arizona (number, nsa)	Employment and hours	2.676
All Employees, Federal (thous of pers., sa), Squared	Employment and hours	2.645
All Employees, Air Transportation (thous of pers., sa)	Employment and hours	2.631
Production and Nonsupervisory Employees, Retail Trade (thous of pers., sa), Squared	Employment and hours	2.629
Of Total Unemployed, % Unemployed 5-14 Weeks (%, sa), Squared	Employment and hours	2.624
Initial Claims in New York (number, nsa)	Employment and hours	2.622
Number Unemployed for 15 Weeks & Over (thous of pers., sa)	Employment and hours	2.618
Initial Claims in Wyoming (number, nsa), Squared	Employment and hours	2.617
Unemployment Rate - 20-24 Yrs. (%, sa), Squared	Employment and hours	2.614

Moody's Seasoned Aaa Corp Bond Yield Relative to Yield on 10Y-T const mat. (%, nsa), Squared	Bond market	2.594
Indexes of agg. wkly payrolls of prod.&nonsup.emp., pro&business ser. (2002=100, sa)	Employment and hours	2.584
Initial Claims in Washington (number, nsa), Squared	Employment and hours	2.582
Initial Claims in Virginia (number, nsa)	Employment and hours	2.571
Leading Index for the United States (%, sa)	Leading indicators	2.564
Equity Market-related Economic Uncertainty (Index, nsa)	Equity market	2.553
CPI-U: Services (1982-1984=100, sa), Squared	Price indices	2.550
EMVT: Intellectual Property Policy(Index, nsa)	Equity market	2.526
Number Unemployed for 27 Weeks & Over (thous of pers., sa)	Employment and hours	2.517
EMVT: Macroeconomic News and Outlook: Other Financial Indicators(Index, nsa)	Equity market	2.511
IP: Durable manufacturing: Aerospace&miscellaneous transp.equip. (2012=100, sa)	Real output measures	2.495
PCE: Services (chain-type price index) (2012=100, sa)	Personal income and expenditures	2.491
Initial Claims in Colorado (number, nsa), Squared	Employment and hours	2.486
Initial Claims in Delaware (number, nsa)	Employment and hours	2.480
CU: Durable Manuf.: Aerosp. and miscellaneous transp. equip. (% of capacity, sa)	Real output measures	2.478
Initial Claims (number, nsa)	Employment and hours	2.458
Housing Starts: 2-4 units (thous of units, sa)	Housing	2.441
Initial Claims in Illinois (number, nsa)	Employment and hours	2.423
Avg.wkly.hrs. of prod.&nonsup. Emplys, Professional and Business Services (Hours, sa)	Employment and hours	2.377
Indexes of agg. wkly payrolls of prod&nonsup. Employees, tot. priv (2002=100, sa), Squared	Employment and hours	2.375
Average Weeks Unemployed (Weeks, sa)	Employment and hours	2.368
Initial Claims in Idaho (number, nsa)	Employment and hours	2.352
CPI-U: Services (1982-1984=100, sa)	Price indices	2.338
CPI-U: all urb.consumers: Food at Home in U.S. City avg. (1982-1984=100, sa)	Price indices	2.336
Continued Claims (Insured Unemployment) in Maine (number, nsa)	Employment and hours	2.313
EMVT: Competition Policy(Index, nsa), Squared	Equity market	2.294
Unemployment Rate - Job Losers (U-2) (%, sa), Squared	Employment and hours	2.291
Initial Claims in Oklahoma (number, nsa)	Employment and hours	2.284
San Francisco Tech Pulse (Jan 2000=100, sa), Squared	Miscellaneous	2.283
Avg weekly hrs of Production and Nonsupervisory Employees, Total Private (Hours, sa)	Employment and hours	2.268
Real M1 Money Stock (bn of 1982-84 usd, sa)	Monetary measures	2.266
Equity Market Volatility Tracker: Macro: Business Investment & Sentiment (Index, nsa), Squared	Sentiment	2.264
Effective Federal Funds Rate (%, nsa), Squared	Miscellaneous	2.264
CPI-U: Fuels and Utilities (1982-1984=100, sa)	Price indices	2.260
Avg hr earnings of Production & Nonsupervisory Employees, Tot priv (usd per Hour, sa), Squared	Employment and hours	2.258
U.S. Imports of Goods by Customs Basis from China (MM of usd, nsa), Squared	Exports and imports	2.258
EMVT: Lawsuit And Tort Reform Supreme Court Decisions(Index, nsa), Squared	Equity market	2.236
New priv.hous. units auth. by buil.per.: 1-unit struc.: Jacksonville, FL (units, sa), Squared	Housing	2.233
CPI-U: Commodities Less Food and Energy Commodities (1982-1984=100, sa), Squared	Price indices	2.230
CPI-U: Energy Services (1982-1984=100, sa)	Price indices	2.217
Of Total Unemployed, % Unemployed Less Than 5 Weeks (%, sa)	Employment and hours	2.214
Indexes of agg. wkly hrs of prod&nonsup. employees, Total Private (2002=100, sa)	Employment and hours	2.209
Initial Claims in Virginia (number, nsa), Squared	Employment and hours	2.207

$\hat{\beta}_2$: 12 months ahead		
Variable name	Category	t-stat
CU: Communications equipment (% of capacity, sa), Squared	Real output measures	9.751
IP: Defense and space equipment (2012=100, sa), Squared	Real output measures	6.814
EMVT: Competition Matters(Index, nsa), Squared	Equity market	5.969
Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate (%, nsa), Squared	Bond market	4.328
Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate (%, nsa)	Bond market	4.274
AEWT: Merc. wholesalers, nondur.goods in Newark, NJ-PA (MD) (thous of pers., sa), Squared	Employment and hours	3.914
EMVT: Competition Matters(Index, nsa)	Equity market	3.796
Unemployment Rate: Aged 55-64: All Persons for the United States (%, sa), Squared	Employment and hours	3.706
CU: Communications equipment (% of capacity, sa)	Real output measures	3.653
HPI (Middle Tier) for Denver, Colorado (Jan 2000=100, sa), Squared	Housing	3.514
All Employees, Government (thous of pers., sa), Squared	Employment and hours	3.427
CU: Computers, communications equipment, and semiconductors (% of capacity, sa), Squared	Real output measures	3.268
Future UOs; % Reporting Increases for FRB - Philadelphia District (%, sa), Squared	Manufacturing activity	3.242

Moody's Seasoned Baa Corporate Bond Minus Federal Funds Rate (%, nsa)	Bond market	3.180
Other Checkable Deposits at Commercial Banks (bn of usd, sa), Squared	Monetary measures	2.978
Continued Claims (Insured Unemployment) in Pennsylvania (number, nsa), Squared	Employment and hours	2.880
Unemployment Rate - Married Men (%, sa)	Employment and hours	2.873
Fama-French Small-minus-Big (%, nsa), Squared	Equity market	2.863
CPI-U: Services by Other Medical Professionals (Dec 1986=100, sa), Squared	Price indices	2.846
EMVT: Lawsuit And Tort Reform Supreme Court Decisions(Index, nsa)	Equity market	2.827
Unemployment Level - Job Losers on Layoff (thous of pers., sa)	Employment and hours	2.806
All Employees, Federal (thous of pers., sa), Squared	Employment and hours	2.747
IP: Durable Goods: Auto parts and allied goods (2012=100, sa)	Real output measures	2.715
Equity Market-related Economic Uncertainty (Index, nsa)	Equity market	2.713
EMVT: Food And Drug Policy(Index, nsa), Squared	Equity market	2.705
Job Losers on Layoff as a % of Total Unemployed (%, sa)	Employment and hours	2.696
EMVT: Food And Drug Policy(Index, nsa)	Equity market	2.673
Continued Claims (Insured Unemployment) in Oklahoma (number, nsa), Squared	Employment and hours	2.659
CPI-U: Cereals and Bakery Products (1982-1984=100, sa)	Price indices	2.604
EMVT: Intellectual Property Policy(Index, nsa)	Equity market	2.588
Import Price (End Use): All imports excluding petroleum (2000=100, nsa)	Exports and imports	2.567
Unemployment Level - New Entrants (thous of pers., sa), Squared	Employment and hours	2.565
OECD based Recession Indicators-U.S. from the Peak through the Trough (+1 or 0, sa)	Leading indicators	2.561
OECD based Recession Indicators-U.S. from the Peak through the Trough (+1 or 0, sa), Squared	Leading indicators	2.561
New priv.hous. units auth. by buil.per.: 1-unit struc.: Houston, TX (units, sa), Squared	Housing	2.520
AEWT: Merc. wholesalers, dur.goods in Riverside-San BO, CA (thous of pers., sa)	Employment and hours	2.503
Equity Market-related Economic Uncertainty (Index, nsa), Squared	Equity market	2.486
Future UOs; % Reporting No Change for FRB - Philadelphia District (%, sa)	Manufacturing activity	2.479
OECD based Recession Ind.-US Peak through the Period preceding trough (+1 or 0, sa)	Leading indicators	2.477
OECD based Recession Ind.-US Peak through the Period preceding trough (+1 or 0, sa), Squared	Leading indicators	2.477
New priv.hous. units auth. by buil.per.: 1-unit struc.: Charlotte-C-G, NC-SC (units, sa), Squared	Housing	2.462
Continued Claims (Insured Unemployment) in Massachusetts (number, nsa), Squared	Employment and hours	2.429
New priv.hous. units auth. by buil.per.: 1-unit struc.: Jacksonville, FL (units, sa), Squared	Housing	2.422
EMVT: Lawsuit And Tort Reform Supreme Court Decisions(Index, nsa), Squared	Equity market	2.418
Employment Level - Agriculture and Related Industries (thous of pers., sa)	Employment and hours	2.400
Unemployment Rate - Job Losers (U-2) (%, sa)	Employment and hours	2.384
Avg weekly earnings of prod.&nonsupervisory Employees, tot.priv (usd per Week, sa), Squared	Employment and hours	2.367
New Entrants as a % of Total Unemployed (%, sa), Squared	Employment and hours	2.363
Avg.wkly.overtime-hrs. of Prod.& nonsupervisory Employees, Dur. Goods (Hours, sa)	Employment and hours	2.363
Avg weekly earnings of prod.&nonsupervisory Employees, tot.priv (usd per Week, sa)	Employment and hours	2.348
Initial Claims in Colorado (number, nsa)	Employment and hours	2.345
Job Leavers as a % of Total Unemployed (%, sa)	Employment and hours	2.338
LI OECD: Component series: Orders: Original series, US (US Dollar, sa)	Leading indicators	2.320
Avg.wkly.hrs. of prod.&nonsup. Emplys, Private Service-Providing (Hours, sa)	Employment and hours	2.316
AEWT: Merc. wholesalers, dur.goods in Riverside-San BO, CA (thous of pers., sa), Squared	Employment and hours	2.300
New priv.hous. units auth. by buil.per.: 1-unit struc.: Tampa-St. P-C, FL (units, sa)	Housing	2.293
Indexes of agg. wkly payrolls of prod&nonsup. Employees, tot. priv (2002=100, sa)	Employment and hours	2.276
New priv.hous. units auth. by buil.per.: 1-unit struc.: Charlotte-C-G, NC-SC (units, sa)	Housing	2.276
Personal interest payments (bn of usd, sa)	Personal income and expenditures	2.240
Number Unemployed for 5-14 Weeks (thous of pers., sa), Squared	Employment and hours	2.237
New priv.hous. units auth. by buil.per.: 1-unit struc.: New York (units, sa)	Housing	2.232
Number Unemployed for 27 Weeks & Over (thous of pers., sa)	Employment and hours	2.223
OECD based Recession Ind.-U.S. Period following the Peak through (+1 or 0, sa)	Leading indicators	2.209
OECD based Recession Ind.-U.S. Period following the Peak through (+1 or 0, sa), Squared	Leading indicators	2.209
Avg hr earnings of prod.& nonsupervisory Employees, Construction (usd per Hour, sa)	Employment and hours	2.190
Indexes of agg. wkly hrs of prod&nonsup. employees, Total Private (2002=100, sa)	Employment and hours	2.146
Initial Claims in Utah (number, nsa)	Employment and hours	2.133
Personal interest payments (bn of usd, sa), Squared	Personal income and expenditures	2.117
S&P/Case-Shiller CO-Denver HPI (Jan 2000=100, sa), Squared	Housing	2.110
EMVT: Litigation Matters(Index, nsa), Squared	Equity market	2.106
Other Checkable Deposits (bn of usd, sa), Squared	Monetary measures	2.099
Moody's Seasoned Aaa Corp Bond Yield Relative to Yield on 10Y-T const mat. (%, nsa), Squared	Bond market	2.097
Pers. cur. transf. receipts: Gov.social benefits to persons: Social security (bn of usd, sa), Squared	Personal income and expenditures	2.083

Of Total Unemployed, % Unemployed 27 Weeks & Over (%, sa)	Employment and hours	2.076
Avg.wkly.overtime-hrs. of Prod.& Nonsupervisory Employees, Manufact. (Hours, sa)	Employment and hours	2.067
CU: Computers, communications equipment, and semiconductors (% of capacity, sa)	Real output measures	2.047
Future UOs; % Reporting Increases for FRB - Philadelphia District (%, sa)	Manufacturing activity	2.045
New Entrants as a % of Total Unemployed (%, sa)	Employment and hours	2.031
Unemployment Rate - 25-54 Yrs., Men (%, sa)	Employment and hours	2.018
Unemployment Rate - Hispanic or Latino (%, sa)	Employment and hours	2.013
New priv.hous. units auth. by buil.per.: 1-unit struc.: Jacksonville, FL (units, sa)	Housing	2.011
HPI (Low Tier) for San Diego, California (Jan 2000=100, sa), Squared	Housing	2.009
CPI-U: Services by Other Medical Professionals (Dec 1986=100, sa)	Price indices	1.999
U.S. Imports of Goods by Customs Basis from Taiwan (MM of usd, nsa), Squared	Exports and imports	1.991
Avg hr earnings of prod. & nonsup. Employees, transp.&warehousing (usd pr hour, sa), Squared	Employment and hours	1.979
3-Month Treasury Bill: Secondary Market Rate (%, nsa), Squared	Bond market	1.975
3-Month Treasury Constant Maturity Rate (%, nsa), Squared	Bond market	1.971
Indexes of agg. wkly payrolls of prod&nonsup. Employees, tot. priv (2002=100, sa), Squared	Employment and hours	1.959
AEWT: Merc. wholesalers, nondur.goods in Newark, NJ-PA (MD) (thous of pers., sa)	Employment and hours	1.951
New priv.hous. units auth. by buil.per.: 1-unit struc.: Utah (units, sa), Squared	Housing	1.945
IP: Defense and space equipment (2012=100, sa)	Real output measures	1.935
CPI-U: Energy Services (1982-1984=100, sa)	Price indices	1.935
HPI (Low Tier) for Denver, Colorado (Jan 2000=100, sa), Squared	Housing	1.926
IP: Durable manufacturing: Fabricated metal product (2012=100, sa)	Real output measures	1.925
Initial Claims in Wyoming (number, nsa)	Employment and hours	1.916
Non-M1 Components of M2 (bn of usd, sa), Squared	Monetary measures	1.916
6-Month Treasury Bill: Secondary Market Rate (%, nsa), Squared	Bond market	1.914
6-Month Treasury Constant Maturity Rate (%, nsa), Squared	Bond market	1.913
Unemployment Rate - Hispanic or Latino (%, sa), Squared	Employment and hours	1.911
Avg weekly hrs of Production and Nonsupervisory Employees, Total Private (Hours, sa)	Employment and hours	1.910

$\hat{\beta}_3$: 1 month ahead		
Variable name	Category	t-stat
New priv.hous. units auth. by buil.per.: 1-unit struc.: Lakeland-W Haven, FL (units, sa), Squared	Housing	6.190
Prices for PCE: Chained Price Index (% Change from Preceding Period, sa), Squared	Personal income and expenditures	5.251
PCE: Chain-type Price Index (2012=100, sa), Squared	Personal income and expenditures	4.916
PCE:: Market-based (chain-type price index) (2012=100, sa), Squared	Personal income and expenditures	4.894
Prices for PCE: Chained Price Index: Market-based PCE (%change from prec.period, sa), Squared	Personal income and expenditures	4.852
New priv.hous. units auth. by buil.per.: 1-unit struc.: Lakeland-W Haven, FL (units, sa)	Housing	4.731
CU: Crude processing (% of capacity, sa), Squared	Real output measures	4.147
PPI-C: Final Demand: Finished Consumer Foods, Crude (1982=100, sa), Squared	Price indices	4.054
CPI-U: All Items (1982-1984=100, sa), Squared	Price indices	3.986
PCE:: Market-based (chain-type price index) (2012=100, sa)	Personal income and expenditures	3.981
IP: Durable manufacturing: Aerospace&miscellaneous transp.equip. (2012=100, sa), Squared	Real output measures	3.930
CU: Durable Manuf.: Aerosp. and miscellaneous transp. equip. (% of capacity, sa), Squared	Real output measures	3.920
PCE: Chain-type Price Index (2012=100, sa)	Personal income and expenditures	3.896
Prices for PCE: Chained Price Index: Market-based PCE (%change from prec.period, sa)	Personal income and expenditures	3.884
CPI-U: All Items Less Food (1982-1984=100, sa)	Price indices	3.850
IP: Mining: Crude oil (2012=100, sa)	Real output measures	3.848
Prices for PCE: Chained Price Index: Nondur.goods (% Change from preced.period, sa)	Personal income and expenditures	3.800
Experimental CPI: Transportation(1982=100, sa)	Price indices	3.799
Prices for PCE: Chained Price Index (% Change from Preceding Period, sa)	Personal income and expenditures	3.778
PCE: Nondurable goods (chain-type price index) (2012=100, sa)	Personal income and expenditures	3.765
CPI-U: All Items Less Medical Care (1982-1984=100, sa), Squared	Price indices	3.738
CPI-U: All Items (1982-1984=100, sa)	Price indices	3.717
CPI-U: All Items Less Food (1982-1984=100, sa), Squared	Price indices	3.717
CPI-U: All Items Less Medical Care (1982-1984=100, sa)	Price indices	3.690
CPI-U: All Items Less Shelter (1982-1984=100, sa), Squared	Price indices	3.648
IP: Mining: Oil and gas extraction (2012=100, sa)	Real output measures	3.648
CU: Nondurable Manufacturing: Chemical (% of capacity, sa), Squared	Real output measures	3.615
CPI-U: All Items Less Shelter (1982-1984=100, sa)	Price indices	3.570
IP: Mining (2012=100, sa), Squared	Real output measures	3.568

IP: Mining: Crude oil (2012=100, sa), Squared	Real output measures	3.567
CPI-U & clerical workers: All Items (1982-1984=100, sa)	Price indices	3.567
CU: Oil and gas extraction (% of capacity, sa)	Real output measures	3.562
CPI-U: Commodities Less Food (1982-1984=100, sa)	Price indices	3.558
Prices for PCE: Chained Price Index: energy goods&ser. (%change from prec.period, sa)	Personal income and expenditures	3.543
Prices for PCE: Chained Price Index: Goods (% Change from Preceding Period, sa)	Personal income and expenditures	3.532
PCE: Goods (chain-type price index) (2012=100, sa)	Personal income and expenditures	3.480
CU: Mining (% of capacity, sa), Squared	Real output measures	3.455
CPI-U & clerical workers: All Items (1982-1984=100, sa), Squared	Price indices	3.447
CU: Crude processing (% of capacity, sa)	Real output measures	3.411
CPI-U: Nondurables (1982-1984=100, sa)	Price indices	3.406
CPI-U: Commodities (1982-1984=100, sa)	Price indices	3.393
CPI-U: Transportation (1982-1984=100, sa)	Price indices	3.374
PCE: Energy goods and services (chain-type price index) (2012=100, sa)	Personal income and expenditures	3.349
CPI-U: Energy (1982-1984=100, sa)	Price indices	3.324
Prices for PCE: Chained Price Index: energy goods&ser. (%change from prec.period, sa), Squared	Personal income and expenditures	3.319
CU: Nondurable Manufacturing: Chemical (% of capacity, sa)	Real output measures	3.288
Experimental CPI: All Items(1982=100, sa)	Price indices	3.287
IP: Nondurable manufacturing: Chemical (2012=100, sa)	Real output measures	3.269
IP: Mining: Oil and gas extraction (2012=100, sa), Squared	Real output measures	3.265
CPI-U: Energy Commodities (1982-1984=100, sa)	Price indices	3.251
CU: Oil and gas extraction (% of capacity, sa), Squared	Real output measures	3.222
U.S. Exports of Goods by F.A.S. Basis to Japan (MM of usd, nsa), Squared	Exports and imports	3.210
CPI-U: Motor Fuel (1982-1984=100, sa)	Price indices	3.204
IP: Nondurable manufacturing: Chemical (2012=100, sa), Squared	Real output measures	3.175
IP: Durable Goods: Aircraft and parts (2012=100, sa), Squared	Real output measures	3.166
CPI-U: Gasoline (All Types) (1982-1984=100, sa)	Price indices	3.096
Experimental CPI: All Items(1982=100, sa), Squared	Price indices	3.086
New priv.hous. units auth. by buil.per.: 1-unit struc.: Orlando-Kissimmee, FL (units, sa), Squared	Housing	3.047
CPI-U: Household Energy (1982-1984=100, sa), Squared	Price indices	3.041
CPI-U: Fuels and Utilities (1982-1984=100, sa), Squared	Price indices	3.039
Unemployment Rate - Hispanic or Latino (%, sa)	Employment and hours	3.023
Import Price (End Use): All commodities (2000=100, nsa)	Exports and imports	3.009
Housing Starts: 2-4 units (thous of units, sa), Squared	Housing	2.961
CPI-U: Utility (Piped) Gas Service (1982-1984=100, sa), Squared	Price indices	2.934
Instantaneous Forward Term Premium 5 Years Hence (%, nsa), Squared	Bond market	2.873
IP: Durable manufacturing: Aerospace&miscellaneous transp.equip. (2012=100, sa)	Real output measures	2.825
Rel. importance weight (Contribution to total IP-index): Oil and gas extraction (%, sa)	Real output measures	2.799
CU: Durable Manuf.: Aerosp. and miscellaneous transp. equip. (% of capacity, sa)	Real output measures	2.794
IP: Mining (2012=100, sa)	Real output measures	2.785
CU: Mining (% of capacity, sa)	Real output measures	2.767
IP: Nondurable Manufacturing (NAICS)(2012=100, sa)	Real output measures	2.752
CU: Nondurable manufacturing (% of capacity, sa)	Real output measures	2.741
CPI-U: Energy (1982-1984=100, sa), Squared	Price indices	2.688
Rental income of persons with capital consumption adjustment (bn of usd, sa)	Personal income and expenditures	2.641
Prices for PCE: Chained Price Index: Nondur.goods (% Change from preced.period, sa), Squared	Personal income and expenditures	2.634
Japan / U.S. Foreign Exchange Rate (Ratio, nsa), Squared	Exchange rates	2.633
IP: Durable Goods: Aircraft and parts (2012=100, sa)	Real output measures	2.623
HPI (High Tier) for Portland, Oregon (Jan 2000=100, sa), Squared	Housing	2.593
Savings and Small Time Deposits - Total (bn of usd, nsa)	Monetary measures	2.589
PCE: Energy goods and services (chain-type price index) (2012=100, sa), Squared	Personal income and expenditures	2.567
PPI-C: Final Demand: Finished Consumer Foods (1982=100, sa), Squared	Price indices	2.536
PCE: Nondurable goods (chain-type price index) (2012=100, sa), Squared	Personal income and expenditures	2.520
Job Leavers as a % of Total Unemployed (%, sa)	Employment and hours	2.515
Housing Starts: 2-4 units (thous of units, sa)	Housing	2.508
Consumer Opinion Surveys: Confidence Indicators: Composite Indic. (Normal=100, sa), Squared	Sentiment	2.504
All Employees, Mining and Logging (thous of pers., sa)	Employment and hours	2.487
Import Price (End Use): All imports excluding petroleum (2000=100, nsa)	Exports and imports	2.481
CPI-U: Commodities (1982-1984=100, sa), Squared	Price indices	2.476
New priv.hous. units auth. by buil.per.: 1-unit struc.: St. Louis, MO-IL (units, sa), Squared	Housing	2.455

CPI-U: Fuel Oil and Other Fuels (1982-1984=100, sa)	Price indices	2.445
PCE: Energy goods and services (bn of usd, sa)	Personal income and expenditures	2.443
PCE: Nondurable Goods (bn of usd, sa)	Personal income and expenditures	2.423
All Employees, Mining (thous of pers., sa)	Employment and hours	2.417
U.S. Government Demand Deposits at Commercial Banks (bn of usd, nsa), Squared	Monetary measures	2.414
Unemployment Level - Job Leavers (thous of pers., sa)	Employment and hours	2.396
CPI-U: Energy Services (1982-1984=100, sa), Squared	Price indices	2.375
All Employees, Health and Personal Care Stores (thous of pers., sa)	Employment and hours	2.339
Unemployment Rate - 55 Yrs. & Over (%, sa), Squared	Employment and hours	2.337
Prices for PCE: Chained Price Index: Goods (% Change from Preceding Period, sa), Squared	Personal income and expenditures	2.335
New priv.hous. units auth. by buil.per.: 1-unit struc.: Albuquerque, NM (units, sa)	Housing	2.333

$\hat{\beta}_3$: 6 months ahead		
Variable name	Category	t-stat
PPI-C: Final Demand: Finished Consumer Foods, Crude (1982=100, sa), Squared	Price indices	6.624
CU: Communications equipment (% of capacity, sa), Squared	Real output measures	4.068
U.S. Exports of Goods by F.A.S. Basis to Japan (MM of usd, nsa), Squared	Exports and imports	3.747
CPI-U: Sugar and Sweets (1982-1984=100, sa)	Price indices	3.649
PPI-C: Farm Products: Slaughter Hogs (1982=100, sa)	Price indices	3.150
CPI-U: Sugar and Sweets (1982-1984=100, sa), Squared	Price indices	3.013
PPI-C: Final Demand: Finished Consumer Foods (1982=100, sa), Squared	Price indices	2.974
Instantaneous Forward Term Premium 6 Years Hence (%, nsa)	Bond market	2.922
New priv.hous. units auth. by buil.per.: 1-unit struc.: Orlando-Kissimmee, FL (units, sa), Squared	Housing	2.743
Business Equipment Loans Owned by Finance Companies, outst. (MM of usd, nsa), Squared	Bond market	2.713
AEWT: Merc. wholesalers, dur.goods in San Jose-S-S Clara, CA (thous of pers., sa), Squared	Employment and hours	2.689
Other Checkable Deposits at Thrift Institutions (bn of usd, nsa)	Monetary measures	2.637
CPI-U & clerical workers: tuition, oth. sch. fees, & childcare (1982-1984=100, sa)	Price indices	2.598
All Employees, Financial Activities (thous of pers., sa)	Employment and hours	2.525
IP: Utilities: Electric power transmission, control, and distribution (2012=100, sa)	Real output measures	2.494
New priv.hous. units auth. by buil.per.: 1-unit struc.: St. Louis, MO-IL (units, sa)	Housing	2.493
Job Leavers as a % of Total Unemployed (%, sa)	Employment and hours	2.488
EMVT: Intellectual Property Policy(Index, nsa)	Equity market	2.475
Housing Starts: 2-4 units (thous of units, sa), Squared	Housing	2.448
Of Total Unemployed, % Unemployed 27 Weeks & Over (%, sa), Squared	Employment and hours	2.428
Unemployment Rate - 55 Yrs. & Over (%, sa), Squared	Employment and hours	2.393
Unemployment Level - Job Leavers (thous of pers., sa), Squared	Employment and hours	2.392
New priv.hous. units auth. by buil.per.: 1-unit struc.: Albuquerque, NM (units, sa)	Housing	2.359
CPI-U: Rent of Shelter (Dec 1982=100, sa)	Price indices	2.349
New priv.hous. units auth. by buil.per.: 1-unit struc.: St. Louis, MO-IL (units, sa), Squared	Housing	2.336
Savings and Small Time Deposits - Total (bn of usd, nsa)	Monetary measures	2.316
Total Revolving Credit Owned and Securitized, Outstanding (bn of usd, nsa)	Bond market	2.288
Personal interest payments (bn of usd, sa)	Personal income and expenditures	2.281
U.S. Exports of Goods by F.A.S. Basis to South Korea (MM of usd, nsa)	Exports and imports	2.272
Initial Claims (number, sa)	Employment and hours	2.255
Initial Claims (number, sa), Squared	Employment and hours	2.243
M2 Money Stock (bn of usd, nsa)	Monetary measures	2.240
EMVT: Housing And Land Management(Index, nsa)	Equity market	2.223
New priv.hous. units auth. by buil.per.: 1-unit struc.: Albuquerque, NM (units, sa), Squared	Housing	2.205
Other Checkable Deposits at Commercial Banks (bn of usd, sa), Squared	Monetary measures	2.180
Unemployment Level - Job Leavers (thous of pers., sa)	Employment and hours	2.171
Personal outlays (bn of usd, sa)	Personal income and expenditures	2.150
CPI-U: Tuition, Other School Fees, and Childcare (1982-1984=100, sa)	Price indices	2.148
IP: Nondurable manufacturing: Food, beverage, and tobacco (2012=100, sa)	Real output measures	2.148
Total Consumer Credit Owned and Securitized, Outstanding (bn of usd, nsa)	Bond market	2.141
Unemployment Rate - 35-44 Yrs. (%, sa), Squared	Employment and hours	2.139
Avg hr earnings of Production & Nonsupervisory Employees, Tot priv (usd per Hour, sa), Squared	Employment and hours	2.123
Initial Claims in Connecticut (number, nsa)	Employment and hours	2.122
New priv. housing units auth. by building permits: 1-unit structures: Texas (units, sa), Squared	Housing	2.115
Non-M1 Components of M2 (bn of usd, nsa)	Monetary measures	2.110

CPI-U: Shelter (1982-1984=100, sa)	Price indices	2.091
CU: Nondurable Manufacturing: Food, beverage, and tobacco (% of capacity, sa)	Real output measures	2.082
Other Checkable Deposits (bn of usd, sa)	Monetary measures	2.082
CPI-U & clerical workers: tuition, oth. sch. fees, & childcare (1982-1984=100, sa), Squared	Price indices	2.081
Total Revolving Credit Owned and Securitized, Outstanding (bn of usd, sa)	Bond market	2.080
EMVT: Trade Policy(Index, nsa), Squared	Equity market	2.076
LI OECD: Component series: Interest rate spread: Normalised, US (Index, nsa)	Leading indicators	2.052
S&P/Case-Shiller NC-Charlotte HPI (Jan 2000=100, sa)	Housing	2.051
Initial Claims in Alaska (number, nsa), Squared	Employment and hours	2.032
New priv.hous. units auth. by buil.per.: 1-unit struc.: Pueblo, CO (units, sa)	Housing	2.023
CPI-U: Rent of Shelter (Dec 1982=100, sa), Squared	Price indices	2.017
New priv.hous. units auth. by buil.per.: 1-unit struc.: Arizona (units, sa)	Housing	2.015
CU: Communications equipment (% of capacity, sa)	Real output measures	2.015
Number Unemployed for 27 Weeks & Over (thous of pers., sa), Squared	Employment and hours	2.009
U.S. Imports of Goods by Customs Basis from China (MM of usd, nsa), Squared	Exports and imports	1.992
Unemployment Rate - Hispanic or Latino (%, sa), Squared	Employment and hours	1.980
Unemployment Rate: Aged 55-64: All Persons for the United States (%, sa), Squared	Employment and hours	1.975
CPI-U: Shelter (1982-1984=100, sa), Squared	Price indices	1.972
New priv.hous. units auth. by buil.per.: 1-unit struc.: Houston, TX (units, sa), Squared	Housing	1.971
Current UOs; % Reporting Increases for FRB - Philadelphia District (%, sa), Squared	Manufacturing activity	1.970
CPI-U: Tobacco and Smoking Products (1982-1984=100, sa), Squared	Price indices	1.962
Pers. cur. transf. receipts: Gov.social benefits to pers.: Unemp.insurance (bn of usd, sa), Squared	Personal income and expenditures	1.962
PCE (bn of usd, sa)	Personal income and expenditures	1.959
Total Consumer Credit Owned and Securitized, Outstanding (bn of usd, sa)	Bond market	1.959
New One Family Homes for Sale in the United States (thous of units, sa)	Housing	1.950
Leading Index for Connecticut (%, sa)	Leading indicators	1.947
AEWT: Merc. wholesalers, dur.goods in Riverside-San BO, CA (thous of pers., sa)	Employment and hours	1.933
Housing Starts: 2-4 units (thous of units, sa)	Housing	1.921
Job Leavers as a % of Total Unemployed (%, sa), Squared	Employment and hours	1.918
U.S. Exports of Goods by F.A.S. Basis to Mexico (MM of usd, nsa), Squared	Exports and imports	1.911
IP: Durable Goods: Engine, turbine, and power transmission equipment (2012=100, sa)	Real output measures	1.909
PPI-C: Final Demand: Priv. capital equip.: Manufacturing Industries (1982=100, sa)	Price indices	1.907
Other Checkable Deposits at Commercial Banks (bn of usd, sa)	Monetary measures	1.903
Employment-Population Ratio - 25-54 Yrs. (%, sa), Squared	Employment and hours	1.896
New priv.hous. units auth. by buil.per.: 1-unit struc.: Phoenix-Mesa-C, AZ (units, sa)	Housing	1.895
IP: Nondurable Consumer Goods (2012=100, sa), Squared	Real output measures	1.893
Initial Claims in Georgia (number, nsa)	Employment and hours	1.878
CPI-U: Tobacco and Smoking Products (1982-1984=100, sa)	Price indices	1.874
CU: Nondurable Manufacturing: Food (% of capacity, sa)	Real output measures	1.874
Initial Claims in Connecticut (number, nsa), Squared	Employment and hours	1.858
Employment Level - All Industries Self-Employed, Unincorporated (thous of pers., sa)	Employment and hours	1.847
PCE: Market-based (bn of usd, sa)	Personal income and expenditures	1.843
EMVT: Trade Policy(Index, nsa)	Equity market	1.832
Rental income of persons with capital consumption adjustment (bn of usd, sa), Squared	Personal income and expenditures	1.820
Leading Index for Louisiana (%, sa), Squared	Leading indicators	1.813
IP: Electric power generation, transmission, and distribution (2012=100, sa)	Real output measures	1.808
Leading Index for Louisiana (%, sa)	Leading indicators	1.801
U.S. Exports of Goods by F.A.S. Basis to World (MM of usd, nsa), Squared	Exports and imports	1.798
Initial Claims in Florida (number, nsa)	Employment and hours	1.792
HPI (Low Tier) for New York, New York (Jan 2000=100, sa)	Housing	1.791
Employment Level - All Industries Self-Employed, Unincorporated (thous of pers., sa), Squared	Employment and hours	1.791
Employment Level - PT Eco Reasons, Slack Work/Bus. Con., All Ind. (thous of pers., sa)	Employment and hours	1.790
All Employees, Residential Building (thous of pers., sa), Squared	Employment and hours	1.788
Indexes of agg. wkly hrs of prod&nonsup. employees, Construction (2002=100, sa)	Employment and hours	1.782
CU: Electric power generation, transmission, and distribution (% of capacity, sa)	Real output measures	1.776

$\hat{\beta}_3$: 12 months ahead		
Variable name	Category	t-stat
PPI-C: Final Demand: Finished Consumer Foods, Crude (1982=100, sa), Squared	Price indices	4.292

Leading Index for Louisiana (%, sa)	Leading indicators	4.162
Instantaneous Forward Term Premium 5 Years Hence (%, nsa)	Miscellaneous	4.136
U.S. Exports of Goods by F.A.S. Basis to Japan (MM of usd, nsa), Squared	Exports and imports	3.360
CU: Crude processing (% of capacity, sa)	Real output measures	3.195
New One Family Homes for Sale in the United States (thous of units, sa)	Housing	3.127
Leading Index for Alaska (%, sa), Squared	Leading indicators	3.070
IP: Durable Goods: Aircraft and parts (2012=100, sa)	Real output measures	2.941
IP: Mining (2012=100, sa)	Real output measures	2.919
Leading Index for Mississippi (%, sa)	Leading indicators	2.915
Leading Index for Mississippi (%, sa), Squared	Leading indicators	2.903
IP: Business Equipment (2012=100, sa)	Real output measures	2.889
CU: Mining (% of capacity, sa)	Real output measures	2.880
PPI-C: Farm Products: Slaughter Hogs (1982=100, sa)	Price indices	2.877
Instantaneous Forward Term Premium 5 Years Hence (%, nsa), Squared	Miscellaneous	2.876
Leading Index for Louisiana (%, sa), Squared	Leading indicators	2.873
U.S. Government Demand Deposits at Commercial Banks (bn of usd, nsa)	Monetary measures	2.872
Leading Index for Alaska (%, sa)	Leading indicators	2.868
CU: Durable Manuf.: Aerosp. and miscellaneous transp. equip. (% of capacity, sa)	Real output measures	2.810
Fama-French Conservative-minus-Aggressive (%, nsa), Squared	Equity market	2.794
New priv.hous. units auth. by buil.per.: 1-unit struc.: Memphis, TN-MS-AR (units, sa), Squared	Housing	2.779
CU: Crude processing (% of capacity, sa), Squared	Real output measures	2.772
U.S. Government Demand Deposits at Commercial Banks (bn of usd, nsa), Squared	Monetary measures	2.761
IP: Durable manufacturing: Aerospace&miscellaneous transp.equip. (2012=100, sa)	Real output measures	2.727
IP: Mining: Oil and gas extraction (2012=100, sa)	Real output measures	2.723
CU: Oil and gas extraction (% of capacity, sa)	Real output measures	2.712
Continued Claims (Insured Unemployment) in Illinois (number, nsa)	Employment and hours	2.696
PPI-C: Final Demand: Finished Consumer Foods (1982=100, sa)	Price indices	2.687
IP: Mining: Crude oil (2012=100, sa)	Real output measures	2.685
Leading Index for Illinois (%, sa)	Leading indicators	2.683
Current NOs; Diffusion for FRB - Philadelphia District (Index, sa)	Manufacturing activity	2.672
PI Receipts on Assets: Personal Interest Income (bn of usd, sa)	Personal income and expenditures	2.642
Unemployment Rate - 55 Yrs. & Over (%, sa), Squared	Employment and hours	2.634
Current Unfilled Orders; Diffusion for FRB - Philadelphia District (Index, sa)	Manufacturing activity	2.616
All Employees, Mining and Logging (thous of pers., sa)	Employment and hours	2.584
Continued Claims (Insured Unemployment) in Connecticut (number, nsa)	Employment and hours	2.579
Initial Claims (number, sa)	Employment and hours	2.576
Indexes of agg. wkly hrs of prod&nonsup. employees, mining&logging (2002=100, sa)	Employment and hours	2.564
CU: Nondurable Manufacturing: Chemical (% of capacity, sa), Squared	Real output measures	2.544
IP: Materials (2012=100, sa)	Real output measures	2.542
All Employees, Goods-Producing (thous of pers., sa)	Employment and hours	2.519
India / U.S. Foreign Exchange Rate (Ratio, nsa), Squared	Miscellaneous	2.510
IP: Nondurable manufacturing: Chemical (2012=100, sa), Squared	Real output measures	2.508
CU: Mining (% of capacity, sa), Squared	Real output measures	2.494
All Employees, Mining (thous of pers., sa)	Employment and hours	2.485
IP: Mining: Crude oil (2012=100, sa), Squared	Real output measures	2.470
IP: Mining (2012=100, sa), Squared	Real output measures	2.469
Instantaneous Forward Term Premium 6 Years Hence (%, nsa), Squared	Miscellaneous	2.460
Continued Claims (Insured Unemployment) in Maryland (number, nsa)	Employment and hours	2.452
S&P/Case-Shiller NC-Charlotte HPI (Jan 2000=100, sa)	Housing	2.450
Small Time Deposits at Commercial Banks (bn of usd, sa)	Monetary measures	2.443
Continued Claims (Insured Unemployment) in Kansas (number, nsa)	Employment and hours	2.441
LI OECD: Component series: Interest rate spread: Normalised, US (Index, nsa)	Leading indicators	2.433
Unemployment Rate - Hispanic or Latino (%, sa), Squared	Employment and hours	2.430
Initial Claims in Wyoming (number, nsa), Squared	Employment and hours	2.423
Business tendency - manuf.: Confidence Indicators: Composite Indicators (Net %, sa)	Sentiment	2.382
LI OECD: Component series: BTS - Business situation: Original series, US (%, sa)	Leading indicators	2.382
Personal interest payments (bn of usd, sa)	Personal income and expenditures	2.377
Continued Claims (Insured Unemployment) in Mississippi (number, nsa), Squared	Employment and hours	2.377
Initial Claims in Connecticut (number, nsa)	Employment and hours	2.369
CU: Total ex. Comp., communications equip., and semiconductors (% of capacity, sa)	Real output measures	2.367

University of Michigan: Consumer Sentiment (1966:Q1=100, nsa), Squared	Sentiment	2.359
LI OECD: Component series: CS - Confidence indicator: Original series, US (Index, sa), Squared	Leading indicators	2.359
Industrial Production Index (2012=100, sa)	Real output measures	2.343
Production of Total Industry in United States (2015=100, sa)	Real output measures	2.343
1Y Treasury Constant Maturity Minus Federal Funds Rate (%, nsa)	Bond market	2.338
New priv.hous. units auth. by buil.per.: 1-unit struc.: Florida (units, sa), Squared	Housing	2.337
Current UOs; % Reporting Increases for FRB - Philadelphia District (%, sa)	Manufacturing activity	2.326
CU: Oil and gas extraction (% of capacity, sa), Squared	Real output measures	2.321
IP: Mining: Oil and gas extraction (2012=100, sa), Squared	Real output measures	2.309
M2 Less Small Time Deposits (bn of usd, sa)	Monetary measures	2.307
Unemployment Rate: Aged 55-64: All Persons for the United States (%, sa), Squared	Employment and hours	2.305
Initial Claims in Wyoming (number, nsa)	Employment and hours	2.299
Small Time Deposits at Commercial Banks (bn of usd, nsa)	Monetary measures	2.285
IP: Durable manufacturing: Machinery (2012=100, sa)	Real output measures	2.280
PPI-C: Farm Products: Slaughter Hogs (1982=100, sa), Squared	Price indices	2.274
CU: Durable Manufacturing: Machinery (% of capacity, sa)	Real output measures	2.269
Continued Claims (Insured Unemployment) in Colorado (number, nsa)	Employment and hours	2.268
Capacity Utilization: Total Industry (% of capacity, sa)	Real output measures	2.266
Current UOs; % Reporting Decreases for FRB - Philadelphia District (%, sa)	Manufacturing activity	2.265
Current UOs; % Reporting Increases for FRB - Philadelphia District (%, sa), Squared	Manufacturing activity	2.262
Hong Kong / U.S. Foreign Exchange Rate (Ratio, nsa), Squared	Miscellaneous	2.260
Initial Claims (number, nsa)	Employment and hours	2.253
CU: Manufacturing excluding hi-tech and motor vehicles and parts (% of capacity, sa)	Real output measures	2.251
Experimental CPI: Medical Care(1982=100, sa), Squared	Price indices	2.248
Savings Deposits - Total (bn of usd, sa)	Monetary measures	2.232
IP: Durable Goods: HVAC, metalworking, & power transmission mach.(2012=100, sa)	Real output measures	2.230
Initial Claims in New Jersey (number, nsa)	Employment and hours	2.220
Business tendency - manuf.: Capacity Utilization (% of capacity, sa)	Sentiment	2.218
Indexes of agg. wkly hrs of prod&nonsup. employees, Construction (2002=100, sa)	Employment and hours	2.216
CPI-U: Alcoholic Beverages (1982-1984=100, sa), Squared	Price indices	2.206
Initial Claims in Ohio (number, nsa)	Employment and hours	2.205
Instantaneous Forward Term Premium 6 Years Hence (%, nsa)	Miscellaneous	2.196
Initial Claims in Pennsylvania (number, nsa)	Employment and hours	2.185
Initial Claims in Indiana (number, nsa)	Employment and hours	2.185
Leading Index for Oklahoma (%, sa), Squared	Leading indicators	2.171
6M Treasury Constant Maturity Minus Federal Funds Rate (%, nsa)	Bond market	2.170
Initial Claims in Illinois (number, nsa)	Employment and hours	2.169
Leading Index for Kansas (%, sa)	Leading indicators	2.167
Average Weeks Unemployed (Weeks, sa)	Employment and hours	2.165

7.3 Appendix 3: Data Description

All explanatory variables used in our forecast model are presented in this appendix. The first table gives an overview of the sources for the variables, with both a short form and the source description.

Short	**Source**
ADP	Automatic Data Processing, Inc.
BBD	Baker, Scott R., Bloom, Nick, Davis, Stephen J.
FED	Board of Governors of the Federal Reserve System (US)
CBOE	Chicago Board Options Exchange
EPU	Economic Policy Uncertainty
Euronext	Euronext Paris
FRBA	Federal Reserve Bank of Atlanta
FRBD	Federal Reserve Bank of Dallas
FRBN	Federal Reserve Bank of New York
FRBP	Federal Reserve Bank of Philadelphia
FRBR	Federal Reserve Bank of Richmond
FRBSF	Federal Reserve Bank of San Francisco
FRBSL	Federal Reserve Bank of St. Louis
ISM	Institute of Supply Management
IMF	International Monetary Fund
French	Kenneth R. French
Moodys	Moody's Corporation
NASDAQ	Nasdaq Composite
NAR	National Association of Realtors
Nikkei	Nikkei Industry Research Institute
OECD	Organization for Economic Co-operation and Development
Shiller	Robert Shiller
SPDJ	S&P Dow Jones Indices LLC
SC	Sahm, Claudia
SSE	Shanghai Stock Exchange
NYSE	The New York Stock Exchange
BEA	U.S. Bureau of Economic Analysis
BEACB	U.S. Bureau of Economic Analysis, U.S. Census Bureau
BLS	U.S. Bureau of Labor Statistics
USCB	U.S. Census Bureau
DHUD	U.S. Census Bureau, Dep. of Housing and Urban Development
USDT	U.S. Department of the Treasury
ETA	U.S. Employment and Training Administration
FHFA	U.S. Federal Housing Finance Agency
UM	University of Michigan
Yale	Yale School of Management

Table 23: List of sources for the explanatory variables

All 1196 variables are listed up in the table below. The vast majority of the variables are retrieved from the Federal Reserve Bank of St.Louis Economic Data (FRED) through their self-developed Excel Add-in, while the remaining variables are retrieved from the following sources: Chicago Board Options Exchange (CBOE), Yale School of Management - International Center of Finance, Bloomberg, Yahoo Finance, and the home page of both Kenneth R. French and Robert Shiller. The columns in the table are structured as follows: series number, ticker symbol, monthly date range, type of transformation, the source of the data and a short description of each variable. This description displays the *unit type*, i.e. whether it is an index, a ratio, an monetary amount, etc. In addition, we get information about whether the time series are seasonally adjusted (SA), or not (NSA). Finally the structure of our transformation codes are as follows: 1 = logarithm, 2 = log first differences, 3 = log second differences, 4 = first differences in percent , 5 = first differences in absolute value , 6 = second differences in absolute value , 7 = no transformation (Level).

Bond market					
1	AAA	1989:01-2020:02	7	Moodys	Moody's Seasoned Aaa Corporate Bond Yield (%, nsa)
2	BBB	1989:01-2020:02	7	Moodys	Moody's Seasoned Baa Corporate Bond Yield (%, nsa)
3	TB3MS	1989:01-2020:02	7	FED	3-Month Treasury Bill: Secondary Market Rate (%, nsa)
4	GS3M	1989:01-2020:02	7	FED	3-Month Treasury Constant Maturity Rate (%, nsa)
5	TB6MS	1989:01-2020:02	7	FED	6-Month Treasury Bill: Secondary Market Rate (%, nsa)
6	GS6M	1989:01-2020:02	7	FED	6-Month Treasury Constant Maturity Rate (%, nsa)
7	GS1	1989:01-2020:02	7	FED	1-Year Treasury Constant Maturity Rate (%, nsa)
8	GS5	1989:01-2020:02	7	FED	5-Year Treasury Constant Maturity Rate (%, nsa)
9	GS10	1989:01-2020:02	7	FED	10-Year Treasury Constant Maturity Rate (%, nsa)
Capacity Utilization measures (CU)					
10	TCU	1967:01-2020:01	2	FED	Capacity Utilization: Total Industry (% of capacity, sa)
11	CAPUTLN2121S	1967:01-2020:01	2	FED	CU: Coal mining (% of capacity, sa)
12	CAPUTLG3342S	1972:01-2020:01	2	FED	CU: Communications equipment (% of capacity, sa)
13	CAPUTLG3341S	1972:01-2020:01	2	FED	CU: Computer and peripheral equipment (% of capacity, sa)
14	CAPUTLHITEK2S	1967:01-2020:01	2	FED	CU: Computers, communications equipment, and semiconductors (% of capacity, sa)
15	CAPUTLB5610CS	1967:01-2020:01	2	FED	CU: Crude processing (% of capacity, sa)
16	CAPUTLG3364T9S	1948:01-2020:01	2	FED	CU: Durable Manuf.: Aerosp. and miscellaneous transp. equip. (% of capacity, sa)
17	CAPUTLG335S	1972:01-2020:01	2	FED	CU: Durable Manuf.: Electrical equip., appliance, and component (% of capacity, sa)
18	CAPUTLGMFDS	1967:01-2020:01	2	FED	CU: Durable Manufacturing (% of capacity, sa)
19	CAPUTLG33611S	1972:01-2020:01	2	FED	CU: Durable Manuf.: Automobile and light duty motor vehicle (% of capacity, sa)
20	CAPUTLG334S	1972:01-2020:01	2	FED	CU: Durable Manufacturing: Computer and electronic product (% of capacity, sa)
21	CAPUTLG332S	1948:01-2020:01	2	FED	CU: Durable Manufacturing: Fabricated metal product (% of capacity, sa)
22	CAPUTLG337S	1967:01-2020:01	2	FED	CU: Durable Manufacturing: Furniture and related product (% of capacity, sa)
23	CAPUTLG3311A2S	1972:01-2020:01	2	FED	CU: Durable manufacturing: Iron and steel products (% of capacity, sa)
24	CAPUTLG333S	1967:01-2020:01	2	FED	CU: Durable Manufacturing: Machinery (% of capacity, sa)
25	CAPUTLG339S	1972:01-2020:01	2	FED	CU: Durable Manufacturing: Miscellaneous (% of capacity, sa)
26	CAPUTLG3361T3S	1948:01-2020:01	2	FED	CU: Durable Manufacturing: Motor vehicles and parts (% of capacity, sa)
27	CAPUTLG327S	1948:01-2020:01	2	FED	CU: Durable Manufacturing: Nonmetallic mineral product (% of capacity, sa)
28	CAPUTLG331S	1967:01-2020:01	2	FED	CU: Durable Manufacturing: Primary metal (% of capacity, sa)
29	CAPUTLG336S	1967:01-2020:01	2	FED	CU: Durable Manufacturing: Transportation equipment (% of capacity, sa)
30	CAPUTLG321S	1972:01-2020:01	2	FED	CU: Durable Manufacturing: Wood product (% of capacity, sa)
31	CAPUTLG2211A2S	1967:01-2020:01	2	FED	CU: Electric and gas utilities (% of capacity, sa)
32	CAPUTLG2211S	1967:01-2020:01	2	FED	CU: Electric power generation, transmission, and distribution (% of capacity, sa)
33	CAPUTLB5640CS	1948:01-2020:01	2	FED	CU: Finished processing (% of capacity, sa)
34	CAPUTLX4HTK2S	1967:01-2020:01	2	FED	CU: Manuf. ex. comp., communications equip., & semiconductors (% of capacity, sa)
35	MCUMFN	1972:01-2020:01	2	FED	CU: Manufacturing (NAICS) (% of capacity, sa)
36	CUMFNS	1948:01-2020:01	2	FED	CU: Manufacturing (SIC) (% of capacity, sa)
37	CAPUTLX4HTMVS	1967:01-2020:01	2	FED	CU: Manufacturing excluding hi-tech and motor vehicles and parts (% of capacity, sa)
38	CAPUTLG2122S	1967:01-2020:01	2	FED	CU: Metal ore mining (% of capacity, sa)
39	CAPUTLG21S	1967:01-2020:01	2	FED	CU: Mining (% of capacity, sa)
40	CAPUTLG212S	1972:01-2020:01	2	FED	CU: Mining (except oil and gas) (% of capacity, sa)
41	CAPUTLG2212S	1967:01-2020:01	2	FED	CU: Natural gas distribution (% of capacity, sa)

42	CAPUTLGMFNS	1967:01-2020:01	2	FED	CU: Nondurable manufacturing (% of capacity, sa)
43	CAPUTLG315S	1972:01-2020:01	2	FED	CU: Nondurable Manufacturing: Apparel (% of capacity, sa)
44	CAPUTLG315A6S	1972:01-2020:01	2	FED	CU: Nondurable Manufacturing: Apparel and leather goods (% of capacity, sa)
45	CAPUTLG312S	1972:01-2020:01	2	FED	CU: Nondurable Manufacturing: Beverage and tobacco product (% of capacity, sa)
46	CAPUTLG325S	1948:01-2020:01	2	FED	CU: Nondurable Manufacturing: Chemical (% of capacity, sa)
47	CAPUTLG311S	1972:01-2020:01	2	FED	CU: Nondurable Manufacturing: Food (% of capacity, sa)
48	CAPUTLG311A2S	1967:01-2020:01	2	FED	CU: Nondurable Manufacturing: Food, beverage, and tobacco (% of capacity, sa)
49	CAPUTLG316S	1967:01-2020:01	2	FED	CU: Nondurable Manufacturing: Leather and allied product (% of capacity, sa)
50	CAPUTLGMFOS	1972:01-2020:01	7	FED	CU: Nondurable Manufacturing: Other manufacturing (% of capacity, sa)
51	CAPUTLG322S	1948:01-2020:01	2	FED	CU: Nondurable Manufacturing: Paper (% of capacity, sa)
52	CAPUTLG324S	1948:01-2020:01	2	FED	CU: Nondurable Manufacturing: Petroleum and coal products (% of capacity, sa)
53	CAPUTLG326S	1948:01-2020:01	2	FED	CU: Nondurable Manufacturing: Plastics and rubber products (% of capacity, sa)
54	CAPUTLG323S	1972:01-2020:01	2	FED	CU: Nondurable Manuf.: Printing & related support activities (% of capacity, sa)
55	CAPUTLG325212S	1972:01-2020:01	2	FED	CU: Nondurable Manufacturing: Synthetic rubber (% of capacity, sa)
56	CAPUTLG313S	1972:01-2020:01	2	FED	CU: Nondurable Manufacturing: Textile mills (% of capacity, sa)
57	CAPUTLG314S	1972:01-2020:01	2	FED	CU: Nondurable Manufacturing: Textile product mills (% of capacity, sa)
58	CAPUTLG313A4S	1972:01-2020:01	2	FED	CU: Nondurable Manufacturing: Textiles and products (% of capacity, sa)
59	CAPUTLG2123S	1967:01-2020:01	2	FED	CU: Nonmetallic mineral mining and quarrying (% of capacity, sa)
60	CAPUTLG211S	1972:01-2020:01	2	FED	CU: Oil and gas extraction (% of capacity, sa)
61	CAPUTLB562A3CS	1948:01-2020:01	2	FED	CU: Primary and semifinished processing (% of capacity, sa)
62	CAPUTLG213S	1972:01-2020:01	2	FED	CU: Support activities for mining (% of capacity, sa)
63	CAPUTLX50HTKS	1967:01-2020:01	2	FED	CU: Total ex. Comp., communications equip., and semiconductors (% of capacity, sa)
64	CAPG2211S	1967:01-2020:01	3	FED	Indu. Capacity: Utilities: Electric power gen., transmission, and dist. (2012=100, sa)
Consumer Price Index (CPI)					
65	CPIAUCSL	1947:01-2020:02	2	BLS	CPI-U: All Items (1982-1984=100, sa)
66	CWSR0000SEFV	1953:01-2020:02	2	BLS	CPI-U & clerical workers: food away from home in U.S. City avg. (1982-1984=100, sa)
67	CWSR0000SAF112	1967:01-2020:02	2	BLS	CPI-U & clerical workers: meats, poultry, fish, & eggs (1982-1984=100, sa)
68	CWSR0000SA0	1947:01-2020:02	2	BLS	CPI-U & clerical workers: All Items (1982-1984=100, sa)
69	CWSR0000SAH	1967:01-2020:02	2	BLS	CPI-U & clerical workers: Housing (1982-1984=100, sa)
70	CWSR0000SEEB	1978:01-2020:02	2	BLS	CPI-U & clerical workers: tuition, oth. sch. fees, & childcare (1982-1984=100, sa)
71	CUSR0000SAF115	1967:01-2020:02	2	BLS	CPI-U: all urb.consumers: Food at Home in U.S. City avg. (1982-1984=100, sa)
72	CUSR0000SETG01	1989:01-2020:02	2	BLS	CPI-U: Airline Fares (1982-1984=100, sa)
73	CUSR0000SAF116	1967:01-2020:02	2	BLS	CPI-U: Alcoholic Beverages (1982-1984=100, sa)
74	CUSR0000SEFW	1978:01-2020:02	2	BLS	CPI-U: Alcoholic Beverages at Home (1982-1984=100, sa)
75	CUSR0000SEFX	1978:01-2020:02	2	BLS	CPI-U: Alcoholic Beverages Away From Home (1982-1984=100, sa)
76	CPILEGSL	1957:01-2020:02	2	BLS	CPI-U: All Items Less Energy (1982-1984=100, sa)
77	CPIULFSL	1947:01-2020:02	2	BLS	CPI-U: All Items Less Food (1982-1984=100, sa)
78	CPILFESL	1957:01-2020:02	2	BLS	CPI-U: All Items Less Food and Energy (1982-1984=100, sa)
79	CUSR0000SA0L5	1957:01-2020:02	2	BLS	CPI-U: All Items Less Medical Care (1982-1984=100, sa)
80	CUSR0000SA0L2	1947:01-2020:02	2	BLS	CPI-U: All Items Less Shelter (1982-1984=100, sa)
81	CPIAPPSL	1947:01-2020:02	2	BLS	CPI-U: Apparel (1982-1984=100, sa)
82	CUSR0000SA311	1947:01-2020:02	2	BLS	CPI-U: Apparel Less Footwear (1982-1984=100, sa)
83	CUSR0000SAF111	1989:01-2020:02	2	BLS	CPI-U: Cereals and Bakery Products (1982-1984=100, sa)
84	CUSR0000SAC	1956:01-2020:02	2	BLS	CPI-U: Commodities (1982-1984=100, sa)
85	CUSR0000SACL1	1956:01-2020:02	2	BLS	CPI-U: Commodities Less Food (1982-1984=100, sa)
86	CUSR0000SACL1E	1957:01-2020:02	2	BLS	CPI-U: Commodities Less Food and Energy Commodities (1982-1984=100, sa)
87	CUSR0000SEFJ	1989:01-2020:02	2	BLS	CPI-U: Dairy and Related Products (1982-1984=100, sa)
88	CUSR0000SAD	1956:01-2020:02	1	BLS	CPI-U: Durables (1982-1984=100, sa)
89	CUSR0000SEEA	1967:01-2020:02	2	BLS	CPI-U: Educational Books and Supplies (1982-1984=100, sa)
90	CUSR0000SEHF01	1952:01-2020:02	2	BLS	CPI-U: Electricity (1982-1984=100, sa)
91	CPIENGSL	1957:01-2020:02	2	BLS	CPI-U: Energy (1982-1984=100, sa)
92	CUSR0000SACE	1957:01-2020:02	2	BLS	CPI-U: Energy Commodities (1982-1984=100, sa)
93	CUSR0000SEHF	1947:01-2020:02	2	BLS	CPI-U: Energy Services (1982-1984=100, sa)
94	CPIUFDSL	1947:01-2020:02	2	BLS	CPI-U: Food (1982-1984=100, sa)
95	CPIFABSL	1967:01-2020:02	2	BLS	CPI-U: Food and Beverages (1982-1984=100, sa)
96	CUSR0000SAF11	1952:01-2020:02	2	BLS	CPI-U: Food at Home (1982-1984=100, sa)
97	CUSR0000SEFV	1953:01-2020:02	2	BLS	CPI-U: Food Away From Home (1982-1984=100, sa)
98	CUSR0000SEAE	1947:01-2020:02	2	BLS	CPI-U: Footwear (1982-1984=100, sa)
99	CUSR0000SAF113	1947:01-2020:02	2	BLS	CPI-U: Fruits and Vegetables (1982-1984=100, sa)

100	CUSR0000SEHE	1947:01-2020:02	2	BLS	CPI-U: Fuel Oil and Other Fuels (1982-1984=100, sa)
101	CUSR0000SAH2	1953:01-2020:02	2	BLS	CPI-U: Fuels and Utilities (1982-1984=100, sa)
102	CUSR0000SETB01	1967:01-2020:02	2	BLS	CPI-U: Gasoline (All Types) (1982-1984=100, sa)
103	CUSR0000SEMD	1978:01-2020:02	2	BLS	CPI-U: Hospital and Related Services (1982-1984=100, sa)
104	CUSR0000SAH21	1967:01-2020:02	2	BLS	CPI-U: Household Energy (1982-1984=100, sa)
105	CUSR0000SAH3	1967:01-2020:02	2	BLS	CPI-U: Household Furnishings and Operations (1982-1984=100, sa)
106	CPIHOSSL	1967:01-2020:02	2	BLS	CPI-U: Housing (1982-1984=100, sa)
107	CUSR0000SAF112	1967:01-2020:02	2	BLS	CPI-U: Meats, Poultry, Fish, and Eggs (1982-1984=100, sa)
108	CPIMEDSL	1947:01-2020:02	2	BLS	CPI-U: Medical Care (1982-1984=100, sa)
109	CUSR0000SAM1	1967:01-2020:02	2	BLS	CPI-U: Medical Care Commodities (1982-1984=100, sa)
110	CUSR0000SAM2	1956:01-2020:02	2	BLS	CPI-U: Medical Care Services (1982-1984=100, sa)
111	CUSR0000SAA1	1947:01-2020:02	2	BLS	CPI-U: Men's and Boys' Apparel (1982-1984=100, sa)
112	CUSR0000SETB	1967:01-2020:02	2	BLS	CPI-U: Motor Fuel (1982-1984=100, sa)
113	CUSR0000SETD	1967:01-2020:02	2	BLS	CPI-U: Motor Vehicle Maintenance and Repair (1982-1984=100, sa)
114	CUSR0000SETA01	1953:01-2020:02	2	BLS	CPI-U: New Vehicles (1982-1984=100, sa)
115	CUSR0000SAF114	1947:01-2020:02	2	BLS	CPI-U: Nonalcoholic Beverages and Beverage Materials (1982-1984=100, sa)
116	CUSR0000SAN	1956:01-2020:02	2	BLS	CPI-U: Nondurables (1982-1984=100, sa)
117	CPIOGSSL	1967:01-2020:02	2	BLS	CPI-U: Other Goods and Services (1982-1984=100, sa)
118	CUSR0000SEHC01	1983:01-2020:02	2	BLS	CPI-U: Owners' Equivalent Rent of Primary Residence (Dec 1982=100, sa)
119	CUSR0000SEHC	1983:01-2020:02	2	BLS	CPI-U: Owners' Equivalent Rent of Residences (Dec 1982=100, sa)
120	CUSR0000SEMC	1980:01-2020:02	2	BLS	CPI-U: Professional Services (1982-1984=100, sa)
121	CUSR0000SEHA	1981:01-2020:02	2	BLS	CPI-U: Rent of Primary Residence (1982-1984=100, sa)
122	CUSR0000SAS2RS	1990:01-2020:02	2	BLS	CPI-U: Rent of Shelter (Dec 1982=100, sa)
123	CUSR0000SAS	1956:01-2020:02	2	BLS	CPI-U: Services (1982-1984=100, sa)
124	CUSR0000SEMC04	1989:01-2020:02	2	BLS	CPI-U: Services by Other Medical Professionals (Dec 1986=100, sa)
125	CUSR0000SASLE	1967:01-2020:02	2	BLS	CPI-U: Services Less Energy Services (1982-1984=100, sa)
126	CUSR0000SASL5	1983:01-2020:02	2	BLS	CPI-U: Services Less Medical Care Services (1982-1984=100, sa)
127	CUSR0000SASL2RS	1985:01-2020:02	2	BLS	CPI-U: Services Less Rent of Shelter (Dec 1982=100, sa)
128	CUSR0000SAH1	1953:01-2020:02	2	BLS	CPI-U: Shelter (1982-1984=100, sa)
129	CUSR0000SEFR	1989:01-2020:02	2	BLS	CPI-U: Sugar and Sweets (1982-1984=100, sa)
130	CUSR0000SEGA	1986:01-2020:02	2	BLS	CPI-U: Tobacco and Smoking Products (1982-1984=100, sa)
131	CUSR0000SERE01	1978:01-2020:02	7	BLS	CPI-U: Toys (1982-1984=100, sa)
132	CPITRNSL	1947:01-2020:02	2	BLS	CPI-U: Transportation (1982-1984=100, sa)
133	CUSR0000SAS4	1956:01-2020:02	2	BLS	CPI-U: Transportation Services (1982-1984=100, sa)
134	CUSR0000SEEB	1978:01-2020:02	2	BLS	CPI-U: Tuition, Other School Fees, and Childcare (1982-1984=100, sa)
135	CUSR0000SETA02	1953:01-2020:02	2	BLS	CPI-U: Used Cars and Trucks (1982-1984=100, sa)
136	CUSR0000SEHF02	1952:01-2020:02	2	BLS	CPI-U: Utility (Piped) Gas Service (1982-1984=100, sa)
137	CUSR0000SAA2	1947:01-2020:02	2	BLS	CPI-U: Women's and Girls' Apparel (1982-1984=100, sa)
138	CPIEHOUSE	1982:12-2020:02	2	BLS	Experimental Consumer Price Index: Housing(1982=100, sa)
139	CPIEALL	1982:12-2020:02	2	BLS	Experimental CPI: All Items(1982=100, sa)
140	CPIEAPPAREL	1982:12-2020:02	2	BLS	Experimental CPI: Apparel(1982=100, sa)
141	CPIEMEDCARE	1982:12-2020:02	2	BLS	Experimental CPI: Medical Care(1982=100, sa)
142	CPIETRANS	1982:12-2020:02	2	BLS	Experimental CPI: Transportation(1982=100, sa)
High Quality Market (HQM) Corporate Bonds					
143	HQMCB10YR	1984:01-2020:02	7	USDT	10-Year HQM Corporate Bond Spot Rate (%, nsa)
144	HQMCB20YR	1984:01-2020:02	7	USDT	20-Year HQM Corporate Bond Spot Rate (%, nsa)
145	HQMCB5YR	1984:01-2020:02	7	USDT	5-Year HQM Corporate Bond Spot Rate (%, nsa)
146	HQMCB30YR	1984:01-2020:02	7	USDT	30-Year HQM Corporate Bond Spot Rate (%, nsa)
147	HQMCB10YRP	1984:01-2020:02	7	USDT	10-Year HQM Corporate Bond Par Yield (%, nsa)
148	HQMCB1YR	1984:01-2020:02	7	USDT	1-Year HQM Corporate Bond Spot Rate (%, nsa)
149	HQMCB15YR	1984:01-2020:02	7	USDT	15-Year HQM Corporate Bond Spot Rate (%, nsa)
150	HQMCB5YRP	1984:01-2020:02	7	USDT	5-Year HQM Corporate Bond Par Yield (%, nsa)
151	HQMCB30YRP	1984:01-2020:02	7	USDT	30-Year HQM Corporate Bond Par Yield (%, nsa)
152	HQMCB2YR	1984:01-2020:02	7	USDT	2-Year HQM Corporate Bond Spot Rate (%, nsa)
153	HQMCB100YR	1984:01-2020:02	2	USDT	100-Year HQM Corporate Bond Spot Rate (%, nsa)
154	HQMCB25YR	1984:01-2020:02	7	USDT	25-Year HQM Corporate Bond Spot Rate (%, nsa)
155	HQMCB3YR	1984:01-2020:02	7	USDT	3-Year HQM Corporate Bond Spot Rate (%, nsa)
156	HQMCB50YR	1984:01-2020:02	2	USDT	50-Year HQM Corporate Bond Spot Rate (%, nsa)
157	HQMCB2YRP	1984:01-2020:02	7	USDT	2-Year HQM Corporate Bond Par Yield (%, nsa)

158	HQMCB12YR	1984:01-2020:02	7	USDT	12-Year HQM Corporate Bond Spot Rate (%, nsa)
159	HQMCB40YR	1984:01-2020:02	2	USDT	40-Year HQM Corporate Bond Spot Rate (%, nsa)
160	HQMCB7YR	1984:01-2020:02	7	USDT	7-Year HQM Corporate Bond Spot Rate (%, nsa)
161	HQMCB6MT	1984:01-2020:02	7	USDT	6 -Month HQM Corporate Bond Spot Rate (%, nsa)
162	HQMCB4YR	1984:01-2020:02	7	USDT	4-Year HQM Corporate Bond Spot Rate (%, nsa)
163	HQMCB18YR	1984:01-2020:02	7	USDT	18-Year HQM Corporate Bond Spot Rate (%, nsa)
164	HQMCB8YR	1984:01-2020:02	7	USDT	8-Year HQM Corporate Bond Spot Rate (%, nsa)
165	HQMCB9YR	1984:01-2020:02	7	USDT	9-Year HQM Corporate Bond Spot Rate (%, nsa)
166	HQMCB6YR	1984:01-2020:02	7	USDT	6-Year HQM Corporate Bond Spot Rate (%, nsa)
167	HQMCB99YR	1984:01-2020:02	2	USDT	99-Year HQM Corporate Bond Spot Rate (%, nsa)
168	HQMCB23YR	1984:01-2020:02	7	USDT	23-Year HQM Corporate Bond Spot Rate (%, nsa)
169	HQMCB16YR	1984:01-2020:02	7	USDT	16-Year HQM Corporate Bond Spot Rate (%, nsa)
170	HQMCB51Y6M	1984:01-2020:02	2	USDT	51.5-Year HQM Corporate Bond Spot Rate (%, nsa)
171	HQMCB90YR	1984:01-2020:02	2	USDT	90-Year HQM Corporate Bond Spot Rate (%, nsa)
172	HQMCB60YR	1984:01-2020:02	2	USDT	60-Year HQM Corporate Bond Spot Rate (%, nsa)
173	HQMCB1Y6M	1984:01-2020:02	7	USDT	1.5-Year HQM Corporate Bond Spot Rate (%, nsa)
174	HQMCB6Y6M	1984:01-2020:02	7	USDT	6.5-Year HQM Corporate Bond Spot Rate (%, nsa)
175	HQMCB35YR	1984:01-2020:02	7	USDT	35-Year HQM Corporate Bond Spot Rate (%, nsa)
176	HQMCB26YR	1984:01-2020:02	7	USDT	26-Year HQM Corporate Bond Spot Rate (%, nsa)
177	HQMCB8Y6M	1984:01-2020:02	7	USDT	8.5-Year HQM Corporate Bond Spot Rate (%, nsa)
178	HQMCB69Y6M	1984:01-2020:02	2	USDT	69.5-Year HQM Corporate Bond Spot Rate (%, nsa)
179	HQMCB70YR	1984:01-2020:02	2	USDT	70-Year HQM Corporate Bond Spot Rate (%, nsa)
180	HQMCB11YR	1984:01-2020:02	7	USDT	11-Year HQM Corporate Bond Spot Rate (%, nsa)
181	HQMCB13YR	1984:01-2020:02	7	USDT	13-Year HQM Corporate Bond Spot Rate (%, nsa)
182	HQMCB79Y6M	1984:01-2020:02	2	USDT	79.5-Year HQM Corporate Bond Spot Rate (%, nsa)
183	HQMCB3Y6M	1984:01-2020:02	7	USDT	3.5-Year HQM Corporate Bond Spot Rate (%, nsa)
184	HQMCB5Y6M	1984:01-2020:02	7	USDT	5.5-Year HQM Corporate Bond Spot Rate (%, nsa)
185	HQMCB7Y6M	1984:01-2020:02	7	USDT	7.5-Year HQM Corporate Bond Spot Rate (%, nsa)
186	HQMCB75YR	1984:01-2020:02	2	USDT	75-Year HQM Corporate Bond Spot Rate (%, nsa)
187	HQMCB2Y6M	1984:01-2020:02	7	USDT	2.5-Year HQM Corporate Bond Spot Rate (%, nsa)
188	HQMCB86Y6M	1984:01-2020:02	2	USDT	86.5-Year HQM Corporate Bond Spot Rate (%, nsa)
189	HQMCB14YR	1984:01-2020:02	7	USDT	14-Year HQM Corporate Bond Spot Rate (%, nsa)
190	HQMCB4Y6M	1984:01-2020:02	7	USDT	4.5-Year HQM Corporate Bond Spot Rate (%, nsa)
191	HQMCB10Y6M	1984:01-2020:02	7	USDT	10.5-Year HQM Corporate Bond Spot Rate (%, nsa)
192	HQMCB27YR	1984:01-2020:02	7	USDT	27-Year HQM Corporate Bond Spot Rate (%, nsa)
193	HQMCB66YR	1984:01-2020:02	2	USDT	66-Year HQM Corporate Bond Spot Rate (%, nsa)
194	HQMCB11Y6M	1984:01-2020:02	7	USDT	11.5-Year HQM Corporate Bond Spot Rate (%, nsa)
195	HQMCB19YR	1984:01-2020:02	7	USDT	19-Year HQM Corporate Bond Spot Rate (%, nsa)
196	HQMCB43YR	1984:01-2020:02	2	USDT	43-Year HQM Corporate Bond Spot Rate (%, nsa)
197	HQMCB59YR	1984:01-2020:02	2	USDT	59-Year HQM Corporate Bond Spot Rate (%, nsa)
198	HQMCB80YR	1984:01-2020:02	2	USDT	80-Year HQM Corporate Bond Spot Rate (%, nsa)
199	HQMCB45YR	1984:01-2020:02	2	USDT	45-Year HQM Corporate Bond Spot Rate (%, nsa)
200	HQMCB54Y6M	1984:01-2020:02	2	USDT	54.5-Year HQM Corporate Bond Spot Rate (%, nsa)
201	HQMCB81YR	1984:01-2020:02	2	USDT	81-Year HQM Corporate Bond Spot Rate (%, nsa)
202	HQMCB22YR	1984:01-2020:02	7	USDT	22-Year HQM Corporate Bond Spot Rate (%, nsa)
203	HQMCB14Y6M	1984:01-2020:02	7	USDT	14.5-Year HQM Corporate Bond Spot Rate (%, nsa)
204	HQMCB73YR	1984:01-2020:02	2	USDT	73-Year HQM Corporate Bond Spot Rate (%, nsa)
205	HQMCB21YR	1984:01-2020:02	7	USDT	21-Year HQM Corporate Bond Spot Rate (%, nsa)
206	HQMCB95Y6M	1984:01-2020:02	2	USDT	95.5-Year HQM Corporate Bond Spot Rate (%, nsa)
207	HQMCB19Y6M	1984:01-2020:02	7	USDT	19.5-Year HQM Corporate Bond Spot Rate (%, nsa)
208	HQMCB24YR	1984:01-2020:02	7	USDT	24-Year HQM Corporate Bond Spot Rate (%, nsa)
209	HQMCB31Y6M	1984:01-2020:02	7	USDT	31.5-Year HQM Corporate Bond Spot Rate (%, nsa)
210	HQMCB52YR	1984:01-2020:02	2	USDT	52-Year HQM Corporate Bond Spot Rate (%, nsa)
211	HQMCB33Y6M	1984:01-2020:02	7	USDT	33.5-Year HQM Corporate Bond Spot Rate (%, nsa)
212	HQMCB90Y6M	1984:01-2020:02	2	USDT	90.5-Year HQM Corporate Bond Spot Rate (%, nsa)
213	HQMCB41YR	1984:01-2020:02	2	USDT	41-Year HQM Corporate Bond Spot Rate (%, nsa)
214	HQMCB55YR	1984:01-2020:02	2	USDT	55-Year HQM Corporate Bond Spot Rate (%, nsa)
215	HQMCB17YR	1984:01-2020:02	7	USDT	17-Year HQM Corporate Bond Spot Rate (%, nsa)
216	HQMCB38Y6M	1984:01-2020:02	2	USDT	38.5-Year HQM Corporate Bond Spot Rate (%, nsa)
217	HQMCB88YR	1984:01-2020:02	2	USDT	88-Year HQM Corporate Bond Spot Rate (%, nsa)

218	HQMCB96YR	1984:01-2020:02	2	USDT	96-Year HQM Corporate Bond Spot Rate (%, nsa)
219	HQMCB79YR	1984:01-2020:02	2	USDT	79-Year HQM Corporate Bond Spot Rate (%, nsa)
220	HQMCB71YR	1984:01-2020:02	2	USDT	71-Year HQM Corporate Bond Spot Rate (%, nsa)
221	HQMCB29YR	1984:01-2020:02	7	USDT	29-Year HQM Corporate Bond Spot Rate (%, nsa)
222	HQMCB28YR	1984:01-2020:02	7	USDT	28-Year HQM Corporate Bond Spot Rate (%, nsa)
223	HQMCB76YR	1984:01-2020:02	2	USDT	76-Year HQM Corporate Bond Spot Rate (%, nsa)
224	HQMCB74Y6M	1984:01-2020:02	2	USDT	74.5-Year HQM Corporate Bond Spot Rate (%, nsa)
225	HQMCB37YR	1984:01-2020:02	2	USDT	37-Year HQM Corporate Bond Spot Rate (%, nsa)
226	HQMCB9Y6M	1984:01-2020:02	7	USDT	9.5-Year HQM Corporate Bond Spot Rate (%, nsa)
227	HQMCB92YR	1984:01-2020:02	2	USDT	92-Year HQM Corporate Bond Spot Rate (%, nsa)
228	HQMCB76Y6M	1984:01-2020:02	2	USDT	76.5-Year HQM Corporate Bond Spot Rate (%, nsa)
229	HQMCB85Y6M	1984:01-2020:02	2	USDT	85.5-Year HQM Corporate Bond Spot Rate (%, nsa)
230	HQMCB46YR	1984:01-2020:02	2	USDT	46-Year HQM Corporate Bond Spot Rate (%, nsa)
231	HQMCB38YR	1984:01-2020:02	2	USDT	38-Year HQM Corporate Bond Spot Rate (%, nsa)
232	HQMCB17Y6M	1984:01-2020:02	7	USDT	17.5-Year HQM Corporate Bond Spot Rate (%, nsa)
233	HQMCB34YR	1984:01-2020:02	7	USDT	34-Year HQM Corporate Bond Spot Rate (%, nsa)
234	HQMCB39YR	1984:01-2020:02	2	USDT	39-Year HQM Corporate Bond Spot Rate (%, nsa)
235	HQMCB35Y6M	1984:01-2020:02	7	USDT	35.5-Year HQM Corporate Bond Spot Rate (%, nsa)
236	HQMCB31YR	1984:01-2020:02	7	USDT	31-Year HQM Corporate Bond Spot Rate (%, nsa)
237	HQMCB41Y6M	1984:01-2020:02	2	USDT	41.5-Year HQM Corporate Bond Spot Rate (%, nsa)
238	HQMCB39Y6M	1984:01-2020:02	2	USDT	39.5-Year HQM Corporate Bond Spot Rate (%, nsa)
239	HQMCB98YR	1984:01-2020:02	2	USDT	98-Year HQM Corporate Bond Spot Rate (%, nsa)
Employment and hours					
240	CES4348100001	1990:01-2020:02	2	BLS	All Employees, Air Transportation (thous of pers., sa)
241	CES4244110001	1972:01-2020:02	2	BLS	All Employees, Automobile Dealers (thous of pers., sa)
242	CES4244800001	1990:01-2020:02	2	BLS	All Employees, Clothing and Clothing Accessories Stores (thous of pers., sa)
243	CES1021210001	1985:01-2020:02	7	BLS	All Employees, Coal Mining (thous of pers., sa)
244	USCONS	1939:01-2020:02	2	BLS	All Employees, Construction (thous of pers., sa)
245	DMANEMP	1939:01-2020:02	7	BLS	All Employees, Durable Goods (thous of pers., sa)
246	USEHS	1939:01-2020:02	2	BLS	All Employees, Education and Health Services (thous of pers., sa)
247	CES6561000001	1990:01-2020:02	2	BLS	All Employees, Educational Services (thous of pers., sa)
248	CES9091000001	1939:01-2020:02	2	BLS	All Employees, Federal (thous of pers., sa)
249	USFIRE	1939:01-2020:02	2	BLS	All Employees, Financial Activities (thous of pers., sa)
250	CES7072200001	1990:01-2020:02	2	BLS	All Employees, Food Services and Drinking Places (thous of pers., sa)
251	CES4244200001	1990:01-2020:02	2	BLS	All Employees, Furniture and Home Furnishings Stores (thous of pers., sa)
252	USGOOD	1939:01-2020:02	2	BLS	All Employees, Goods-Producing (thous of pers., sa)
253	USGOVT	1939:01-2020:02	2	BLS	All Employees, Government (thous of pers., sa)
254	CES4244600001	1990:01-2020:02	2	BLS	All Employees, Health and Personal Care Stores (thous of pers., sa)
255	CES6562000101	1990:01-2020:02	2	BLS	All Employees, Health Care (thous of pers., sa)
256	USINFO	1939:01-2020:02	2	BLS	All Employees, Information (thous of pers., sa)
257	USLAH	1939:01-2020:02	2	BLS	All Employees, Leisure and Hospitality (thous of pers., sa)
258	MANEMP	1939:01-2020:02	7	BLS	All Employees, Manufacturing (thous of pers., sa)
259	USMINE	1939:01-2020:02	2	BLS	All Employees, Mining and Logging (thous of pers., sa)
260	CES1021000001	1958:01-2020:02	2	BLS	All Employees, Mining (thous of pers., sa)
261	CES3133600101	1990:01-2020:02	2	BLS	All Employees, Motor Vehicles and Parts (thous of pers., sa)
262	NDMANEMP	1939:01-2020:02	7	BLS	All Employees, Nondurable Goods (thous of pers., sa)
263	CES1021100001	1972:01-2020:02	2	BLS	All Employees, Oil and Gas Extraction (thous of pers., sa)
264	CES0800000001	1939:01-2020:02	2	BLS	All Employees, Private Service-Providing (thous of pers., sa)
265	USPBS	1939:01-2020:02	2	BLS	All Employees, Professional and Business Services (thous of pers., sa)
266	CES2023610001	1985:01-2020:02	2	BLS	All Employees, Residential Building (thous of pers., sa)
267	USTRADE	1939:01-2020:02	2	BLS	All Employees, Retail Trade (thous of pers., sa)
268	SRVPRD	1939:01-2020:02	2	BLS	All Employees, Service-Providing (thous of pers., sa)
269	TEMPHELPS	1990:01-2020:02	2	BLS	All Employees, Temporary Help Services (thous of pers., sa)
270	PAYEMS	1939:01-2020:02	2	BLS	All Employees, Total Nonfarm (thous of pers., sa)
271	USPRIV	1939:01-2020:02	2	BLS	All Employees, Total Private (thous of pers., sa)
272	USTPU	1939:01-2020:02	2	BLS	All Employees, Trade, Transportation, and Utilities (thous of pers., sa)
273	CES4300000001	1972:01-2020:02	2	BLS	All Employees, Transportation and Warehousing (thous of pers., sa)
274	CES4348400001	1990:01-2020:02	2	BLS	All Employees, Truck Transportation (thous of pers., sa)
275	CES4349300001	1990:01-2020:02	2	BLS	All Employees, Warehousing and Storage (thous of pers., sa)

276	USWTRADE	1939:01-2020:02	2	BLS	All Employees, Wholesale Trade (AEWT) (thous of pers., sa)
277	SMU06000004142320001SA	1990:01-2020:01	2	FRBSL	AEWT: Furniture & home furnishing merc. wholesalers. Cali. (thous of pers., sa)
278	SMU06000004142370001SA	1990:01-2020:01	2	FRBSL	AEWT: h.ware, & plumbing & heat. equip. & sup. merc. whole. Cali (thous of pers., sa)
279	SMU06000004142330001SA	1990:01-2020:01	2	FRBSL	AEWT: lumber & ot. construction materials merc. wholesalers. Cali (thous of pers., sa)
280	SMU26000004142300001SA	1990:01-2020:01	2	FRBSL	AEWT: Merchant wholesalers, durable goods in Michigan (thous of pers., sa)
281	SMU33000004142300001SA	1990:01-2020:01	2	FRBSL	AEWT: Merc. wholesalers, dur.goods in New Hampshire (thous of pers., sa)
282	SMU36356144142300001SA	1990:01-2020:01	7	FRBSL	AEWT: Merc. wholesalers, dur.goods in NY-NJ (MD) (thous of pers., sa)
283	SMU06401404142300001SA	1990:01-2020:01	2	FRBSL	AEWT: Merc. wholesalers, dur.goods in Riverside-San BO, CA (thous of pers., sa)
284	SMU06419404142300001SA	1990:01-2020:01	2	FRBSL	AEWT: Merc. wholesalers, dur.goods in San Jose-S-S Clara, CA (thous of pers., sa)
285	SMU34350844142400001SA	1990:01-2020:01	2	FRBSL	AEWT: Merc. wholesalers, nondur.goods in Newark, NJ-PA (MD) (thous of pers., sa)
286	SMU26000004142310001SA	1990:01-2020:01	2	FRBSL	AEWT: Motor veh.&.parts & sup. merc. wholesalers, Michigan (thous of pers., sa)
287	CES2000000007	1947:01-2020:02	2	BLS	Avg.wkly.hrs. of Production and Nonsupervisory Employees, Construction (Hours, sa)
288	CES3100000007	1939:01-2020:02	2	BLS	Avg.wkly.hrs. of prod.&nonsup. Emplys, Durable Goods (Hours, sa)
289	CES0600000007	1947:01-2020:02	2	BLS	Avg.wkly.hrs. of prod.&nonsup. Emplys, Goods-Producing (Hours, sa)
290	CES0800000007	1964:01-2020:02	2	BLS	Avg.wkly.hrs. of prod.&nonsup. Emplys, Private Service-Providing (Hours, sa)
291	CES6000000007	1964:01-2020:02	2	BLS	Avg.wkly.hrs. of prod.&nonsup. Emplys, Professional and Business Services (Hours, sa)
292	CES4200000007	1972:01-2020:02	2	BLS	Avg.wkly.hrs. of prod.&nonsup. Emplys, Retail Trade (Hours, sa)
293	CES4000000007	1964:01-2020:02	2	BLS	Avg.wkly.hrs. of prod.&nonsup. Emplys, Trade, Transportation, and Utilities (Hours, sa)
294	CES3100000009	1956:01-2020:02	2	BLS	Avg.wkly.overtime-hrs. of Prod.& nonsupervisory Employees, Dur. Goods (Hours, sa)
295	AWOTMAN	1956:01-2020:02	2	BLS	Avg.wkly.overtime-hrs. of Prod.& Nonsupervisory Employees, Manufact. (Hours, sa)
296	CES3200000009	1956:01-2020:02	2	BLS	Avg.wkly.overtime-hrs. of prod.& nonsupervisory employees, nondur. goods (Hours, sa)
297	UEMPMEAN	1948:01-2020:02	2	BLS	Average Weeks Unemployed (Weeks, sa)
298	CES2000000008	1947:01-2020:02	2	BLS	Avg hr earnings of prod.& nonsupervisory Employees, Construction (usd per Hour, sa)
299	CES3000000008	1939:01-2020:02	2	BLS	Avg hr earnings of prod.&nonsupervisory Employees, Manufacturing (usd per Hour, sa)
300	AHETPI	1964:01-2020:02	2	BLS	Avg hr earnings of Production & Nonsupervisory Employees, Tot priv (usd per Hour, sa)
301	CES4300000008	1972:01-2020:02	2	BLS	Avg hr earnings of prod. & nonsup. Employees, transp.&warehousing (usd pr hour, sa)
302	CES0500000030	1964:01-2020:02	2	BLS	Avg weekly earnings of prod.&nonsupervisory Employees, tot.priv (usd per Week, sa)
303	AWHMAN	1939:01-2020:02	2	BLS	Avg weekly hrs of Production & Nonsupervisory Employees, Manufacturing (Hours, sa)
304	AWHNONAG	1964:01-2020:02	2	BLS	Avg weekly hrs of Production and Nonsupervisory Employees, Total Private (Hours, sa)
305	CLF16OV	1989:01-2020:02	2	BLS	Civilian Labor Force Level 1989-01-01 to 2020-02-01 (thous of pers., sa)
306	W209RC1	1959:01-2020:01	2	BEA	Compensation of employees, received (bn of usd, sa)
307	A132RC1	1959:01-2020:01	2	BEA	Compensation of employees, Received: wage & salary Disb.: priv. Ind. (bn of usd, sa)
308	LNS12500000	1968:01-2020:02	2	BLS	Employed, Usually Work Full Time (thous of pers., sa)
309	LNS12600000	1968:01-2020:02	2	BLS	Employed, Usually Work Part Time (thous of pers., sa)
310	LNS12000060	1948:01-2020:02	2	BLS	Employment Level - 25-54 Yrs. (thous of pers., sa)
311	LNS12034560	1948:01-2020:02	2	BLS	Employment Level - Agriculture and Related Industries (thous of pers., sa)
312	LNS12027714	1948:01-2020:02	2	BLS	Employment Level - All Industries Self-Employed, Unincorporated (thous of pers., sa)
313	LNS12000006	1972:01-2020:02	2	BLS	Employment Level - Black or African American (thous of pers., sa)
314	LNS12032194	1955:05-2020:02	2	BLS	Employment Level - Part-Time for Economic Reasons, All Industries (thous of pers., sa)
315	LNS12032197	1955:05-2020:02	2	BLS	Employment Level - PT,Economic Reasons, Nonagricultural Ind.(thous of pers., sa)
316	LNS12032195	1955:05-2020:02	2	BLS	Employment Level - PT Eco Reasons, Slack Work/Bus. Con., All Ind. (thous of pers., sa)
317	LNS12000002	1948:01-2020:02	2	BLS	Employment Level - Women (thous of pers., sa)
318	CE16OV	1948:01-2020:02	2	BLS	Employment Level (thous of pers., sa)
319	LREM64TTUSM156S	1977:01-2020:02	2	OECD	Employment Rate: Aged 15-64: All Persons for the United States (%, sa)
320	LREM25TTUSM156S	1977:01-2020:02	2	OECD	Employment Rate: Aged 25-54: All Persons for the United States (%, sa)
321	LREM25FEUSM156S	1977:01-2020:02	2	OECD	Employment Rate: Aged 25-54: Females for the United States (%, sa)
322	LREM25MAUSM156S	1977:01-2020:02	2	OECD	Employment Rate: Aged 25-54: Males for the United States (%, sa)
323	LNS12300060	1948:01-2020:02	2	BLS	Employment-Population Ratio - 25-54 Yrs. (%, sa)
324	LNS12300006	1972:01-2020:02	2	BLS	Employment-Population Ratio - Black or African American (%, sa)
325	LNS12300001	1948:01-2020:02	2	BLS	Employment-Population Ratio - Men (%, sa)
326	LNS12300002	1948:01-2020:02	2	BLS	Employment-Population Ratio - Women (%, sa)
327	EMRATIO	1948:01-2020:02	2	BLS	Employment-Population Ratio (%, sa)
328	LRHUTTTTUSM156S	1960:01-2020:02	2	OECD	Harmonized Unemployment Rate: Total: All Persons for the United States (%, sa)
329	CES2000000034	1947:01-2020:02	2	BLS	Indexes of agg. wkly hrs of prod&nonsup. employees, Construction (2002=100, sa)
330	CES5500000034	1964:01-2020:02	2	BLS	Indexes of agg. wkly hrs of prod&nonsup. employees, Fin. Activities (2002=100, sa)
331	CES7000000034	1964:01-2020:02	2	BLS	Indexes of agg. wkly hrs of prod&nonsup. employees, leisure&hosp (2002=100, sa)
332	CES3000000034	1939:01-2020:02	7	BLS	Indexes of agg. wkly hrs of prod&nonsup. employees, Manufacturing (2002=100, sa)
333	CES1000000034	1947:01-2020:02	2	BLS	Indexes of agg. wkly hrs of prod&nonsup. employees, mining&logging (2002=100, sa)
334	CES4200000034	1972:01-2020:02	2	BLS	Indexes of agg. wkly hrs of prod&nonsup. employees, Retail Trade (2002=100, sa)
335	AWHI	1964:01-2020:02	2	BLS	Indexes of agg. wkly hrs of prod&nonsup. employees, Total Private (2002=100, sa)

336	CES4142000034	1972:01-2020:02	2	BLS	Indexes of agg. wkly hrs of prod&nonsup. employees, Wholesale Trade (2002=100, sa)
337	CES3000000035	1939:01-2020:02	2	BLS	Indexes of agg. wkly payrolls of prod. & nonsup. emp., manufacturing (2002=100, sa)
338	CES6000000035	1964:01-2020:02	2	BLS	Indexes of agg. wkly payrolls of prod.&nonsup.emp., pro&business ser. (2002=100, sa)
339	CES0500000035	1964:01-2020:02	2	BLS	Indexes of agg. wkly payrolls of prod&nonsup. Employees, tot. priv (2002=100, sa)
340	LNS13023706	1967:01-2020:02	2	BLS	Job Leavers as a % of Total Unemployed (%, sa)
341	LNS13023622	1967:01-2020:02	2	BLS	Job Losers as a % of Total Unemployed (%, sa)
342	LNS13026511	1967:01-2020:02	2	BLS	Job Losers Not on Layoff as a % of Total Unemployed (%, sa)
343	LNS13023654	1967:01-2020:02	2	BLS	Job Losers on Layoff as a % of Total Unemployed (%, sa)
344	LNS17000000	1990:02-2020:02	2	BLS	Labor Force Flows Employed to Employed (thous of pers., sa)
345	LNS17800000	1990:02-2020:02	2	BLS	Labor Force Flows Employed to Not in Labor Force (thous of pers., sa)
346	LNS17400000	1990:02-2020:02	2	BLS	Labor Force Flows Employed to Unemployed (thous of pers., sa)
347	LNS17200000	1990:02-2020:02	2	BLS	Labor Force Flows Not in Labor Force to Employed (thous of pers., sa)
348	LNS17600000	1990:02-2020:02	2	BLS	Labor Force Flows Not in Labor Force to Unemployed (thous of pers., sa)
349	LNS17100000	1990:02-2020:02	2	BLS	Labor Force Flows Unemployed to Employed (thous of pers., sa)
350	LNS17900000	1990:02-2020:02	2	BLS	Labor Force Flows Unemployed to Not in Labor Force (thous of pers., sa)
351	LNS17500000	1990:02-2020:02	2	BLS	Labor Force Flows Unemployed to Unemployed (thous of pers., sa)
352	LNS11300002	1948:01-2020:02	2	BLS	Labor Force Participation Rate - Women (%, sa)
353	CIVPART	1989:01-2020:01	2	BLS	Labor Force Participation Rate (%, sa)
354	UEMPMED	1967:07-2020:02	2	BLS	Median Weeks Unemployed (Weeks, sa)
355	LNS13023570	1967:01-2020:02	2	BLS	New Entrants as a % of Total Unemployed (%, sa)
356	UEMP15OV	1948:01-2020:02	2	BLS	Number Unemployed for 15 Weeks & Over (thous of pers., sa)
357	UEMP15T26	1948:01-2020:02	2	BLS	Number Unemployed for 15-26 Weeks (thous of pers., sa)
358	UEMP27OV	1948:01-2020:02	2	BLS	Number Unemployed for 27 Weeks & Over (thous of pers., sa)
359	UEMP5TO14	1948:01-2020:02	2	BLS	Number Unemployed for 5-14 Weeks (thous of pers., sa)
360	UEMPLT5	1948:01-2020:02	2	BLS	Number Unemployed for Less Than 5 Weeks (thous of pers., sa)
361	LNS13008517	1948:01-2020:02	2	BLS	Of Total Unemployed, % Unemployed 15 Weeks & Over (%, sa)
362	LNS13025702	1948:01-2020:02	2	BLS	Of Total Unemployed, % Unemployed 15-26 Weeks (%, sa)
363	LNS13025703	1948:01-2020:02	2	BLS	Of Total Unemployed, % Unemployed 27 Weeks & Over (%, sa)
364	LNS13025701	1948:01-2020:02	2	BLS	Of Total Unemployed, % Unemployed 5-14 Weeks (%, sa)
365	LNS13008397	1948:01-2020:02	2	BLS	Of Total Unemployed, % Unemployed Less Than 5 Weeks (%, sa)
366	U1RATE	1948:01-2020:02	2	BLS	% of Civilian Labor Force Unemployed 15 Weeks and Over (U-1) (%, sa)
367	CES4200000006	1972:01-2020:02	2	BLS	Production and Nonsupervisory Employees, Retail Trade (thous of pers., sa)
368	CES0500000006	1964:01-2020:02	2	BLS	Production and Nonsupervisory Employees, Total Private (thous of pers., sa)
369	LNS13023558	1967:01-2020:02	2	BLS	Reentrants to Labor Force as a % of Total Unemployed (%, sa)
370	LNS13000032	1972:01-2020:02	2	BLS	Unemployment Level -20 Yrs.&Over, Black or Afr.American Women (thous of pers., sa)
371	LNS13000060	1948:01-2020:02	2	BLS	Unemployment Level - 25-54 Yrs. (thous of pers., sa)
372	LNS13000006	1972:01-2020:02	2	BLS	Unemployment Level - Black or African American (thous of pers., sa)
373	LNS13023705	1967:01-2020:02	2	BLS	Unemployment Level - Job Leavers (thous of pers., sa)
374	LNS13025699	1967:01-2020:02	2	BLS	Unemployment Level - Job Losers Not on Layoff (thous of pers., sa)
375	LNS13023653	1967:01-2020:02	2	BLS	Unemployment Level - Job Losers on Layoff (thous of pers., sa)
376	LNS13023621	1967:01-2020:02	2	BLS	Unemployment Level - Job Losers (thous of pers., sa)
377	LNS13200000	1963:01-2020:02	2	BLS	Unemployment Level - Looking For Part-Time Work (thous of pers., sa)
378	LNS13000001	1948:01-2020:02	2	BLS	Unemployment Level - Men (thous of pers., sa)
379	LNS13023569	1967:01-2020:02	2	BLS	Unemployment Level - New Entrants (thous of pers., sa)
380	LNS13023557	1967:01-2020:02	2	BLS	Unemployment Level - Reentrants to Labor Force (thous of pers., sa)
381	LNS13000002	1948:01-2020:02	2	BLS	Unemployment Level - Women (thous of pers., sa)
382	UNEMPLOY	1948:01-2020:02	2	BLS	Unemployment Level (thous of pers., sa)
383	LNS14000012	1948:01-2020:02	2	BLS	Unemployment Rate - 16-19 Yrs. (%, sa)
384	LNS14000018	1972:01-2020:02	2	BLS	Unemployment Rate - 16-19 Yrs., Black or African American (%, sa)
385	LNS14000015	1954:01-2020:02	2	BLS	Unemployment Rate - 16-19 Yrs., White (%, sa)
386	LNS14024887	1948:01-2020:02	2	BLS	Unemployment Rate - 16-24 Yrs. (%, sa)
387	LNS14000088	1948:01-2020:02	2	BLS	Unemployment Rate - 18-19 Yrs. (%, sa)
388	LNS14000319	1948:01-2020:02	2	BLS	Unemployment Rate - 18-19 Yrs., Women (%, sa)
389	LNS14000024	1948:01-2020:02	2	BLS	Unemployment Rate - 20 Yrs. & Over (%, sa)
390	LNS14000031	1972:01-2020:02	2	BLS	Unemployment Rate - 20 Yrs. & Over, Black or African American Men (%, sa)
391	LNS14000032	1972:01-2020:02	2	BLS	Unemployment Rate - 20 Yrs. & Over, Black or African American Women (%, sa)
392	LNS14000025	1948:01-2020:02	2	BLS	Unemployment Rate - 20 Yrs. & Over, Men (%, sa)
393	LNS14000028	1954:01-2020:02	2	BLS	Unemployment Rate - 20 Yrs. & Over, White Men (%, sa)
394	LNS14000029	1954:01-2020:02	2	BLS	Unemployment Rate - 20 Yrs. & Over, White Women (%, sa)
395	LNS14000026	1948:01-2020:02	2	BLS	Unemployment Rate - 20 Yrs. & Over, Women (%, sa)

396	LNS14000036	1948:01-2020:02	2	BLS	Unemployment Rate - 20-24 Yrs. (%, sa)
397	LNS14000048	1948:01-2020:02	2	BLS	Unemployment Rate - 25 Yrs. & Over (%, sa)
398	LNS14000089	1948:01-2020:02	2	BLS	Unemployment Rate - 25-34 Yrs. (%, sa)
399	LNS14000060	1948:01-2020:02	2	BLS	Unemployment Rate - 25-54 Yrs. (%, sa)
400	LNS14000061	1948:01-2020:02	2	BLS	Unemployment Rate - 25-54 Yrs., Men (%, sa)
401	LNS14000091	1948:01-2020:02	2	BLS	Unemployment Rate - 35-44 Yrs. (%, sa)
402	LNS14024230	1948:01-2020:02	2	BLS	Unemployment Rate - 55 Yrs. & Over (%, sa)
403	LNS14000006	1972:01-2020:02	2	BLS	Unemployment Rate - Black or African American (%, sa)
404	LNS14000009	1973:03-2020:02	2	BLS	Unemployment Rate - Hispanic or Latino (%, sa)
405	U2RATE	1967:01-2020:02	2	BLS	Unemployment Rate - Job Losers (U-2) (%, sa)
406	LNS14000150	1955:01-2020:02	2	BLS	Unemployment Rate - Married Men (%, sa)
407	LNS14000315	1955:01-2020:02	2	BLS	Unemployment Rate - Married Women (%, sa)
408	LNS14000001	1948:01-2020:02	2	BLS	Unemployment Rate - Men (%, sa)
409	LNS14000003	1954:01-2020:02	2	BLS	Unemployment Rate - White (%, sa)
410	LNS14000002	1948:01-2020:02	2	BLS	Unemployment Rate - Women (%, sa)
411	LNS14100000	1968:01-2020:02	2	BLS	Unemployment Rate Full-Time Workers (%, sa)
412	LNS14200000	1968:01-2020:02	2	BLS	Unemployment Rate Part-Time Workers (%, sa)
413	UNRATE	1948:01-2020:02	2	BLS	Unemployment Rate (%, sa)
414	LRUN24TTUSM156S	1960:01-2020:02	2	OECD	Unemployment Rate: Aged 15-24: All Persons for the United States (%, sa)
415	LRUN64TTUSM156S	1970:01-2020:02	2	OECD	Unemployment Rate: Aged 15-64: All Persons for the United States (%, sa)
416	LRUN25TTUSM156S	1960:01-2020:02	2	OECD	Unemployment Rate: Aged 25-54: All Persons for the United States (%, sa)
417	LRUN55TTUSM156S	1970:01-2020:02	2	OECD	Unemployment Rate: Aged 55-64: All Persons for the United States (%, sa)
Equity Market Volatility Tracker (EMVT)					
418	EMVOVERALLEMV	1985:01-2020:02	7	BBD	EMVT: Overall(Index, nsa)
419	EMVGOVTSPEND	1985:01-2020:02	7	BBD	EMVT: Government Spending Deficits And Debt(Index, nsa)
420	EMVFINCRISES	1985:01-2020:02	7	BBD	EMVT: Financial Crises(Index, nsa)
421	EMVMACROINTEREST	1985:01-2020:02	7	BBD	EMVT: Macroeconomic News and Outlook: Interest Rates(Index, nsa)
422	EMVMACROINFLATION	1985:01-2020:02	7	BBD	EMVT: Macroeconomic News and Outlook: Inflation(Index, nsa)
423	EMVMONETARYPOL	1985:01-2020:02	7	BBD	EMVT: Monetary Policy(Index, nsa)
424	EMVENRGYENVREG	1985:01-2020:02	7	BBD	EMVT: Energy And Environmental Regulation(Index, nsa)
425	EMVELECTGOVRN	1985:01-2020:02	7	BBD	EMVT: Elections And Political Governance(Index, nsa)
426	EMVMACRORE	1985:01-2020:02	7	BBD	EMVT: Macroeconomic News and Outlook: Real Estate Markets(Index, nsa)
427	EMVCOMMMKT	1985:01-2020:02	7	BBD	EMVT: Commodity Markets(Index, nsa)
428	EMVEXRATES	1985:01-2020:02	7	BBD	EMVT: Exchange Rates(Index, nsa)
429	EMVMACROTRADE	1985:01-2020:02	7	BBD	EMVT: Macroeconomic News and Outlook: Trade(Index, nsa)
430	EMVHEALTHCAREMAT	1985:01-2020:02	7	BBD	EMVT: Healthcare Matters(Index, nsa)
431	EMVTRADEPOLEMV	1985:01-2020:02	7	BBD	EMVT: Trade Policy(Index, nsa)
432	EMVMACRONEWS	1985:01-2020:02	7	BBD	EMVT: Macroeconomic News And Outlook(Index, nsa)
433	EMVMACROFININD	1985:01-2020:02	7	BBD	EMVT: Macroeconomic News and Outlook: Other Financial Indicators(Index, nsa)
434	EMVAGRPOLICY	1985:01-2020:02	7	BBD	EMVT: Agricultural Policy(Index, nsa)
435	EMVPOLRLTDEMV	1985:01-2020:02	7	BBD	EMVT: Policy Related(Index, nsa)
436	EMVFOODDRUG	1985:01-2020:02	7	BBD	EMVT: Food And Drug Policy(Index, nsa)
437	EMVMACROBROAD	1985:01-2020:02	7	BBD	EMVT: Macroeconomic News and Outlook: Broad Quantity Indicators(Index, nsa)
438	EMVWELFARE	1985:01-2020:02	7	BBD	EMVT: Entitlement And Welfare Programs(Index, nsa)
439	EMVFINREG	1985:01-2020:02	7	BBD	EMVT: Financial Regulation(Index, nsa)
440	EMVTRADEPUBUTEMV	1985:01-2020:02	7	BBD	EMVT: Transportation, Infrastructure, and Public Utilities(Index, nsa)
441	EMVTAXESEMV	1985:01-2020:02	7	BBD	EMVT: Taxes(Index, nsa)
442	EMVCOMPMAT	1985:01-2020:02	7	BBD	EMVT: Competition Matters(Index, nsa)
443	EMVNATSEC	1985:01-2020:02	7	BBD	EMVT: National Security Policy(Index, nsa)
444	EMVHEALTHCAREPOL	1985:01-2020:02	7	BBD	EMVT: Healthcare Policy(Index, nsa)
445	EMVREGEMV	1985:01-2020:02	7	BBD	EMVT: Regulation(Index, nsa)
446	EMVHOUSELANDMGMT	1985:01-2020:02	7	BBD	EMVT: Housing And Land Management(Index, nsa)
447	EMVLAWTORT	1985:01-2020:02	7	BBD	EMVT: Lawsuit And Tort Reform Supreme Court Decisions(Index, nsa)
448	EMVMACROLABORMKT	1985:01-2020:02	7	BBD	EMVT: Macroeconomic News and Outlook: Labor Markets(Index, nsa)
449	EMVOTHERREG	1985:01-2020:02	7	BBD	EMVT: Other Regulation(Index, nsa)
450	EMVIPPOL	1985:01-2020:02	7	BBD	EMVT: Intellectual Property Policy(Index, nsa)
451	EMVIPMAT	1985:01-2020:02	7	BBD	EMVT: Intellectual Property Matters(Index, nsa)
452	EMVLABORDISPUTES	1985:01-2020:02	7	BBD	EMVT: Labor Disputes(Index, nsa)
453	EMVLITGMAT	1985:01-2020:02	7	BBD	EMVT: Litigation Matters(Index, nsa)

454	EMVCOMPPOL	1985:01-2020:02	7	BBD	EMVT: Competition Policy(Index, nsa)
455	EMNLABORREG	1985:01-2020:02	7	BBD	EMVT: Labor Regulations(Index, nsa)
456	EMVGOVTSPENT	1985:01-2020:02	7	BBD	EMVT: Government Sponsored Enterprises(Index, nsa)
Exports					
457	IQAG	1985:03-2020:02	2	BLS	Export Price (End Use): Agricultural commodities (2000=100, nsa)
458	IQ	1983:09-2020:02	2	BLS	Export Price (End Use): All commodities (2000=100, nsa)
459	IQ2	1978:12-2020:02	2	BLS	Export Price (End Use): Capital goods (2000=100, nsa)
460	XTEXVA01USM657S	1960:01-2019:12	7	OECD	Exports: Value Goods for the United States (Growth Rate Previous Period, sa)
461	XTEXVA01USM659S	1960:01-2019:12	7	OECD	Exports: Value Goods for the United States (growth rate same period previous year, sa)
462	XTEXVA01USM664S	1960:01-2019:12	2	OECD	Exports: Value Goods for the United States (National currency, Monthly Level, sa)
463	XTEXVA01USM667S	1960:01-2019:12	2	OECD	Exports: Value Goods for the United States (US usd Monthly Level, sa)
464	EXPCA	1985:01-2020:01	2	BEACB	U.S. Exports of Goods by F.A.S. Basis to Canada (MM of usd, nsa)
465	EXPGE	1985:01-2020:01	2	BEACB	U.S. Exports of Goods by F.A.S. Basis to Germany (MM of usd, nsa)
466	EXPJP	1985:01-2020:01	2	BEACB	U.S. Exports of Goods by F.A.S. Basis to Japan (MM of usd, nsa)
467	EXPMX	1985:01-2020:01	2	BEACB	U.S. Exports of Goods by F.A.S. Basis to Mexico (MM of usd, nsa)
468	EXPKR	1985:01-2020:01	2	BEACB	U.S. Exports of Goods by F.A.S. Basis to South Korea (MM of usd, nsa)
469	EXPUK	1985:01-2020:01	2	BEACB	U.S. Exports of Goods by F.A.S. Basis to the United Kingdom (MM of usd, nsa)
470	EXP0015	1987:01-2020:01	2	BEACB	U.S. Exports of Goods by F.A.S. Basis to World (MM of usd, nsa)
471	EXP0004	1989:01-2020:01	2	BEACB	U.S. Exports of Goods by F.A.S. Basis to World (MM of usd, sa)
Fitted Instantaneous Forward Rates					
472	THREEFF1	1990:01-2020:02	7	FED	Fitted Instantaneous Forward Rate 1 Year Hence (%, nsa)
473	THREEFF10	1990:01-2020:02	2	FED	Fitted Instantaneous Forward Rate 10 Years Hence (%, nsa)
474	THREEFF2	1990:01-2020:02	2	FED	Fitted Instantaneous Forward Rate 2 Years Hence (%, nsa)
475	THREEFF3	1990:01-2020:02	2	FED	Fitted Instantaneous Forward Rate 3 Years Hence (%, nsa)
476	THREEFF4	1990:01-2020:02	2	FED	Fitted Instantaneous Forward Rate 4 Years Hence (%, nsa)
477	THREEFF5	1990:01-2020:02	2	FED	Fitted Instantaneous Forward Rate 5 Years Hence (%, nsa)
478	THREEFF6	1990:01-2020:02	2	FED	Fitted Instantaneous Forward Rate 6 Years Hence (%, nsa)
479	THREEFF7	1990:01-2020:02	2	FED	Fitted Instantaneous Forward Rate 7 Years Hence (%, nsa)
480	THREEFF8	1990:01-2020:02	2	FED	Fitted Instantaneous Forward Rate 8 Years Hence (%, nsa)
481	THREEFF9	1990:01-2020:02	2	FED	Fitted Instantaneous Forward Rate 9 Years Hence (%, nsa)
482	THREEFFTP1	1990:01-2020:02	7	FED	Instantaneous Forward Term Premium 1 Year Hence (%, nsa)
483	THREEFFTP10	1990:01-2020:02	4	FED	Instantaneous Forward Term Premium 10 Years Hence (%, nsa)
484	THREEFFTP2	1990:01-2020:02	7	FED	Instantaneous Forward Term Premium 2 Years Hence (%, nsa)
485	THREEFFTP3	1990:01-2020:02	7	FED	Instantaneous Forward Term Premium 3 Years Hence (%, nsa)
486	THREEFFTP4	1990:01-2020:02	7	FED	Instantaneous Forward Term Premium 4 Years Hence (%, nsa)
487	THREEFFTP5	1990:01-2020:02	4	FED	Instantaneous Forward Term Premium 5 Years Hence (%, nsa)
488	THREEFFTP6	1990:01-2020:02	4	FED	Instantaneous Forward Term Premium 6 Years Hence (%, nsa)
489	THREEFFTP7	1990:01-2020:02	4	FED	Instantaneous Forward Term Premium 7 Years Hence (%, nsa)
490	THREEFFTP8	1990:01-2020:02	4	FED	Instantaneous Forward Term Premium 8 Years Hence (%, nsa)
491	THREEFFTP9	1990:01-2020:02	4	FED	Instantaneous Forward Term Premium 9 Years Hence (%, nsa)
Foreign Stock Index					
492	NIKKEI225	1989:01-2020:02	2	Nikkei	Nikkei 225 Monthly Close 1989-01-01 to 2020-02-01 (Index, nsa)
493	NYSEComp	1989:01-2020:02	2	NYSE	NYSE Composite Monthly Close 1989-01-01 to 2020-02-01 (Index, nsa)
494	NASDAQComp	1989:01-2020:02	2	NASDAQ	NASDAQ Composite Monthly Close 1989-01-01 to 2020-02-01 (Index, nsa)
495	CAC40	1990:03-2020:02	2	Euronext	CAC40 Monthly Close 1990-03-01 to 2020-02-01 (Index, nsa)
Foreign Exchange Rates					
496	EXUSUK	1989:01-2020:02	2	FED	U.S. / U.K. Foreign Exchange Rate (Ratio, nsa)
497	EXSIUS	1989:01-2020:02	2	FED	Singapore / U.S. Foreign Exchange Rate (Ratio, nsa)
498	EXHKUS	1989:01-2020:02	2	FED	Hong Kong / U.S. Foreign Exchange Rate (Ratio, nsa)
499	EXSZUS	1989:01-2020:02	2	FED	Switzerland / U.S. Foreign Exchange Rate (Ratio, nsa)
500	EXKOUS	1989:01-2020:02	2	FED	South Korea / U.S. Foreign Exchange Rate (Ratio, nsa)
501	EXINUS	1989:01-2020:02	2	FED	India / U.S. Foreign Exchange Rate (Ratio, nsa)
502	EXCAUS	1989:01-2020:02	2	FED	Canada / U.S. Foreign Exchange Rate (Ratio, nsa)
503	EXJPUS	1989:01-2020:02	2	FED	Japan / U.S. Foreign Exchange Rate (Ratio, nsa)
504	EXUSAL	1989:01-2020:02	2	FED	U.S. / Australia Foreign Exchange Rate (Ratio, nsa)
505	EXCHUS	1989:01-2020:02	2	FED	China / U.S. Foreign Exchange Rate (Ratio, nsa)

Home Price Index (HPI)

506	CSUSHPISA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller U.S. National HPI (Jan 2000=100, sa)
507	SFXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller CA-San Francisco HPI (Jan 2000=100, sa)
508	LXXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller CA-Los Angeles HPI (Jan 2000=100, sa)
509	NYXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller NY-New York HPI (Jan 2000=100, sa)
510	BOXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller MA-Boston HPI (Jan 2000=100, sa)
511	SDXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller CA-San Diego HPI (Jan 2000=100, sa)
512	CHXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller IL-Chicago HPI (Jan 2000=100, sa)
513	DNXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller CO-Denver HPI (Jan 2000=100, sa)
514	WDXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller DC-Washington HPI (Jan 2000=100, sa)
515	POXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller OR-Portland HPI (Jan 2000=100, sa)
516	SPCS10RSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller 10-City Composite HPI (Jan 2000=100, sa)
517	MNXRSA	1989:01-2019:12	2	SPDJ	S&P/Case-Shiller MN-Minneapolis HPI (Jan 2000=100, sa)
518	TPXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller FL-Tampa HPI (Jan 2000=100, sa)
519	SEXRSA	1990:01-2019:12	2	SPDJ	S&P/Case-Shiller WA-Seattle HPI (Jan 2000=100, sa)
520	CEXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller OH-Cleveland HPI (Jan 2000=100, sa)
521	PHXRSA	1989:01-2019:12	2	SPDJ	S&P/Case-Shiller AZ-Phoenix HPI (Jan 2000=100, sa)
522	LVXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller NV-Las Vegas HPI (Jan 2000=100, sa)
523	MIXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller FL-Miami HPI (Jan 2000=100, sa)
524	PHXRHTSA	1989:01-2019:12	2	SPDJ	HPI (High Tier) for Phoenix, Arizona (Jan 2000=100, sa)
525	CRXRSA	1987:01-2019:12	2	SPDJ	S&P/Case-Shiller NC-Charlotte HPI (Jan 2000=100, sa)
526	LXXRHTSA	1987:01-2019:12	2	SPDJ	HPI (High Tier) for Los Angeles, California (Jan 2000=100, sa)
527	NYXRHTSA	1987:01-2019:12	2	SPDJ	HPI (High Tier) for New York, New York (Jan 2000=100, sa)
528	BOXRHTSA	1987:01-2019:12	2	SPDJ	HPI (High Tier) for Boston, Massachusetts (Jan 2000=100, sa)
529	SDXRHTSA	1989:01-2019:12	2	SPDJ	HPI (High Tier) for San Diego, California (Jan 2000=100, sa)
530	SDXRLTSA	1989:01-2019:12	2	SPDJ	HPI (Low Tier) for San Diego, California (Jan 2000=100, sa)
531	DNXRHTSA	1987:01-2019:12	2	SPDJ	HPI (High Tier) for Denver, Colorado (Jan 2000=100, sa)
532	NYXRLTSA	1987:01-2019:12	2	SPDJ	HPI (Low Tier) for New York, New York (Jan 2000=100, sa)
533	SFXRHTSA	1987:01-2019:12	2	SPDJ	HPI (High Tier) for San Francisco, California (Jan 2000=100, sa)
534	SEXRHTSA	1990:01-2019:12	2	SPDJ	HPI (High Tier) for Seattle, Washington (Jan 2000=100, sa)
535	NYXRMTSA	1987:01-2019:12	2	SPDJ	HPI (Middle Tier) for New York, New York (Jan 2000=100, sa)
536	SEXRLTSA	1990:01-2019:12	2	SPDJ	HPI (Low Tier) for Seattle, Washington (Jan 2000=100, sa)
537	TPXRHTSA	1987:01-2019:12	2	SPDJ	HPI (High Tier) for Tampa, Florida (Jan 2000=100, sa)
538	SDXRMTSA	1989:01-2019:12	2	SPDJ	HPI (Middle Tier) for San Diego, California (Jan 2000=100, sa)
539	SEXRMTSA	1990:01-2019:12	2	SPDJ	HPI (Middle Tier) for Seattle, Washington (Jan 2000=100, sa)
540	MNXRHTSA	1989:01-2019:12	2	SPDJ	HPI (High Tier) for Minneapolis, Minnesota (Jan 2000=100, sa)
541	SFXRLTSA	1987:01-2019:12	2	SPDJ	HPI (Low Tier) for San Francisco, California (Jan 2000=100, sa)
542	MIXRHTSA	1987:01-2019:12	2	SPDJ	HPI (High Tier) for Miami, Florida (Jan 2000=100, sa)
543	SFXRMTSA	1987:01-2019:12	2	SPDJ	HPI (Middle Tier) for San Francisco, California (Jan 2000=100, sa)
544	POXRLTSA	1987:01-2019:12	2	SPDJ	HPI (Low Tier) for Portland, Oregon (Jan 2000=100, sa)
545	WDXRHTSA	1987:01-2019:12	2	SPDJ	HPI (High Tier) for Washington D.C. (Jan 2000=100, sa)
546	POXRMTSA	1987:01-2019:12	2	SPDJ	HPI (Middle Tier) for Portland, Oregon (Jan 2000=100, sa)
547	LXXRLTSA	1987:01-2019:12	2	SPDJ	HPI (Low Tier) for Los Angeles, California (Jan 2000=100, sa)
548	BOXRLTSA	1987:01-2019:12	2	SPDJ	HPI (Low Tier) for Boston, Massachusetts (Jan 2000=100, sa)
549	PHXRLTSA	1989:01-2019:12	2	SPDJ	HPI (Low Tier) for Phoenix, Arizona (Jan 2000=100, sa)
550	LXXRMTSA	1987:01-2019:12	2	SPDJ	HPI (Middle Tier) for Los Angeles, California (Jan 2000=100, sa)
551	MIXRLTSA	1987:01-2019:12	2	SPDJ	HPI (Low Tier) for Miami, Florida (Jan 2000=100, sa)
552	POXRHTSA	1987:01-2019:12	2	SPDJ	HPI (High Tier) for Portland, Oregon (Jan 2000=100, sa)
553	TPXRLTSA	1987:01-2019:12	2	SPDJ	HPI (Low Tier) for Tampa, Florida (Jan 2000=100, sa)
554	PHXRMTSA	1989:01-2019:12	2	SPDJ	HPI (Middle Tier) for Phoenix, Arizona (Jan 2000=100, sa)
555	WDXRLTSA	1987:01-2019:12	2	SPDJ	HPI (Low Tier) for Washington D.C. (Jan 2000=100, sa)
556	DNXRLTSA	1987:01-2019:12	2	SPDJ	HPI (Low Tier) for Denver, Colorado (Jan 2000=100, sa)
557	BOXRMTSA	1987:01-2019:12	2	SPDJ	HPI (Middle Tier) for Boston, Massachusetts (Jan 2000=100, sa)
558	MNXRLTSA	1989:01-2019:12	2	SPDJ	HPI (Low Tier) for Minneapolis, Minnesota (Jan 2000=100, sa)
559	DNXRMTSA	1987:01-2019:12	2	SPDJ	HPI (Middle Tier) for Denver, Colorado (Jan 2000=100, sa)
560	TPXRMTSA	1987:01-2019:12	2	SPDJ	HPI (Middle Tier) for Tampa, Florida (Jan 2000=100, sa)
561	WDXRMTSA	1987:01-2019:12	2	SPDJ	HPI (Middle Tier) for Washington D.C. (Jan 2000=100, sa)
562	MNXRMTSA	1989:01-2019:12	2	SPDJ	HPI (Middle Tier) for Minneapolis, Minnesota (Jan 2000=100, sa)
563	MIXRMTSA	1987:01-2019:12	2	SPDJ	HPI (Middle Tier) for Miami, Florida (Jan 2000=100, sa)

Housing starts and sales

564	HOUST	1959:01-2020:02	2	DHUD	Housing Starts: Total: New Privately Owned Housing units Started (thous of units, sa)
565	HOUST1F	1959:01-2020:02	2	DHUD	Privately Owned Housing Starts: 1-Unit Structures (thous of units, sa)
566	HOUST5F	1959:01-2020:02	2	DHUD	Privately Owned Housing Starts: 5-Unit Structures or More (thous of units, sa)
567	HOUSTMW	1959:01-2020:02	2	DHUD	Housing Starts in Midwest Census Region (thous of units, sa)
568	HOUSTW	1959:01-2020:02	2	DHUD	Housing Starts in West Census Region (thous of units, sa)
569	HOUSTS	1959:01-2020:02	2	DHUD	Housing Starts in South Census Region (thous of units, sa)
570	HOUSTNE	1959:01-2020:02	2	DHUD	Housing Starts in Northeast Census Region (thous of units, sa)
571	HOUST2F	1959:01-2020:02	7	DHUD	Housing Starts: 2-4 units (thous of units, sa)
572	HOUSTW1F	1984:01-2020:02	2	DHUD	Housing Starts for 1-Unit Structures in West Census Region (thous of units, sa)
573	HOUSTNE1F	1984:01-2020:02	2	DHUD	Housing Starts for 1-Unit Structures in Northeast Census Region (thous of units, sa)
574	HOUSTMW1F	1984:01-2020:02	2	DHUD	Housing Starts for 1-Unit Structures in Midwest Census Region (thous of units, sa)
575	HOUSTS1F	1984:01-2020:02	2	DHUD	Housing Starts for 1-Unit Structures in South Census Region (thous of units, sa)
576	HSN1F	1963:01-2020:01	2	DHUD	New One Family Houses Sold: United States (thous, sa)
577	HNFSEPUSSA	1963:01-2020:01	2	DHUD	New One Family Homes for Sale in the United States (thous of units, sa)
578	HSN1FW	1973:01-2020:01	2	DHUD	New One Family Houses Sold in West Census Region (thous, sa)
579	HSN1FS	1973:01-2020:01	2	DHUD	New One Family Houses Sold in South Census Region (thous, sa)
580	HSN1FNE	1973:01-2020:01	2	DHUD	New One Family Houses Sold in Northeast Census Region (thous, sa)
581	HSN1FMW	1973:01-2020:01	2	DHUD	New One Family Houses Sold in Midwest Census Region (thous, sa)
582	TXBP1FHSA	1988:01-2020:01	2	USCB	New priv. housing units auth. by building permits: 1-unit structures: Texas (units, sa)
583	DALL148BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Dallas-Fort WA, TX (units, sa)
584	PHOE004BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Phoenix-Mesa-C, AZ (units, sa)
585	FLBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Florida (units, sa)
586	ALBU735BP1FHSA	1988:01-2020:01	7	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Albuquerque, NM (units, sa)
587	RIVE106BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Riverside-San B-O, CA (units, sa)
588	ODES248BP1FHSA	1988:01-2020:01	7	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Odessa, TX (units, sa)
589	PORT941BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Portland-Vancouver-H (units, sa)
590	HOUS448BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Houston, TX (units, sa)
591	STLBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: St. Louis, MO-IL (units, sa)
592	CHAR737BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Charlotte-C-G, NC-SC (units, sa)
593	MIAM112BP1FHSA	1988:01-2020:01	7	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Miami-FB LP, FL (units, sa)
594	LASV832BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Las Vegas-H-P, NV (units, sa)
595	LOIBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Louisville-Jeff., KY-IN (units, sa)
596	CSOUBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: South Census Region (units, sa)
597	NASH947BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Nashville-D-MF, TN (units, sa)
598	CABP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: California (units, sa)
599	SANA748BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: San Antonio-NB, TX (units, sa)
600	ORLA712BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Orlando-Kissimmee, FL (units, sa)
601	MABP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Massachusetts (units, sa)
602	MNBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Minnesota (units, sa)
603	AZBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Arizona (units, sa)
604	MPHBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Memphis, TN-MS-AR (units, sa)
605	MINN427BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Minneapolis-St. PB (units, sa)
606	CHIC917BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Chicago-Naperville-E (units, sa)
607	COBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Colorado (units, sa)
608	TAMP312BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Tampa-St. P-C, FL (units, sa)
609	PUEB308BP1FHSA	1988:01-2020:01	7	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Pueblo, CO (units, sa)
610	UTBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Utah (units, sa)
611	NYBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: New York (units, sa)
612	SCBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: South Carolina (units, sa)
613	ATLA013BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Atlanta-Sandy S-A, GA (units, sa)
614	WIBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Wisconsin (units, sa)
615	CLMBP1FHSA	1988:01-2020:01	7	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Columbia, MO (units, sa)
616	ILBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Illinois (units, sa)
617	PALM312BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Palm Bay-M-T, FL (units, sa)
618	JACK212BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Jacksonville, FL (units, sa)
619	LAKE412BP1FHSA	1988:01-2020:01	7	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Lakeland-W Haven, FL (units, sa)
620	NJBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: New Jersey (units, sa)
621	BOIS216BP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Boise City, ID (units, sa)

622	PENS812BP1FHSA	1988:01-2020:01	7	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Pensacola-Ferry PB, FL (units, sa)
623	NDBP1FHSA	1988:01-2020:01	7	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: North Dakota (units, sa)
624	CTBP1FHSA	1988:01-2020:01	2	USCB	New priv.hous. units auth. by buil.per.: 1-unit struc.: Connecticut (units, sa)

Imports

625	IR	1982:09-2020:02	2	BLS	Import Price (End Use): All commodities (2000=100, nsa)
626	IREXPET	1985:03-2020:02	2	BLS	Import Price (End Use): All imports excluding petroleum (2000=100, nsa)
627	IR4	1982:06-2020:02	2	BLS	Import Price (End Use): Consumer goods, excluding automotives (2000=100, nsa)
628	XTIMVA01USM657S	1960:01-2019:12	7	OECD	Imports: Value Goods for the United States (Growth Rate Previous Period, sa)
629	XTIMVA01USM659S	1960:01-2019:12	7	OECD	Imports: Value Goods for the U.S. (Growth Rate Same Period Previous Year, sa)
630	XTIMVA01USM664S	1960:01-2019:12	2	OECD	Imports: Value Goods for the United States (National currency, Monthly Level, sa)
631	XTIMVA01USM667S	1960:01-2019:12	2	OECD	Imports: Value Goods for the United States (US usd Monthly Level, sa)
632	IMPCA	1985:01-2020:01	2	BEACB	U.S. Imports of Goods by Customs Basis from Canada (MM of usd, nsa)
633	IMPCH	1985:01-2020:01	2	BEACB	U.S. Imports of Goods by Customs Basis from China (MM of usd, nsa)
634	IMPFR	1985:01-2020:01	2	BEACB	U.S. Imports of Goods by Customs Basis from France (MM of usd, nsa)
635	IMPGE	1985:01-2020:01	2	BEACB	U.S. Imports of Goods by Customs Basis from Germany (MM of usd, nsa)
636	IMP5600	1985:01-2020:01	2	BEACB	U.S. Imports of Goods by Customs Basis from Indonesia (MM of usd, nsa)
637	IMPJP	1985:01-2020:01	2	BEACB	U.S. Imports of Goods by Customs Basis from Japan (MM of usd, nsa)
638	IMPMX	1985:01-2020:01	2	BEACB	U.S. Imports of Goods by Customs Basis from Mexico (MM of usd, nsa)
639	IMPKR	1985:01-2020:01	2	BEACB	U.S. Imports of Goods by Customs Basis from South Korea (MM of usd, nsa)
640	IMP5830	1985:01-2020:01	2	BEACB	U.S. Imports of Goods by Customs Basis from Taiwan (MM of usd, nsa)
641	IMPUK	1985:01-2020:01	2	BEACB	U.S. Imports of Goods by Customs Basis from the United Kingdom (MM of usd, nsa)
642	IMP3070	1985:01-2020:01	2	BEACB	U.S. Imports of Goods by Customs Basis from Venezuela (MM of usd, nsa)
643	IMP0015	1987:01-2020:01	2	BEACB	U.S. Imports of Goods by Customs Basis from World (MM of usd, nsa)
644	IMP0004	1989:01-2020:01	2	BEACB	U.S. Imports of Goods by Customs Basis from World (MM of usd, sa)

Industrial Production (IP)

645	INDPRO	1919:01-2020:01	2	FED	Industrial Production Index (2012=100, sa)
646	IPBUSEQ	1947:01-2020:01	2	FED	IP: Business Equipment (2012=100, sa)
647	IPHITEK2S	1967:01-2020:01	2	FED	IP: Computers, communications equipment, and semiconductors (2012=100, sa)
648	IPB54100S	1947:01-2020:01	2	FED	IP: Construction supplies (2012=100, sa)
649	IPCONGD	1939:01-2020:01	2	FED	IP: Consumer Goods (2012=100, sa)
650	IPB52300S	1947:01-2020:01	2	FED	IP: Defense and space equipment (2012=100, sa)
651	IPDCONGD	1947:01-2020:01	2	FED	IP: Durable Consumer Goods (2012=100, sa)
652	IPG3331S	1972:01-2020:01	2	FED	IP: Durable Goods: Agriculture, construction, and mining machinery (2012=100, sa)
653	IPG336411T3S	1972:01-2020:01	2	FED	IP: Durable Goods: Aircraft and parts (2012=100, sa)
654	IPB51112S	1947:01-2020:01	2	FED	IP: Durable Goods: Auto parts and allied goods (2012=100, sa)
655	IPG336111S	1972:01-2020:01	2	FED	IP: Durable Goods: Automobile (2012=100, sa)
656	IPB51110S	1947:01-2020:01	2	FED	IP: Durable Goods: Automotive products (2012=100, sa)
657	IPG3273S	1972:01-2020:01	2	FED	IP: Durable Goods: Cement and concrete product (2012=100, sa)
658	IPG3336S	1972:01-2020:01	2	FED	IP: Durable Goods: Engine, turbine, and power transmission equipment (2012=100, sa)
659	IPG3272S	1972:01-2020:01	2	FED	IP: Durable Goods: Glass and glass product (2012=100, sa)
660	IPG33612S	1972:01-2020:01	2	FED	IP: Durable Goods: Heavy duty truck (2012=100, sa)
661	IPG3352S	1972:01-2020:01	2	FED	IP: Durable Goods: Household appliance (2012=100, sa)
662	IPB511221S	1967:01-2020:01	2	FED	IP: Durable Goods: Household appliances (2012=100, sa)
663	IPG3334T6S	1972:01-2020:01	2	FED	IP: Durable Goods: HVAC, metalworking, & power transmission mach.(2012=100, sa)
664	IPG3311A2S	1972:01-2020:01	2	FED	IP: Durable Goods: Iron and steel products (2012=100, sa)
665	IPN3391S	1972:01-2020:01	2	FED	IP: Durable Goods: Medical equipment and supplies (2012=100, sa)
666	IPG3344S	1972:01-2020:01	2	FED	IP: Durable Goods: Semiconductor and other electronic component (2012=100, sa)
667	IPG336212S	1972:01-2020:01	2	FED	IP: Durable Goods: Truck trailer (2012=100, sa)
668	IPDMAN	1972:01-2020:01	2	FED	IP: Durable Manufacturing (NAICS)(2012=100, sa)
669	IPG3364T9S	1972:01-2020:01	2	FED	IP: Durable manufacturing: Aerospace&miscellaneous transp.equip. (2012=100, sa)
670	IPG334S	1972:01-2020:01	2	FED	IP: Durable manufacturing: Computer and electronic product (2012=100, sa)
671	IPG335S	1972:01-2020:01	2	FED	IP: Durable manufacturing: Electrical equip., appliance, and component (2012=100, sa)
672	IPG332S	1972:01-2020:01	2	FED	IP: Durable manufacturing: Fabricated metal product (2012=100, sa)
673	IPG337S	1972:01-2020:01	2	FED	IP: Durable manufacturing: Furniture and related product (2012=100, sa)
674	IPG333S	1972:01-2020:01	2	FED	IP: Durable manufacturing: Machinery (2012=100, sa)
675	IPG339S	1972:01-2020:01	2	FED	IP: Durable manufacturing: Miscellaneous (2012=100, sa)
676	IPG3361T3S	1972:01-2020:01	2	FED	IP: Durable manufacturing: Motor vehicles and parts (2012=100, sa)
677	IPG327S	1972:01-2020:01	2	FED	IP: Durable manufacturing: Nonmetallic mineral product (2012=100, sa)

678	IPG331S	1972:01-2020:01	2	FED	IP: Durable manufacturing: Primary metal (2012=100, sa)
679	IPG321S	1972:01-2020:01	2	FED	IP: Durable manufacturing: Wood product (2012=100, sa)
680	IPUTIL	1939:01-2020:01	2	FED	IP: Electric and Gas Utilities (2012=100, sa)
681	IPG2211S	1972:01-2020:01	2	FED	IP: Electric power generation, transmission, and distribution (2012=100, sa)
682	IPB50089S	1967:01-2020:01	2	FED	IP: Energy Materials: Energy, total (2012=100, sa)
683	IPFINAL	1939:01-2020:01	2	FED	IP: Final Products (Market Group) (2012=100, sa)
684	IPFPNSS	1939:01-2020:01	2	FED	IP: Final Products and Nonindustrial Supplies (2012=100, sa)
685	IPMAN	1972:01-2020:01	2	FED	IP: Manufacturing (NAICS)(2012=100, sa)
686	IPMANSICS	1919:01-2020:01	2	FED	IP: Manufacturing (SIC)(2012=100, sa)
687	IPMAT	1939:01-2020:01	2	FED	IP: Materials (2012=100, sa)
688	IPMINE	1919:01-2020:01	2	FED	IP: Mining (2012=100, sa)
689	IPN2121S	1972:01-2020:01	2	FED	IP: Mining: Coal mining (2012=100, sa)
690	IPG21223S	1972:01-2020:01	2	FED	IP: Mining: Copper, nickel, lead, and zinc mining (2012=100, sa)
691	IPG211111CS	1972:01-2020:01	2	FED	IP: Mining: Crude oil (2012=100, sa)
692	IPN213111S	1972:01-2020:01	2	FED	IP: Mining: Drilling oil and gas wells (2012=100, sa)
693	IPG21222S	1972:01-2020:01	2	FED	IP: Mining: Gold ore and silver ore mining (2012=100, sa)
694	IPG211S	1972:01-2020:01	2	FED	IP: Mining: Oil and gas extraction (2012=100, sa)
695	IPNCONGD	1947:01-2020:01	2	FED	IP: Nondurable Consumer Goods (2012=100, sa)
696	IPB51213S	1954:01-2020:01	2	FED	IP: Nondurable Goods: Chemical products (2012=100, sa)
697	IPG32551S	1972:01-2020:01	2	FED	IP: Nondurable Goods: Paint and coating (2012=100, sa)
698	IPG3254S	1972:01-2020:01	2	FED	IP: Nondurable Goods: Pharmaceutical and medicine (2012=100, sa)
699	IPG3261S	1972:01-2020:01	2	FED	IP: Nondurable Goods: Plastics product (2012=100, sa)
700	IPNMAN	1972:01-2020:01	2	FED	IP: Nondurable Manufacturing (NAICS)(2012=100, sa)
701	IPG315A6S	1972:01-2020:01	7	FED	IP: Nondurable manufacturing: Apparel and leather goods (2012=100, sa)
702	IPG325S	1972:01-2020:01	2	FED	IP: Nondurable manufacturing: Chemical (2012=100, sa)
703	IPG311A2S	1972:01-2020:01	2	FED	IP: Nondurable manufacturing: Food, beverage, and tobacco (2012=100, sa)
704	IPG322S	1972:01-2020:01	2	FED	IP: Nondurable manufacturing: Paper (2012=100, sa)
705	IPG324S	1972:01-2020:01	2	FED	IP: Nondurable manufacturing: Petroleum and coal products (2012=100, sa)
706	IPG326S	1972:01-2020:01	2	FED	IP: Nondurable manufacturing: Plastics and rubber products (2012=100, sa)
707	IPG323S	1972:01-2020:01	1	FED	IP: Nondurable manufacturing: Printing and related support activities (2012=100, sa)
708	IPG313A4S	1972:01-2020:01	1	FED	IP: Nondurable manufacturing: Textiles and products (2012=100, sa)
709	IPB53122S	1954:01-2020:01	2	FED	IP: Semiconductors, printed circuit boards, and other (2012=100, sa)
710	IPG22111S	1972:01-2020:01	2	FED	IP: Utilities: Electric power generation (2012=100, sa)
711	IPG22112S	1972:01-2020:01	2	FED	IP: Utilities: Electric power transmission, control, and distribution (2012=100, sa)
712	MVATOTASSS	1967:01-2020:01	2	FED	Motor Vehicle Assemblies: Total motor vehicle assemblies (MM of units, sa)
713	USAPROINDMISMEI	1960:01-2020:01	2	OECD	Production of Total Industry in United States (2015=100, sa)
714	RIWG211111CS	1972:01-2020:01	2	FED	Rel. importance weight (Contribution to total IP-index): Extraction: Crude oil (%, sa)
715	RIWG211S	1972:01-2020:01	2	FED	Rel. importance weight (Contribution to total IP-index): Oil and gas extraction (%, sa)
Jobless claims					
716	ICNSA	1967:01-2020:05	7	ETA	Initial Claims (number, nsa)
717	ICSA	1967:01-2020:05	2	ETA	Initial Claims (number, sa)
718	ALICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Alabama (number, nsa)
719	AKICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Alaska (number, nsa)
720	AZICLAIMS	1986:02-2020:05	2	ETA	Initial Claims in Arizona (number, nsa)
721	ARICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Arkansas (number, nsa)
722	CAICLAIMS	1986:02-2020:05	2	ETA	Initial Claims in California (number, nsa)
723	COICLAIMS	1985:09-2020:05	7	ETA	Initial Claims in Colorado (number, nsa)
724	CTICLAIMS	1985:10-2020:05	7	ETA	Initial Claims in Connecticut (number, nsa)
725	DEICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Delaware (number, nsa)
726	FLICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Florida (number, nsa)
727	GAICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Georgia (number, nsa)
728	HIICLAIMS	1985:04-2020:05	7	ETA	Initial Claims in Hawaii (number, nsa)
729	IDICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Idaho (number, nsa)
730	ILICLAIMS	1984:08-2020:05	7	ETA	Initial Claims in Illinois (number, nsa)
731	INICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Indiana (number, nsa)
732	IAICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Iowa (number, nsa)
733	KSICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Kansas (number, nsa)
734	KYICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Kentucky (number, nsa)
735	LAICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Louisiana (number, nsa)

736	MEICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Maine (number, nsa)
737	MDICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Maryland (number, nsa)
738	MAICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Massachusetts (number, nsa)
739	MIICLAIMS	1985:10-2020:05	7	ETA	Initial Claims in Michigan (number, nsa)
740	MNICLAIMS	1984:06-2020:05	7	ETA	Initial Claims in Minnesota (number, nsa)
741	MSICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Mississippi (number, nsa)
742	MOICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Missouri (number, nsa)
743	MTICLAIMS	1985:10-2020:05	7	ETA	Initial Claims in Montana (number, nsa)
744	NEICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Nebraska (number, nsa)
745	NVICLAIMS	1986:02-2020:05	2	ETA	Initial Claims in Nevada (number, nsa)
746	NHICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in New Hampshire (number, nsa)
747	NJICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in New Jersey (number, nsa)
748	NMICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in New Mexico (number, nsa)
749	NYICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in New York (number, nsa)
750	NCICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in North Carolina (number, nsa)
751	NDICLAIMS	1985:10-2020:05	7	ETA	Initial Claims in North Dakota (number, nsa)
752	OHICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Ohio (number, nsa)
753	OKICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Oklahoma (number, nsa)
754	ORICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Oregon (number, nsa)
755	PAICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Pennsylvania (number, nsa)
756	RIICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Rhode Island (number, nsa)
757	SCICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in South Carolina (number, nsa)
758	SDICLAIMS	1985:09-2020:05	7	ETA	Initial Claims in South Dakota (number, nsa)
759	TNICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Tennessee (number, nsa)
760	TXICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Texas (number, nsa)
761	DCICLAIMS	1986:01-2020:05	7	ETA	Initial Claims in the District of Columbia (number, nsa)
762	UTICLAIMS	1985:09-2020:05	7	ETA	Initial Claims in Utah (number, nsa)
763	VTICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Vermont (number, nsa)
764	VAICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Virginia (number, nsa)
765	WAICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Washington (number, nsa)
766	WVICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in West Virginia (number, nsa)
767	WIICLAIMS	1986:02-2020:05	7	ETA	Initial Claims in Wisconsin (number, nsa)
768	WYICLAIMS	1985:09-2020:05	7	ETA	Initial Claims in Wyoming (number, nsa)
769	CCNSA	1967:01-2020:05	2	ETA	Continued Claims (Insured Unemployment) (number, nsa)
770	ALCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Alabama (number, nsa)
771	AKCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Alaska (number, nsa)
772	AZCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Arizona (number, nsa)
773	ARCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Arkansas (number, nsa)
774	CACCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in California (number, nsa)
775	COCCLAIMS	1985:09-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Colorado (number, nsa)
776	CTCCLAIMS	1985:09-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Connecticut (number, nsa)
777	DECCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Delaware (number, nsa)
778	FLCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Florida (number, nsa)
779	GACCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Georgia (number, nsa)
780	HICCLAIMS	1985:03-2020:04	7	ETA	Continued Claims (Insured Unemployment) in Hawaii (number, nsa)
781	IDCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Idaho (number, nsa)
782	ILCCLAIMS	1984:07-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Illinois (number, nsa)
783	INCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Indiana (number, nsa)
784	IACCLAIMS	1986:02-2020:04	7	ETA	Continued Claims (Insured Unemployment) in Iowa (number, nsa)
785	KSCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Kansas (number, nsa)
786	KYCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Kentucky (number, nsa)
787	LACCLAIMS	1986:02-2020:04	7	ETA	Continued Claims (Insured Unemployment) in Louisiana (number, nsa)
788	MECCLAIMS	1986:02-2020:04	7	ETA	Continued Claims (Insured Unemployment) in Maine (number, nsa)
789	MDCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Maryland (number, nsa)
790	MACCLAIMS	1986:01-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Massachusetts (number, nsa)
791	MICCLAIMS	1985:09-2020:04	7	ETA	Continued Claims (Insured Unemployment) in Michigan (number, nsa)
792	MNCCLAIMS	1984:06-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Minnesota (number, nsa)
793	MSCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Mississippi (number, nsa)
794	MOCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Missouri (number, nsa)
795	MTCCLAIMS	1985:09-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Montana (number, nsa)

796	NECCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Nebraska (number, nsa)
797	NVCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Nevada (number, nsa)
798	NJCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in New Jersey (number, nsa)
799	NYCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in New York (number, nsa)
800	NCCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in North Carolina (number, nsa)
801	NDCCLAIMS	1985:10-2020:04	7	ETA	Continued Claims (Insured Unemployment) in North Dakota (number, nsa)
802	OHCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Ohio (number, nsa)
803	OKCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Oklahoma (number, nsa)
804	ORCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Oregon (number, nsa)
805	PACCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Pennsylvania (number, nsa)
806	SCCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in South Carolina (number, nsa)
807	TNCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Tennessee (number, nsa)
808	TXCCLAIMS	1986:01-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Texas (number, nsa)
809	DCCCLAIMS	1986:01-2020:04	2	ETA	Continued Claims (Insured Unemployment) in the District of Columbia (number, nsa)
810	UTCCLAIMS	1985:09-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Utah (number, nsa)
811	VTCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Vermont (number, nsa)
812	VACCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Virginia (number, nsa)
813	WACCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Washington (number, nsa)
814	WVCCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in West Virginia (number, nsa)
815	WICCLAIMS	1986:02-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Wisconsin (number, nsa)
816	WYCCLAIMS	1985:09-2020:04	2	ETA	Continued Claims (Insured Unemployment) in Wyoming (number, nsa)
Interest rate spreads					
817	T10Y2YM	1976:06-2020:02	5	FRBSL	10Y Treasury const. mat. minus 2Y Treasury const. mat. (%, nsa)
818	T10Y3MM	1982:01-2020:02	5	FRBSL	10Y Treasury const. mat. minus 3M Treasury const. mat. (%, nsa)
819	BAAFFM	1954:07-2020:02	2	FRBSL	Moody's Seasoned Baa Corporate Bond Minus Federal Funds Rate (%, nsa)
820	TB3SMFFM	1954:07-2020:02	7	FRBSL	3-Month Treasury Bill Minus Federal Funds Rate (%, nsa)
821	BAA10YM	1953:04-2020:02	2	FRBSL	Moody's Seasoned Baa Corp Bond Yield Relative to Yield on 10Y-T cont mat. (%, nsa)
822	T10YFFM	1954:07-2020:02	5	FRBSL	10-Year Treasury Constant Maturity Minus Federal Funds Rate (%, nsa)
823	AAAFFM	1954:07-2020:02	2	FRBSL	Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate (%, nsa)
824	AAA10YM	1953:04-2020:02	2	FRBSL	Moody's Seasoned Aaa Corp Bond Yield Relative to Yield on 10Y-T const mat. (%, nsa)
825	T5YFFM	1954:07-2020:02	4	FRBSL	5Y Treasury Constant Maturity Minus Federal Funds Rate (%, nsa)
826	T3MFFM	1982:01-2020:02	7	FRBSL	3M Treasury Constant Maturity Minus Federal Funds Rate (%, nsa)
827	T1YFFM	1954:07-2020:02	7	FRBSL	1Y Treasury Constant Maturity Minus Federal Funds Rate (%, nsa)
828	T6MFFM	1982:01-2020:02	7	FRBSL	6M Treasury Constant Maturity Minus Federal Funds Rate (%, nsa)
829	TEDRATE	1989:01-2020:02	7	FRBSL	TED Spread (%, nsa)
Loans outstanding					
830	DTBOENM	1985:06-2020:01	2	FED	Business Equipment Loans & Leases Owned by Fin. Companies, outst. (MM of usd, nsa)
831	DTBOELNM	1985:06-2020:01	2	FED	Business Equipment Loans Owned by Finance Companies, outst. (MM of usd, nsa)
832	DTBOVNM	1980:06-2020:01	2	FED	Business Motor Vehicle Loans&Leases Owned by fin.comp., outst. (MM of usd, nsa)
833	DTBOVLRNM	1980:06-2020:01	2	FED	Business Retail Motor Vehicle Loans Owned by Fin. Companies, outst. (MM of usd, nsa)
834	DTBOVLWNM	1980:06-2020:01	2	FED	Business Wholesale Motor Vehicle Loans Owned by fin.comp., outst. (MM of usd, nsa)
835	DTCOLNVHFNM	1943:01-2020:01	2	FED	Consumer Motor Vehicle Loans Owned by Finance Companies, outst. (MM of usd, nsa)
836	DTCNLNVHFNM	1989:01-2020:01	2	FED	Consumer Motor Vehicle Loans Securitized by Fin. Companies, outst. (MM of usd, nsa)
837	REVOLNCU	1984:01-2020:01	2	FED	Consumer Revolving Credit Owned by Credit Unions, Outstanding (bn of usd, nsa)
838	REVOLNDI	1968:01-2020:01	2	FED	Consumer Revolving Credit Owned by Depository Institutions, outst. (bn of usd, nsa)
839	REVOLNFC	1984:12-2020:01	2	FED	Consumer Revolving Credit Owned by Finance Companies, Outstanding (bn of usd, nsa)
840	REVOLNNFC	1970:01-2020:01	2	FED	Consumer Revolving Credit Owned by Nonfinancial Businesses, outst. (bn of usd, nsa)
841	NREVNCU	1943:01-2020:01	2	FED	Nonrevolving Consumer Loans Owned by Credit Unions, Outstanding (bn of usd, nsa)
842	NREVNDI	1943:01-2020:01	2	FED	Nonrevolving Consumer Loans Owned by Depository inst., outst. (bn of usd, nsa)
843	NREVNFC	1943:01-2020:01	2	FED	Nonrevolving Consumer Loans Owned by Finance Companies, outst. (bn of usd, nsa)
844	NREVNNFC	1943:01-2020:01	2	FED	Nonrevolving Consumer Loans Owned by Nonfin. Businesses, outst. (bn of usd, nsa)
845	NREVNGOV	1977:01-2020:01	2	FED	Nonrevolving Consumer Loans Owned by the Fed Gov, outst. (bn of usd, nsa)
846	DTROSNM	1970:06-2020:01	2	FED	One to Four Fam. Real Estate Loans Owned by Fin.companies, outst. (MM of usd, nsa)
847	DTCOLNOHFNM	1943:01-2020:01	2	FED	Other Consumer Loans Owned by Finance Companies, Outstanding (MM of usd, nsa)
848	DTCNLNOHFNM	1989:01-2020:01	2	FED	Other Consumer Loans Securitized by Finance Companies, outst. (MM of usd, nsa)
849	DTROONM	1970:06-2020:01	2	FED	Other Real Estate Loans Owned by Finance Companies, Outstanding (MM of usd, nsa)
850	NREVNSEC	1989:01-2020:01	2	FED	Securitized Consumer Nonrevolving Credit, Outstanding (bn of usd, nsa)
851	TOTALSEC	1989:01-2020:01	2	FED	Securitized Total Consumer Loans, Outstanding (bn of usd, nsa)

852	DTBTNM	1980:06-2020:01	2	FED	Total business loans&leases owned & Securitized by fin.comp., outst. (MM of usd, nsa)
853	DTBTM	1985:06-2020:01	2	FED	Total Business loans & leases Owned & securitized by fin.comp., outst. (MM of usd, sa)
854	TOTALNS	1943:01-2020:01	2	FED	Total Consumer Credit Owned and Securitized, Outstanding (bn of usd, nsa)
855	TOTALSL	1943:01-2020:01	2	FED	Total Consumer Credit Owned and Securitized, Outstanding (bn of usd, sa)
856	DTCTHFNM	1943:01-2020:01	2	FED	Total cons. loans&leases Owned & Securitized by fin.comp., outst. (MM of usd, nsa)
857	DTCTHFM	1985:06-2020:01	2	FED	Total cons. loans&leases Owned & Securitized by fin.comp., outst. (MM of usd, sa)
858	TOTALTCU	1943:01-2020:01	2	FED	Total Consumer Loans Owned by Credit Unions, Outstanding (bn of usd, nsa)
859	TOTALDI	1943:01-2020:01	2	FED	Total Consumer Loans Owned by Depository Institutions, Outstanding (bn of usd, nsa)
860	TOTALGOV	1977:01-2020:01	2	FED	Total Consumer Loans Owned by Federal Government, Outstanding (bn of usd, nsa)
861	TOTALFC	1943:01-2020:01	2	FED	Total Consumer Loans Owned by Finance Companies, Outstanding (bn of usd, nsa)
862	TOTALNFC	1943:01-2020:01	2	FED	Total Consumer Loans Owned by Nonfinancial Businesses, Outstanding (bn of usd, nsa)
863	DTTHFXDFBANM	1943:02-2020:01	7	FED	Total Loans and Leases outst. at Domestic Finance Companies, Flow (MM of usd, nsa)
864	DTTHFXDFBANA	1943:02-2020:01	7	FED	Total Loans and Leases outst. at Domestic Finance Companies, Flow (MM of usd, nsa)
865	DTTHFXDFBAA	1970:07-2020:01	7	FED	Total Loans and Leases outst. at Domestic Finance Companies, Flow (MM of usd, sa)
866	DTTHFXDFBAM	1970:07-2020:01	7	FED	Total Loans and Leases outst. at Domestic Finance Companies, Flow (MM of usd, sa)
867	DTTHFNM	1943:01-2020:01	2	FED	Total Loans and Leases outst. at Domestic Finance Companies, outst. (MM of usd, nsa)
868	DTTHFM	1970:06-2020:01	2	FED	Total Loans and Leases outst. at Domestic Finance Companies, outst. (MM of usd, sa)
869	NONREVNS	1943:01-2020:01	2	FED	Total Nonrevolving Credit Owned and Securitized, Outstanding (bn of usd, nsa)
870	NONREVSL	1943:01-2020:01	2	FED	Total Nonrevolving Credit Owned and Securitized, Outstanding (bn of usd, sa)
871	DTRTNM	1970:06-2020:01	2	FED	Total Real Estate Loans Owned and Securitized by fin.comp., outst. (MM of usd, nsa)
872	DTRTM	1970:06-2020:01	2	FED	Total Real Estate Loans Owned and Securitized by fin.comp., outst. (MM of usd, sa)
873	REVOLNS	1968:01-2020:01	2	FED	Total Revolving Credit Owned and Securitized, Outstanding (bn of usd, nsa)
874	REVOLSL	1968:01-2020:01	2	FED	Total Revolving Credit Owned and Securitized, Outstanding (bn of usd, sa)
Manufacturing and trade					
875	CMRMTSPL	1967:01-2019:12	2	FRBSL	Real Manufacturing and Trade Industries Sales (MM of Chained 2012 usd, sa)
876	INVCMRMTSPL	1967:01-2019:12	2	FRBSL	Real Manufacturing and Trade Inventories (Chained 2012 usd, sa)
Money Stock					
877	CURRNS	1947:01-2020:02	2	FED	Currency Component of M1 (bn of usd, nsa)
878	CURRSL	1947:01-2020:02	2	FED	Currency Component of M1 (bn of usd, sa)
879	CURRDD	1959:01-2020:02	2	FED	Currency Component of M1 Plus Demand Deposits (bn of usd, sa)
880	DDDFCBNS	1959:01-2020:02	2	FED	Demand Deposits Due to Foreign Commercial Banks (bn of usd, nsa)
881	DDDFOINS	1959:01-2020:02	2	FED	Demand Deposits Due to Foreign Official Institutions (bn of usd, nsa)
882	DEMDEPNS	1959:01-2020:02	2	FED	Demand Deposits: Total (bn of usd, nsa)
883	DEMDEPSL	1959:01-2020:02	2	FED	Demand Deposits: Total (bn of usd, sa)
884	IMFNS	1974:01-2020:02	2	FED	Institutional Money Funds (bn of usd, nsa)
885	IMFSL	1974:01-2020:02	2	FED	Institutional Money Funds (bn of usd, sa)
886	IRA	1962:11-2020:02	2	FED	IRA and Keogh Accounts - Total (bn of usd, nsa)
887	IRACB	1967:12-2020:02	2	FED	IRA and Keogh Accounts at Commercial Banks (bn of usd, nsa)
888	IRATI	1959:01-2020:02	2	FED	IRA and Keogh accounts at thrift institutions (bn of usd, nsa)
889	MANMM101USM657S	1960:01-2020:01	7	OECD	M1 for the United States (Growth Rate Previous Period, sa)
890	MANMM101USM189S	1960:01-2020:01	2	OECD	M1 for the United States (National Currency, sa)
891	M1NS	1959:01-2020:02	2	FED	M1 Money Stock (bn of usd, nsa)
892	M1SL	1959:01-2020:02	2	FED	M1 Money Stock (bn of usd, sa)
893	M2MNS	1959:01-2020:02	2	FRBSL	M2 Less Small Time Deposits (bn of usd, nsa)
894	M2MSL	1959:01-2020:02	2	FRBSL	M2 Less Small Time Deposits (bn of usd, sa)
895	M2NS	1959:01-2020:02	2	FED	M2 Money Stock (bn of usd, nsa)
896	M2SL	1959:01-2020:02	2	FED	M2 Money Stock (bn of usd, sa)
897	MABMM301USM657S	1960:01-2020:01	7	OECD	M3 for the United States (Growth Rate Previous Period, sa)
898	MABMM301USM189S	1960:01-2020:01	2	OECD	M3 for the United States (National Currency, sa)
899	MZMNS	1959:01-2020:02	2	FRBSL	MZM Money Stock (bn of usd, nsa)
900	MZMSL	1959:01-2020:02	2	FRBSL	MZM Money Stock (bn of usd, sa)
901	NOM1M2N	1959:01-2020:02	2	FED	Non-M1 Components of M2 (bn of usd, nsa)
902	NOM1M2	1959:01-2020:02	2	FED	Non-M1 Components of M2 (bn of usd, sa)
903	OCDSL	1963:01-2020:02	2	FED	Other Checkable Deposits (bn of usd, sa)
904	OCDNS	1963:01-2020:02	2	FED	Other Checkable Deposits (bn of usd, sa)
905	OCDCBN	1959:01-2020:02	2	FED	Other Checkable Deposits at Commercial Banks (bn of usd, nsa)
906	OCDCBS	1959:01-2020:02	2	FED	Other Checkable Deposits at Commercial Banks (bn of usd, sa)
907	OCDTIN	1959:01-2020:02	2	FED	Other Checkable Deposits at Thrift Institutions (bn of usd, nsa)

908	OCDTIS	1959:01-2020:02	2	FED	Other Checkable Deposits at Thrift Institutions (bn of usd, sa)
909	M1REAL	1959:01-2020:02	2	FRBSL	Real M1 Money Stock (bn of 1982-84 usd, sa)
910	M2REAL	1959:01-2020:02	2	FRBSL	Real M2 Money Stock (bn of 1982-84 usd, sa)
911	MZMREAL	1959:01-2020:02	2	FRBSL	Real MZM Money Stock (bn of 1982-84 usd, sa)
912	RMFNS	1973:11-2020:02	2	FED	Retail Money Funds (bn of usd, nsa)
913	SVSTNS	1959:01-2020:02	2	FED	Savings and Small Time Deposits - Total (bn of usd, nsa)
914	SVSTSL	1959:01-2020:02	2	FED	Savings and Small Time Deposits - Total (bn of usd, sa)
915	SVSTCBNS	1959:01-2020:02	2	FED	Savings and Small Time Deposits at Commercial Banks (bn of usd, nsa)
916	SVSTCBSL	1959:01-2020:02	2	FED	Savings and Small Time Deposits at Commercial Banks (bn of usd, sa)
917	SAVINGNS	1959:01-2020:02	2	FED	Savings Deposits - Total (bn of usd, nsa)
918	SAVINGSL	1959:01-2020:02	2	FED	Savings Deposits - Total (bn of usd, sa)
919	SVGCBNS	1959:01-2020:02	2	FED	Savings Deposits at Commercial Banks (bn of usd, nsa)
920	SVGCBSL	1959:01-2020:02	2	FED	Savings Deposits at Commercial Banks (bn of usd, sa)
921	SVGTNS	1959:01-2020:02	2	FED	Savings Deposits at Thrift Institutions (bn of usd, nsa)
922	SVGTI	1959:01-2020:02	2	FED	Savings Deposits at Thrift Institutions (bn of usd, sa)
923	STDNS	1959:01-2020:02	7	FED	Small Time Deposits - Total (bn of usd, nsa)
924	STDSL	1959:01-2020:02	7	FED	Small Time Deposits - Total (bn of usd, sa)
925	STDCBNS	1959:01-2020:02	2	FED	Small Time Deposits at Commercial Banks (bn of usd, nsa)
926	STDCBSL	1959:01-2020:02	2	FED	Small Time Deposits at Commercial Banks (bn of usd, sa)
927	STDTNS	1959:01-2020:02	7	FED	Small Time Deposits at Thrift Institutions (bn of usd, nsa)
928	STDTI	1959:01-2020:02	7	FED	Small Time Deposits at Thrift Institutions (bn of usd, sa)
929	TSDFBOI	1959:01-2020:02	2	FED	Time & savings deposits due to foreign banks and official institutions (bn of usd, nsa)
930	TCDNS	1959:01-2020:02	2	FED	Total Checkable Deposits (bn of usd, nsa)
931	TCDSL	1959:01-2020:02	2	FED	Total Checkable Deposits (bn of usd, sa)
932	USGVDDNS	1959:01-2020:02	7	FED	U.S. Government Demand Deposits & Note Balances - Total (bn of usd, nsa)
933	USGDCB	1959:01-2020:02	7	FED	U.S. Government Demand Deposits at Commercial Banks (bn of usd, nsa)
934	NBCB	1978:11-2020:02	7	FED	U.S. Government Note Balances at Depository Institutions (bn of usd, nsa)
935	GDBFRM	1959:01-2020:02	2	FED	US government deposits: General account balance at Fed Reserve (bn of usd, nsa)
936	GDTSDCBM	1959:01-2020:02	2	FED	US government deposits: Time & savings deposits at commercial banks (bn of usd, nsa)
937	GDTCBM	1959:01-2020:02	7	FED	US government deposits: Total cash balance (bn of usd, nsa)
New orders (NOs)					
938	NOCDFSA066MSFRBPHI	1968:05-2020:03	7	FRBP	Current NOs; Diffusion for FRB - Philadelphia District (Index, sa)
939	UOCDFSA066MSFRBPHI	1968:05-2020:03	7	FRBP	Current Unfilled Orders; Diffusion for FRB - Philadelphia District (Index, sa)
940	NOFDFSA066MSFRBPHI	1968:05-2020:03	7	FRBP	Future NOs; Diffusion for FRB - Philadelphia District (Index, sa)
New Private Housing Units Authorized (NPHUA)					
941	PERMITNE1	1988:01-2020:02	2	DHUD	NPHUA (thous of units, sa)
942	PERMIT1	1960:01-2020:02	2	DHUD	NPHUA by Building Permits - in Structures with 1 Unit (thous of units, sa)
943	PERMIT24	1960:01-2020:02	2	DHUD	NPHUA by Building Permits - in Structures with 2 to 4 units (thous of units, sa)
944	PERMIT5	1960:01-2020:02	2	DHUD	NPHUA by Building Permits - in Structures with 5 units (thous of units, sa)
945	PERMIT	1960:01-2020:02	2	DHUD	NPHUA by Building Permits (thous of units, sa)
946	PERMITMW1	1988:01-2020:02	2	DHUD	NPHUA by Building Permits: Struct.- 1 Unit, Midwest Census Reg. (thous of units, sa)
947	PERMITS1	1988:01-2020:02	2	DHUD	NPHUA by Building Permits: Struct.- 1 Unit, South Census Region (thous of units, sa)
948	PERMITW1	1988:01-2020:02	2	DHUD	NPHUA by Building Permits: Struct.- 1 Unit, West Census Region (thous of units, sa)
949	PERMITMW	1960:01-2020:02	2	DHUD	NPHUA by Building Permits in the Midwest Census Region (thous of units, sa)
950	PERMITNE	1960:01-2020:02	2	DHUD	NPHUA by Building Permits in the Northeast Census Region (thous of units, sa)
951	PERMITS	1960:01-2020:02	2	DHUD	NPHUA by Building Permits in the South Census Region (thous of units, sa)
952	PERMITW	1960:01-2020:02	2	DHUD	NPHUA by Building Permits in the West Census Region (thous of units, sa)
Leading Index					
953	USSLIND	1982:01-2020:02	5	FRBP	Leading Index for the United States (%, sa)
954	CASLIND	1982:01-2020:02	4	FRBP	Leading Index for California (%, sa)
955	TXSLIND	1982:01-2020:02	4	FRBP	Leading Index for Texas (%, sa)
956	OHSLIND	1982:01-2020:02	7	FRBP	Leading Index for Ohio (%, sa)
957	FLSLIND	1982:01-2020:02	5	FRBP	Leading Index for Florida (%, sa)
958	COSLIND	1982:01-2020:02	4	FRBP	Leading Index for Colorado (%, sa)
959	NYSLIND	1982:01-2020:02	7	FRBP	Leading Index for New York (%, sa)
960	WASLIND	1982:01-2020:02	7	FRBP	Leading Index for Washington (%, sa)
961	ALSLIND	1982:01-2020:02	7	FRBP	Leading Index for Alabama (%, sa)

962	OKSLIND	1982:01-2020:02	7	FRBP	Leading Index for Oklahoma (%, sa)
963	MOSLIND	1982:01-2020:02	7	FRBP	Leading Index for Missouri (%, sa)
964	TNSLIND	1982:01-2020:02	7	FRBP	Leading Index for Tennessee (%, sa)
965	LASLIND	1982:01-2020:02	7	FRBP	Leading Index for Louisiana (%, sa)
966	AZSLIND	1982:01-2020:02	7	FRBP	Leading Index for Arizona (%, sa)
967	MNSLIND	1982:01-2020:02	7	FRBP	Leading Index for Minnesota (%, sa)
968	WISLIND	1982:01-2020:02	7	FRBP	Leading Index for Wisconsin (%, sa)
969	MISLIND	1982:01-2020:02	7	FRBP	Leading Index for Michigan (%, sa)
970	CTSLIND	1982:01-2020:02	7	FRBP	Leading Index for Connecticut (%, sa)
971	GASLIND	1982:01-2020:02	4	FRBP	Leading Index for Georgia (%, sa)
972	NCSLIND	1982:01-2020:02	4	FRBP	Leading Index for North Carolina (%, sa)
973	KYSLIND	1982:01-2020:02	7	FRBP	Leading Index for Kentucky (%, sa)
974	INSLIND	1982:01-2020:02	7	FRBP	Leading Index for Indiana (%, sa)
975	AKSLIND	1982:01-2020:02	7	FRBP	Leading Index for Alaska (%, sa)
976	VASLIND	1982:01-2020:02	4	FRBP	Leading Index for Virginia (%, sa)
977	IASLIND	1982:01-2020:02	7	FRBP	Leading Index for Iowa (%, sa)
978	ILSLIND	1982:01-2020:02	7	FRBP	Leading Index for Illinois (%, sa)
979	ORSLIND	1982:01-2020:02	7	FRBP	Leading Index for Oregon (%, sa)
980	SCSLIND	1982:01-2020:02	7	FRBP	Leading Index for South Carolina (%, sa)
981	PASLIND	1982:01-2020:02	7	FRBP	Leading Index for Pennsylvania (%, sa)
982	NVSLIND	1982:01-2020:02	4	FRBP	Leading Index for Nevada (%, sa)
983	HISLIND	1982:01-2020:02	7	FRBP	Leading Index for Hawaii (%, sa)
984	KSSLIND	1982:01-2020:02	7	FRBP	Leading Index for Kansas (%, sa)
985	IDSLIND	1982:01-2020:02	5	FRBP	Leading Index for Idaho (%, sa)
986	ARSLIND	1982:01-2020:02	4	FRBP	Leading Index for Arkansas (%, sa)
987	MASLIND	1982:01-2020:02	7	FRBP	Leading Index for Massachusetts (%, sa)
988	MDSLIND	1982:01-2020:02	7	FRBP	Leading Index for Maryland (%, sa)
989	NMSLIND	1982:01-2020:02	7	FRBP	Leading Index for New Mexico (%, sa)
990	MTSLIND	1982:01-2020:02	7	FRBP	Leading Index for Montana (%, sa)
991	UTSLIND	1982:01-2020:02	7	FRBP	Leading Index for Utah (%, sa)
992	SDSLIND	1982:01-2020:02	7	FRBP	Leading Index for South Dakota (%, sa)
993	WVSLIND	1982:01-2020:02	7	FRBP	Leading Index for West Virginia (%, sa)
994	NESLIND	1982:01-2020:02	4	FRBP	Leading Index for Nebraska (%, sa)
995	NJSLIND	1982:01-2020:02	7	FRBP	Leading Index for New Jersey (%, sa)
996	MESLIND	1982:01-2020:02	7	FRBP	Leading Index for Maine (%, sa)
997	WYSLIND	1982:01-2020:02	7	FRBP	Leading Index for Wyoming (%, sa)
998	NDSLIND	1982:01-2020:02	7	FRBP	Leading Index for North Dakota (%, sa)
999	DESLIND	1982:01-2020:02	7	FRBP	Leading Index for Delaware (%, sa)
1000	VTSLIND	1982:01-2020:02	7	FRBP	Leading Index for Vermont (%, sa)
1001	MSSLIND	1982:01-2020:02	7	FRBP	Leading Index for Mississippi (%, sa)
1002	NHSLIND	1982:01-2020:02	4	FRBP	Leading Index for New Hampshire (%, sa)
1003	RISLIND	1982:01-2020:02	7	FRBP	Leading Index for Rhode Island (%, sa)

Leading Indicators OECD (LI OECD)

1004	USALOCOBSNOSTSAM	1960:01-2020:01	2	OECD	LI OECD: Component series: BTS - Business situation: Normalised, US (Index, sa)
1005	USALOCOBSORSTSAM	1960:01-2020:01	7	OECD	LI OECD: Component series: BTS - Business situation: Original series, US (%, sa)
1006	USALOCODWNOSTSAM	1960:01-2019:12	3	OECD	LI OECD: Component series: Construction: Normalised, US (Index, sa)
1007	USALOCODWORMLSAM	1960:01-2019:12	2	OECD	LI OECD: Component series: Construction: Original series, US (Number, sa)
1008	USALOCOCINOSTSAM	1978:01-2020:01	2	OECD	LI OECD: Component series: CS - Confidence indicator: Normalised, US (Index, sa)
1009	USALOCOCIORSTSAM	1978:01-2020:01	2	OECD	LI OECD: Component series: CS - Confidence indicator: Original series, US (Index, sa)
1010	USALOCOHSORSTSAM	1960:01-2020:01	2	OECD	LI OECD: Component series: Hours: Original series, US (Hours, sa)
1011	USALOCOSINOSTSAM	1960:01-2020:01	2	OECD	LI OECD: Component series: Interest rate spread: Normalised, US (Index, nsa)
1012	USALOCOSIORSTM	1960:01-2020:01	5	OECD	LI OECD: Component series: Interest rate spread: Original series, US (%, sa)
1013	USALOCOODNOSTSAM	1960:01-2019:12	2	OECD	LI OECD: Component series: Orders: Normalised, US (Index, sa)
1014	USALOCOODORNCMLSAM	1960:01-2019:12	2	OECD	LI OECD: Component series: Orders: Original series, US (US Dollar, sa)
1015	USALOCOSPNOSTSAM	1960:01-2020:01	2	OECD	LI OECD: Component series: Share prices: Normalised, US (Index, sa)
1016	USALOCOSPORIXOBM	1960:01-2020:01	2	OECD	LI OECD: Component series: Share prices: Original series, US (2015=100, nsa)
1017	USALOLITOAASTSAM	1960:01-2019:12	2	OECD	LI OECD: Leading indicators: CLI: Amplitude adjusted, US (Index, sa)
1018	USALOLITONOSTSAM	1960:01-2019:12	2	OECD	LI OECD: Leading indicators: CLI: Normalised, US (Index, sa)
1019	USALOLITOTRGYSAM	1960:01-2019:12	4	OECD	LI OECD: Leading ind.: CLI: Trend restored-US (Gr.rate same period prev.year, sa)

1020	USALOLITOTRSTSAM	1960:01-2019:12	3	OECD	LI OECD: Leading indicators: CLI: Trend restored, US (Index, sa)
1021	USALORSGPRTSTSAM	1960:01-2019:12	2	OECD	LI OECD: Reference series: Gross Domestic Product: Ratio to trend, US (Index, sa)
1022	USARECP	1947:02-2019:12	7	FRBSL	OECD based Recession Ind.-US Peak through the Period preceding trough (+1 or 0, sa)
1023	USARECM	1947:02-2019:12	7	FRBSL	OECD based Recession Indicators-U.S. from the Peak through the Trough (+1 or 0, sa)
1024	USAREC	1947:02-2019:12	7	FRBSL	OECD based Recession Ind.-U.S. Period following the Peak through (+1 or 0, sa)
Personal Consumption Expenditures (PCE)					
1025	PCE	1959:01-2020:01	2	BEA	PCE (bn of usd, sa)
1026	PCEPILFE	1959:01-2020:01	2	BEA	PCE Excluding Food and Energy (Chain-Type Price Index) (2012=100, sa)
1027	PCEPI	1959:01-2020:01	2	BEA	PCE: Chain-type Price Index (2012=100, sa)
1028	DDURRG3M086SBEA	1959:01-2020:01	7	BEA	PCE: Durable goods (chain-type price index) (2012=100, sa)
1029	PCEDG	1959:01-2020:01	2	BEA	PCE: Durable Goods (bn of usd, sa)
1030	DNRGRG3M086SBEA	1959:01-2020:01	2	BEA	PCE: Energy goods and services (chain-type price index) (2012=100, sa)
1031	DNRGRC1M027SBEA	1959:01-2020:01	2	BEA	PCE: Energy goods and services (bn of usd, sa)
1032	DPCCRC1M027SBEA	1959:01-2020:01	2	BEA	PCE: excluding food and energy (bn of usd, sa)
1033	DFXARC1M027SBEA	1959:01-2020:01	2	BEA	PCE: Food (bn of usd, sa)
1034	DGDSRG3M086SBEA	1959:01-2020:01	2	BEA	PCE: Goods (chain-type price index) (2012=100, sa)
1035	DGDSRC1	1959:01-2020:01	2	BEA	PCE: Goods (bn of usd, sa)
1036	DPCMRC1M027SBEA	1987:01-2020:01	2	BEA	PCE: Market-based (bn of usd, sa)
1037	DPCXRG3M086SBEA	1987:01-2020:01	2	BEA	PCE: Market-based PCE ex. food & energy (chain-type price index) (2012=100, sa)
1038	DNDGRG3M086SBEA	1959:01-2020:01	2	BEA	PCE: Nondurable goods (chain-type price index) (2012=100, sa)
1039	PCEND	1959:01-2020:01	2	BEA	PCE: Nondurable Goods (bn of usd, sa)
1040	DSERRG3M086SBEA	1959:01-2020:01	2	BEA	PCE: Services (chain-type price index) (2012=100, sa)
1041	PCES	1959:01-2020:01	2	BEA	PCE: Services (bn of usd, sa)
1042	DFXARG3M086SBEA	1959:01-2020:01	2	BEA	PCE:: Food (chain-type price index) (2012=100, sa)
1043	DPCMRG3M086SBEA	1987:01-2020:01	2	BEA	PCE:: Market-based (chain-type price index) (2012=100, sa)
1044	DPCXRC1M027SBEA	1987:01-2020:01	2	BEA	PCE:: Market-based PCE excluding food and energy (bn of usd, sa)
1045	DPCERGM1M225SBEA	1959:02-2020:01	7	BEA	Prices for PCE: Chained Price Index (% Change from Preceding Period, sa)
1046	DNRGRGM1M225SBEA	1959:02-2020:01	7	BEA	Prices for PCE: Chained Price Index: energy goods&ser. (%change from prec.period, sa)
1047	DFXARGM1M225SBEA	1959:02-2020:01	7	BEA	Prices for PCE: Chained Price Index: Food (% Change from Preceding Period, sa)
1048	DGDSRGM1M225SBEA	1959:02-2020:01	7	BEA	Prices for PCE: Chained Price Index: Goods (% Change from Preceding Period, sa)
1049	DDURRGM1M225SBEA	1959:02-2020:01	7	BEA	Prices for PCE: Chained Price Index: Dur.goods (% Change from Preceding Period, sa)
1050	DNDGRGM1M225SBEA	1959:02-2020:01	7	BEA	Prices for PCE: Chained Price Index: Nondur.goods (% Change from preced.period, sa)
1051	DPCMRGM1M225SBEA	1987:02-2020:01	7	BEA	Prices for PCE: Chained Price Index: Market-based PCE (%change from prec.period, sa)
1052	DPCXRGM1M225SBEA	1987:02-2020:01	7	BEA	Prices for PCE: Chained Price Index: MB ex food&energy (%change from pre.period, sa)
1053	DPCCRGM1M225SBEA	1959:02-2020:01	7	BEA	Prices for PCE: Chained P-Index: PCE ex food&energy (%change from prec.period, sa)
1054	DSERRGM1M225SBEA	1959:02-2020:01	7	BEA	Prices for PCE: Chained Price Index: Services (% Change from Preceding Period, sa)
1055	DPCERA3M086SBEA	1959:01-2020:01	2	BEA	Real PCE (chain-type quantity index) (2012=100, sa)
1056	DPCERAM1M225NBEA	1959:02-2020:01	7	BEA	Real PCE (% Change from Preceding Period, sa)
1057	DPCCRA3M086SBEA	1959:01-2020:01	2	BEA	Real PCE excluding food and energy (chain-type quantity index) (2012=100, sa)
1058	DDURRA3M086SBEA	1959:01-2020:01	2	BEA	Real PCE: Durable goods (chain-type quantity index) (2012=100, sa)
1059	DNRGRA3M086SBEA	1959:01-2020:01	2	BEA	Real PCE: Energy goods and services (chain-type quantity index) (2012=100, sa)
1060	DNRGRAM1M225NBEA	1959:02-2020:01	7	BEA	Real PCE: Energy goods and services (% Change from Preceding Period, sa)
1061	DFXARA3M086SBEA	1959:01-2020:01	2	BEA	Real PCE: Food (chain-type quantity index) (2012=100, sa)
1062	DFXARAM1M225NBEA	1959:02-2020:01	7	BEA	Real PCE: Food (% Change from Preceding Period, sa)
1063	DGDSRA3M086SBEA	1959:01-2020:01	2	BEA	Real PCE: Goods (chain-type quantity index) (2012=100, sa)
1064	DGDSRAM1M225NBEA	1959:02-2020:01	7	BEA	Real PCE: Goods (% Change from Preceding Period, sa)
1065	DDURRAM1M225NBEA	1959:02-2020:01	7	BEA	Real PCE: Goods: Durable goods (% Change from Preceding Period, sa)
1066	DNDGRAM1M225NBEA	1959:02-2020:01	7	BEA	Real PCE: Goods: Nondurable goods (% Change from Preceding Period, sa)
1067	DPCMRA3M086SBEA	1987:01-2020:01	2	BEA	Real PCE: Market-based (chain-type quantity index) (2012=100, sa)
1068	DPCMRAM1M225NBEA	1987:02-2020:01	7	BEA	Real PCE: Market-based PCE (% Change from Preceding Period, sa)
1069	DPCXRA3M086SBEA	1987:01-2020:01	2	BEA	Real PCE: Market-based PCE ex food&energy (chain-type quantity index)(2012=100, sa)
1070	DPCXRAM1M225NBEA	1987:02-2020:01	7	BEA	Real PCE: Market-based PCE ex food and energy (% Change from Preceding Period, sa)
1071	DNDGRA3M086SBEA	1959:01-2020:01	2	BEA	Real PCE: Nondurable goods (chain-type quantity index) (2012=100, sa)
1072	DPCCRAM1M225NBEA	1959:02-2020:01	7	BEA	Real PCE: PCE excluding food and energy (% Change from Preceding Period, sa)
1073	DSERRA3M086SBEA	1959:01-2020:01	2	BEA	Real PCE: Services (chain-type quantity index) (2012=100, sa)
1074	DSERRAM1M225NBEA	1959:02-2020:01	7	BEA	Real PCE: Services (% Change from Preceding Period, sa)
Personal Income					
1075	DSPI	1959:01-2020:01	2	BEA	Disposable PI (bn of usd, sa)

1076	A229RC0	1959:01-2020:01	2	BEA	Disposable PI: Per capita: Current dollars (usd, sa)
1077	W055RC1	1959:01-2020:01	2	BEA	Personal current taxes (bn of usd, sa)
1078	W211RC1	1959:01-2020:01	2	BEA	Personal current transfer payments (bn of usd, sa)
1079	W062RC1M027SBEA	1959:01-2020:01	2	BEA	Personal current transfer payments: to government (bn of usd, sa)
1080	B070RC1M027SBEA	1959:01-2020:01	2	BEA	Pers. cur. transfer payments: to the rest of the world (net) (bn of usd, sa)
1081	PCTR	1959:01-2020:01	2	BEA	Pers. cur. transfer receipts (bn of usd, sa)
1082	A063RC1	1959:01-2020:01	2	BEA	Pers. cur. transf. receipts: Gov. social benefits to persons (bn of usd, sa)
1083	W729RC1	1966:01-2020:01	2	BEA	Pers. cur. transf. receipts: Gov. social benefits to persons: Medicaid (bn of usd, sa)
1084	W824RC1	1966:07-2020:01	2	BEA	Pers. cur. transf. receipts: Gov. social benefits to persons: Medicare (bn of usd, sa)
1085	W827RC1	1959:01-2020:01	2	BEA	Pers. cur. transf. receipts: Gov. social benefits to persons: Other (bn of usd, sa)
1086	W823RC1	1959:01-2020:01	2	BEA	Pers. cur. transf. receipts: Gov.social benefits to persons: Social security (bn of usd, sa)
1087	W825RC1	1959:01-2020:01	2	BEA	Pers. cur. transf. receipts: Gov.social benefits to pers.: Unemp.insurance (bn of usd, sa)
1088	W826RC1	1959:01-2020:01	2	BEA	Pers. cur. transf. receipts: Gov.social benef. to pers.: Veterans' benefits (bn of usd, sa)
1089	PI	1959:01-2020:01	2	BEA	PI (bn of usd, sa)
1090	PIROA	1959:01-2020:01	2	BEA	PI Receipts on Assets (bn of usd, sa)
1091	PDI	1959:01-2020:01	2	BEA	PI Receipts on Assets: Personal Dividend Income (bn of usd, sa)
1092	PII	1959:01-2020:01	2	BEA	PI Receipts on Assets: Personal Interest Income (bn of usd, sa)
1093	B069RC1	1959:01-2020:01	2	BEA	Personal interest payments (bn of usd, sa)
1094	A068RC1	1959:01-2020:01	2	BEA	Personal outlays (bn of usd, sa)
1095	PMSAVE	1959:01-2020:01	2	BEA	Personal Saving (bn of usd, sa)
1096	PSAVERT	1959:01-2020:01	2	BEA	Personal Saving Rate (%, sa)
1097	DSPIC96	1959:01-2020:01	2	BEA	Real Disposable PI (bn of Chained 2012 usd, sa)
1098	A229RX0	1959:01-2020:01	2	BEA	Real Disposable PI: Per Capita (Chained 2012 usd, sa)
1099	RPI	1959:01-2020:01	2	BEA	Real PI (bn of Chained 2012 usd, sa)
1100	W875RX1	1959:01-2020:01	2	BEA	Real personal income excluding current transfer receipts (bn of Chained 2012 usd, sa)
1101	A048RC1	1959:01-2020:01	2	BEA	Rental income of persons with capital consumption adjustment (bn of usd, sa)
Producer Price Index by Commodity					
1102	WPSFD49207	1947:04-2020:02	2	BLS	PPI-C: Final Demand: Finished Goods (1982=100, sa)
1103	WPSFD4131	1974:01-2020:02	2	BLS	PPI-C: Final Demand: Finished Goods Less Foods and Energy (1982=100, sa)
1104	WPS1321	1973:01-2020:02	2	BLS	PPI-C: Nonmetallic Mineral Prod.: Cons.sand, gravel&crushed stone (1982=100, sa)
1105	WPSFD41312	1947:04-2020:02	2	BLS	PPI-C: Final Demand: Private Capital Equipment (1982=100, sa)
1106	WPSID612	1973:01-2020:02	2	BLS	PPI-C: Intermediate Demand: Materials&comp., construction (1982=100, sa)
1107	WPSID62	1947:04-2020:02	2	BLS	PPI-C: Intermediate Demand by Commodity Type: Unprocessed Goods (1982=100, sa)
1108	WPSID61	1947:04-2020:02	2	BLS	PPI-C: Intermediate Demand by Commodity Type: Processed Goods (1982=100, sa)
1109	WPSFD49502	1947:04-2020:02	2	BLS	PPI-C: Final Demand: Personal Consump.goods (Finished con.goods)(1982=100, sa)
1110	WPSFD41311	1974:01-2020:02	2	BLS	PPI-C: Final Demand: Finished Consumer Goods Less Foods and Energy (1982=100, sa)
1111	WPS132101	1984:01-2020:02	2	BLS	PPI-C: Nonmetallic Mineral Products: Const.sand, gravel&crushed stone (1982=100, sa)
1112	WPS057303	1985:06-2020:02	2	BLS	PPI-C: Fuels and Related Products and Power: No. 2 Diesel Fuel (1982=100, sa)
1113	WPSFD413121	1975:01-2020:02	2	BLS	PPI-C: Final Demand: Priv. capital equip.: Manufacturing Industries (1982=100, sa)
1114	WPSFD4121	1974:01-2020:02	2	BLS	PPI-C: Final Demand: Finished Consumer Energy Goods (1982=100, sa)
1115	WPSFD4111	1947:04-2020:02	2	BLS	PPI-C: Final Demand: Finished Consumer Foods (1982=100, sa)
1116	WPSID69111	1947:04-2020:02	2	BLS	PPI-C: Intermed. Demand,C-Type: Processed Materials ex foods&feeds (1982=100, sa)
1117	WPS102302	1974:01-2020:02	2	BLS	PPI-C: Metals and Metal Products: Aluminum Base Scrap (1982=100, sa)
1118	WPSFD41113	1973:01-2020:02	2	BLS	PPI-C: Final Demand: Finished Consumer Foods, Crude (1982=100, sa)
1119	WPS022104	1974:01-2020:02	2	BLS	PPI-C: Processed Foods&fe.: Pork prod., fresh, frozen, ex Sausage (1982=100, sa)
1120	WPS1411	1975:01-2020:02	2	BLS	PPI-C: Transportation Equipment: Motor Vehicles (1982=100, sa)
1121	WPS057	1967:01-2020:02	2	BLS	PPI-C: Fuels & Related Products & Power: Petroleum Products, Refined (1982=100, sa)
1122	WPSID69115	1974:01-2020:02	2	BLS	PPI-C: Intermediate Demand, C-type: Processed mat. ex Foods&Energy (1982=100, sa)
1123	WPSID61111	1973:01-2020:02	2	BLS	PPI-C: Intermediate Demand by C-Type: Materials: Food Manufacturing (1982=100, sa)
1124	WPS0132	1967:01-2020:02	2	BLS	PPI-C: Farm Products: Slaughter Hogs (1982=100, sa)
1125	WPS057302	1975:01-2020:02	2	BLS	PPI-C: Fuels & Related Products & Power: Home heating oil & distillates (1982=100, sa)
Retail Sales (RS)					
1126	LAUTOSA	1976:01-2020:02	2	BEA	Motor Vehicle RS: Domestic and Foreign Autos (MM of units, sa)
1127	DAUTOSAAR	1967:01-2020:02	2	BEA	Motor Vehicle RS: Domestic Autos (MM of units, sa)
1128	DAUTOSA	1967:01-2020:02	2	BEA	Motor Vehicle RS: Domestic Autos (thous of units, sa)
1129	DLTRUCKSSAAR	1967:01-2020:02	2	BEA	Motor Vehicle RS: Domestic Light Weight Trucks (MM of units, sa)
1130	DLTRUCKSSA	1967:01-2020:02	2	BEA	Motor Vehicle RS: Domestic Light Weight Trucks (thous of units, sa)
1131	FAUTOSAAR	1967:01-2020:02	2	BEA	Motor Vehicle RS: Foreign Autos (MM of units, sa)

1132	FAUTOSA	1967:01-2020:02	2	BEA	Motor Vehicle RS: Foreign Autos (thous of units, sa)
1133	FLTRUCKSSAAR	1976:01-2020:02	2	BEA	Motor Vehicle RS: Foreign Light Weight Trucks (MM of units, sa)
1134	HTRUCKSSAAR	1967:01-2020:02	2	BEA	Motor Vehicle RS: Heavy Weight Trucks (MM of units, sa)
1135	HTRUCKSSA	1967:01-2020:02	2	BEA	Motor Vehicle RS: Heavy Weight Trucks (thous of units, sa)
1136	LTRUCKSA	1976:01-2020:02	2	BEA	Motor Vehicle RS: Light Weight Trucks (MM of units, sa)
1137	RMFSL	1973:11-2020:02	2	FED	Retail Money Funds (bn of usd, sa)
1138	USASARTMISMEI	1960:01-2019:12	2	OECD	Total Retail Trade in United States (2015=100, sa)
1139	TOTALSA	1976:01-2020:02	2	BEA	Total Vehicle Sales (MM of units, sa)
Sentiment					
1140	BSCURT02USM160S	1967:01-2020:01	2	OECD	Business tendency - manuf.: Capacity Utilization (% of capacity, sa)
1141	BSCICP02USM460S	1960:01-2020:02	7	OECD	Business tendency - manuf.: Confidence Indicators: Composite Indicators (Net %, sa)
1142	BSCICP03USM665S	1960:01-2020:02	2	OECD	Business tendency - manuf.: Confidence Indic.: Composite Indic. (Normal=100, sa)
1143	BSXRLV02USM086S	1990:01-2020:02	7	OECD	Business tendency - manuf.: Export Order Books or Demand: Level (%, sa)
1144	BSOITE02USM460S	1960:01-2020:02	7	OECD	Business tendency - manuf.: Orders Inflow: Tendency (Net %, sa)
1145	BSPRTE02USM460S	1960:01-2020:02	7	OECD	Business tendency - manufacturing: Production: Tendency (Net %, sa)
1146	CSCICP03USM665S	1960:01-2020:02	2	OECD	Consumer Opinion Surveys: Confidence Indicators: Composite Indic. (Normal=100, sa)
1147	CSINFT02USM460S	1978:01-2020:02	2	OECD	Consumer Opinion Surveys: Consumer Prices: Future Tendency of Inflation (Net %, sa)
1148	EMVMACROBUS	1985:01-2020:02	7	BBD	Equity Market Volatility Tracker: Macro: Business Investment & Sentiment (Index, nsa)
1149	EMVMACROCONSUME	1985:01-2020:02	7	BBD	Equity Market Volatility Tracker: Macro: Consumer Spending & Sentiment (Index, nsa)
1150	UMCSENT	1952:11-2020:01	2	UM	University of Michigan: Consumer Sentiment (1966:Q1=100, nsa)
1151	MICH	1978:01-2020:01	2	UM	University of Michigan: Inflation Expectation (%, nsa)
Unfilled Orders (UOs)					
1152	UOCDSA156MSFRBPHI	1968:05-2020:03	7	FRBP	Current UOs; % Reporting Decreases for FRB - Philadelphia District (%, sa)
1153	UOCISA156MSFRBPHI	1968:05-2020:03	7	FRBP	Current UOs; % Reporting Increases for FRB - Philadelphia District (%, sa)
1154	UOCNSA156MSFRBPHI	1968:05-2020:03	2	FRBP	Current UOs; % Reporting No Change for FRB - Philadelphia District (%, sa)
1155	UOFDFSA066MSFRBPHI	1968:05-2020:03	7	FRBP	Future UOs; Diffusion for FRB - Philadelphia District (Index, sa)
1156	UOFDSA156MSFRBPHI	1968:05-2020:03	7	FRBP	Future UOs; % Reporting Decreases for FRB - Philadelphia District (%, sa)
1157	UOFISA156MSFRBPHI	1968:05-2020:03	2	FRBP	Future UOs; % Reporting Increases for FRB - Philadelphia District (%, sa)
1158	UOFNSA156MSFRBPHI	1968:05-2020:03	2	FRBP	Future UOs; % Reporting No Change for FRB - Philadelphia District (%, sa)
US stock market					
1159	SPL	1988:12-2020:02	2	Shiller	S&P500 Level (Index, nsa)
1160	SPD	1988:12-2020:02	2	Shiller	S&P500 Dividends (Index, nsa)
1161	SPE	1988:12-2020:02	2	Shiller	S&P500 Earnings (Index, nsa)
1162	SPRP	1988:12-2020:02	2	Shiller	S&P500 Real Prices (Index, nsa)
1163	SPRD	1988:12-2020:02	2	Shiller	S&P500 Real Dividends (Index, nsa)
1164	SPRTRP	1988:12-2020:02	2	Shiller	S&P500 Real Total Return Price (Index, nsa)
1165	SPRE	1988:12-2020:02	2	Shiller	S&P500 Real Eearnings (Index, nsa)
1166	SPRTRSCALEDEARN	1988:12-2020:02	2	Shiller	S&P500 Real TR Scaled Earnings (Index, nsa)
1167	SPCAPE	1988:12-2020:02	2	Shiller	S&P500 Shiller's CAPE (Index, nsa)
1168	SPTRCAPE	1988:12-2020:02	2	Shiller	S&P500 Shiller's TRCAPE (Index, nsa)
1169	FFSMB	1988:12-2020:01	7	French	Fama-French Small-minus-Big (%, nsa)
1170	FFHML	1988:12-2020:01	7	French	Fama-French High-minus-Low (%, nsa)
1171	FFRMW	1988:12-2020:01	7	French	Fama-French Robust-minus-Weak (%, nsa)
1172	FFCMA	1988:12-2020:01	7	French	Fama-French Conservative-minus-Aggressive (%, nsa)
Volatility index					
1173	VIXCLS	1990:01-2020:03	7	CBOE	CBOE Volatility Index: VIX (Index, nsa)
1174	VXOCLS	1986:01-2020:03	7	CBOE	CBOE S&P 100 Volatility Index: VXO (Index, nsa)
Miscellaneous					
1175	FEDFUNDS	1989:01-2020:02	7	FRBN	Effective Federal Funds Rate (%, nsa)
1176	WLEMUINDXD	1989:01-2020:02	7	EPU	Equity Market-related Economic Uncertainty (Index, nsa)
1177	EXCSRESNS	1989:01-2020:01	2	FRBSL	Excess Reserves of Depository Institutions (MM of usd, nsa)
1178	PRUBBUSDM	1990:01-2020:02	2	IMF	Global price of Rubber (U.S. Cents per Pound, nsa)
1179	PSHRIUSDM	1990:01-2020:02	2	IMF	Global price of Shrimp (U.S. usd per Kilogram, nsa)
1180	MBCURRCIR	1989:01-2020:02	2	FED	Monetary Base; Currency in Circulation (MM of usd, nsa)
1181	BOGMBBM	1989:01-2020:02	2	FED	Monetary Base; Total Balances Maintained (MM of usd, nsa)

1182	BOGMBASE	1989:01-2020:01	2	FED	Monetary Base; Total, MM of usd (MM of usd, nsa)
1183	MVAAUTLTTS	1977:01-2020:01	2	FED	Motor Vehicle Assemblies: Autos and light truck assemblies (MM of units, sa)
1184	MVAHMTRCKS	1979:01-2020:01	2	FED	Motor Vehicle Assemblies: Heavy and medium truck assemblies (MM of units, sa)
1185	NAPMPMI	1989:01-2020:02	2	ISM	NAPM NAPMPMI (Index, sa)
1186	UKX	1989:01-2020:02	2	ISM	NAPM UKX (Index, sa)
1187	RTWVDCA684NMFRBDAL	1988:01-2020:01	2	FRBD	Real Trade-Weighted Value of the dollar for California (Jan 1988=100, nsa)
1188	RTWVDNY684NMFRBDAL	1988:01-2020:01	2	FRBD	Real Trade-Weighted Value of the dollar for New York (Jan 1988=100, nsa)
1189	RTWVDTX684NMFRBDAL	1988:01-2020:01	2	FRBD	Real Trade-Weighted Value of the dollar for Texas (Jan 1988=100, nsa)
1190	SAHMREALTIME	1959:12-2020:02	5	SC	Real-time Sahm Rule Recession Indicator (%age Points, sa)
1191	SAHMCURRENT	1949:03-2020:02	5	SC	Sahm Rule Recession Indicator (%age Points, sa)
1192	SFTPINDM114SFRBSF	1971:04-2020:02	2	FRBSF	San Francisco Tech Pulse (Jan 2000=100, sa)
1193	SFTPAGRM158SFRBSF	1971:05-2020:02	7	FRBSF	San Francisco Tech Pulse (% Change at Annual Rate, sa)
1194	SFTPGR12M159SFRBSF	1972:04-2020:02	4	FRBSF	San Francisco Tech Pulse (% Change from Year Ago, sa)
1195	BORROW	1989:01-2020:02	7	FED	Total Borrowings of Depository Institutions from the Federal Reserve (bn of usd, nsa)
1196	RESBALNS	1989:01-2020:02	2	FED	Total Reserve Balances Maintained with Federal Reserve Banks (bn of usd, nsa)