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Forecasting Net Charge-Off Rates of Banks: A PLS Approach

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Abstract

This chapter relies on a factor-based forecasting model for net charge-off rates of banks in a data-rich environment. More specifically, we employ a partial least squares (PLS) method to extract target-specific factors and find that it outperforms the principal component approach in-sample by construction. Further, we apply PLS to out-of-sample forecasting exercises for aggregate bank net charge-off rates on various loans as well as for similar individual bank rates using over 250 quarterly macroeconomic data from 1987Q1 to 2016Q4. Our empirical results demonstrate superior performance of PLS over benchmark models, including both a stationary autoregressive type model and a nonstationary random walk model. Our approach can help banks identify important variables that contribute to bank losses so that they are better able to contain losses to manageable levels.

Keywords: Net Charge-Off Rates; Partial Least Squares; Principal Component Analysis; Dynamic Factors; Out-of-Sample Forecasts

JEL Classification: C38; C53; G17; G32

1. Introduction

Banks provide important products and services to individuals and firms in countries throughout the world. Their goal is to serve their customers while at the same time earn profits that are acceptable to the shareholders. As banks attempt to accomplish these tasks on an ongoing basis, they must necessarily balance risk and return. Too much risk can lead to failure, while too little return can disappoint shareholders. This means that banks are constantly engaging in a balancing act as they try to achieve an acceptable tradeoff.

Banks, however, do not choose the tradeoff between risk and return by themselves. Instead, various bank regulatory and supervisory authorities assist, and sometimes quite forcibly, in this effort. More to the point, banks in countries everywhere are highly regulated with respect to many of their business practices to promote safer and sounder banking systems. Serious trouble arises when a bank incurs losses that deplete its capital. When such a situation is widespread throughout the banking sector, as occurred in the U.S. in 2007-2008, the result is a banking crisis, which can lead to bank bailouts, which actually happened in the U.S. in the Fall of 2008. Worse yet, this can lead to a severe recession, as also occurred in the U.S. from late 2009 to the summer of 2009.

To avoid individual and widespread bank losses, and associated failures, banks try to identify those variables that are most likely to contribute to the most losses, which better enables them to contain the losses to manageable levels. They have every incentive to do so otherwise the outcome may be their eventual closure, or even seizure by the regulatory authorities, with adverse outcomes to shareholders. In addition, the authorities and accounting guidelines require that a procedure be in place for forecasting losses. In particular, banks will provision for anticipated losses on loans and thereby build up a reserve for loan losses. Regulators and auditing firms can then evaluate whether the allowances made for such losses are adequate for likely future financial and economic developments.

The purpose of our paper is to evaluate the forecasting accuracy with respect to bank losses of a partial least squares (PLS) model as compared to two simpler benchmark models. Although there may be other approaches, the advantage of the PLS model is that it allows one to include more predictor variables than observations in forecasting a target variable. This is clearly likely to be the case in the banking industry, with local, national, and in some cases international, factors affecting the performance of individual banks as well as the entire banking system. Our specific focus is on forecasting bank losses, or net charge-offs, using a PLS model and comparing its performance to the benchmark models. Typically, when one tries to identify predictor variables, the number is restricted to be less than the number of observations. However, in reality, as already noted, there are generally far more variables that can affect the net charge-off rates of banks than the number of available observations in any forecasting exercise. We therefore use a PLS model to obtain forecasts for net charge-off rates for all banks and two very big banks based on more than two hundred predictor variables, as discussed in more detail below.

The remainder of the paper proceeds as follows. In the next section, we review thirteen articles in several business disciplines that use partial least squares in an empirical analysis. As will be seen, there is a relative paucity of studies using this technique in the banking literature. The third section describes and explains factor-based forecasting models with partial least squares, including those used in this article. It also contains our basis for choosing the best forecasting model for net charge-offs of banks. The fourth section contains our empirical findings regarding forecasts over various horizons and an evaluation of forecast accuracy based on a comparison of the PLS model to the benchmark models. The last section contains a summary and conclusions.

2. Literature Review

Based upon a check of relatively recent articles, we were able to identify thirteen papers that use PLS in an empirical examination involving several business disciplines. In particular, we found three articles focusing on accounting issues, one article addressing retailing branding, four articles that deal with more general finance topics, and five articles that are in the banking industry and therefore more closely related to our paper. Admittedly, there no doubt are other papers in various business disciplines that also use PLS, especially in the accounting field, as noted in a few of the papers we review.

Of the three accounting articles, Lee et al. (2011) explains the benefits of using PLS as well as compares and contrasts it with both ordinary least squares and covariance-based structural equation modeling. Moreover, general guidelines are provided for the usage of PLS and its use in the accounting literature is discussed. The authors point out that the usage in accounting has been limited, though much of the usage has conformed to best practice guidelines. In a related vein, Goh et al. (2014) discuss how partial least squares-structural equation modelling can be used in archival financial accounting research. They also point out that PLS is a non-parametric method that is suitable for non-normally distributed data in an analysis, which prior empirical studies find is often the case. The third accounting article by Larson and Kenny (1995) was published nearly thirty years ago and empirically examines the relationship between developing countries' equity market development and economic growth due to the adoption of International Accounting Standards. Based on PLS, they find that the mere adoption of such standards does not guarantee greater equity market development or economic growth. In the fourth accounting article, Nitzl (2016) emphasizes the importance of PLS in situations in which only a weak theory exists and therefore a set of different possible influences have to be tested. In this respect, it is noted that management accounting research frequently has exploratory elements because the theoretical basis is often weak. The author concludes that PLS should not be neglected by management accounting researchers in the future.

Turning to the article on retail branding, or "retail equity", Arnett et al. (2003) use PLS to develop parsimonious measures for retail equity. More specifically, they find it to be a useful tool that can be used to construct an index for assessing the success (failure) of marketing strategies and tactics, among other uses. The conclusion is that PLS provides a method that yields an easy to use index that can be employed by both marketing managers and researchers.

The four papers that focus on more mainstream financial issues are relatively recent, all released or published in 2013 or later, with the exception of one paper published in 2006. The article by Kelly and Pruitt (2013) is quite important because it tackles a challenging problem in empirical asset pricing, which is to exploit the information contained in a large number of predictor variables but limited by a relatively short time series. As they explain, a solution is provided by PLS, which has the properties in a factor model setting that apply to the asset pricing model considered by them. The authors note that principal components (PCs) can also be used to condense information from a large number of predictor variables into a small number of predictive factors. However, PLS condenses the predictors according to covariance with the forecast target and chooses a liner combination of predictors that is optimal for forecasting. In contrast, the PC approach condenses the predictors according to covariance within the predictors. Based on this difference in approaches, Kelly and Pruitt (2013) point out that the components that best describe predictor variation are not necessarily the factors most useful for forecasting, and therefore PCs can produce suboptimal forecasts. They conclude that their empirical results obtained from PLS "stand in contrast" to those implied by standard models of asset prices.

The paper by Huang et al. (2015) develops a new investor sentiment index aligned for predicting the aggregate stock market return. They use PLs in their empirical work, noting that the method was recently introduced to the finance literature by Kelly and Pruett (2013), which is the paper just discussed. Huang and coauthors find that their new index performs much better than most of the commonly used macroeconomic variables do and improves substantially the forecasting power for a cross-section of stock returns formed on industry, size, value, and momentum. Moreover, they attribute the success of the investor sentiment index to the use of the PLS approach that exploits more efficiently the information in proxies than existing procedures do. This provides further motivation for the use of PLS in our empirical work.

The paper by Lie et al. (2017) also focuses on stock returns, but more specifically on predicting the stock market risk premium. They point out that Cochrane (2008) emphasized that understanding the variation in the market risk-premium has important implications in all areas of finance. The authors new approach is to construct a comprehensive index of corporate activities that is used to predict the stock market return, but one that is constructed using the PLS approach. They find that ignoring the information in corporate activities when using PLS clearly impedes the ability of the asset pricing models in explaining asset returns.

In a more narrowly focused finance paper, Laitinen (2006) demonstrates the use of PLS in predicting payment default based upon data for Finland. The results indicate that when using only two PLS-factors as predictors one obtains an equal classification accuracy nearly the same as when an original eight variables are used. The conclusion is that PLS provides a powerful method to reduce dimensions in default prediction, particularly when there are many predictors and they are highly collinear.

Given that our paper relies on PLS as the method chosen to forecast net charge-off rates in the banking sector, we now discuss the use of this technique in the banking literature. In this regard, five papers have been identified that use PLS. Perhaps the limited number of papers is not surprising insofar as one of the papers points out that the advantages of this technique have hardly been exploited in the banking discipline. The author of the paper that makes this point, Avkiran (2018), provides a discussion of the use of PLS in structural equation modelling as an introduction to a book entitled "Rise of the Partial Least Squares Structural Equation Modelling: an Application in Banking". In contrast, Ayadurai and Eskadurai (2018) actually apply PLS to examine the drivers of bank soundness in the G7 countries during the period 2003-2013. The empirical results indicate that based on 17 manifest variables there are six constructs that are a direct cause and eight constructs that are an indirect cause of bank soundness. In particular, it is found that banks placed high importance on off-balance sheet and capital activities, and thereby taking on more risk.

An interesting and timely article is by Avkiran et al. (forthcoming). They provide the first application of PLS in financial stress testing, as far as we know. The specific focus is on the transmission of systemic risk from the shadow-banking sector to the regulated banking sector. The empirical results indicate that a substantial degree of the variation in systemic risk in the regulated banking sector is explained by micro-level and macro-level linkages that can be traced to shadow banking. They conclude that this is an insight due to the use of PLS.

The last two banking papers addresses issues mainly related to customers. The paper by Poolthong and Mandhachitara (2009) examine the way in which social responsibility initiatives can influence perceived service quality and brand effect from the perspective of retail banking customers. Based on an analysis of the responses of 275 bank customers to a questionnaire using PLS, the results indicate that perceived service quality is positively associated with brand effect mediated by trust. In the other paper, Bontis et al. (2007) also use survey data based on 8,098 respondents to study the mediating effect of organizational reputation on service recommendation and customer loyalty. The results obtained using PLS indicate that the relationship between corporate reputation and profitability may reside in reputation's influence on customer loyalty, and that reputation plays an important role as regards customer satisfaction.

In summary, it is clear form these thirteen papers that PLS was the method used to obtain new and interesting results. The different papers, moreover, identified the advantages gained by using PLS as compared to the more traditional procedures used in the respective business disciplines. It was also clear that even though PLS might have considerable advantages it is still a relatively under-employed method in most of these disciplines, especially banking.

We now turn to an application of PLS in an important issue in banking, namely, forecasting losses incurred by banks in their normal course of operation accurately to avoid losses sizeable enough to jeopardize their very ongoing existence.

3. Factor-Based Forecasting Models with Partial Least Squares

3.1. Partial Least Squares Factors

We employ the Partial Least Squares (PLS) approach in an analysis of the net charge-off rates for banks to extract the target-specific factors from a wide range of variables that influence the performance of banks for our out-of-sample forecasting exercises. For PLS, consider the following linear regression model. Abstracting from deterministic terms,

$$y_t = x_t'\beta + \varepsilon_t,\ \ t = 1, 2, \dots, T, \tag{1}$$

where y_t is the target variable, net charge-off rate, $x_t = [x_{1,t}, x_{2,t}, \dots, x_{N,t}]'$ is an $N \times 1$ vector of predictor variables, bank-specific and macroeconomic variables, β is an $N \times 1$ vector of coefficients, and ε_t is the random error term.

The PLS method is a useful tool, especially when $N > T$. The reason is when the number of observations (T) is less than the number of predictors (N), the ordinary least squares estimator is not well-defined. Instead of estimating a full regression with all the predictors given by equation (1), PLS employs a data dimensionality reduction method via the following regression model.

$$y_t = c_t'\delta + \varepsilon_t, \tag{2}$$

where $c_t = [c_{1,t}, c_{2,t}, \dots, c_{R,t}]'$ is an $R \times 1$ ($R < N_{\overline{,}}$) vector of PLS components or factors and δ is an $R \times 1$ vector of coefficients. PLS factors are linear combinations of N predictors. That is,

$$c_t = w'x_t, \tag{3}$$

where $w = [w_1, w_1, \dots, w_R]'$ is an $N \times R$ weighting matrix and its r^{th} column vector $w_r = [w_{r,1}, w_{r,2}, \dots, w_{r,N}]'$ is an $N \times 1$ vector of weights on predictor variables for the r^{th} factor ($r = 1, \dots, R$).

The PLS estimator chooses δ that minimizes the sum of squared residuals from equation (2) instead of choosing β to do the same in equation (1). As Andersson (2009) shows, there are many available PLS algorithms that work well. We use Helland's (1990) algorithm that is intuitively appealing to obtain PLS factors for the j-period ahead target variable, y_{t+j}, $j = 1,2, \dots, k$, as described in the following steps.

First, the first PLS factor $c_{1,t}$ is determined by the following linear combinations of the predictor variables x_t.

$$c_{1,t} = \sum_{i=1}^{N} w_{i,1}\, x_{i,t}, \tag{4}$$

where $w_{i,1} = Cov(y_{t+j}, x_{i,t})$ is the loading parameter that is the covariance between the target and each predictor.

Second, we regress y_{t+j} and $x_{i,t}$ on $c_{1,t}$ then obtain the residuals, $y_{t+j} - \hat{y}_{t+j}$ and $x_{i,t} - \hat{x}_{i,t}$, then repeat the process described by equation (4) to obtain the second PLS factor $c_{2,t}$. Note that $c_{2,t}$ is orthogonal to $c_{1,t}$, that is, $c_{2,t}$ contains new predictive content that is not contained in $c_{1,t}$.

Repeat the steps described until one obtains all R factors, $c_{1,t}, c_{2,t}, \dots, c_{R,t}$ that are orthogonal to one another.

3.2. PLS Factor Forecasting Models

We employ two PLS factor-based forecasting models (Kim and Ko, 2017) based on two benchmark models, the nonstationary random walk model and a stationary autoregressive model. For notational simplicity, we abstract from all deterministic terms, although all estimations are implemented with an intercept.

The first model augments the following random walk (RW) model,

$$y_{t+j}^{RW} = y_t + u_{t+j},\ j = 1, 2, \dots, k, \tag{5}$$

where $u_{t+j} = \sum_{i=1}^{j} \varepsilon_{t+i}$ and ε_t is a white noise process. The PLSRW model extends the RW model given by equation (5) by adding the PLS factors as follows.

$$y_{t+j}^{PLSRW} = y_t + \rho_j' c_t + u_{t+j}, \tag{6}$$

Note that the ordinary least squares (OLS) estimation for equation (6) is not feasible because the coefficient on y_t is predetermined. To deal with this problem, we regress $y_{t+j}^{PLSRW} - y_t$ on c_t to get the OLS estimate for ρ_j, $\hat{\rho}_j$. Adding y_t back to both sides, we obtain the j-period ahead forecast from the PLSRW model as follows.

$$\hat{y}_{t+j}^{PLSRW} = y_t + \hat{\rho}_j' c_t, \tag{7}$$

while the forecast from the benchmark RW model is,

$$\hat{y}_{t+j}^{RW} = y_t, \tag{8}$$

which is nested by equation (7) when $\rho_j = 0$.

The second model uses the following autoregressive (AR) model,

$$y_{t+j}^{AR} = \alpha_j y_t + u_{t+j}, \tag{9}$$

where α_j is less than one in absolute value. Note that equation (9) coincides with an AR (1) model with the persistence parameter α when $\alpha_j = \alpha^j$ and $u_{t+j} = \sum_{i=1}^{j} \alpha^{i-1} \varepsilon_{t+i}$ and ε_t is a white noise process. The PLSAR model extends the AR model given by equation (9) by adding the PLS factors as follows.

$$y_{t+j}^{PLSAR} = \alpha_j y_t + \rho_j' c_t + u_{t+j}, \tag{10}$$

Using the OLS estimates of the coefficients for equation (10), we obtain the j-period ahead forecast from the PLSAR model as follows.

$$\hat{y}_{t+j}^{PLSAR} = \hat{\alpha}_j y_t + \hat{\rho}_j' c_t, \tag{11}$$

while the forecast from the benchmark AR model is,

$$\hat{y}_{t+j}^{AR} = \hat{\alpha}_j y_t, \tag{12}$$

which is again nested by equation (11) when $\rho_j = 0$.

3.3. Out-of-Sample Forecasting Evaluations

We evaluate the out-of-sample predictability of the target variable using the following two forecast exercise schemes:

1. We first employ an expanding window (recursive) scheme. Using the initial T_o observations, we estimate the PLS factors c_t from $\{y_t, x_t\}_{t=1}^{T_o}$. Using the factor estimates, we obtain the j-period ahead out-of-sample forecast for the target variable $\hat{y}_{t+j}$ by equations (7), (8), (11), and (12). Then, we obtain the prediction errors for each model.

2. Then, we expand the data by adding one more observation and re-estimate the factors from $\{y_t, x_t\}_{t=1}^{T_o+1}$, which are used to formulate the next forecast, $\hat{y}_{t+j+1}$, which gives another set

of prediction errors. We repeat the process until we obtain the last forecast $\hat{y}_T$ using the last set of factor estimates obtained from $\{y_t, x_t\}_{t=1}^{T-j-1}$.

We also employ a fixed-size rolling window method, which may perform better than the recursive method when structural breaks are present. After the first step in obtaining $\hat{y}_{t+j}$, we add one observation but remove the earliest observation in the next step in obtaining $\hat{y}_{t+j+1}$, which maintains the same number of observations (fixed-size window). That is, we re-estimate the PLS factors utilizing the data $\{y_t, x_t\}_{t=2}^{T_O+1}$ instead of $\{y_t, x_t\}_{t=1}^{T_O+1}$ as in the recursive scheme. Again, we repeat until we forecast the last observation $\hat{y}_T$ using the last set of factor estimates obtained from $\{y_t, x_t\}_{t=T-T_0-j}^{T-j-1}$.

We employ the ratio of the root mean square prediction error (RRMSPE) to evaluate the out-of-sample prediction accuracy of our PLS factor forecasting models. RRMSPE is calculated as follows.

$$RRMSPE = \frac{\sqrt{\frac{1}{T-T_0-j}\sum_{t=T_0+j+1}^{T}\left(\varepsilon_{t+j|t}^{BM}\right)^2}}{\sqrt{\frac{1}{T-T_0-j}\sum_{t=T_0+j+1}^{T}\left(\varepsilon_{t+j|t}^{PLS}\right)^2}}, \tag{13}$$

where $\varepsilon_{t+j|t}^{X}$ denotes the forecasting error from the model X which refers to either of the two benchmark (BM) models (RW or AR) or one of the three competing models (PLS, PLSRW, or PLSAR). We employ the squared error loss function in equation (13), although the absolute error loss function could be used. Our PLS models outperform the benchmark models when RRMSPE is greater than 1.

4. Applications

4.1. Data Description and In-Sample Analysis

4.1.1. Data Description

We obtained quarterly data on the net charge-off rates for all banks from FRED Economic Data at the Federal Reserve Bank of St. Louis website for 1987 Q1 to 2016 Q4. Figure 1 shows the net charge-off rates on seven different types of loans as well as all loans. Note that there is a substantial heterogeneity in the rates for the different types of loans over the nearly 30-year period. All charge-off rates except for loans to finance agricultural production tend to experience relatively high charge-off rates for several quarters following the banking crisis of 2007-2008 and the severe recession from late 2007 to the summer of 2009. Note also that commercial and industrial loans tend to have three relatively high peaks as compared to the other types of loans, which indicates that such loans are among the riskiest loans.

Figure 1 around here

We also obtained data on 249 macroeconomic variables for the same sample period noted above from a beta version Fred-QD (https://research.stlouisfed.org/econ/mccracken/fred-databases/). As Table 1 shows, the macroeconomic variables are grouped into 14 categories. More specifically, Group 1 includes 23 national income and product account variables, Group 2 includes 18 industrial production variables, Group 3 includes 49 employment and unemployment variables, Group 4 includes 13 housing variables, Group 5 includes 11 inventories, orders, and sales variables, Group 6 includes 47 prices variables, Group 7 includes 14 earnings and productivity variables, Group 8 includes 22 interest rates variables, Group 9 includes 17 money and credit variables, Group 10 includes 9 household balance sheets variables, Group 11 includes 5 exchange rates variables, Group 12 includes 2 other variables, Group 13 includes 5 stock market variables, and Group 14 includes 13 non-household balance sheets variables. The list of all the variables employed in our study is provided in an Appendix. It is important to note that all of these variables can influence the performance of banks, including the losses incurred on loans to support various purchases by both individuals and businesses. This means that PLS is an appropriate method to take into account such a large number of variables given the limited number of observations.

Table 1 around here

It should be noted that most macroeconomic variables are better approximated by nonstationary stochastic processes. To obtain the PLS factors consistently, we therefore first difference the macroeconomic variables to estimate the factors. In what follows, we denote Δc_t as the PLS factors from these differenced predictor variables, Δx_t, whereas c_t is the level PLS factors that are obtained by re-integrating Δc_t, that is, $c_t = \sum_{i=1}^{t} \Delta c_i$.

4.1.2. In-Sample Analysis

In Figure 2, we plot both the R^2 and adjusted R^2 obtained from least squares regressions of the target variable y_t on the estimated PLS factors (red line) and PC factors (blue line) for up to 12 factors ($R = 12$) as well as their cumulative R^2 for the charge-off rates on all loans for all banks. Note that the factors are orthogonal to each other, thus the cumulative or cumulative adjusted R^2 indicate how much variation of the net charge-off rates is explained by the bank-specific and macroeconomic variables jointly. It should be also noted that PLS models outperform one of the popularly used alternative models based on a principal component (PC) analysis (e.g., see Stock and Watson, 2002). That is, PLS factors provide much better in-sample fit performance than PC factors. For example, the R^2 from PLS factors (R=1) exceeds 0.5, whereas that from PC factors (R=1) slightly exceeds 0.1 for the net charge-off rate for all loans. Given Δc_t is estimated using the covariance between the target and the predictor variables, this result is not surprising as well as the finding that the adjusted R^2 plot shows almost identical in-sample fit as that of the R^2.

One notable point to be made is that unlike the PLS factors, the contribution of the PC factors do not necessarily diminish when the number of factors increases. This is because the PC factors are estimated solely from the variance-covariance matrix of the predictor variables, while the PLS factors are formulated to obtain the most predictive content of the target variable from the predictors. Note that the R^2 from the PC factors is the highest for the fourth factor estimate, whereas the contribution of the PLS factors to R^2 are the highest for the first factor estimate. That is, the marginal R^2 decreases when we regress the net charge-off rates on subsequent PLS factors. In contrast, the PC approach considers covariance within the predictors, so that the marginal R^2 does not necessarily decrease as the number of factors increases.

Figure 2 around here

Figure 3 reports estimated PLS factors, Δc_t, for up to 6 factors in panel (a) for all bank charge-off rates on all loans and in panel (b) for all bank charge-off rates on agricultural loans, respectively. As can be seen in Figure 1, agricultural loans show a high degree of heterogeneity in comparison with other types of charge-off rates. It should be noted that the PLS factors of all loans are quite different from those of agricultural loans. Such distinct factor estimates form the PLS implies that the performance for all bank charge-off rates on all loans and for all bank charge-off rates on agricultural loans will differ in the out-of-sample forecasting exercises we report in next section.

Furthermore, Figure 4 shows their associated factor loading coefficient estimates. These two series show very different estimated PLS weighting matrices. For example, Group 1 (National Income and Product Account by the BEA) and Group 3 (Employment and Unemployment) contribute more to the first PLS factor estimate for the all bank charge-off rates on all loans, while Group 6 (Prices) contributes more to that for all bank charge-off rates on agricultural loans. The weights on other predictor variables for the other five PLS factor estimates show substantial heterogeneity across all 14 categorized predictor groups. However, since we are mainly interested in the out-of-sample forecasting performance of the PLS model compared to other competing models, we do not attempt to trace individual bank-specific and macroeconomic variables incorporated in these factors.

Figures 3 and 4 around here

4.2. Forecasting Charge-Off Rates

4.2.1. All Bank Charge-Off Rates

Out-of-sample predictability evaluations for the all banks charge-off rate on all loans are reported in Figures 5 and 6 for the recursive and the rolling window scheme, respectively. We use $p_{50\%}$ for the sample split point, that is, the initial 50 percent of observations are used as a training set to formulate the first out-of-sample forecast in implementing forecasting exercises via the recursive scheme as well as the rolling window scheme. We report results with the PLSAR for up to 12 forecast horizons (3 years) with up to 12 estimated common factors. That is, we report 144 RRMSPE's in each graph. Darker areas indicate the cases in which the PLSAR model outperforms both benchmark models, RW and AR models.

In Figure 5, we use the recursive scheme to calculate RRMSPE of the PLSAR relative to that of the RW or AR benchmark models. The PLSAR model overall dominates the two benchmark models. When comparted to the AR benchmark model, however, the AR benchmark model outperforms the PLSAR model over most horizons with a small number of factors. As the forecast horizons and the number of factors employed in forecasting increase, the PLSAR model outperforms the AR benchmark model.

In Figure 6, we implement the rolling window scheme to calculate RRMSPE of the PLSAR relative to that of the RW and AR benchmark models. Similar to the results from the recursive scheme, the PLSAR model outperforms the two benchmark models, especially when the number of forecast horizons increases and when more factors are employed in forecasting. Of course, as noted earlier, more factors are appropriate insofar as losses on loans are determined by many variables, including both bank-specific and macroeconomic variables. However, the two benchmark models provide more accurate forecasts over some horizons than the PLSAR model, depending on the number of factors employed in forecasting. In particular, the RW and AR benchmark models outperform the PLSAR model over most horizons with a small number of factors. Similar to the findings from the recursive scheme, as the forecast horizons and the number of factors employed in forecasting increases, the PLSAR model outperforms the RW and AR benchmark models. Instead of the PLSAR model, when using the PLSRW as our suggested model, we find similar results.

In summary, we do not find any advantages associated with using the rolling window method as compared to the recursive method, since more observations help enhance the out-of-sample predictability of the PLS factor forecasting models.

Figures 5 and 6 around here

4.2.2. Individual Bank Charge-Off Rates

In the previous section, we are able to determine which of the two forecast schemes, recursive or rolling window, provides the better forecast of the net charge-off rates on all loans. As also noted, since the recursive scheme helps enhance out-of-sample predictability of the PLS factor forecasting models, we report our findings for the net charge-off rates on all loans of two big and important banks, Bank of America and JPMorgan Chase, using the recursive forecast scheme.

The sample period covers 1991:Q1 to 2016:Q4. We obtain the net charge-off rates for the two banks from the Consolidated Financial Statements for Bank Holding Companies (the FR Y-9C form) from the Federal Reserve Bank of Chicago website. Figure 7 shows similar out-of-sample forecast results for the net charge-off rates on all loans for Bank of America. In general, the PLSAR model outperforms the two benchmark models for most forecast horizons. However, the two benchmark models provide better forecasting accuracy over some horizons than the PLSAR model. In particular, the AR benchmark outperforms the PLSAR model over different horizons more often compared to the RW benchmark.

Figures 7 around here

Figure 8 shows out-of-sample forecast results for the net charge-off rates on all loans for JPMorgan Chase. Consistent with the previous results, the PLSAR model outperforms the two benchmark models for most forecast horizons. For this bank, the PLSAR dominates the RW benchmark model no matter how many forecast horizons are used and the number of factors employed in forecasting. However, the AR benchmark model still provides a more accurate forecast over some horizons than the PLSAR model when the number of factors employed in forecasting is relatively small, which has the downside of omitting important variables that influence losses on loans. Unlike out-of-sample predictability evaluations for the all banks charge-off rates on all loans, we do not find a similar pattern for the two individual banks. In other words, as the forecast horizons and the number of factors employed in forecasting increase, the PLSAR model outperforms the RW and AR benchmark models.

Figures 8 around here

5. Conclusions

We have evaluated the forecasting accuracy of a partial least squares (PLS) model as compared to two simpler benchmark models because it allows one to include more predictor variables than observations in forecasting bank losses, or net charge-offs. This is important insofar as there are generally far more variables that can affect the net charge-off rates of banks than the number of available observations in any forecasting exercise. We therefore used a PLS model to obtain forecasts for net charge-off rates for all banks and two very big banks based on more than two hundred predictor variables for the period1991:Q1 to 2016:Q4.

Based on both a rolling window scheme and a recursive scheme, we find that the PLSAR model outperforms the two benchmark models for forecasting the net charge-off rate for all banks, especially when the number of forecast horizons increases and when more factors are employed in forecasting. In general, the PLSAR model outperforms the benchmark models for most forecast horizons in the case of the net charge-off rate on all loans for Bank of America. When forecasting the net charge-off rates on all loans for JPMorgan Chase, we also find that the PLSAR model outperforms the benchmark models for most forecast horizons. Moreover, for this bank, the PLSAR dominates the RW benchmark model no matter how many forecast horizons are used and the number of factors employed in forecasting.

In summary, given the importance of forecasting a variety of bank variables, including net charge-offs, that are affected by numerous factors, the PLS model has the key advantage that it does not constrain the number of predictors to be less than the number of observations in a forecasting exercise. This is important reason to make future use of such a model in forecasting a wider range of target variables than simply net charge-off rates.

Figure 1. Net Charge-Off Rates

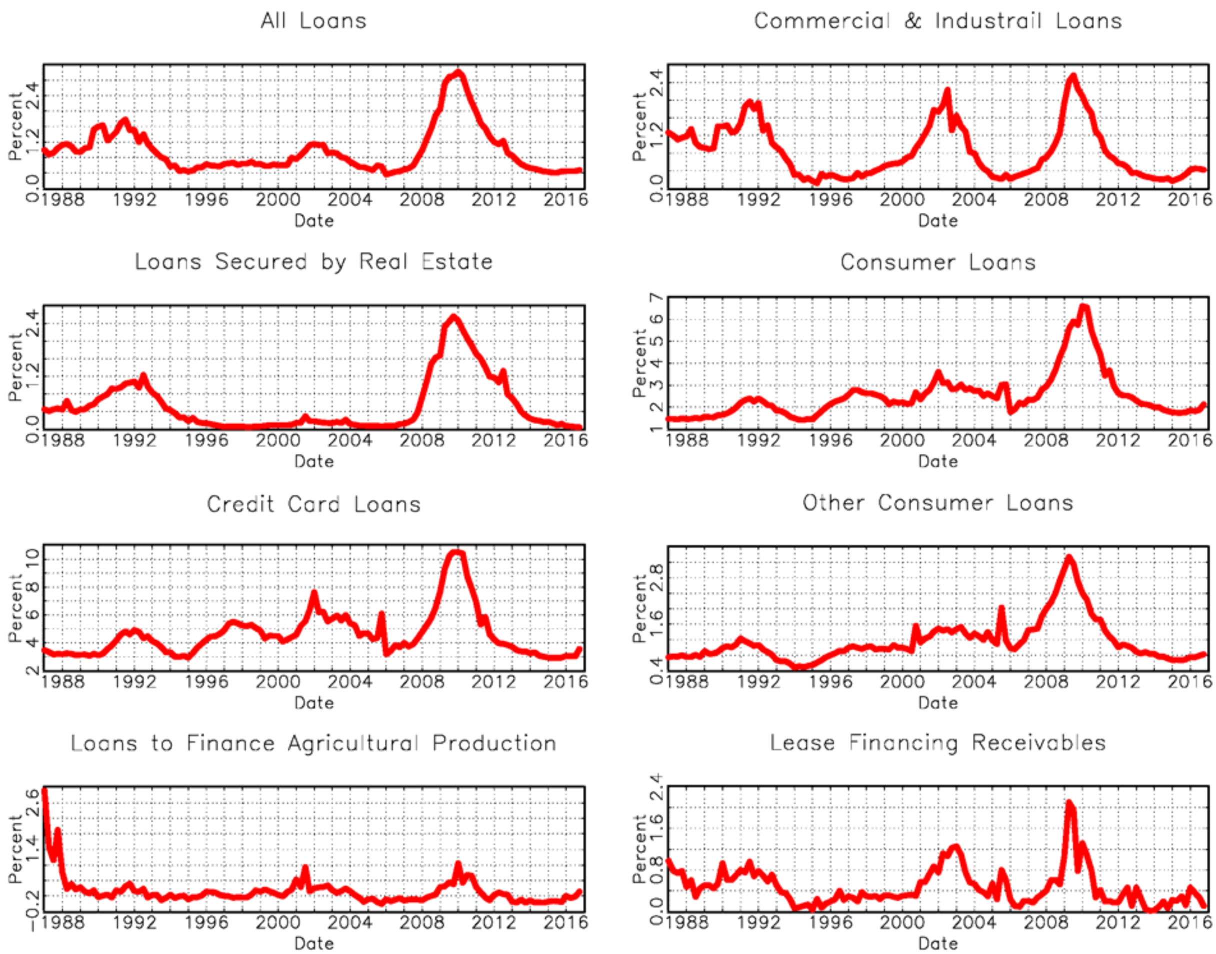


Table 1. Macroeconomic Data Classification

Group 1 (1-23)	: National Income and Product Account by the BEA
Group 2 (24-41)	: Industrial Production
Group 3 (42-90)	: Employment and Unemployment
Group 4 (91-103)	: Housing
Group 5 (104-114)	: Inventories, Orders, and Sales
Group 6 (115-161)	: Prices
Group 7 (162-175)	: Earnings and Productivity
Group 8 (176-197)	: Interest Rates
Group 9 (198-214)	: Money and Credit
Group 10 (215-223)	: Household Balance Sheets
Group 11 (224-228)	: Exchange Rates
Group 12 (229-230)	: Other
Group 13 (231-236)	: Stock Markets
Group 14 (237-249)	: Non-Household Balance Sheets

Figure 2. In-Sample Fit Analysis: Net Charge-Off Rates on All Loans

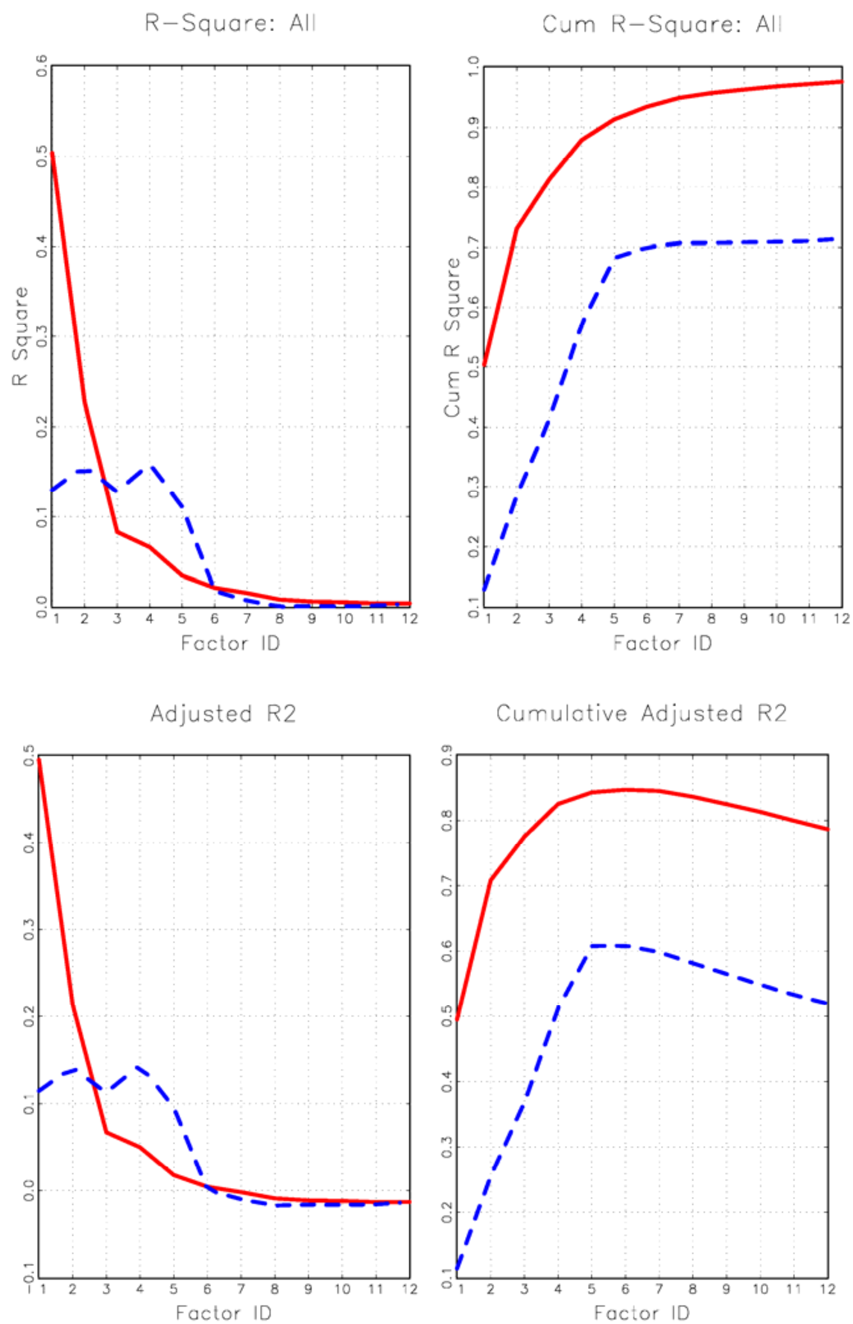
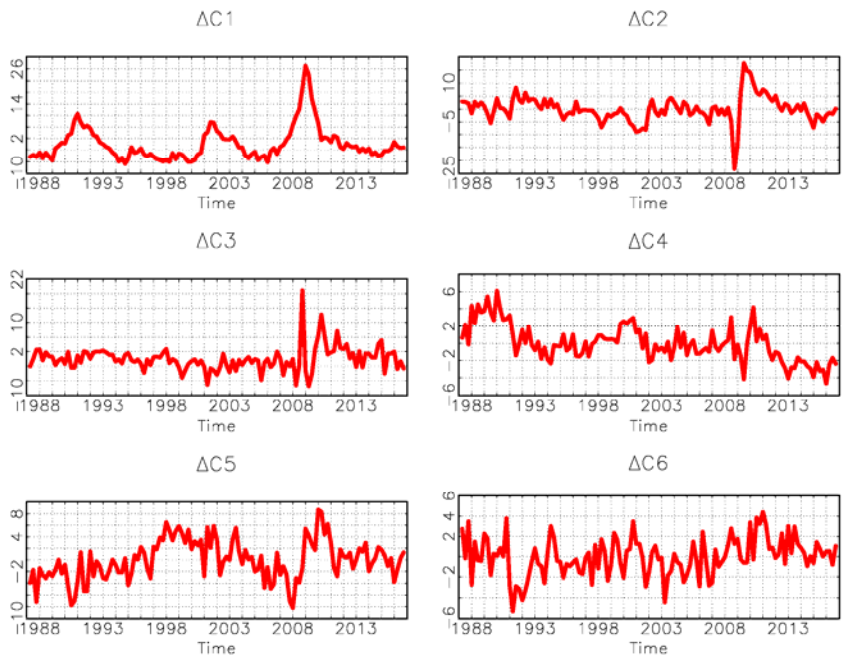


Figure 3. PLS Factor Estimates

(a) Net Charge-Off Rates: All Loans



(b) Net Charge-Off Rates: Agricultural Loans

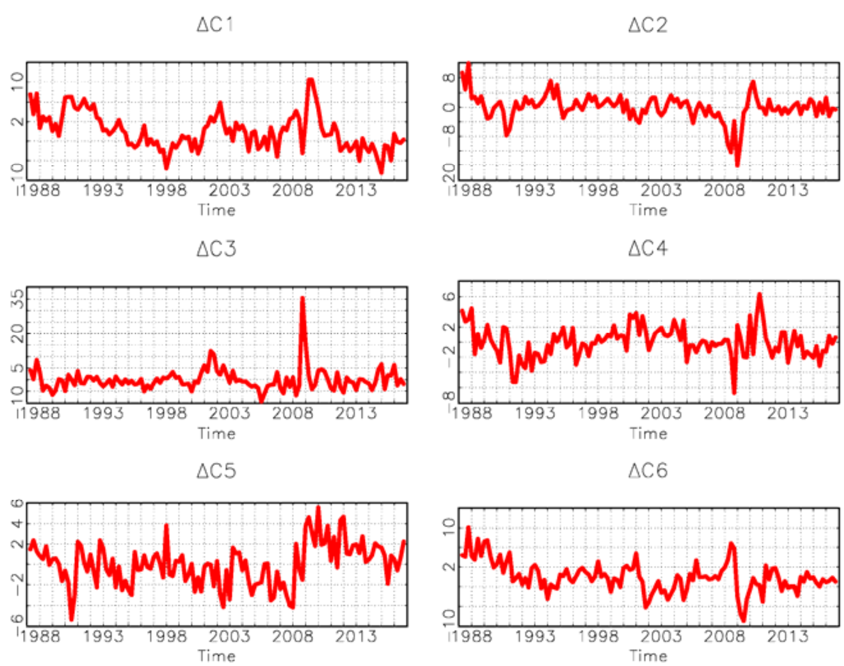
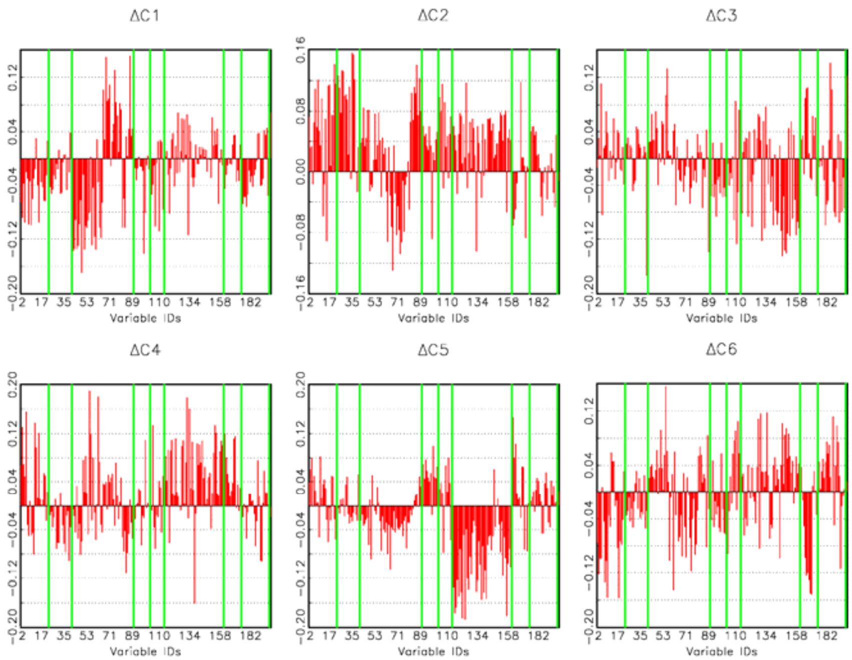


Figure 4. PLS Weighting Matrix Estimates

(a) Net Charge-Off Rates: All Loans



(b) Net Charge-Off Rates: Agricultural Loans

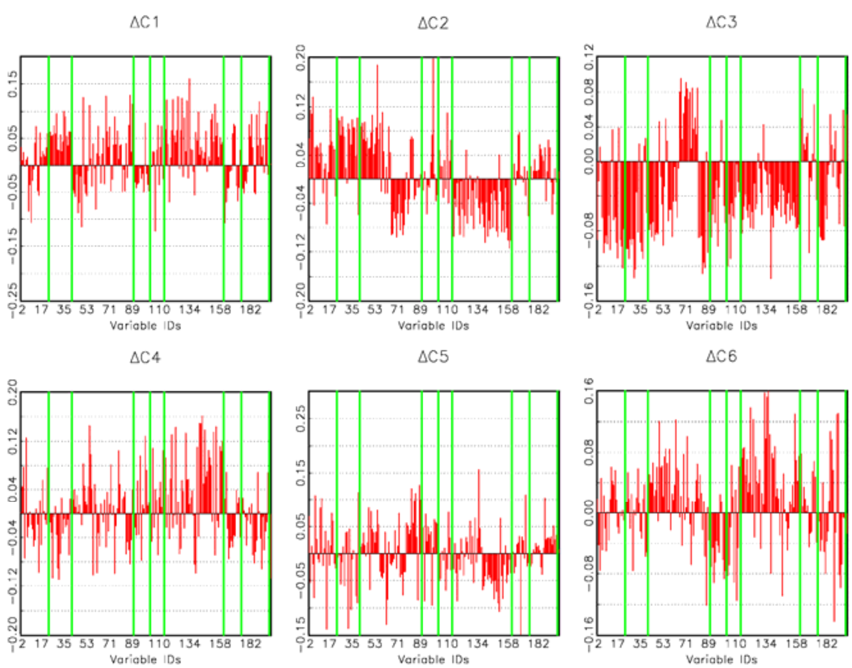
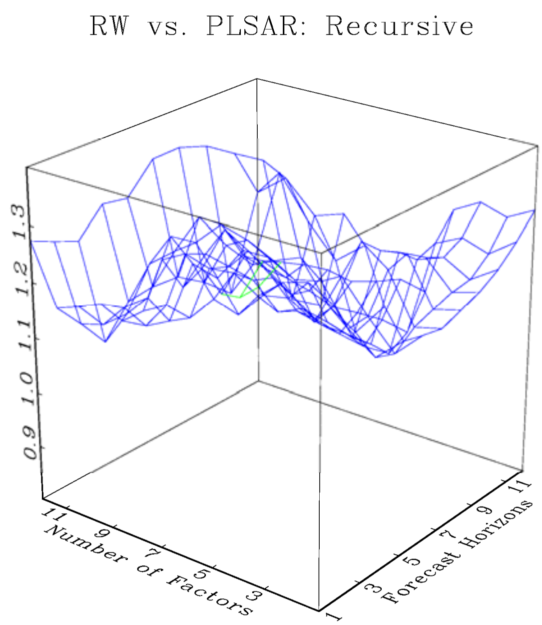


Figure 5. Out-of-Sample Predictability: Recursive Scheme for the PLSAR Model



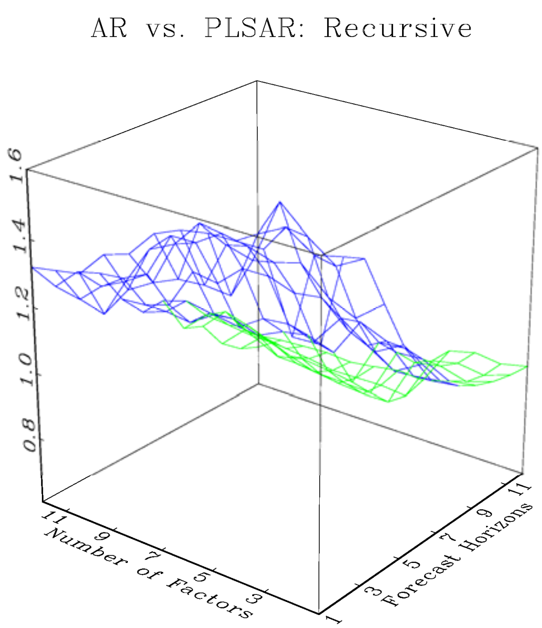
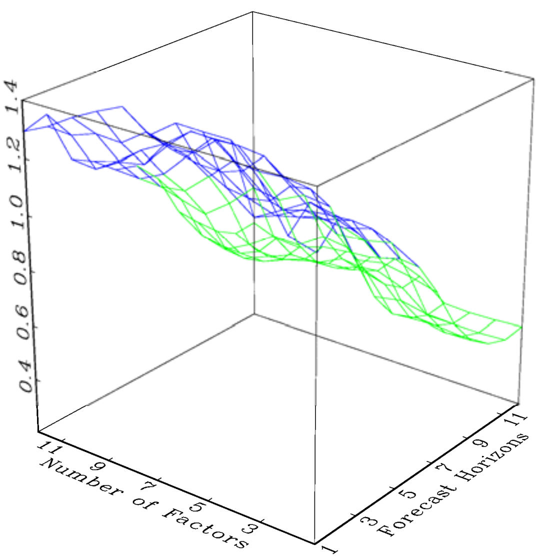


Figure 6. Out-of-Sample Predictability: Rolling-Window Scheme for the PLSAR Model

RW vs. PLSAR: Rolling



AR vs. PLSAR: Rolling

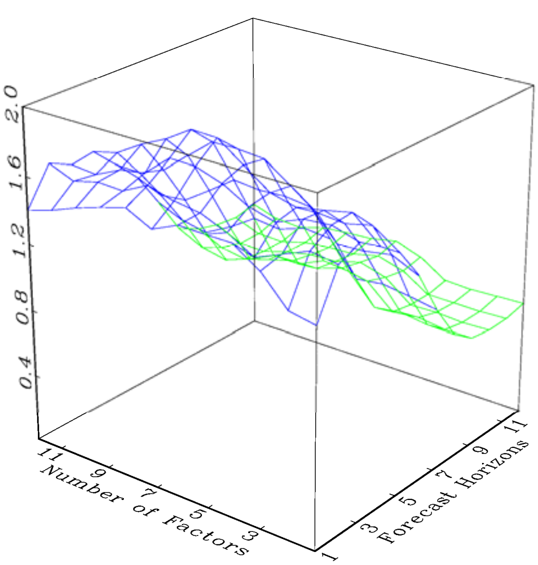
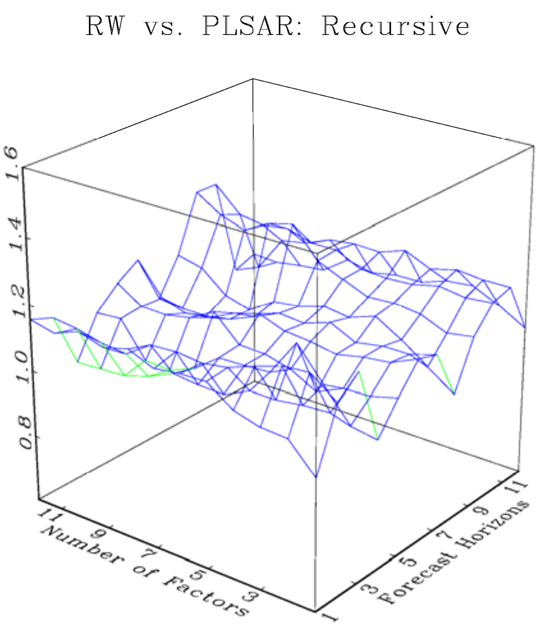


Figure 7. Out-of-Sample Predictability: Bank of America



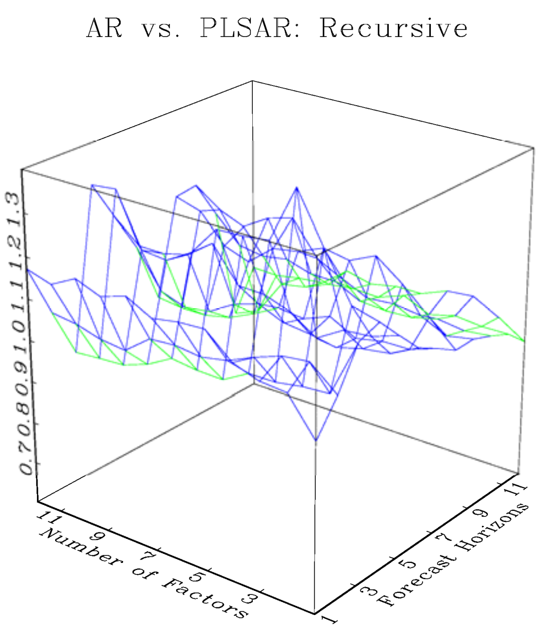
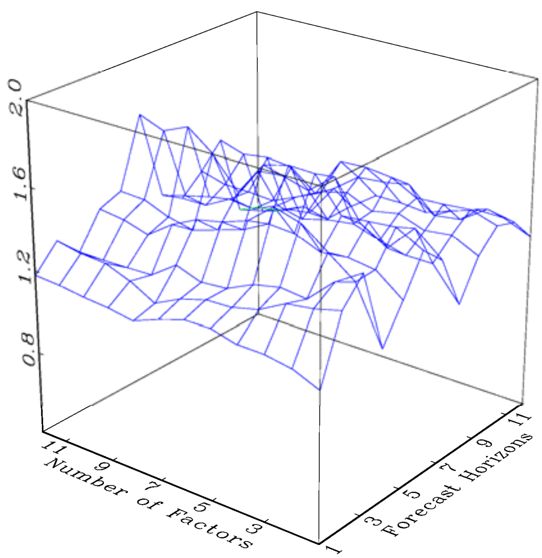
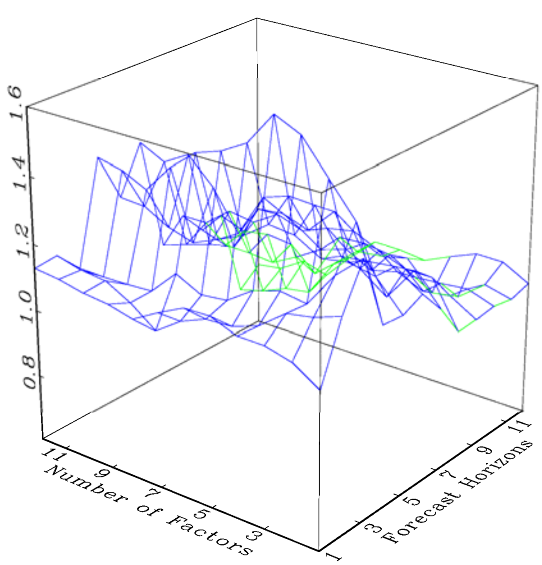


Figure 8. Out-of-Sample Predictability: Chase

RW vs. PLSAR: Recursive



AR vs. PLSAR: Recursive



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Appendix

Group 1: NIPA

id	description
1	Real Gross Domestic Product, 3 Decimal (Billions of Chained 2009 Dollars)
2	Real Personal Consumption Expenditures (Billions of Chained 2009
3	Real Personal Consumption expenditures: Durable goods (Billions of 2009 Dollars), deflated using PCE
4	Real Personal Consumption Expenditures: Services (Billions of 2009 deflated using PCE
5	Real Personal Consumption Expenditures: Nondurable Goods (Billions of Dollars), deflated using PCE
6	Real Gross Private Domestic Investment, 3 decimal (Billions of Chained Dollars)
7	Real private fixed investment (Billions of Chained 2009 Dollars), deflated using PCE
8	Real Gross Private Domestic Investment: Fixed Investment: Nonresidential: Equipment (Billions of Chained 2009 Dollars), deflated using PCE
9	Real private fixed investment: Nonresidential (Billions of Chained 2009 Dollars), deflated using PCE
10	Real private fixed investment: Residential (Billions of Chained 2009 deflated using PCE
11	Shares of gross domestic product: Gross private domestic investment: in private inventories (Percent)
12	Real Government Consumption Expenditures & Gross Investment (Billions Chained 2009 Dollars)
13	Real Government Consumption Expenditures and Gross Investment: (Percent Change from Preceding Period)
14	Real Federal Government Current Receipts (Billions of Chained 2009 deflated using PCE
15	Real government state and local consumption expenditures (Billions of Chained 2009 Dollars), deflated using PCE
16	Real Exports of Goods & Services, 3 Decimal (Billions of Chained 2009 Dollars)
17	Real Imports of Goods & Services, 3 Decimal (Billions of Chained 2009 Dollars)
18	Real Disposable Personal Income (Billions of Chained 2009 Dollars)
19	Nonfarm Business Sector: Real Output (Index 2009=100)
20	Business Sector: Real Output (Index 2009=100)
21	Manufacturing Sector: Real Output (Index 2009=100)
194	Shares of gross domestic product: Exports of goods and services (Percent)
195	Shares of gross domestic product: Imports of goods and services (Percent)

Group 2: Industrial Production

id	description
22	Industrial Index (Index 2012=100)
23	Industrial Final Products (Market Group) (Index 2012=100)
24	Industrial Consumer Goods (Index 2012=100)
25	Industrial Materials (Index 2012=100)
26	Industrial Durable Materials (Index 2012=100)
27	Industrial Nondurable Materials (Index 2012=100)
28	Industrial Durable Consumer Goods (Index 2012=100)
29	Industrial Durable Goods: Automotive products (Index
30	Industrial Nondurable Consumer Goods (Index 2012=100)
31	Industrial Business Equipment (Index 2012=100)
32	Industrial Consumer energy products (Index 2012=100)
33	Capacity Utilization: Total Industry (Percent of Capacity)
34	Capacity Utilization: Manufacturing (SIC) (Percent of Capacity)
198	Industrial Production: Manufacturing (SIC) (Index 2012=100)
199	Industrial Production: Residential Utilities (Index 2012=100)
200	Industrial Production: Fuels (Index 2012=100)
201	ISM Manufacturing: Production Index
205	ISM Manufacturing: PMI Composite Index

Group 3: Employment and Unemployment

id	description
35	All Employees: Total nonfarm (Thousands of Persons)
36	All Employees: Total Private Industries (Thousands of Persons)
37	All Employees: Manufacturing (Thousands of Persons)
38	All Employees: Service-Providing Industries (Thousands of Persons)
39	All Employees: Goods-Producing Industries (Thousands of Persons)
40	All Employees: Durable goods (Thousands of Persons)
41	All Employees: Nondurable goods (Thousands of Persons)
42	All Employees: Construction (Thousands of Persons)
43	All Employees: Education & Health Services (Thousands of Persons)
44	All Employees: Financial Activities (Thousands of Persons)
45	All Employees: Information Services (Thousands of Persons)
46	All Employees: Professional & Business Services (Thousands of Persons)
47	All Employees: Leisure & Hospitality (Thousands of Persons)
48	All Employees: Other Services (Thousands of Persons)
49	All Employees: Mining and logging (Thousands of Persons)
50	All Employees: Trade, Transportation & Utilities (Thousands of Persons)
51	All Employees: Government (Thousands of Persons)
52	All Employees: Retail Trade (Thousands of Persons)
53	All Employees: Wholesale Trade (Thousands of Persons)
54	All Employees: Government: Federal (Thousands of Persons)
55	All Employees: Government: State Government (Thousands of Persons)
56	All Employees: Government: Local Government (Thousands of Persons)
57	Civilian Employment (Thousands of Persons)
58	Civilian Labor Force Participation Rate (Percent)
59	Civilian Unemployment Rate (Percent)
60	Unemployment Rate less than 27 weeks (Percent)
61	Unemployment Rate for more than 27 weeks (Percent)
62	Unemployment Rate - 16 to 19 years (Percent)
63	Unemployment Rate - 20 years and over, Men (Percent)
64	Unemployment Rate - 20 years and over, Women (Percent)
65	Number of Civilians Unemployed - Less Than 5 Weeks (Thousands of
66	Number of Civilians Unemployed for 5 to 14 Weeks (Thousands of Persons)
67	Number of Civilians Unemployed for 15 to 26 Weeks (Thousands of Persons)
68	Number of Civilians Unemployed for 27 Weeks and Over (Thousands of
69	Unemployment Level - Job Losers (Thousands of Persons)
70	Unemployment Level - Reentrants to Labor Force (Thousands of Persons)
71	Unemployment Level - Job Leavers (Thousands of Persons)
72	Unemployment Level - New Entrants (Thousands of Persons)

Group 3: Employment and Unemployment, continued

id	description
73	Employment Level - Part-Time for Economic Reasons, All Industries (Thousands of Persons)
74	Business Sector: Hours of All Persons (Index 2009=100)
75	Manufacturing Sector: Hours of All Persons (Index 2009=100)
76	Nonfarm Business Sector: Hours of All Persons (Index 2009=100)
77	Average Weekly Hours of Production and Nonsupervisory Employees: (Hours)
78	Average Weekly Hours Of Production And Nonsupervisory Employees: Total private (Hours)
79	Average Weekly Overtime Hours of Production and Nonsupervisory Employees: Manufacturing (Hours)
80	Help-Wanted Index
202	Average (Mean) Duration of Unemployment (Weeks)
203	Average Weekly Hours of Production and Nonsupervisory Employees: Goods-
204	ISM Manufacturing: Employment Index
229	Ratio of Help Wanted/No. Unemployed
230	Initial Claims

Group 4: Housing

id	description
81	Housing Starts: Total: New Privately Owned Housing Units Started Units)
82	Privately Owned Housing Starts: 5-Unit Structures or More (Thousands of
83	New Private Housing Units Authorized by Building Permits (Thousands of
84	Housing Starts in Midwest Census Region (Thousands of Units)
85	Housing Starts in Northeast Census Region (Thousands of Units)
86	Housing Starts in South Census Region (Thousands of Units)
87	Housing Starts in West Census Region (Thousands of Units)
183	All-Transactions House Price Index for the United States (Index 1980 Q1=100)
184	S&P/Case-Shiller 10-City Composite Home Price Index (Index January 2000 = 100)
185	S&P/Case-Shiller 20-City Composite Home Price Index (Index January 2000 = 100)
236	New Private Housing Units Authorized by Building Permits in the Northeast Census Region (Thousands, SAAR)
237	New Private Housing Units Authorized by Building Permits in the Midwest Census Region (Thousands, SAAR)
238	New Private Housing Units Authorized by Building Permits in the South Region (Thousands, SAAR)
239	New Private Housing Units Authorized by Building Permits in the West Census Region (Thousands, SAAR)

Group 5: Inventories, Orders, and Sales

id	description
88	Real Manufacturing and Trade Industries Sales (Millions of Chained 2009 Dollars)
89	Real Retail and Food Services Sales (Millions of Chained 2009 Dollars), by Core PCE
90	Real Manufacturers' New Orders: Durable Goods (Millions of 2009 Dollars), deflated by Core PCE
91	Real Value of Manufacturers' New Orders for Consumer Goods Industries (Million of 2009 Dollars), deflated by Core PCE
92	Real Value of Manufacturers' Unfilled Orders for Durable Goods Industries (Million of 2009 Dollars), deflated by Core PCE
93	Real Value of Manufacturers' New Orders for Capital Goods: Nondefense Capital Goods Industries (Million of 2009 Dollars), deflated by Core PCE
94	ISM Manufacturing: Supplier Deliveries Index (lin)
95	Real Manufacturing and Trade Inventories (Millions of 2009 Dollars)
206	ISM Manufacturing: New Orders Index
207	ISM Manufacturing: Inventories Index
231	Total Business Inventories (Millions of Dollars)
232	Total Business: Inventories to Sales Ratio

Group 6: Prices

id	description
96	Personal Consumption Expenditures: Chain-type Price Index (Index 2009=100)
97	Personal Consumption Expenditures Excluding Food and Energy (Chain-Type Price Index) (Index 2009=100)
98	Gross Domestic Product: Chain-type Price Index (Index 2009=100)
99	Gross Private Domestic Investment: Chain-type Price Index (Index 2009=100)
100	Business Sector: Implicit Price Deflator (Index 2009=100)
101	Personal consumption expenditures: Goods (chain-type price index)
102	Personal consumption expenditures: Durable goods (chain-type price index)
103	Personal consumption expenditures: Services (chain-type price index)
104	Personal consumption expenditures: Nondurable goods (chain-type index)
105	Personal consumption expenditures: Services: Household consumption expenditures (chain-type price index)
106	Personal consumption expenditures: Durable goods: Motor vehicles parts (chain-type price index)
107	Personal consumption expenditures: Durable goods: Furnishings and durable household equipment (chain-type price index)
108	Personal consumption expenditures: Durable goods: Recreational and vehicles (chain-type price index)
109	Personal consumption expenditures: Durable goods: Other durable (chain-type price index)
110	Personal consumption expenditures: Nondurable goods: Food and beverages purchased for off-premises consumption (chain-type price index)
111	Personal consumption expenditures: Nondurable goods: Clothing and footwear (chain-type price index)
112	Personal consumption expenditures: Nondurable goods: Gasoline and other energy goods (chain-type price index)
113	Personal consumption expenditures: Nondurable goods: Other nondurable goods (chain-type price index)
114	Personal consumption expenditures: Services: Housing and utilities (chain-type price index)
115	Personal consumption expenditures: Services: Health care (chain-type price index)
116	Personal consumption expenditures: Transportation services (chain-price index)

Group 6: Prices, continued

id	description
117	Personal consumption expenditures: Recreation services (chain-type price index)
118	Personal consumption expenditures: Services: Food services and accommodations (chain-type price index)
119	Personal consumption expenditures: Financial services and insurance (chain-type price index)
120	Personal consumption expenditures: Other services (chain-type price index)
121	Consumer Price Index for All Urban Consumers: All Items (Index 1982-84=100)
122	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy (Index 1982-84=100)
123	Producer Price Index by Commodity for Finished Goods (Index
124	Producer Price Index for All Commodities (Index 1982=100)
125	Producer Price Index by Commodity for Finished Consumer Goods 1982=100)
126	Producer Price Index by Commodity for Finished Consumer Foods 1982=100)
127	Producer Price Index by Commodity Industrial Commodities (Index 1982=100)
128	Producer Price Index by Commodity Intermediate Materials: Supplies & Components (Index 1982=100)
129	ISM Manufacturing: Prices Index (Index)
130	Producer Price Index by Commodity for Fuels and Related Products Power: Natural Gas (Index 1982=100)
131	Producer Price Index by Commodity for Fuels and Related Products Power: Crude Petroleum (Domestic Production) (Index 1982=100)
132	Real Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma (2009 Dollars per Barrel), deflated by Core PCE
214	Producer Price Index: Crude Materials for Further Processing (Index 1982=100)
215	Producer Price Index: Commodities: Metals and metal products: nonferrous metals (Index 1982=100)
216	Consumer Price Index for All Urban Consumers: Apparel (Index 1982-84=100)
217	Consumer Price Index for All Urban Consumers: Transportation (Index 1982-84=100)
218	Consumer Price Index for All Urban Consumers: Medical Care (Index 1982-84=100)
219	Consumer Price Index for All Urban Consumers: Commodities (Index 1982-84=100)
220	Consumer Price Index for All Urban Consumers: Durables (Index 1982-84=100)
221	Consumer Price Index for All Urban Consumers: Services (Index 1982-84=100)
222	Consumer Price Index for All Urban Consumers: All Items Less Food (Index 1982-84=100)
223	Consumer Price Index for All Urban Consumers: All items less shelter (Index 1982-84=100)
224	Consumer Price Index for All Urban Consumers: All items less medical care (Index 1982-84=100)
242	CPI for All Urban Consumers: Owners' equivalent rent of residences (Index Dec 1982=100)

Group 7: Earnings and Productivity

id	description
133	Real Average Hourly Earnings of Production and Nonsupervisory Employees: Private (2009 Dollars per Hour), deflated by Core PCE
134	Real Average Hourly Earnings of Production and Nonsupervisory Employees: Construction (2009 Dollars per Hour), deflated by Core PCE
135	Real Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing (2009 Dollars per Hour), deflated by Core PCE
136	Manufacturing Sector: Real Compensation Per Hour (Index 2009=100)
137	Nonfarm Business Sector: Real Compensation Per Hour (Index 2009=100)
138	Business Sector: Real Compensation Per Hour (Index 2009=100)
139	Manufacturing Sector: Real Output Per Hour of All Persons (Index 2009=100)
140	Nonfarm Business Sector: Real Output Per Hour of All Persons (Index
141	Business Sector: Real Output Per Hour of All Persons (Index 2009=100)
142	Business Sector: Unit Labor Cost (Index 2009=100)
143	Manufacturing Sector: Unit Labor Cost (Index 2009=100)
144	Nonfarm Business Sector: Unit Labor Cost (Index 2009=100)
145	Nonfarm Business Sector: Unit Nonlabor Payments (Index 2009=100)
225	Average Hourly Earnings of Production and Nonsupervisory Employees: Goods-Producing (Dollars per Hour)

Group 8: Interest Rates

id	description
146	Effective Federal Funds Rate (Percent)
147	3-Month Treasury Bill: Secondary Market Rate (Percent)
148	6-Month Treasury Bill: Secondary Market Rate (Percent)
149	3-Month Eurodollar Deposit Rate (London) (Percent)
150	1-Year Treasury Constant Maturity Rate (Percent)
151	10-Year Treasury Constant Maturity Rate (Percent)
152	30-Year Conventional Mortgage Rate (Percent)
153	Moody’s Seasoned Aaa Corporate Bond Yield (Percent)
154	Moody’s Seasoned Baa Corporate Bond Yield (Percent)
155	Moody’s Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity (Percent)
156	30-Year Conventional Mortgage Rate Relative to 10-Year Treasury Constant (Percent)
157	6-Month Treasury Bill Minus 3-Month Treasury Bill, secondary market (Percent)
158	1-Year Treasury Constant Maturity Minus 3-Month Treasury Bill, secondary (Percent)
159	10-Year Treasury Constant Maturity Minus 3-Month Treasury Bill, secondary (Percent)
160	3-Month Commercial Paper Minus 3-Month Treasury Bill, secondary market
161	3-Month Eurodollar Deposit Minus 3-Month Treasury Bill, secondary market
210	5-Year Treasury Constant Maturity Rate
211	3-Month Treasury Constant Maturity Minus Federal Funds Rate
212	5-Year Treasury Constant Maturity Minus Federal Funds Rate
213	Moody’s Seasoned Aaa Corporate Bond Minus Federal Funds Rate
234	3-Month AA Financial Commercial Paper Rate
235	3-Month Commercial Paper Minus Federal Funds Rate

Group 9: Money and Credit

id	description
162	St. Louis Adjusted Monetary Base (Billions of 1982-84 Dollars), deflated by
163	Real Institutional Money Funds (Billions of 2009 Dollars), deflated by Core
164	Real M1 Money Stock (Billions of 1982-84 Dollars), deflated by CPI
165	Real M2 Money Stock (Billions of 1982-84 Dollars), deflated by CPI
166	Real MZM Money Stock (Billions of 1982-84 Dollars), deflated by CPI
167	Real Commercial and Industrial Loans, All Commercial Banks (Billions of U.S. Dollars), deflated by Core PCE
168	Real Consumer Loans at All Commercial Banks (Billions of 2009 U.S. deflated by Core PCE
169	Total Real Nonrevolving Credit Owned and Securitized, Outstanding (Billions Dollars), deflated by Core PCE
170	Real Real Estate Loans, All Commercial Banks (Billions of 2009 U.S. deflated by Core PCE
171	Total Real Revolving Credit Owned and Securitized, Outstanding (Billions of 2009 Dollars), deflated by Core PCE
172	Total Consumer Credit Outstanding, deflated by Core PCE
173	FRB Senior Loans Officer Opions. Net Percentage of Domestic Respondents Reporting Increased Willingness to Make Consumer Installment Loans
208	Total Reserves of Depository Institutions (Billions of Dollars)
209	Reserves Of Depository Institutions, Nonborrowed (Millions of Dollars)
226	Consumer Motor Vehicle Loans Outstanding Owned by Finance Companies (Millions of Dollars)
227	Total Consumer Loans and Leases Outstanding Owned and Securitized by Finance Companies (Millions of Dollars)
228	Securities in Bank Credit at All Commercial Banks (Billions of Dollars)

Group 10: Household Balance Sheets

id	description
174	Real Total Assets of Households and Nonprofit Organizations (Billions of 2009 Dollars), deflated by Core PCE
175	Real Total Liabilities of Households and Nonprofit Organizations (Billions of Dollars), deflated by Core PCE
176	Liabilities of Households and Nonprofit Organizations Relative to Personal Disposable Income (Percent)
177	Real Net Worth of Households and Nonprofit Organizations (Billions of 2009 Dollars), deflated by Core PCE
178	Net Worth of Households and Nonprofit Organizations Relative to Disposable Personal Income (Percent)
179	Real Assets of Households and Nonprofit Organizations excluding Real Estate Assets (Billions of 2009 Dollars), deflated by Core PCE
180	Real Real Estate Assets of Households and Nonprofit Organizations (Billions 2009 Dollars), deflated by Core PCE
181	Real Total Financial Assets of Households and Nonprofit Organizations of 2009 Dollars), deflated by Core PCE
233	Nonrevolving consumer credit to Personal Income

Group 11: Exchange Rates

id	description
186	Trade Weighted U.S. Dollar Index: Major Currencies (Index March
187	U.S. / Euro Foreign Exchange Rate (U.S. Dollars to One Euro)
188	Switzerland / U.S. Foreign Exchange Rate
189	Japan / U.S. Foreign Exchange Rate
190	U.S. / U.K. Foreign Exchange Rate
191	Canada / U.S. Foreign Exchange Rate

Group 11: Exchange Rates

id	description
192	University of Michigan: Consumer Sentiment (Index 1st Quarter 1966=100)
193	Economic Policy Uncertainty Index for United States

Group 13: Stock Markets

id	description
182	CBOE S&P 100 Volatility Index: VXO
240	Nikkei Stock Average
241	NASDAQ Composite (Index Feb 5, 1971=100)
254	S&P's Common Stock Price Index: Composite
255	S&P's Common Stock Price Index: Industrials
256	S&P's Composite Common Stock: Dividend Yield
257	S&P's Composite Common Stock: Price-Earnings Ratio

Group 14: Non-Household Balance Sheets

id	description
196	Federal Debt: Total Public Debt as Percent of GDP (Percent)
197	Real Federal Debt: Total Public Debt (Millions of 2009 Dollars), deflated by
243	Real Nonfinancial Corporate Business Sector Liabilities (Billions of 2009 Deflated by Implicit Price Deflator for Business Sector IPDBS
244	Nonfinancial Corporate Business Sector Liabilities to Disposable Business Income (Percent)
245	Real Nonfinancial Corporate Business Sector Assets (Billions of 2009 Dollars), Deflated by Implicit Price Deflator for Business Sector IPDBS
246	Real Nonfinancial Corporate Business Sector Net Worth (Billions of 2009 Deflated by Implicit Price Deflator for Business Sector IPDBS
247	Nonfinancial Corporate Business Sector Net Worth to Disposable Business (Percent)
248	Real Nonfinancial Noncorporate Business Sector Liabilities (Billions of 2009 Dollars), Deflated by Implicit Price Deflator for Business Sector IPDBS
249	Nonfinancial Noncorporate Business Sector Liabilities to Disposable Business Income (Percent)
250	Real Nonfinancial Noncorporate Business Sector Assets (Billions of 2009 Deflated by Implicit Price Deflator for Business Sector IPDBS
251	Real Nonfinancial Noncorporate Business Sector Net Worth (Billions of 2009 Dollars), Deflated by Implicit Price Deflator for Business Sector IPDBS
252	Nonfinancial Noncorporate Business Sector Net Worth to Disposable Business Income (Percent)
253	Real Disposable Business Income, Billions of 2009 Dollars (Corporate cash flow with IVA minus taxes on corporate income, deflated by Implicit Price Deflator Business Sector IPDBS)