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Hyeongwoo Kim and Jisoo Son

Auburn University

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Hyeongwoo Kim* and Jisoo Son†
Auburn University

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Abstract

Charge-offs signal important information about the riskiness of loan portfolios in the banking system, which can generate systemic risk towards deep recessions. We compiled the net charge-off rate (COR) data of the top 10 bank holding companies (BHCs) in the U.S., utilizing consolidated financial statements. We propose factor-augmented forecasting models for CORs by estimating latent common factors, including targeted factors, via an array of data dimensionality reduction methods for a large panel of macroeconomic predictors. Our models outperform the benchmark models especially well for business loan CORs, while enhancing predictive contents for consumer loans are harder at short horizons. Real activity factors enhance the out-of-sample predictability for business loan CORs even when financial sector factors are excluded.

Keywords: Net Charge-Off Rate; Bank Holding Companies; Principal Component Analysis; Partial Least Squares; Out-of-Sample Forecast

JEL Classification: C38; C53; C55; G01; G17

*Department of Economics, Auburn University, 138 Miller Hall, Auburn, AL 36849. Tel: +1-334-844-2928. Email: gmmkim@gmail.com.

†Department of Economics, Auburn University, 101 Miller Hall, Auburn, AL 36849. Tel: +1-334-844-2903. Email: jzs0221@auburn.edu.

1 Introduction

This paper proposes a factor-augmented forecasting model framework for the net charge-off rate (COR) of the top 10 bank holding companies (BHCs) in the U.S. To estimate latent factors, including targeted ones, we utilize an array of data dimensionality reduction approaches for a large panel of macroeconomic predictors in the U.S. For this purpose, we compiled individual top 10 BHCs' CORs for all loans, business loans, and consumer loans, in addition to the average COR of these BHCs in each loan category.

Net charge-offs are the dollar amount of loans removed from the books (gross charge-offs), that is, charged against loss reserves, minus any subsequent recoveries. The net charge-off rate (COR) of a bank is defined as the net charge-off divided by its average outstanding loans. Naturally, COR signals important information about the quality or riskiness of a bank's loan portfolio.

Lessons learned from the recent subprime mortgage crisis and the ensuing Great Recession highlight the importance of well-functioning financial markets in promoting sustainable economic prosperity. Financial crises tend to come to a surprise realization, generating harmful spillover to real activity sectors. Furthermore, Reinhart and Rogoff (2009) show that financial market meltdown can result in more painful recessions for long periods of time. As can be seen in Figure 1, the top 10 COR tends to rise rapidly before recessions begin. COR spread, all banks COR minus top 10 BHCs COR, also exhibits similar countercyclical dynamics. Longer duration of the recessions are observed in the early 1990s and in the late 2000s when COR and its spread soared rapidly.

Figure 1 around here

These observations imply that good forecasting models for CORs can be beneficial to not only bankers but also policy makers, because CORs can serve as an Early Warning Signal (EWS) of economic downturns, providing timely information on potential vulnerability in financial markets. There's an array of research works that attempts to predict the stability of financial markets in the current literature. For instance, Eichengreen, Rose, and Wyplosz (1995), Sachs, Tornell, and Velasco (1996), and Frankel and Saravelos (2012) used linear regression frameworks to test what economic variables help predicting the occurrence of crises while parametric discrete choice models were employed by Frankel and Rose (1996) and Cipollini and Kapetanios (2009). Quite a few others use nonparametric signal detection approaches. See among others, Kaminsky, Lizondo, and Reinhart (1998), Brüggemann and Linne (1999), Berg and Pattillo (1999), Bussiere and Mulder (1999), Edison (2003), Berg, Borensztein, and Pattillo (2005), EI-Shagi, Knedlik, and von Schweinitz (2013), and Christensen and Li (2014).

To this end, it is crucial to choose a proper measure that quantifies the potential risk in financial markets. Since the seminal work of Girton and Roper (1977), many researchers have used the Exchange Market Pressure (EMP) index that is designed to detect the turbulence in the money and foreign exchange markets. See Tanner (2002) for a review. One alternative measure that is rapidly gaining popularity is the financial stress index (FSI). Unlike the EMP index, FSIs are typically constructed using a broad range of financial market variables. See Kliesen, Owyang, and Vermann (2012) for a survey on FSIs. Some recent studies investigate the out-of-sample predictability of FSIs as a proxy for financial market vulnerability. See among others, Christensen and Li (2014), Kim and Shi (2021), Kim, Shi, and Kim (2020) and Kim and Ko (2020).

The present paper proposes factor-augmented forecasting models for an alternative measure of incoming financial distress variable, that is, the net charge-off rate that contains information on the quality of a bank's loan portfolio. We extract latent common factors by applying data dimensionality reduction methods to a large panel of nonstationary macro predictors such as the method of the principal components (PC) and the partial least squares (PLS) method (Wold, 1982).

Following the work of Stock and Watson (2002), there has been an influx of papers that use PC to perform predictions of key macroeconomic variables. For example, Engel, Mark, and West (2015), GreenawayâĂŘMcGrevy, Mark, Sul, and Wu (2018), Kim and Park (2020), and Behera, Kim, and Kim (2022) demonstrate that factor-based models outperform the random walk model in out-of-sample forecasting exercises for exchange rates. West and Wong (2014), Chen, Jackson, Kim, and Resiandini (2014), and Chiaie, Ferrara, and Giannone (2022) show that latent factors contain useful in-sample and out-of-sample information for commodity price dynamics.

Notwithstanding its popularity in the current literature, PC comes with potential drawbacks. Boivin and Ng (2006) pointed out that the performance of the PC method may be limited if useful predictive contents for the target are in a certain factor that may be dominated by other factors, because PC extracts common factors solely from predictor variables. On the other hand, PLS utilizes the covariance structure between the target and predictors to generate customized target-specific factors. See Kelly and Pruitt (2015) and Groen and Kapetanios (2016) for some comparisons between the PC and PLS approaches. In what follows, we demonstrate that the models with PLS factors indeed perform better than PC factor models as well as the benchmark models.

For our analysis, we constructed the net charge-off rate data of the top 10 U.S. BHCs, utilizing consolidated financial statements (FR Y-9C: Schedules HI-B and HC-C) for the period of 1986:III to 2021:I. To extract latent common factors, we obtained a large panel of 237 quarterly frequency predictors from the FRED-QD for the same sample period that includes both real activity and financial sector variables. We assess and compare the out-of-sample predictability of our models with the stationary autoregressive and the random walk benchmark models via the relative root mean square prediction error ($RRMSPE$) statistics.[1] Our major findings are tri-folds.

First, our factor-augmented forecasting models tend to outperform both benchmark models especially when PLS factors are utilized. Second, our models perform better for CORs of business loans but less successful for consumer loan CORs. These findings imply business loan CORs are more closely related with business cycle factors from macroeconomic predictors. Consumer loan CORs are more difficult to predict as they exhibit highly persistent dynamics. Thirdly, real activity factors are more useful to predict business cycle CORs, often dominating the performance of all factor models. This is in line with the work of Boivin and Ng (2006) who demonstrate that more

[1] See Barth, Joo, Kim, Lee, Maglic, and Shen (2020) for similar research using the aggregate COR in the U.S. banking sector.

data are not necessarily useful when noisy predictors are present. Our results complement the work of Liu, Moon, and Schorfheide (2023) who propose a panel Tobit model with heteroskedasticity to generate forecasts for bank-level loan charge-off rates for small banks that have a large cross-section (large N) of short time series (small T) of censored observations.

The rest of the paper is organized as follows. Section 2 describes our factor-augmented forecasting models and the out-of-sample forecasts schemes used in the present paper. We also explain our evaluation methods for our models. In Section 3, we provide data descriptions and initial look at the data. Some in-sample analysis of our models is also presented. Section 4 reports our out-of-sample forecast results utilizing all factors as well as factors from subsets of the predictors. Section 5 concludes.

2 The Forecasting Model with Latent Factors

This section presents our factor-augmented forecasting models for the charge-off rate (COR) of U.S. bank holding companies (BHCs). We consider two benchmark models: the nonstationary random walk model and a stationary autoregressive (AR) model. These benchmark models are augmented with latent common factors that are estimated via an array of data dimensionality reduction methods for a large panel of macroeconomic time series data, including the Principal Component (PC) and the Partial Least Squares (PLS) methods for nonstationary predictors.

2.1 Data Dimensionality Reduction Methods to Estimate Latent Factors

2.1.1 Principal Component Approach

Since the seminal work of Stock and Watson (2002), PC has been popularly employed in the current macroeconomic and international finance literature. To employ this approach, consider a large panel of N macroeconomic $T \times 1$ time series predictors/variables, $\mathbf{x} = [\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_N]$, where $\mathbf{x}_i = [x_{i,1}, x_{i,2}, ..., x_{i,T}]'$, $i = 1, ..., N$. Abstracting from deterministic terms, we assume the following factor structure for each predictor $\mathbf{x}_i$,

$$x_{i,t} = \boldsymbol{\lambda}_i' \mathbf{f}_t^{PC} + \varepsilon_{i,t}, \tag{1}$$

where $\mathbf{f}_t = \left[f_{1,t}^{PC}, f_{2,t}^{PC}, \cdots, f_{R,t}^{PC} \right]'$ is an $R \times 1$ vector of *latent* time-varying *common* factors at time t. $\boldsymbol{\lambda}_i = [\lambda_{i,1}, \lambda_{i,2}, \cdots, \lambda_{i,R}]'$ denotes an $R \times 1$ vector of time-invariant but idiosyncratic factor loading coefficients for $\mathbf{x}_i$. That is, $\boldsymbol{\lambda}_i' \mathbf{f}_t^{PC}$ describes the underlying data generating process from the common source in the economy, while $\varepsilon_{i,t}$ is the idiosyncratic error term only for i^{th} predictor $x_{i,t}$.

It should be noted that estimating the latent common factors via PC may be spurious if $\varepsilon_{i,t}$ is nonstationary. Since most macroeconomic time series variables are better approximated by an integrated stochastic process, see Nelson and Plosser (1982), we apply the PC method for the first-differenced data as follows to estimate the factors consistently.

$$\Delta x_{i,t} = \boldsymbol{\lambda}_i' \Delta \mathbf{f}_t^{PC} + \Delta \varepsilon_{i,t} \tag{2}$$

for $t = 2, \cdots, T$. See Bai and Ng (2004) for more detailed explanation on this approach. Estimates for the idiosyncratic components are naturally given by the residuals $\Delta\hat{\varepsilon}_{i,t} = \Delta\tilde{x}_{i,t} - \hat{\boldsymbol{\lambda}}_i' \Delta\hat{\mathbf{f}}_t^{PC}$. Level factors and level error terms are recovered via cumulative summation,

$$\hat{\varepsilon}_{i,t} = \sum_{s=2}^{t} \Delta\hat{\varepsilon}_{i,s}, \ \hat{\mathbf{f}}_t^{PC} = \sum_{s=2}^{t} \Delta\hat{\mathbf{f}}_s^{PC} \tag{3}$$

Note that our approach yields consistent factor estimates even when $\mathbf{x}$ includes stationary variables because differencing $I(0)$ variables result in $I(-1)$, which is still stationary.[2]

2.1.2 Target-Specific Factor Estimations via Partial Least Squares

Unlike PC, the PLS approach estimates target-specific factors that are customized for the variable of interest.[3] Let $co_{i,j,t}$ denote the net charge-off rate (COR) for loan type j of a bank holding company i at time t. Abstracting from deterministic terms, consider the following linear regression model.

$$co_{i,j,t} = \Delta\mathbf{x}_t' \boldsymbol{\beta} + e_{i,j,t}, \tag{4}$$

where $\Delta\mathbf{x}_t = [\Delta x_{1,t}, \Delta x_{2,t}, ..., \Delta x_{N,t}]'$ is an $N \times 1$ vector of predictor variables at time $t = 1, ..., T$, while $\boldsymbol{\beta}$ is an $N \times 1$ vector of associated coefficients. $e_{i,j,t}$ is an error term. Note that we employ the first-differenced predictor variables as in the previous subsection for PC.

PLS is particularly useful for sparse regression models with many predictors. Rewrite (4) as follows,

$$\begin{aligned} co_{i,j,t} &= \Delta\mathbf{x}_t' \mathbf{w} \boldsymbol{\theta} + u_t \\ &= \Delta\mathbf{f}_{i,j,t}^{PLS'} \boldsymbol{\theta} + u_t \end{aligned} \tag{5}$$

where $\Delta\mathbf{f}_{i,j,t}^{pls} = \left[\Delta f_{1,i,j,t}^{PLS}, \Delta f_{2,i,j,t}^{PLS}, ..., \Delta f_{R,i,j,t}^{PLS}\right]'$, $R < N$ is an $R \times 1$ vector of PLS factors for COR of a bank i for j type loan. Note that the PLS factor is a linear combination of *all* predictor variables,

$$\Delta\mathbf{f}_{i,j,t}^{PLS} = \mathbf{w}' \Delta\mathbf{x}_t, \tag{6}$$

where $\mathbf{w}_{i,j} = [\mathbf{w}_{1,i,j}, \mathbf{w}_{2,i,j}, ..., \mathbf{w}_{R,i,j}]$ is an $N \times R$ weighting matrix. That is, $\mathbf{w}_r = [w_{1,i,j,r}, .., w_{N,i,j,,r}]'$,

[2] Alternatively, one may continue to difference the variables until the null of nonstationarity hypothesis is rejected via a unit root test, e.g., augmented Dickey-Fuller test. Although this approach is statistically more rigorous, it may not be practically useful because unit root tests often provides contradicting statistical inferences in small samples when the test specification changes. See Cheung and Lai (1995).

[3] Kelly and Pruitt (2015) and Behera, Kim, and Kim (2022) estimated target specific latent common factors by combining least absolute shrinkage and selection operator (LASSO) with PLS and PC. Bai and Ng (2008) introduced an approach to apply the method of principal components to targeted predictors.

$r = 1, ..., R$, is an $N \times 1$ vector of weights on predictor variables for the r^{th} PLS factor, $\Delta f^{PLS}_{r,i,j,t}$. $\boldsymbol{\theta}$ is an $R \times 1$ vector of PLS regression coefficients. Note that PLS regression minimizes the sum of squared residuals from the equation (5) for $\boldsymbol{\theta}$ instead of $\boldsymbol{\beta}$ in (4), resulting in target specific factor estimates for $co_{i,j,t}$. In what follows, we augment the benchmark forecasting model with estimated PLS factors $\Delta\hat{\mathbf{f}}^{PLS}_{i,j,t}$ to make our models to be comparable with the PC factors. That is, we do not utilize $\boldsymbol{\theta}$ for our out-of-sample forecasting exercises in the present paper.

We estimate PLS factors following the sequential procedure proposed by Helland (1990) as follows.[4] First, $\Delta\hat{f}^{PLS}_{1i,j,t}$ is pinned down by the following linear combinations of the predictors in $\Delta\mathbf{x}_t$.

$$\Delta\hat{f}^{PLS}_{1,i,j,t} = \sum_{s=1}^{N} w_{s,1}\Delta x_{s,t}, \tag{7}$$

where the loading (weight) $w_{s,1}$ is given by $Cov(co_{i,j,t}, \Delta x_{s,t})$. Next, we regress $co_{i,j,t}$ and $\Delta x_{s,t}$ on $\Delta\hat{f}^{PLS}_{1,i,j,t}$ then get the residuals to remove the explained component by the first factor $\Delta\hat{f}^{PLS}_{1,i,j,t}$. The second factor estimate $\Delta\hat{f}^{PLS}_{2,i,j,t}$ is then obtained similarly as in (7) with $w_{s,2} = Cov(\widetilde{co}_{i,j,t}, \Delta\tilde{x}_{s,t})$. We repeat until the R^{th} factor $\Delta\hat{f}^{PLS}_{R,i,j,t}$ is obtained.

2.2 Factor Augmented Forecasting Models

2.2.1 Factor Augmented Nonstationary Model

We augment two benchmark forecasting models, nonstationary random walk (RW) model and stationary autoregressive (AR) model by adding latent factor estimates to improve the out-of-sample predictability of the model. For simplicity, we denote $\boldsymbol{\Delta}\hat{\mathbf{f}}_t$ a vector of latent factors obtained either by PC or PLS.

Our nonstationary RW benchmark model for COR (co_t) is,

$$co^{BM_{RW}}_{t+1} = co_t + \eta_{t+1}, \tag{8}$$

where η_{t+1} is a white noise process, which implies $co^{BM_{RW}}_{t+j} = co_t + \sum_{s=1}^{j}\eta_{t+s}$. Therefore, the j-period ahead forecast is the following.

$$\widehat{co}^{BM_{RW}}_{t+j|t} = co_t \tag{9}$$

Augmenting the RW model by adding $\Delta\hat{\mathbf{f}}_t$ to (8), we obtain the following. Abstracting from deterministic terms,

$$co^{F_{RW}}_{t+j} = co_t + \boldsymbol{\gamma}_j'\boldsymbol{\Delta}\hat{\mathbf{f}}_t + \sum_{s=1}^{j}\eta_{t+s},\ j = 1, 2, .., k, \tag{10}$$

Note that (10) nests the RW model (8) when $\boldsymbol{\gamma}_j = \mathbf{0}$.[5]

[4] See Andersson (2009) for a brief survey on available PLS estimation algorithms.

[5] Note that this specification is inconsistent with our earlier specification described in (4) that requires stationarity of the target variable q_t. Practically speaking, however, the random walk type models often perform well in forecasting persistent variables. Furthermore, it is often difficult to distinguish highly persistent or near unit root variables

Note that we cannot use the unrestricted LS for (10) because the coefficient on co_t is restricted to be one. To resolve this problem, we first regress the long-differenced target variable $co_{t+j} - co_t$ on $\Delta\hat{\mathbf{f}}_t$ to obtain the consistent estimate $\hat{\boldsymbol{\gamma}}_j$ assuming that $co_{t+j} - co_t$ is stationary. Adding co_t back to the fitted value yields the following.

$$\widehat{co}_{t+j|t}^{F_{RW}} = co_t + \hat{\boldsymbol{\gamma}}_j' \Delta\hat{\mathbf{f}}_t \tag{11}$$

2.2.2 Factor Augmented Stationary Forecasting Model

Our second benchmark is motivated by the following *stationary* AR(1)-type stochastic process.[6]

$$co_{t+j}^{BM_{AR}} = \alpha_j co_t + u_{t+j},\ j = 1, 2, .., k, \tag{12}$$

where $|\alpha_j| < 1$ for stationarity. (12) implies the following j-period ahead forecast.

$$\widehat{co}_{t+j|t}^{BM_{AR}} = \hat{\alpha}_j co_t, \tag{13}$$

where $\hat{\alpha}_j$ is the LS estimate of α_j.

Similarly as in (10), our second factor-augmented forecasting model is,

$$co_{t+j}^{F_{AR}} = \alpha_j co_t + \boldsymbol{\beta}_j' \boldsymbol{\Delta}\hat{\mathbf{f}}_t + u_{t+j},\ j = 1, 2, .., k \tag{14}$$

Therefore, we obtain the following j-period ahead forecast for the target variable,

$$\widehat{co}_{t+j|t}^{F_{AR}} = \hat{\alpha}_j co_t + \hat{\boldsymbol{\beta}}_j' \Delta\hat{\mathbf{f}}_t, \tag{15}$$

where $\hat{\alpha}_j$ and $\hat{\boldsymbol{\beta}}_j$ are the least squares coefficient estimates. Note that (14) nests the stationary benchmark model (12) when $\boldsymbol{\Delta}\hat{\mathbf{f}}_t$ does not contain any useful predictive contents for co_{t+j}, that is, $\boldsymbol{\beta}_j = 0$.

2.3 Evaluation Methods

We evaluate the out-of-sample predictability of our factor-augmented forecasting models using a recursive (expanding) window scheme as follows.[7]

We begin with estimating the first set of factors $\left\{\Delta\hat{\mathbf{f}}_t\right\}_{t=1}^{T_0}$ using either PC or PLS for the initial $T_0 < T$ observations, $\{co_t, \Delta x_{i,t}\}_{t=1}^{T_0}$, $i = 1, 2, ..., N$. Then, we formulate the first forecast $\widehat{co}_{t+j|t}$ as explained in the previous section. Then, one observation is added for the second round forecasting.

from stationary variables (observational equivalence), leading us to the two mutually exclusive stochastic processes described in (10) and (14).

[6] We employ a direct forecasting model by regressing co_{t+j} *directly* on the current value co_t. Alternatively, one may employ a *recursive* forecasting approach with an AR(1) model, $co_{t+1} = \alpha co_t + \varepsilon_{t+1}$, which implies $\alpha_j = \hat{\alpha}^j$ under this approach.

[7] Alternatively, fixed-size rolling window schemes may be used which may perform better if the underlying data generating process changes. We do not employ this scheme as the results turn out to be less robust.

That is, we re-estimate $\left\{\Delta\hat{\mathbf{f}}_t\right\}_{t=1}^{T_0+1}$ from $\{co_t, \Delta x_{i,t}\}_{t=1}^{T_0+1}$, $i = 1, 2, ..., N$, formulating the second round forecast, co_{T_0+j+1}. We repeat until we forecast the last observation, co_T.

To evaluate the out-of-sample prediction accuracy of our factor-augmented models, we use the ratio of the root mean square prediction error ($RRMSPE$) defined as follows,

$$RRMSPE(j) = \frac{\sqrt{\frac{1}{T-T_0-j}\sum_{t=T_0+j}^{T}\left(\varepsilon_{t+j|t}^{F}\right)^2}}{\sqrt{\frac{1}{T-T_0-j}\sum_{t=T_0+j}^{T}\left(\varepsilon_{t+j|t}^{BM}\right)^2}}, \tag{16}$$

where

$$\varepsilon_{t+j|t}^{BM} = co_{t+j} - \widehat{co}_{t+j|t}^{BM},\ \varepsilon_{t+j|t}^{F} = co_{t+j} - \widehat{co}_{t+j|t}^{F} \tag{17}$$

Note that our factor models outperform the benchmark model when $RRMSPE$ is less than 1.[8]

3 The Empirics

3.1 Data Descriptions and Initial Look at the Data

3.1.1 Net Charge-Off Rates of the Top 10 Bank Holding Companies

We constructed the net charge-off rate (COR) on three different types of loans of the top 10 bank holding companies (BHCs) in the U.S., following the guidelines given in the FR Y-9C reports that are obtained from the Federal Reserve Bank of Chicago. The amount of gross charge-offs and recoveries are obtained from Schedule HI-B, while we acquired the amount of outstanding loans from Schedule HC-C. Observations are quarterly and span from 1986:III to 2021:I. We removed seasonality in the data using X-13ARIMA-SEATS prior to estimation.

The National Information Center (NIC) provides the relevant information on BHCs and other institutions, both domestic and foreign financial entities, that are operating in the U.S. under the supervision of the Federal Reserve system. We selected the top 10 BHCs based on the book or market value of total assets as of September 30, 2021 among the top 25 largest BHCs with a balanced loan structure with sufficient data availability.[9] We excluded some large BHCs such as Goldman Sachs, Morgan Stanley, and Charles Schwab, because those institutions lack sufficient business and consumer loan data that we are particularly interested. See Table 1 for information about these top 10 BHCs used in this paper.

Table 1 around here

[8] Alternatively, one may employ the ratio of the root mean absolute prediction error ($RRMAPE$). That is, the loss function is defined with the absolute value instead of the squared value. $RRMAPE$ tends to perform more reliably in the presence of outliers. Results are overall qualitatively similar.

[9] The values of assets are measured by book value for the fixed assets and by the market value of the securities.

Table 1 also reports the average shares of business and consumer loans out of the total outstanding loans of each BHC. For example, JPM's average shares of the business and consumer loans are 26.3% and 20.1%, respectively. That is, its loan structure includes over 50% of the total loans in the categories of the real estate, credit card, and other consumer loans.[10] In what follows, we report greater predictive contents of macroeconomic latent factors for the business loans in comparison with consumer loans, which implies that our factor-based forecasting models would work better for the CORs of business loans than those of consumer loans.

As can be seen in Figure 2, we also note that the shares of these loans are far from being stable over time. Shares of other loans overall exhibit an upward trend until the beginning of the sub-prime mortgage market crisis near 2005-6, declining afterwards which may reflect decreases in their business in real estate loan activities. The shares of business loans often demonstrate a mirror image of these other loan shares, which implies BHCs may adjust their business loan activities considering the profitability of other type loan business. Consumer loan shares are overall the smallest in most BHCs.

Figure 2 around here

In addition to the individual BHC-level COR data, we created the top 10 average COR ($co_{t10,j,t}$) by utilizing the total loan amount of the top 10 BHCs and their associated total net charge-offs as follows.

$$co_{t10,j,t} = \frac{\sum_{i=1}^{10} co_{i,j,t}}{\sum_{i=1}^{10} loan_{i,j,t}}, \tag{18}$$

where $cor_{i,j,t}$ denotes the amount of net charge-offs on loan type j of a top 10 BHC i at time t while $loan_{i,j,t}$ is its associated amount of outstanding loans. The average CORs of all U.S. banks are obtained from the FRED. Figure 3 reports dynamics of the CORs of the top 10 BHCs as well as the top 10 average CORs in the first column. As we mentioned earlier, CORs tend to rise rapidly before the onset of recessions such as the Great Recession. In the second column, we report figures of individual COR deviations from the top 10 average COR. The top 10 average CORs seem reasonable approximation of overall dynamics of individual CORs. The business loan CORs seem to show more homogeneous dynamics while consumer loan CORs exhibit greater variability across BHCs.

Figure 3 around here

Table 2 present summary statistics of CORs of the top 10 individual BHCs as well as the three measures of aggregate CORs of top 10, top 100, and all banks. The means tends to be greater than the median values especially for business and all loans CORs, resulting in overall positive skewness.

[10] CORs in these three loans have shorter sample periods, 1991:I-2021:I. We also observed substantially more N.A. observations than business and consumer loan charge-off data. We decided not to use these type CORs in this paper.

For consumer loan CORs, the median was roughly close to the mean values. All three type loan CORs exhibit highly leptokurtic distributions, namely, fat-tail distributions that are likely to occur in financial market data. The Jarque-Bera statistics (Jarque and Bera, 1980, 1987) rejects the null hypothesis of normal distribution for all cases.[11] The consumer loan COR tend to show higher standard deviations as seen in Figure 3.

Table 2 around here

3.1.2 Cross-Section Properties of Net Charge-Off Rates

This subsection investigates the cross-section properties of CORs in the banking sector via the pair-wise cross-correlation analysis of CORs in each type loans. For this, we first remove serial correlation in $co_{i,t}$ using the following augmented Dickey-Fuller regression.[12]

$$co_{i,t} = c + \alpha co_{i,t} + \sum_{s=1}^{p} \beta_j \Delta co_{i,t} + \varepsilon_{i,t} \tag{19}$$

We then calculate the pair-wise correlation coefficients $\hat{\rho}_{i,j}$, $i, j = 1, ...N$ using the residuals $\hat{\varepsilon}_{i,t}$ and $\hat{\varepsilon}_{j,t}$ from (19) for top 10 individual BHCs and three aggregate measures, that is, average CORs of the top 10, top 100, and all banks. Also, we present the following cross-section dependence (CD) test statistic proposed by Pesaran (2021).

$$CD = \left(\frac{2T}{N(N-1)}\right)^{1/2} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{i,j}\right) \to^{d} \mathcal{N}(0,1), \tag{20}$$

where T denotes the number of observations.

We report two heatmaps in Figure 4 for the business loan CORs (upper panel) and the consumer loan CORs (lower panel). Excluding $\hat{\rho}_{i,j}$ of the aggregate measures, the cross-correlations of business loan CORs range from 0.010 (JPM and BAC) to 0.784 (BAC and KEY), whereas from -0.120 (PNC and BMO) to 0.651 (JPM and BAC) for consumer loan CORs. The correlations range from -0.165 (USB and PMO) and 0.538 (TFC and KEY) for all loan CORs.[13]

We note much lighter color in the upper-left area of the business loan COR heatmap. In fact, the correlations with JPM, $\hat{\rho}_{JPM,j}$, tend to be low, similarly as those with WFC. As can be seen in Table 3, their average correlations are 0.193 and 0.204 for JPM and WFC, respectively, which are lower than those of other top 10 BHCs. The average correlation of all top 10 BHCs is 0.366 (0.330 including aggregate CORs) It should be noted, however, that $\hat{\rho}_{i,j}$ is overall higher for business loan

[11] We employ the critical values from Deb and Sefton (1996) to avoid size distortion problems in using the asymptotic critical values.

[12] We use the general to specific rule with a maximum two lags to select the optimal number of lags.

[13] The heatmap of all loan CORs is not reported to save space. It is available upon request.

CORs in comparison with consumer loan CORs. Average $\hat{\rho}_{i,j}$ of consumer loan CORs is 0.287 (0.255 including aggregate CORs) which is substantially lower than that of business loan CORs. Average correlations are lower for consumer loan CORs for 8 out of 10 BHCs with exceptions of JPM and CFG.

The corss-section dependence (CD) test statistics supports the presence of common drivers in CORs, rejecting the null hypothesis of cross-section independence at the 1% significance level for all three type loan CORs. We notice that p-value of the business loan CORs is lower than that of consumer loan CORs, which implies stronger cross-section dependence in the business loan CORs.

Figure 4 around here

Table 3 around here

3.1.3 Large Panel of Macroeconomic Data

We obtained 237 quarterly frequency macroeconomic time series variables from the FRED-QD database, matching the sample period with that of the COR data. We log-transformed all quantity variables prior to estimations, while those in percent such as interest rates and unemployment rates were divided by 100.

We categorized these macroeconomic variables into 14 groups. Groups #1 through #6 include 118 real activity predictors, while groups #7 to #14 are nominal/financial sector variables. In addition to extracting latent factors from all predictors, we also estimate real activity factors and financial factors separately to separately track the sources of the predictability, if any, for CORs. See Table A1 in the Appendix for more detailed information.

3.2 Factor Model In-Sample Analysis

This section provides some useful in-sample properties of the factor estimates that are obtained from CORs of the top 10 BHCs and the large panel of macroeconomic predictors. We first present estimated level factors in Figure 5, which are visually more tractable, that is, $\hat{f}_{i,t} = \sum_{s=2}^{t} \Delta \hat{f}_{i,s}$, $i = 1, 2$. PC factors are reported in the top left panel, whereas PLS factors appear in other three panels, because PLS yields factors to fit each target COR data.

As can be seen in Figure 5, the estimated level factors exhibit strong co-movement with each other. This implies that PLS level factors for each type CORs are likely to be correlated with business cycle dynamics, because PC factors are estimated utilizing differenced macro/finance predictors, generating business cycle related factors. Also, this implies that both PC factors and PLS factors are likely to share predictive contents for the CORs. We note, however, that PC factors overall demonstrate more similar dynamics with PLS factors for all loan CORs and business loan

CORs, while PLS factors for consumer loan CORs exhibit more pronounced dynamics in comparison with these other factors. In what follows, we report our factor augmented forecasting models tend to perform better for all loan CORs and business loan CORs than for consumer loan CORs.

Figure 5 around here

Figure 6 reports the R^2 statistics and the cumulative R^2 statistics of PC and PLS factors for up to 12 factors. By construction, PLS factors provide a better in-sample fit than PC factors because PLS utilizes the covariance between the target (CORs) and the predictor variables, while PC factors are extracted only from the variance-covariance structure of macro/finance predictor variables. Putting it differently, the PLS method yields superior in-sample performance relative to the PC method.

Note that, unlike PC factors, the cumulative R^2 statistics of PLS factors exhibit positive slopes at a decreasing rate. This is because our PLS algorithm sequentially estimates orthogonalized common factors using residuals of the target and predictors as explained earlier in Section 2. On the other hand, the PC method utilizes predictors only without considering the target variable, additional R^2 values do not necessarily decrease. For example, $\hat{f}^{PC}_{4,t}$ seems to have the highest in-sample explanatory power for all three CORs.

Figure 6 around here

Following Ludvigson and Ng (2009), we investigate the source of the estimated common factors via the marginal R^2 analysis. That is, we regress each predictor onto the common factor to measure how much of the variation in each predictor can be explained by the common factor. Results are reported in Figure 7.

The first PC common factor, $\Delta\hat{f}^{PC}_{1,t}$, seems to be heavily correlated with real activity predictors (groups #1 through #6) such as NIPA (#1, ID 1-22), industrial production (#2, ID 23-38), and labor market condition (#3, ID 39-87) macroeconomic variables. $\Delta\hat{f}^{PC}_{2,t}$ is likely to be coming mainly from price predictors (#7, ID 119-166), while $\Delta\hat{f}^{PC}_{3,t}$ explains substantial variations of financial market predictors such as exchange rates (#10, ID 202-206), stock markets (#11, ID 207-213), and household balance sheets variables (#13, ID 216-224). On the other hand, $\Delta\hat{f}^{PC}_{4,t}$ exhibits overall balanced marginal R^2 statistics distribution for both the real activity and the nominal/financial sector variable groups.

The marginal R^2 statistics of the PLS factors exhibit similar distributions, especially between $\Delta\hat{f}^{PLS}_{i,A,t}$ (all loans CORs) and $\Delta\hat{f}^{PLS}_{i,B,t}$ (business loans CORs). The marginal R^2 statistics of $\Delta\hat{f}^{PLS}_{1,A,t}$ and $\Delta\hat{f}^{PLS}_{1,B,t}$ are distributed overall evenly except the price predictors (#7), while $\Delta\hat{f}^{PLS}_{1,C,t}$ (consumer loans CORs) explains the variations of the most predictors including group #7 variables. Overall, the third and fourth PLS common factors, $\Delta\hat{f}^{PLS}_{i,j,t}, i = 3, 4$ and $j = A, B, C$, seem to explain the variations of the nominal/finance variables (#7 through #14) more, while the first and the second PLS factors are more closely correlated with real activity variables (#1 through #6).

Figure 7 around here

4 Out-of-Sample Prediction Performance

We implement an array of out-of-sample (OOS) forecast exercises for the CORs of the top 10 individual BHCs as well as the two aggregate CORs. Employing a recursive scheme, we evaluate the OOS predictability of our factor-augmented forecasting model in comparison with the two benchmark models, utilizing PC and PLS for 237 quarterly frequency time series predictors. Motivated by the work of Boivin and Ng (2006), we also assess the predictability of our models when factors are extracted from subsets of the panel data such as real activity groups and nominal/financial sector groups.

4.1 Out-of-Sample Predictability of the Total Macro Factors

We report the $RRMSPE$ statistics (16) for an array of factor augmented forecasting models in comparison with the random walk (RW) benchmark model. The $RRMSPE$ statistics with the stationary autoregressive model is also presented. Recall that competing models perform better than the benchmark RW model when the $RRMSPE$ is less than one.

We begin with the OOS forecasts for all loans CORs. Figure 8 compares the 1-quarter ahead out-of-sample prediction performance of the two factor-augmented stationary AR model forecasts, $\widehat{co}_{t+1|t}^{PLSAR}$ and $\widehat{co}_{t+1|t}^{PCAR}$, the two factor-augmented nonstationary RW model forecasts, $\widehat{co}_{t+1|t}^{PLSRW}$ and $\widehat{co}_{t+1|t}^{PCRW}$, and the AR benchmark model forecast, $\widehat{co}_{t+1|t}^{AR}$. Results overall imply that our factor-augmented forecasting models yield substantial improvement in short-term predictability over the both benchmark models. Detailed analysis is as follows.

We observe that $\widehat{co}_{t+1|t}^{AR}$ outperforms the benchmark $\widehat{co}_{t+1|t}^{RW}$ ($RRMSPE < 1$) for five BHCs (JPM, WFC, USB, PNC, BMO) but not for the rest of BHCs (BAC, TFC, FITB, CFG, KEY). We note that $\widehat{co}_{t+1|t}^{AR}$ performs worse than $\widehat{co}_{t+1|t}^{RW}$ for the two aggregate CORs, the top 10 average COR and the average COR of all banks. In most cases, $\widehat{co}_{t+1|t}^{PLSAR}$ and $\widehat{co}_{t+1|t}^{PCAR}$ exhibit solid performance over the benchmark models. $\widehat{co}_{t+1|t}^{PLSRW}$ also outperforms $\widehat{co}_{t+1|t}^{RW}$ when sufficiently large number of factors are used, while $\widehat{co}_{t+1|t}^{PCRW}$ does not perform very well no matter how many factors are employed. The PLS factors $\Delta\hat{f}_{i,A,t}^{PLS}$ seem to play an important role in enhancing the predictability consistently even with a single factor $\Delta\hat{f}_{1,A,t}^{PLS}$.

Figure 8 around here

Figure 9 provides the $RRMSPE$ statistics for the 2-quarter ahead OOS prediction models. $\widehat{co}^{AR}_{t+2|t}$ outperforms the benchmark $\widehat{co}^{RW}_{t+2|t}$ for five BHCs (JPM, WFC, USB, PNC, BMO) again but not for the rest of BHCs. $\widehat{co}^{AR}_{t+2|t}$ also performs worse than $\widehat{co}^{RW}_{t+2|t}$ again for the two aggregate CORs, but the $RRMSPE$ statistics are closer to one when the forecast horizon rises from 1 to 2. In fact, the performance of $\widehat{co}^{AR}_{t+2|t}$ improved in most cases. $\widehat{co}^{PLSAR}_{t+2|t}$ and $\widehat{co}^{PCAR}_{t+2|t}$ continue to outperform the benchmark model $\widehat{co}^{RW}_{t+2|t}$, and so does $\widehat{co}^{PLSRW}_{t+1|t}$ when sufficiently large number of factors are used. For the aggregate CORs, our factor-augmented forecasting models again demonstrate superior predictability over the benchmark models.

Figure 9 around here

Figures 10 and 11 report the $RRMSPE$ statistics for the 4-quarter (1-year) and 8-quarter (2-year) ahead OOS prediction models. It should be noted that the predictability of the stationary benchmark model, $\widehat{co}^{AR}_{t+4|t}$ and $\widehat{co}^{AR}_{t+8|t}$, continues to improve in the longer-horizon OOS forecasting exercises, reflecting that the deviations of CORs tend to quickly revert back to their equilibrium paths. Our factor-augmented models outperform the benchmark RW model. However, additional information gains by adding factors seem to diminish as we can see that $\widehat{co}^{PLSAR}_{t+8|t}$ and $\widehat{co}^{PCAR}_{t+8|t}$ perform similarly well as $\widehat{co}^{AR}_{t+8|t}$. See Table A2 in the Appendix for more detailed results for the aggregate CORs of the top 10 banks and all U.S. banks.

Figures 10 around here

Figures 11 around here

We now turn to the performance of our forecasting models for disaggregated level CORs, that is, business loan CORs and consumer loan CORs. Figure 12 reports the $RRMSPE$ statistics for the business loan CORs of the top 10 banks and those of all U.S. banks for the 1-quarter to 8-quarter ahead forecasts. $\widehat{co}^{PLSAR}_{t+j|t}$, $\widehat{co}^{PCAR}_{t+j|t}$, and $\widehat{co}^{PLSRW}_{t+j|t}$ again outperform the nonstationary RW model in most cases. These factor models overall outperform the stationary AR model at short horizons ($H = 1, 2$), whereas additional gains over $\widehat{co}^{AR}_{t+j|t}$ appear to diminish as the forecast horizon gets longer. See Table A3 in the Appendix for more detailed results.

Figure 12 around here

As can be seen in Figure 13, our forecasting models fail to outperform the benchmark consistently for consumer loan CORs in comparison with the performance for business loan CORs. $\widehat{co}^{PLSAR}_{t+j|t}$, $\widehat{co}^{PCAR}_{t+j|t}$, and $\widehat{co}^{PLSRW}_{t+j|t}$ overall outperform both benchmark models, $\widehat{co}^{AR}_{t+j|t}$ and $\widehat{co}^{RW}_{t+j|t}$, in the 1-quarter and 4-quarter ahead forecasts for consumer loan CORs of all U.S. BHCs, but not for the top 10 average COR for consumer loans. Our factor-augmented models still demonstrate good predictability at longer horizons. See Table A4 in the Appendix for more detailed results.

One interesting finding is that $\widehat{co}^{AR}_{t+j|t}$ better than $\widehat{co}^{RW}_{t+j|t}$ only in sufficiently longer-horizon forecasts, which is in stark contrast with previous results for business loan CORs. This reminds our in-sample findings we reported earlier. Consumer loan CORs tend to exhibit greater degree of idiosyncratic dynamics (Figure 3) as well as substantially greater standard deviations (Table 2). Although most level factors tend to demonstrate a (near) unit root process, the level factors from consumer loan CORs, $\hat{f}^{PLS}_{i,C,t}$, show even more persistent dynamics (Figure 3), which may be related with the Martingale property of consumption.

Figure 13 around here

4.2 Real Activity vs. Nominal/Financial Factors

As shown by Boivin and Ng (2006), more variables are not necessarily better for the purpose of forecasting if some predictors do not possess useful predictive contents. Including such variables can increase noise in making predictions. In a similar vein, Behera and Kim (2019) demonstrate that factors extracted from real activity variables, excluding financial sector variables, tend to yield greater predictive contents for U.S. real effective exchange rate at longer horizons.[14]

Figure 14 presents the $RRMSPE$ statistics of our PLS factor-augmented OOS forecasting models for the all loan COR of the top 10 BHCs, using total factors, real activity factors (groups #1 to #6, data ID 1-118), and financial/nominal factors (groups #7 to #14, data ID 119-237).[15] Results imply that the total factor model ($\widehat{co}^{PLSAR}_{t+j|t}$) and financial factor model ($\widehat{co}^{PLSAR-F}_{t+j|t}$) perform similarly well, outperforming both benchmark models. The real factor model ($\widehat{co}^{PLSAR-R}_{t+j|t}$) also overall outperforms both benchmark models but worse than other factor models. See Tables A5 and A6 in the Appendix for more detailed results.

Figure 14 around here

Figure 15 present our forecasting exercises with these subset factors for the business loan COR of the top 10 BHCs. Results are in stark contrast with those for the all loan COR. We note that $\widehat{co}^{PLSAR-R}_{t+j|t}$ overall outperform not only the benchmark models, $\widehat{co}^{AR}_{t+j|t}$ and $\widehat{co}^{RW}_{t+j|t}$, but also other factor-augmented models $\widehat{co}^{PLSAR}_{t+j|t}$ and $\widehat{co}^{PLSAR-F}_{t+j|t}$. The PLS real factor model and the total factor model both outperform greatly over other models at the 1-quart ahead forecast horizon, implying that real activity predictors contain most important predictable contents for the business loan COR.

[14] Similarly, Behera, Kim, and Kim (2022) show that only U.S. factors play an important role in out-of-sample forecasting the KRW-USD real exchange rate, while Korean factors tend to serve as noise in forecasting. They explain such superior predictability of U.S. factors using high degree co-movement behavior of many bilateral exchange rates relative to the U.S.

[15] PC Factor-augmented models perform similarly. Results are available upon request.

$\widehat{co}_{t+j|t}^{PLSAR-R}$ strongly dominate other models at the 2-quarter and the 4-quarter forecast horizons. It continues to outperform others at 8-quarter horizon but marginally. These findings imply that business loan CORs are heavily influenced by macroeconomic real activity, whereas finance factors play a limited role in predicting business loan CORs. See Tables A7 and A8 in the Appendix for more detailed results.

Figure 15 around here

Figure 16 confirms our earlier findings regarding the difficulty to yield substantial enhancement in predictability gains from factors for consumer loan CORs. It should be noted that neither our factor-augmented forecasting models nor the stationary AR benchmark model consistently outperform the nonstationary RW model ($\widehat{co}_{t+j|t}^{RW}$). These findings are again consistent with substantially persistent dynamics (close to a unit root process) of consumer loan CORs. See Tables A9 and A10 in the Appendix for more detailed results.

Figure 16 around here

5 Concluding Remarks

This paper proposes factor-augmented forecasting models for the net charge-off rate (COR) of the top 10 U.S. bank holding companies (BHCs) in a data rich environment. COR signals the changes in riskiness of a bank's loan portfolio, which may cause harmful and persistent spillover not only to other financial markets but also into real sector of the economy. Our forecasting models, therefore, may serve as an Early Warning Signal (EWS), providing timely information on signs of financial market instability.

We apply an array of data dimensionality reduction methods to a large panel of 237 quarterly frequency macroeconomic variables from 1986:III to 2021:I. After extracting latent common factors via Principal Component (PC) and Partial Least Squares (PLS), we augment the benchmark model with estimated factors to enhance the out-of-sample predictability for CORs.

We assess the prediction accuracy of our models with two benchmark models, the stationary autoregressive and the nonstationary random walk models. Our factor-augmented models outperform the benchmark models in forecasting the business loan CORs (and all loan CORs) substantially better than the consumer loan CORs. We interpret these findings as evidence that business loan CORs are heavily influenced by latent factors from the underlying forces that drive business cycle dynamics of the economy. Consumer loan CORs exhibit substantially more persistent dynamics that might be due to a Martingale property of consumption, rendering limited gains from using latent factors.

Factors obtained from real activity predictors tend to enhance the out-of-sample predictability of business loan CORs. Finance factors often fail to provide additional contribution for business CORs in the presence of real factors, although they also contain stand-alone useful predictive contents for CORs. These findings are in line with the work of Boivin and Ng (2006) who demonstrated the importance of relevant common factors for the target variable.

References

ANDERSSON, M. (2009): "A Comparison of Nine PLS1 Algorithms," *Journal of Chemometrics*, 23, 518–529.

BAI, J., AND S. NG (2004): "A PANIC Attack on Unit Roots and Cointegration," *Econometrica*, 72(4), 1127–1177.

——— (2008): "Forecasting economic time series using targeted predictors," *Journal of Econometrics*, 146(2), 304–317.

BARTH, J. R., S. JOO, H. KIM, K. B. LEE, S. MAGLIC, AND X. SHEN (2020): "Forecasting Net Charge-Off Rates of Banks: A PLS Approach," in *HANDBOOK OF FINANCIAL ECONOMETRICS, MATHEMATICS, STATISTICS, AND MACHINE LEARNING*, ed. by C. F. Lee, and J. C. Lee, World Scientific Book Chapters, chap. 63, pp. 2265–2301. World Scientific Publishing Co. Pte. Ltd.

BEHERA, S., AND H. KIM (2019): "Forecasting Dollar Real Exchange Rates and the Role of Real Activity Factors," Auburn Economics Working Paper Series auwp2019-04, Department of Economics, Auburn University.

BEHERA, S., H. KIM, AND S. KIM (2022): "Superior Predictability of American Factors of the Won/Dollar Real Exchange Rate," Auburn Economics Working Paper Series auwp2022-03, Department of Economics, Auburn University.

BERG, A., E. BORENSZTEIN, AND C. PATTILLO (2005): "Assessing Early Warning Systems: How Have They Worked in Practice?," IMF Working Paper 04/52. International Monetary Fund.

BERG, A., AND C. PATTILLO (1999): "Predicting Currency Crises: The Indicators Approach and an Alternative," *Journal of International Money and Finance*, 18(4), 561–586.

BOIVIN, J., AND S. NG (2006): "Are more data always better for factor analysis?," *Journal of Econometrics*, 132(1), 169–194.

BRÜGGEMANN, A., AND T. LINNE (1999): "How Good are Leading Indicators for Currency and Banking Crises in Central and Eastern Europe? An Empirical Test," IWH Discussion Papers, 95.Halle Institute for Economic Research.

BUSSIERE, M., AND C. MULDER (1999): "External Vulnerability in Emerging Market Economies - How High Liquidity Can Offset Weak Fundamentals and the Effects of Contagion," IMF Working Papers 99/88.

CHEN, S.-L., J. D. JACKSON, H. KIM, AND P. RESIANDINI (2014): "What Drives Commodity Prices?," *American Journal of Agricultural Economics*, 96(5), 1455–1468.

Cheung, Y.-W., and K. S. Lai (1995): "Lag Order and Critical Values of the Augmented Dickey-Fuller Test," *Journal of Business & Economic Statistics*, 13(3), 277–80.

Chiaie, S. D., L. Ferrara, and D. Giannone (2022): "Common factors of commodity prices," *Journal of Applied Econometrics*, 37(3), 461–476.

Christensen, I., and F. Li (2014): "Predicting financial stress events: A signal extraction approach," *Journal of Financial Stability*, 14(C), 54–65.

Cipollini, A., and G. Kapetanios (2009): "Forecasting Financial Crises and Contagion in Asia using Dynamic Factor Analysis," *Journal of Empirical Finance*, 16(2), 188–200.

Deb, P., and M. Sefton (1996): "The Distribution of a Lagrange Multiplier Test of Normality," *Economics Letter*, 51, 123–130.

Edison, H. J. (2003): "Do indicators of financial crises work? An evaluation of an early warning system.," *International Journal of Finance and Economics*, 8 (1), 11–53.

EI-Shagi, M., T. Knedlik, and G. von Schweinitz (2013): "Predicting Financial Crises: The (Statistical) Significance of the Signals Approach," *Journal of International Money and Finance*, 35, 75–103.

Eichengreen, B., A. K. Rose, and C. Wyplosz (1995): "Exchange Market Mayhem: The Antecedents and Aftermath of Speculative Attacks," *Economic Policy*, 10 (21), 249–312.

Engel, C., N. Mark, and K. West (2015): "Factor Model Forecasts of Exchange Rates," *Econometric Reviews*, 34(1-2), 32–55.

Frankel, J., and G. Saravelos (2012): "Can leading indicators assess country vulnerability? Evidence from the 2008–09 global financial crisis," *Journal of International Economics*, 87, 216 –231.

Frankel, J. A., and A. K. Rose (1996): "Currency crashes in emerging markets: an empirical treatment," *Journal of International Economics*, 41 (3/4), 351–366.

Girton, and Roper (1977): "A Monetary Model of Exchange Market Pressure Applied to the Postwar Canadian Experience," *American Economic Review*, 67, 537–548.

GreenawayÂĂŘMcGrevy, R., N. C. Mark, D. Sul, and J. Wu (2018): "Identifying Exchange Rate Common Factors," *International Economic Review*, 59(4), 2193–2218.

Groen, J., and G. Kapetanios (2016): "Revisiting useful approaches to data-rich macroeconomic forecasting," *Computational Statistics and Data Analysis*, 100, 221–239.

Helland, I. S. (1990): "Partial Least Squares Regression and Statistical Models," *Scandinavian Journal of Statistics*, 17, 97–114.

Jarque, C. M., and A. K. Bera (1980): "Efficient tests for normality, homoscedasticity and serial independence of regression residuals," *Economics Letters*, 6(3), 255–259.

——— (1987): "A test for normality of observations and regression residuals," *International Statistical Review*, 55, 163–172.

Kaminsky, G., S. Lizondo, and C. Reinhart (1998): "Leading indicators of currency crises," IMF Working Paper No. 45 International Monetary Fund.

Kelly, B., and S. Pruitt (2015): "The three-pass regression filter: A new approach to forecasting using many predictors," *Journal of Econometrics*, 186(2), 294–316.

Kim, H., and K. Ko (2020): "Improving forecast accuracy of financial vulnerability: PLS factor model approach," *Economic Modelling*, 88(C), 341–355.

Kim, H., and W. Shi (2021): "Forecasting financial vulnerability in the USA: A factor model approach," *Journal of Forecasting*, 40(3), 439–457.

Kim, H., W. Shi, and H. H. Kim (2020): "Forecasting financial stress indices in Korea: a factor model approach," *Empirical Economics*, 59(6), 2859–2898.

Kim, Y., and C. Park (2020): "Are exchange rates disconnected from macroeconomic variables? Evidence from the factor approach," *Empirical Economics*, 58(4), 1713–1747.

Kliesen, K. L., M. T. Owyang, and E. K. Vermann (2012): "Disentangling diverse measures: a survey of financial stress indexes," *Review*, (Sep), 369–398.

Liu, L., H. R. Moon, and F. Schorfheide (2023): "Forecasting with a panel Tobit model," *Quantitative Economics*, 14(1), 117–159.

Ludvigson, S., and S. Ng (2009): "Macro Factors in Bond Risk Premia," *Review of Financial Studies*, 22(12), 5027–5067.

Nelson, C. R., and C. I. Plosser (1982): "Trends and random walks in macroeconmic time series : Some evidence and implications," *Journal of Monetary Economics*, 10(2), 139–162.

Pesaran, M. H. (2021): "General diagnostic tests for cross-sectional dependence in panels," *Empirical Economics*, 60(1), 13–50.

Reinhart, C. M., and K. S. Rogoff (2009): *This Time Is Different: Eight Centuries of Financial Folly*, vol. 1 of *Economics Books*. Princeton University Press.

Sachs, J., A. Tornell, and A. Velasco (1996): "Financial Crises in Emerging Markets: The Lessons from 1995," *Brookings Papers on Economic Activity*, 27(1), 147–199.

Stock, J. H., and M. W. Watson (2002): "Macroeconomic Forecasting using Diffusion Indexes," *Journal of Business and Economic Statistics*, 20(2), 147–162.

TANNER, E. (2002): “Exchange Market Pressure, Currency Crises, and Monetary Policy; Additional Evidence From Emerging Markets,” IMF Working Papers No. 02/14.

WEST, K. D., AND K.-F. WONG (2014): “A factor model for co-movements of commodity prices,” *Journal of International Money and Finance*, 42(C), 289–309.

WOLD, H. (1982): *Soft modelling: the basic design and some extensions*, vol. 1 of *Systems under indirect observation, Part II*. North-Holland, Amsterdam.

Table 1. Top 10 Bank Holding Companies

Name	ID	RSSDID	Location	Asset ($ Mil)	Busi (%)	Cons (%)
JPMorgan	JPM	1039502	New York, NY	3,757,576	26.3	20.1
Bank of America	BAC	1073757	Charlotte, NC	3,085,446	26.9	17.8
Wells Fargo	WFC	1120754	San Francisco, CA	1,954,901	19.7	20.9
U.S. Bancorp	USB	1119794	Minneapolis, MN	567,495	28.5	18.2
PNC	PNC	1069778	Pittsburgh, PA	554,457	32.1	13.8
Truist	TFC	1074156	Charlotte, NC	529,884	16.5	13.5
Fifth Third	FITB	1070345	Cincinnati, OH	207,731	27.7	18.6
BMO	BMO	1245415	Wilmington, DE	195,146	34.6	13.4
Citizens	CFG	1132449	Providence, RI	187,549	19.6	17.7
Keycorp	KEY	1068025	Cleveland, OH	187,198	28.8	17.4

Note: The top 10 bank holding companies (BHCs) are selected based on the dollar value of total assets as of September 30, 2021 among the largest BHCs with balanced available loan data we are interested in. Some large BHCs such as Goldman Sachs, Morgan Stanley, and Charles Schwab were excluded due to lack of sufficient business and consumer loan data. Busi and Cons denote the average shares of business loans and consumer loans, respectively, of each BHC during the sample period.

Table 2. Summary Statistics: Top 10 Charge-Off Rates

			All Loans COR					
ID	Mean	Median	Std Dev	Min	Max	Skew	Kurt	JB
JPM	0.710	0.519	0.474	0.251	2.447	2.284	19.821	1747
BAC	0.561	0.386	0.491	0.185	2.568	0.300	9.643	256
WFC	0.553	0.461	0.371	0.135	1.932	-0.018	7.523	118
USB	0.574	0.485	0.330	0.179	2.060	0.868	15.449	908
PNC	0.382	0.284	0.359	-0.098	2.086	1.792	16.630	1142
TFC	0.318	0.220	0.287	0.061	1.565	0.368	21.438	1958
FITB	0.423	0.276	0.422	0.100	2.075	2.990	23.269	2568
BMO	0.385	0.284	0.385	-0.162	1.889	0.776	11.956	475
CFG	0.350	0.218	0.308	0.057	1.545	1.308	10.325	348
KEY	0.456	0.302	0.458	0.099	2.379	2.105	18.596	1501
Top 10	0.568	0.419	0.391	0.200	2.313	2.821	15.998	1154
Top 100	1.025	0.740	0.671	0.390	3.360	1.386	10.472	365
All Banks	0.912	0.650	0.577	0.330	3.020	0.989	7.502	139
			Business Loans COR					
ID	Mean	Median	Std Dev	Min	Max	Skew	Kurt	JB
JPM	0.547	0.324	0.544	0.035	2.926	1.790	10.565	403
BAC	0.413	0.251	0.457	-0.260	2.718	0.733	9.423	250
WFC	0.499	0.378	0.411	0.027	2.213	0.409	6.404	70
USB	0.447	0.247	0.515	-0.322	2.894	0.109	6.033	53
PNC	0.470	0.248	0.692	-0.390	5.534	3.864	35.348	6360
TFC	0.293	0.214	0.249	-0.052	1.197	-0.386	9.403	239
FITB	0.397	0.301	0.353	-0.033	2.263	1.481	12.941	619
BMO	0.491	0.298	0.688	-0.531	4.916	2.512	31.441	4796
CFG	0.363	0.227	0.453	-0.364	2.334	0.358	15.148	851
KEY	0.445	0.200	0.610	-0.281	3.939	-0.454	15.197	860
Top 10	0.466	0.317	0.379	0.045	1.638	0.637	5.961	60
Top 100	0.745	0.520	0.615	0.030	2.660	1.342	7.297	148
All Banks	0.784	0.510	0.608	0.120	2.650	0.569	5.172	35
			Consumer Loans COR					
ID	Mean	Median	Std Dev	Min	Max	Skew	Kurt	JB
JPM	1.698	1.545	0.842	0.580	5.056	0.890	16.411	1052
BAC	1.649	1.287	0.991	0.782	5.550	-1.297	16.153	1033
WFC	1.344	1.229	0.546	0.560	4.098	1.662	21.962	2131
USB	1.396	1.309	0.546	0.298	2.882	-0.284	8.350	166
PNC	0.689	0.580	0.539	0.113	3.446	0.293	17.694	1243
TFC	0.965	0.990	0.438	0.202	2.515	0.424	15.801	946
FITB	0.708	0.591	0.367	0.223	2.080	2.243	15.057	952
BMO	0.580	0.377	0.508	0.109	2.122	-5.333	55.606	16567
CFG	0.616	0.582	0.361	0.036	1.972	-0.605	8.526	184
KEY	0.932	0.944	0.467	0.291	2.614	0.619	10.300	315
Top 10	1.424	1.329	0.708	0.634	4.143	-1.563	21.632	2052
Top 100	2.643	2.400	1.023	1.500	7.080	-0.370	7.888	141
All Banks	2.452	2.280	1.001	1.350	6.700	-0.369	7.690	130

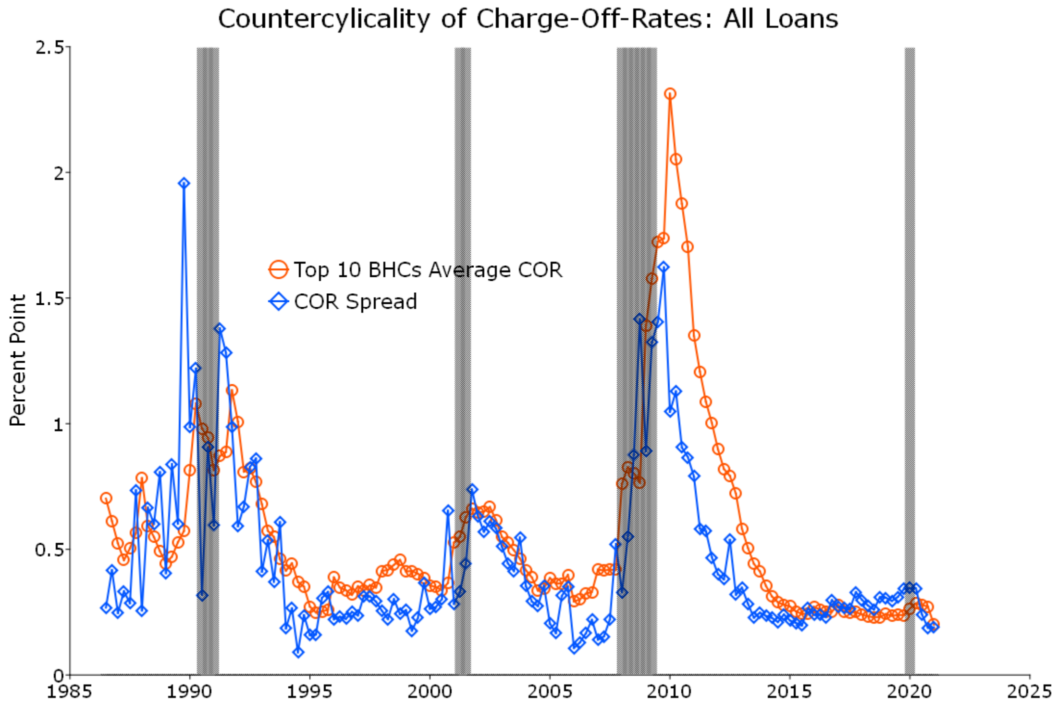
Note: Skew and Kurt denote skewness and kurtosis, respectively. Results overall imply an asymmetric and fat-tailed distribution of COR. JB denotes the Jarque-Bera statistics (Jarque and Bera, 1980, 1987; Deb and Sefton, 1996). The test rejects the null hypothesis of normality for all cases at any conventional significance level when the critical values from Deb and Sefton (1996).

Table 3. Cross-Section Dependence in the Top 10 Charge-Off Rates

	Average Cross-Correlations ($\hat{\rho}_i$)		
	$co_{i,All,t}$	$co_{i,Bus,t}$	$co_{i,Con,t}$
JPM	0.345	0.193	0.397
BAC	0.409	0.465	0.414
WFC	0.259	0.204	0.186
USB	0.238	0.466	0.333
PNC	0.234	0.381	0.206
TFC	0.323	0.431	0.290
FITB	0.213	0.383	0.327
BMO	0.178	0.399	0.110
CFG	0.309	0.271	0.317
KEY	0.343	0.469	0.294
Top 10	0.398	0.372	0.463
Top 100	0.278	0.449	0.363
All Banks	0.214	0.475	0.362
Average $\hat{\rho}_i$	0.228	0.330	0.255
CD	$23.515^{\ddagger}$	$33.968^{\ddagger}$	$26.279^{\ddagger}$

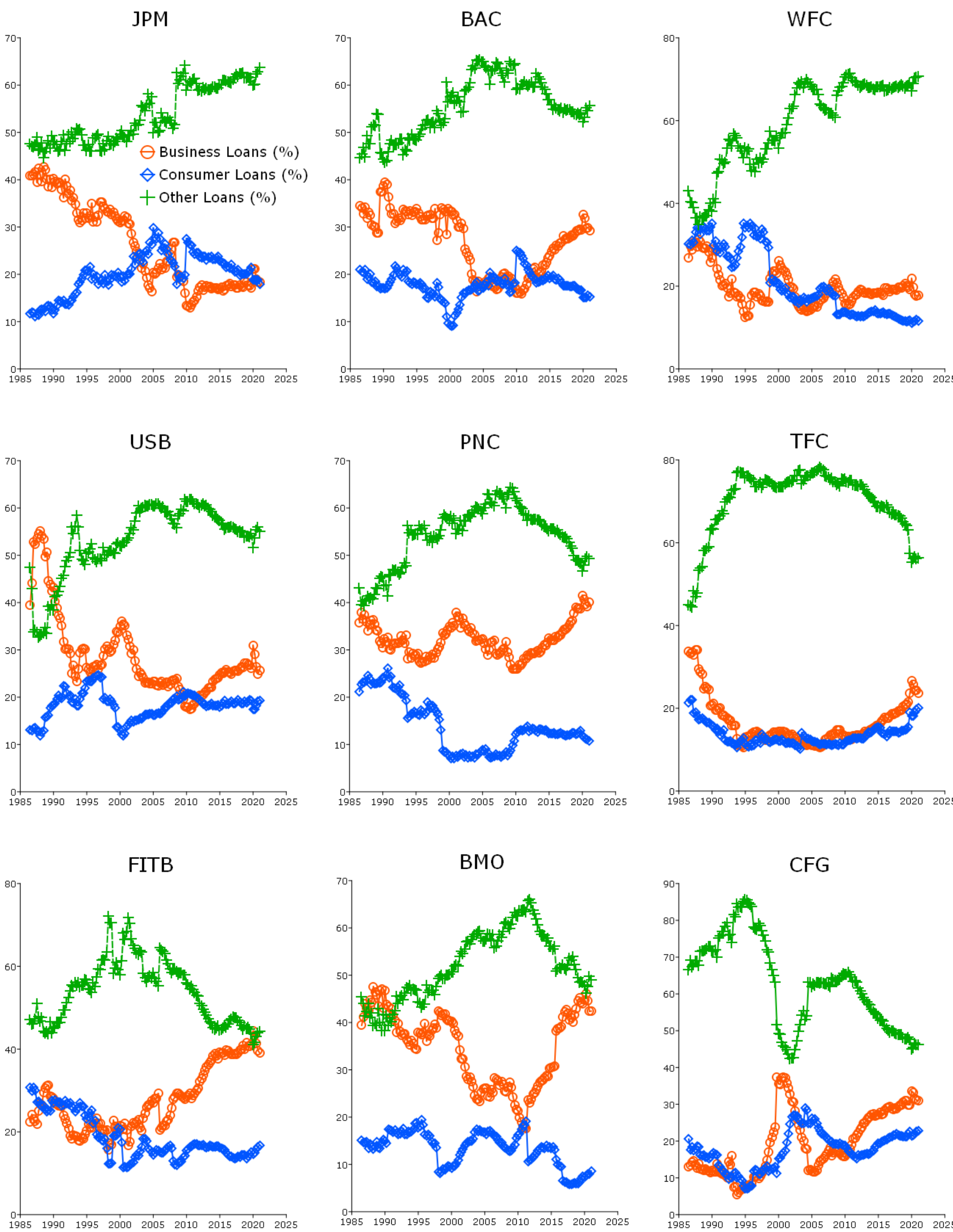
Note: $\hat{\rho}_{i,j}$ denotes the cross-correlations of the residuals $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ from the ADF regressions. We report the average cross-correlations of each CORs, $\hat{\rho}_i = N^{-1}\sum_{i \neq j} \hat{\rho}_{i,j}$. Average $\hat{\rho}_i$ is the average value of all CORs' average cross-correlations. CD denotes the cross-section dependence statistics from Pesaran (2021). The superscript ‡ denotes a rejection at the 1% signficance level.

Figure 1. Dynamics of Charge-off-Rates



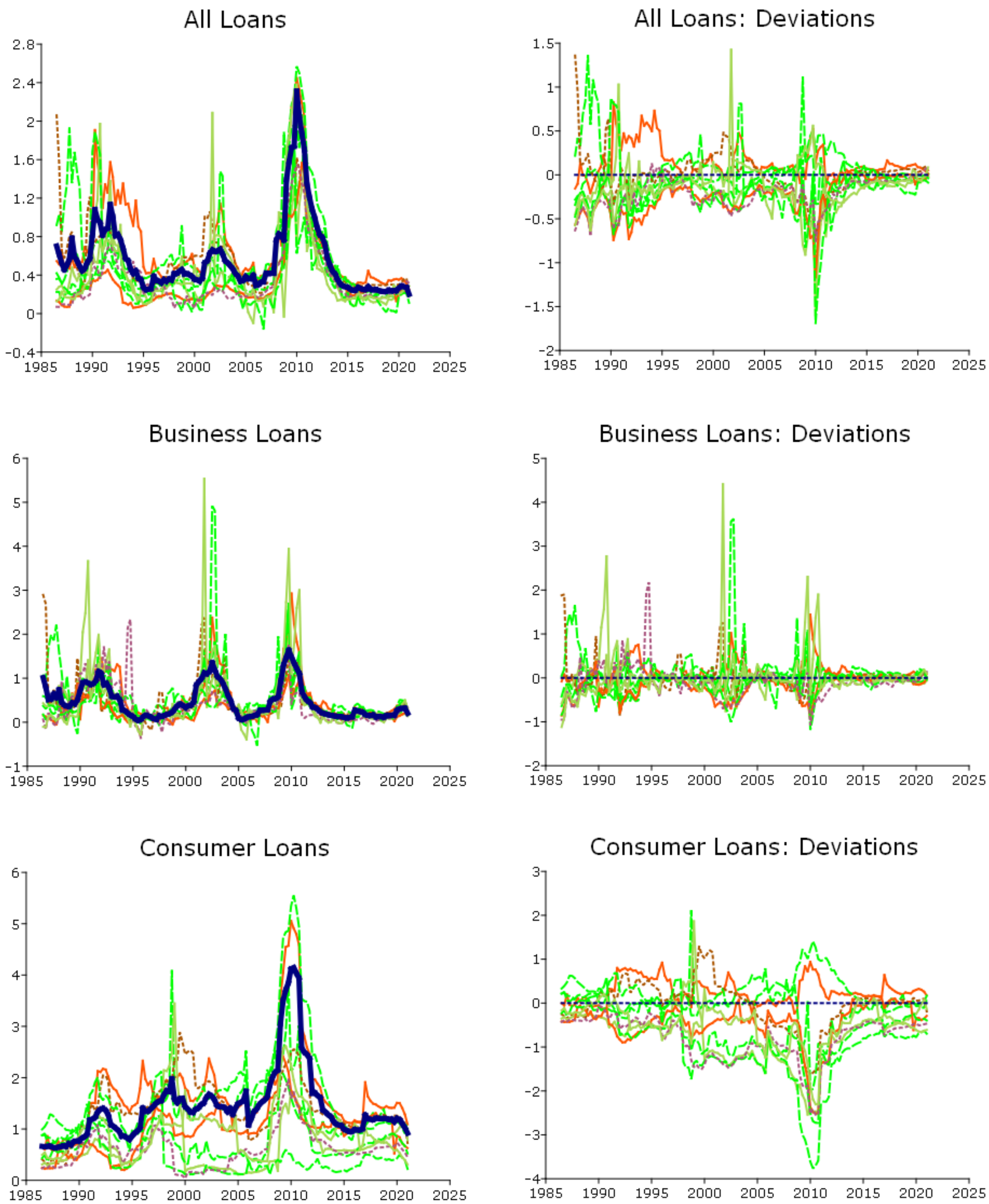
Note: We report the average COR of all loans of the top 10 BHCs in the U.S., and the COR spread which is defined by the average COR of all U.S. banks minus the top 10 COR. Shaded areas denote recessions.

Figure 2. Top 10 Business, Consumer, and Other Loan Shares



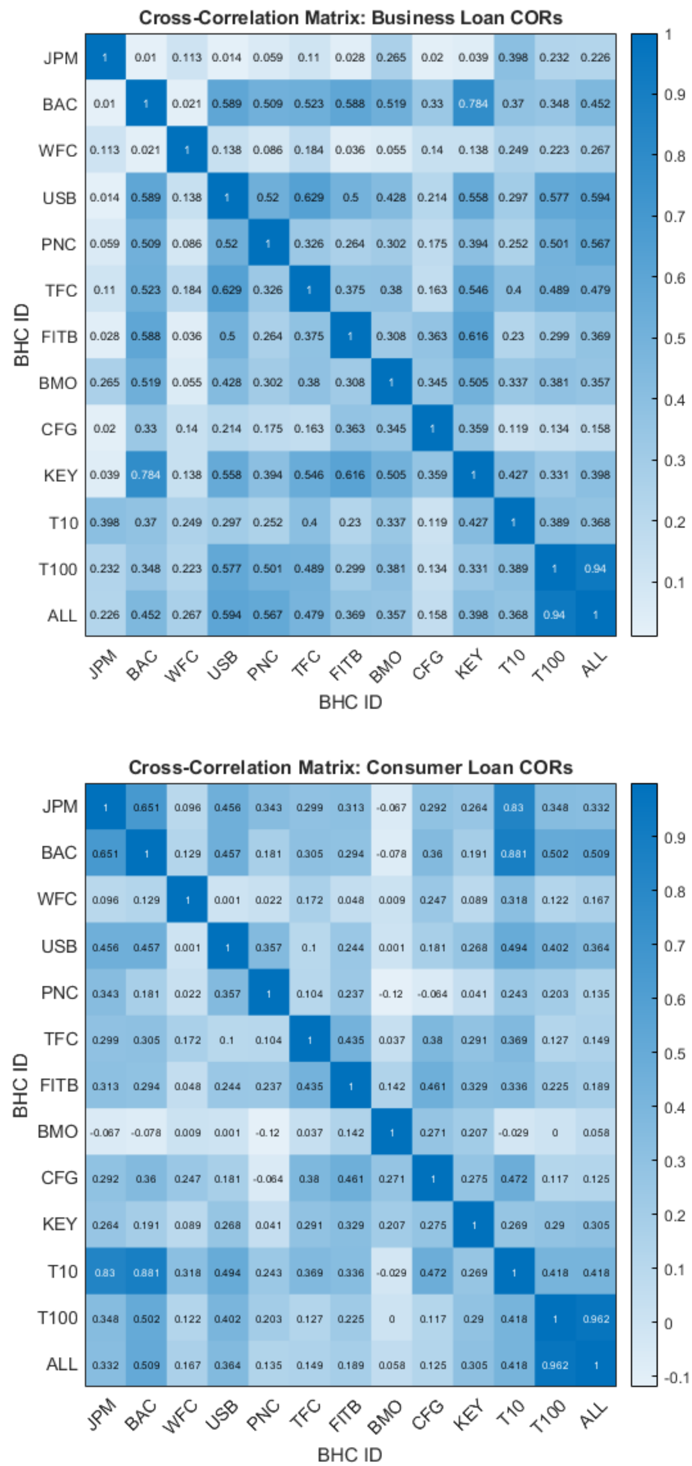
Note: The business/consumer loan shares are as the percent (%) of all outstanding loan amounts of each BHC. Other loan shares are also as the percent of all loan amounts, and were calculated by subtracting business and consumer loans from all outstanding loans.

Figure 3. Top 10 Net Charge-Off Rates



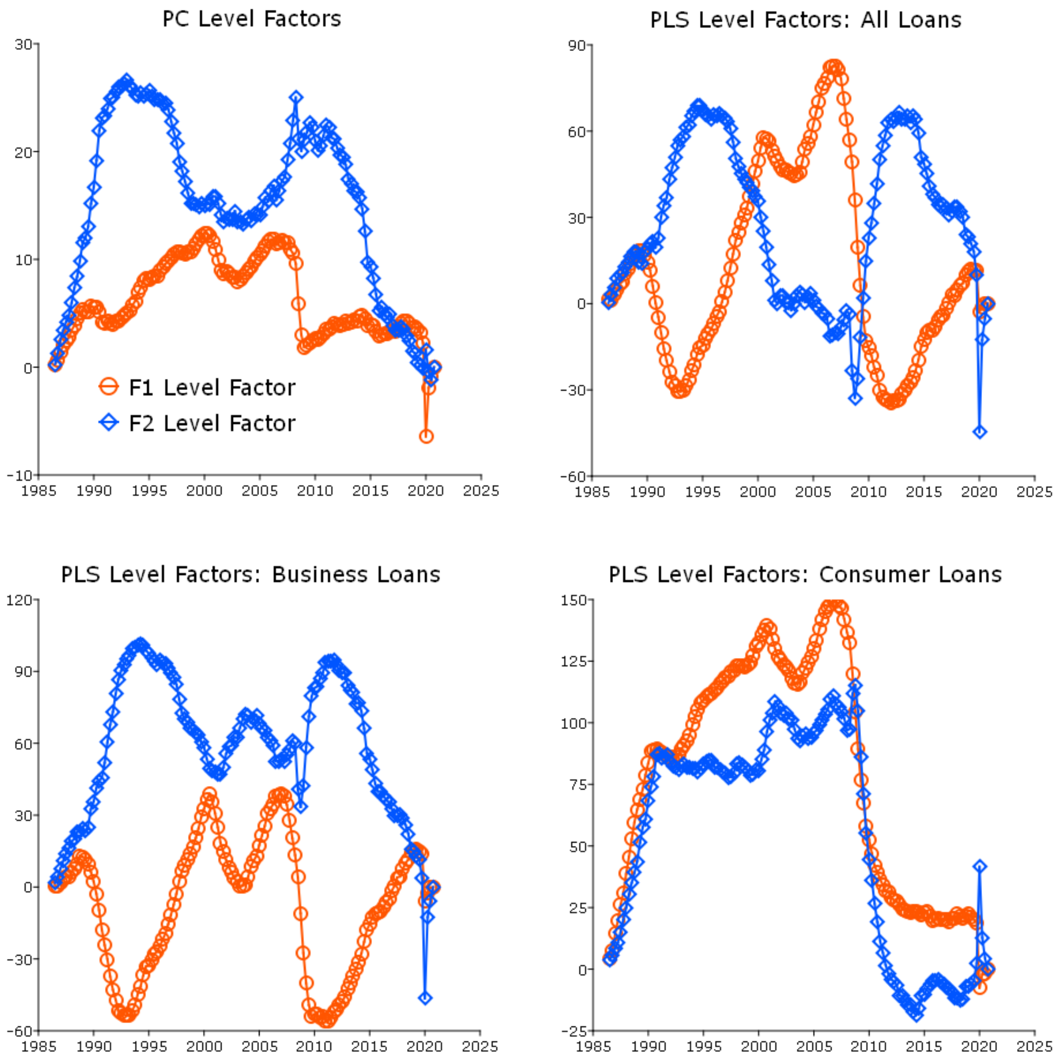
Note: The solid bold lines in the first column are the average net charge-off rates (CORs) of the top 10 BHCs, whereas individual CORs are lighter lines. The figures in the second column are deviations of individual CORs from the average rates.

Figure 4. Cross-Correlation Matrix of Net Charge-Off Rates



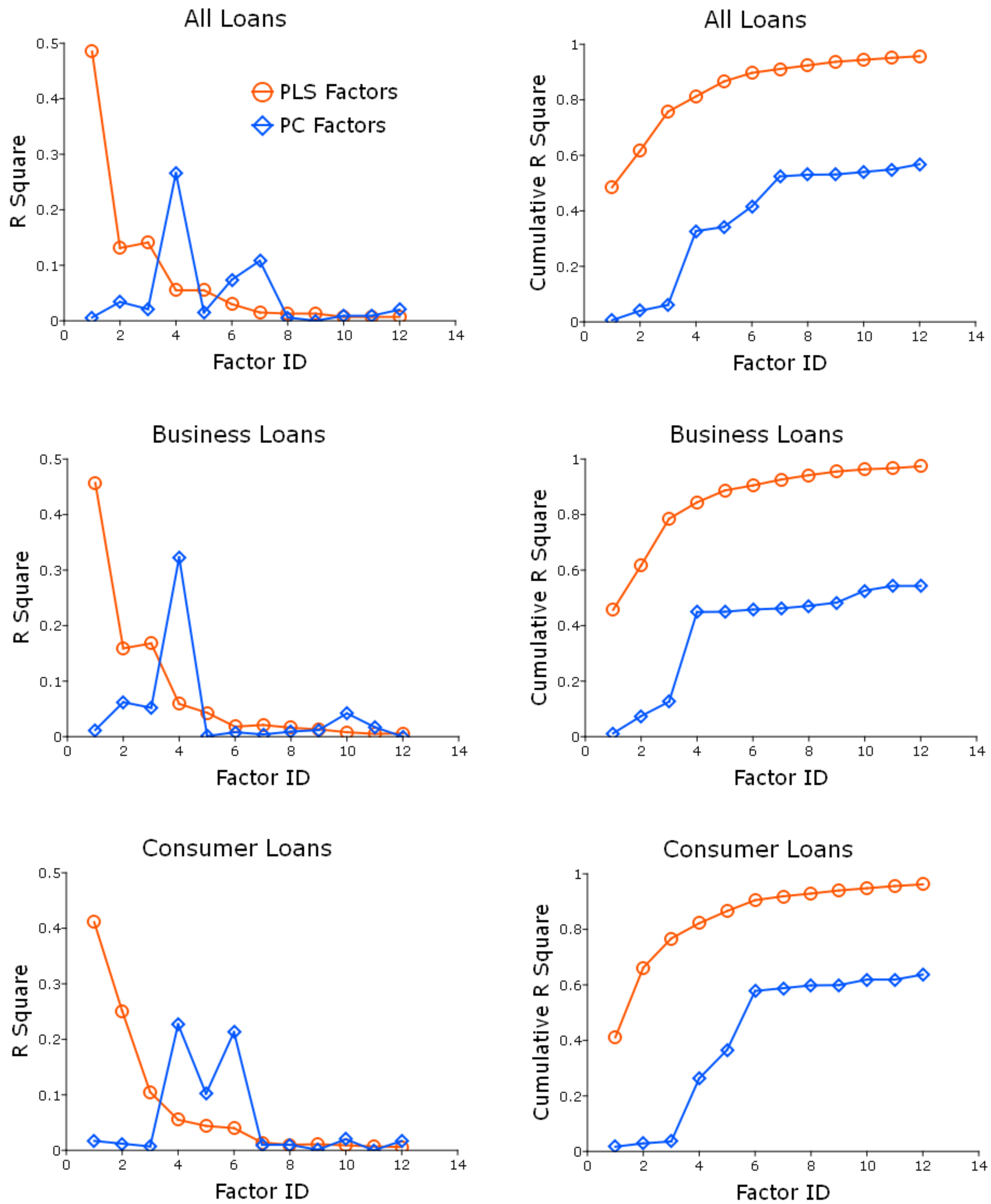
Note: The heatmap reports the cross-correlations ($\hat{\rho}_{i,j}$) of the residuals $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ from the ADF regressions of each pair of CORs.

Figure 5. Level Common Factor Estimates for Top 10 CORs



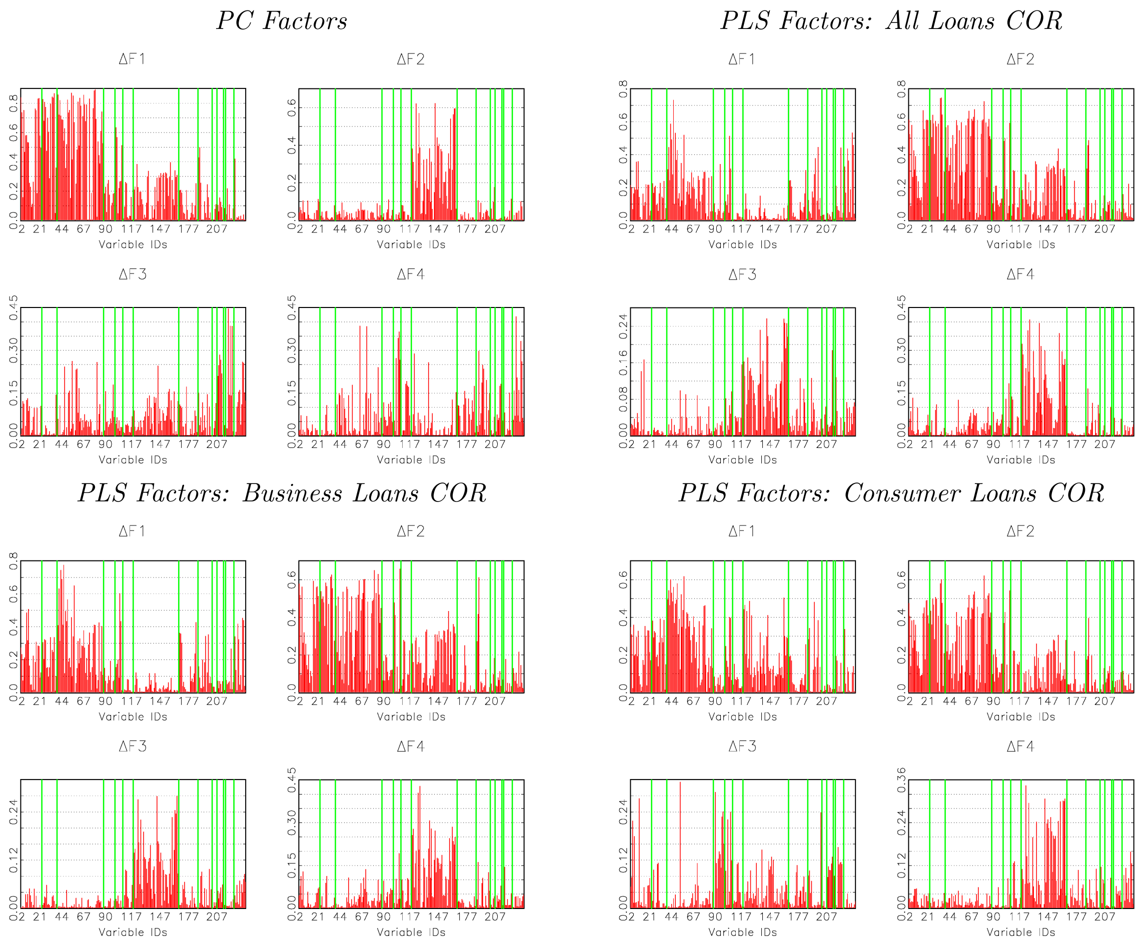
Note: We obtained up to 4 factors by applying the method of the principal components to 237 quarterly frequency macroeconomic time series variables. Level factors are obtained by re-integrating estimated common factors. PLS factors are target-specific factors for each type loans.

Figure 6. In-Sample Fit Analysis of Factor Estimates



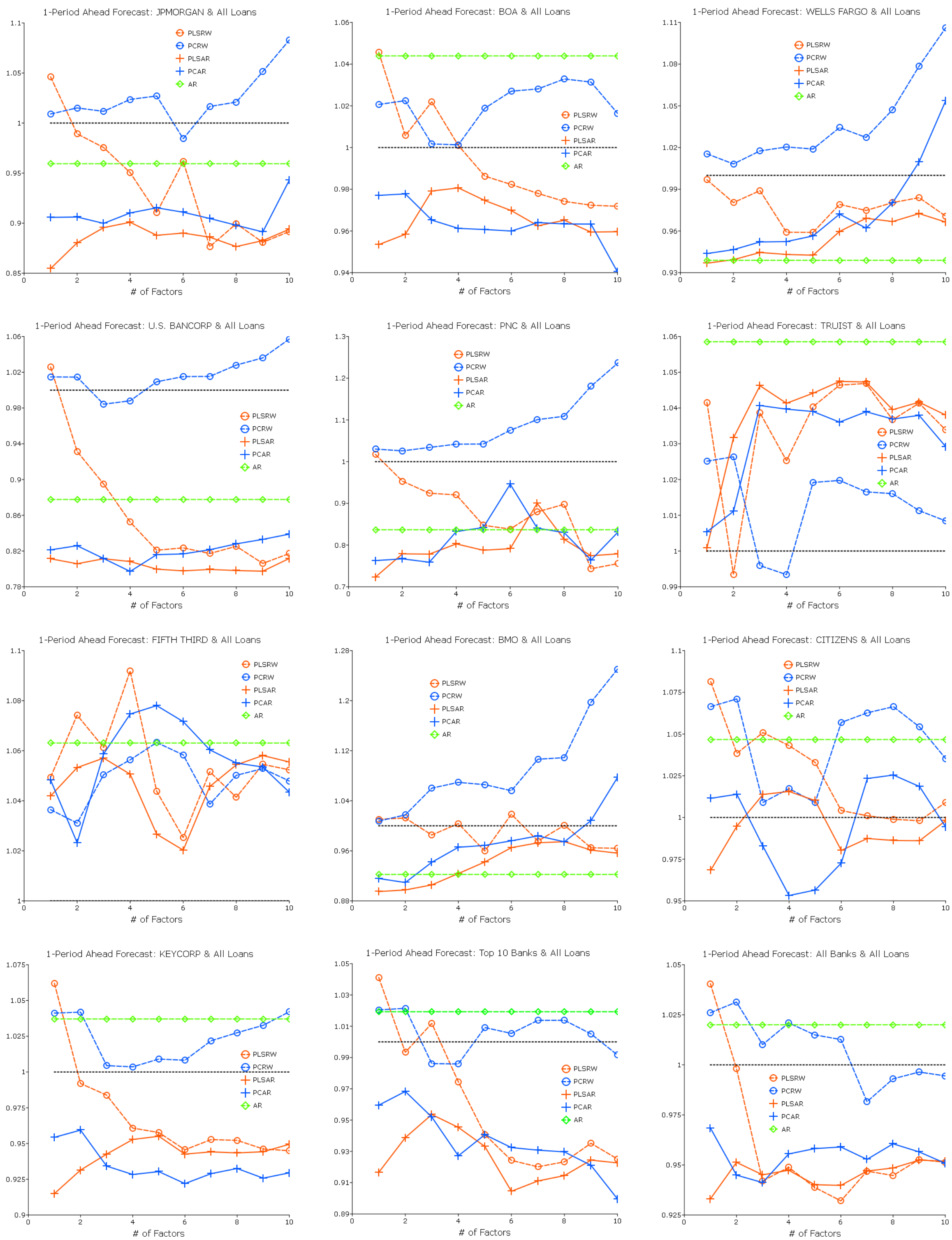
Note: Estimated R^2 are reported in the first column, while cumulative value figures are in the second column.

Figure 7. Marginal R^2 Analysis



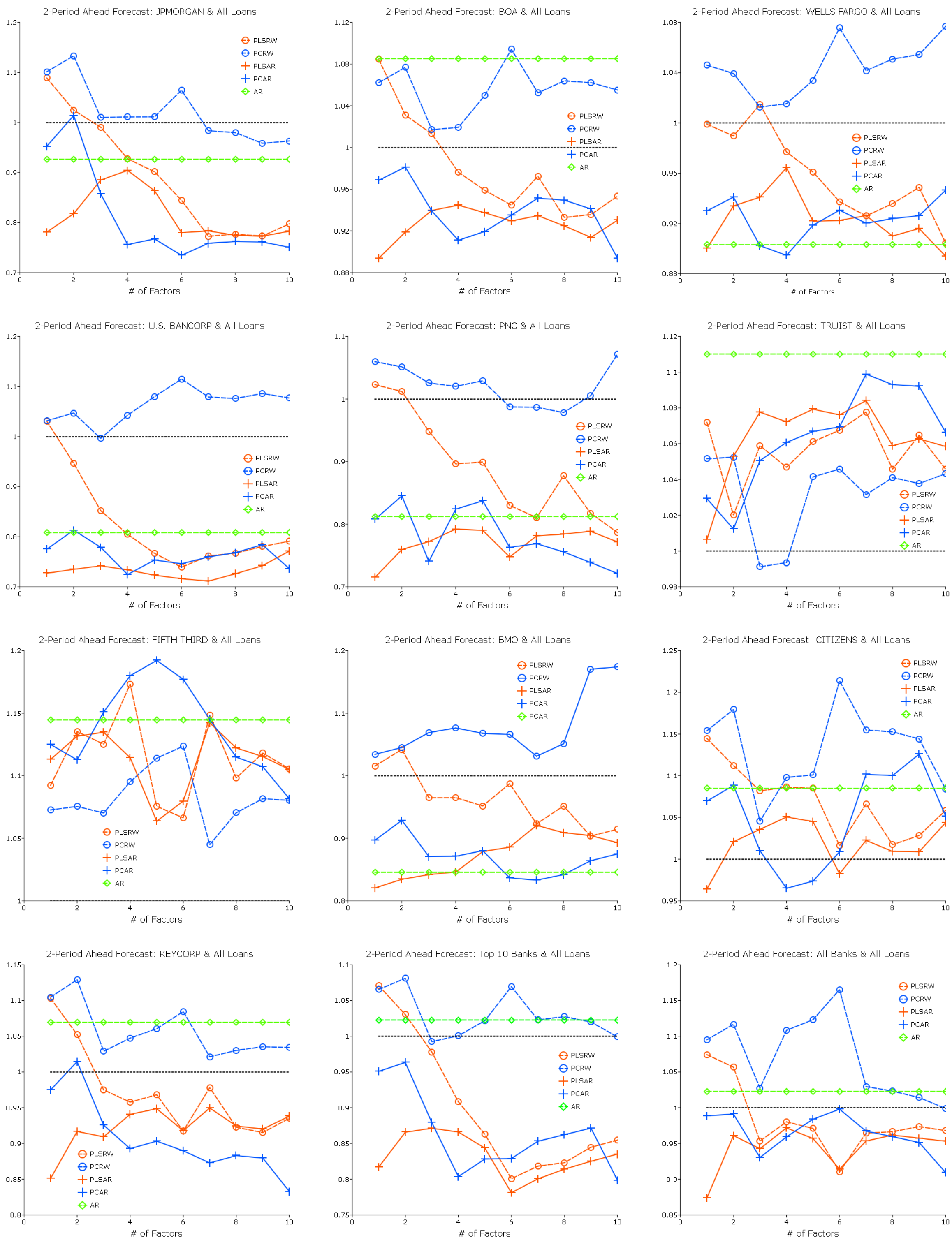
Note: The marginal R^2 is obtained by regressing each of the individual time series variables onto each estimated factor, one at a time, using the full sample of data. The individual series in each group are separated by vertical lines. The data IDs are on the x-axis.

Figure 8. 1-Period Ahead Out-of-Sample Forecast Peformance: All Loans COR



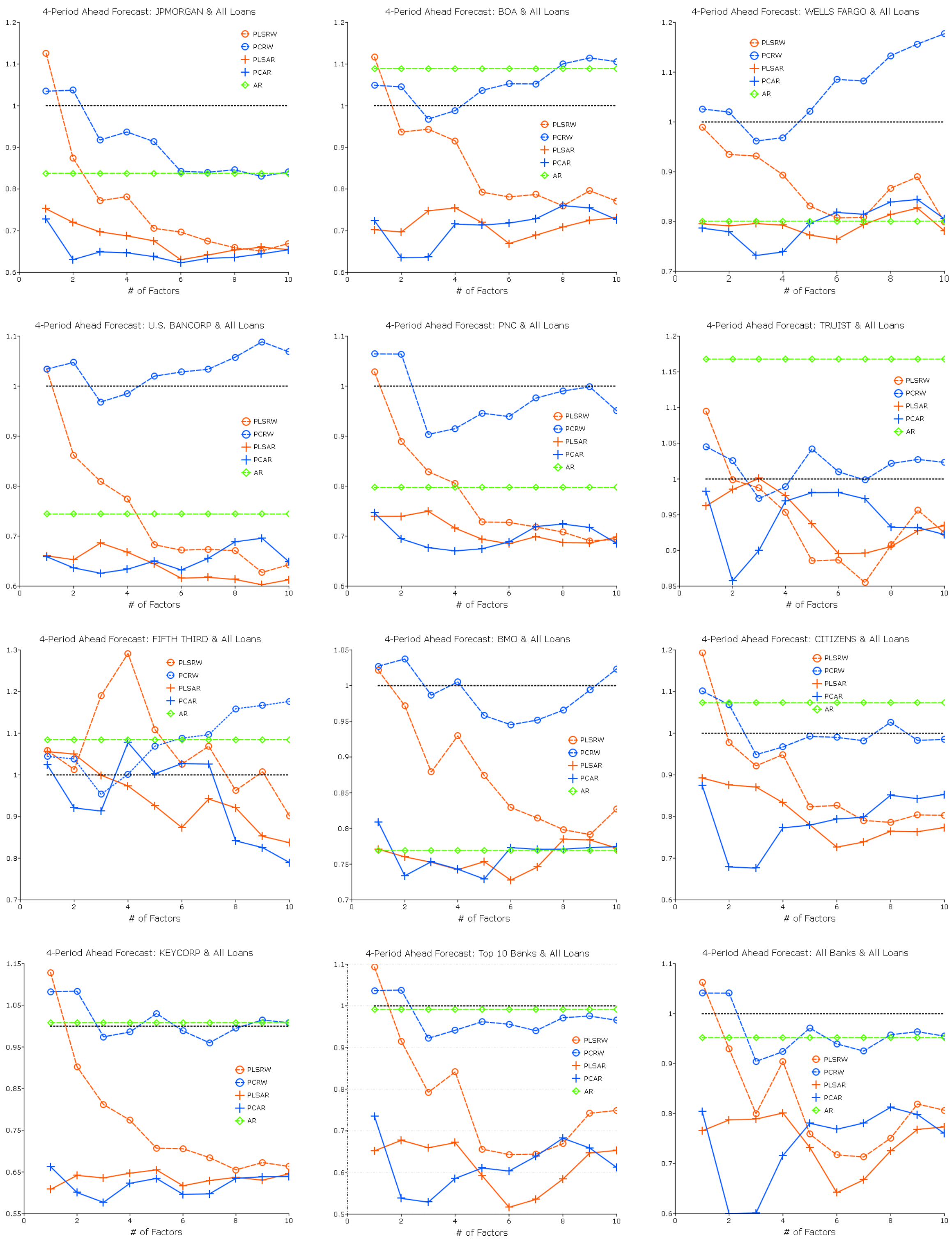
Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess the 1-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for all loan CORs of top 10 individual BHCs and the two aggregate CORs.

Figure 9. 2-Period Ahead Out-of-Sample Forecast Peformance: All Loans COR



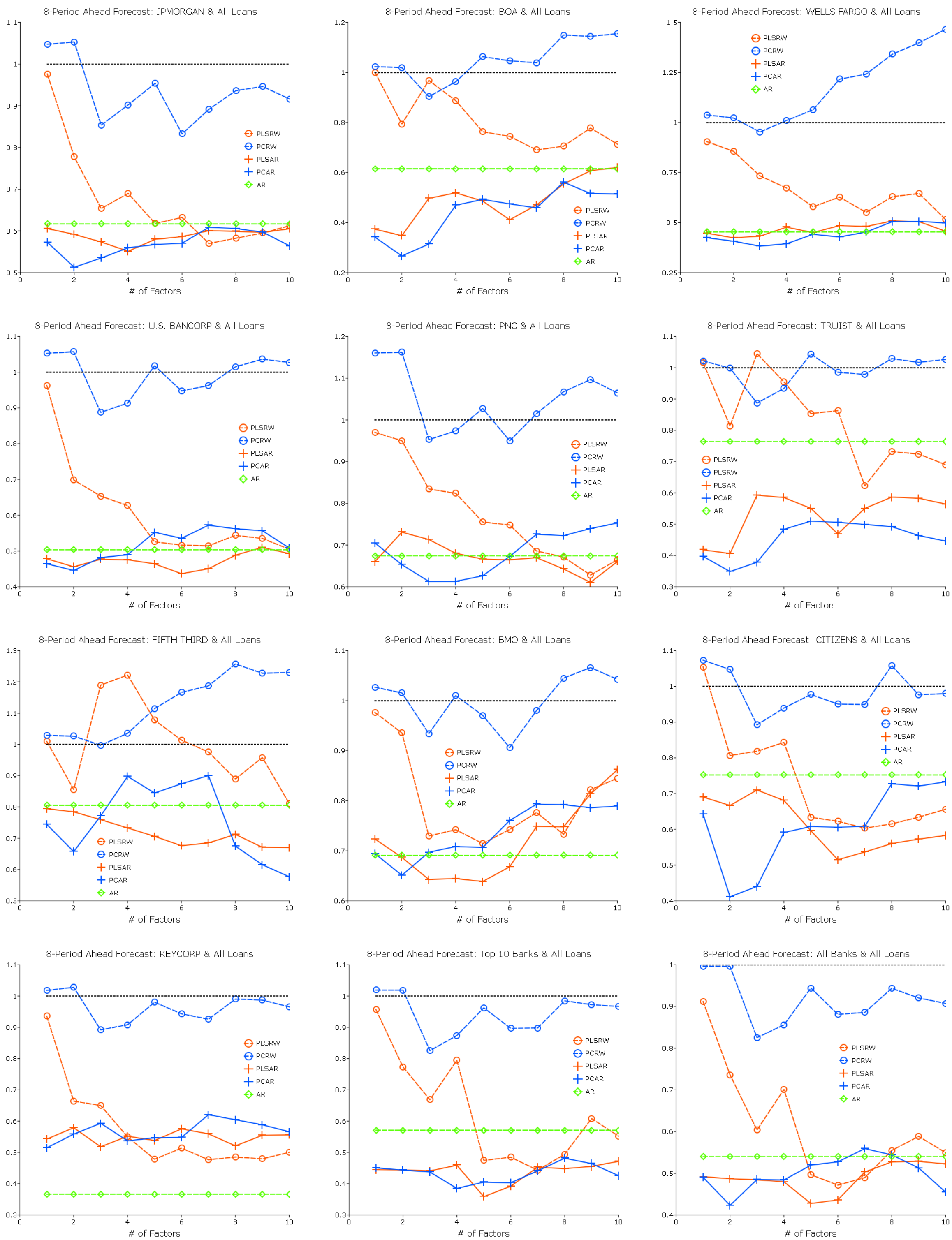
Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess the 2-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for all loan CORs of top 10 individual BHCs and the two aggregate CORs.

Figure 10. 4-Period Ahead Out-of-Sample Forecast Peformance: All Loans COR



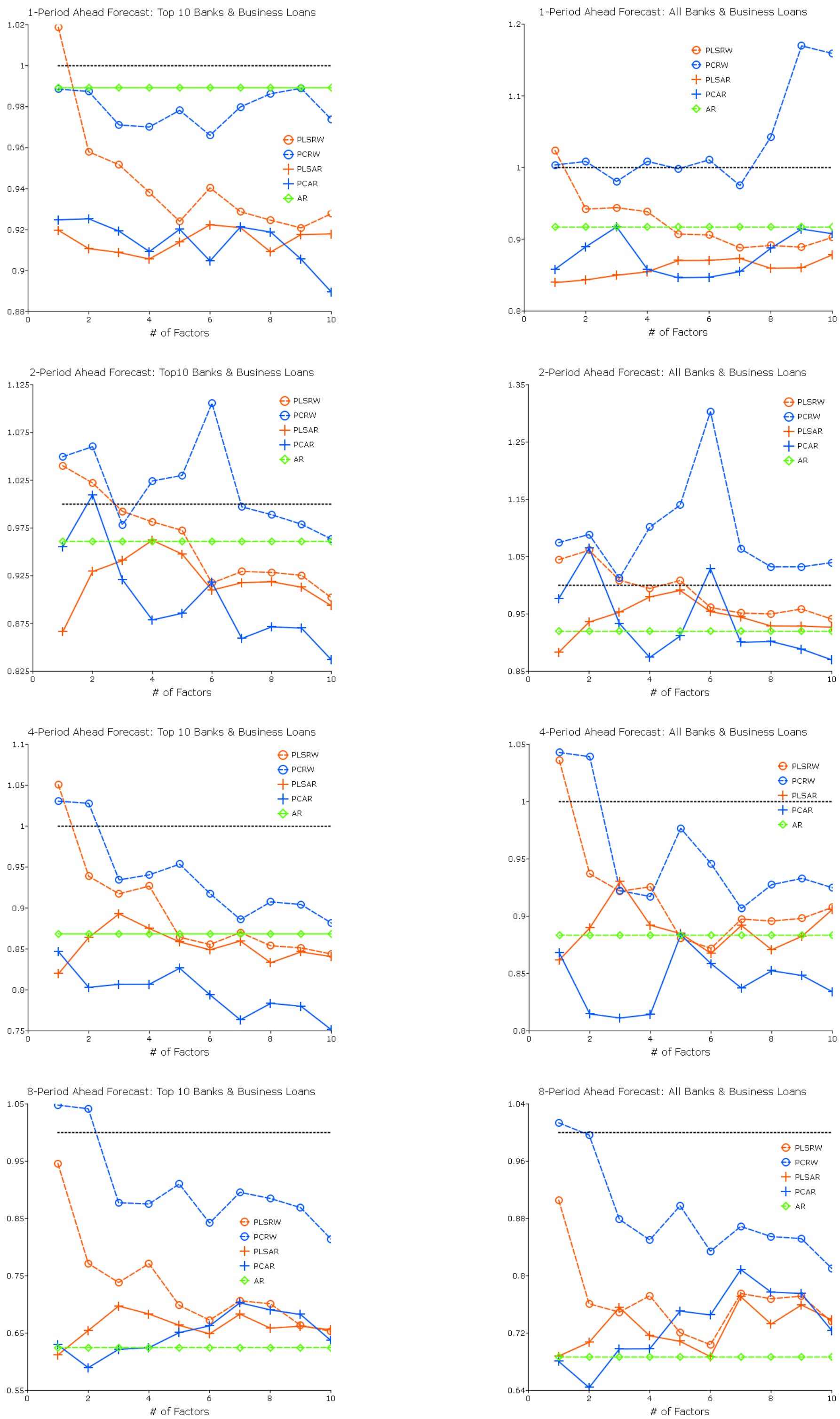
Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess the 4-quarter (1-year) ahead out-of-sample predictability of our factor models with up to 10 factors for all loan CORs of top 10 individual BHCs and the two aggregate CORs.

Figure 11. 8-Period Ahead Out-of-Sample Forecast Peformance: All Loans COR



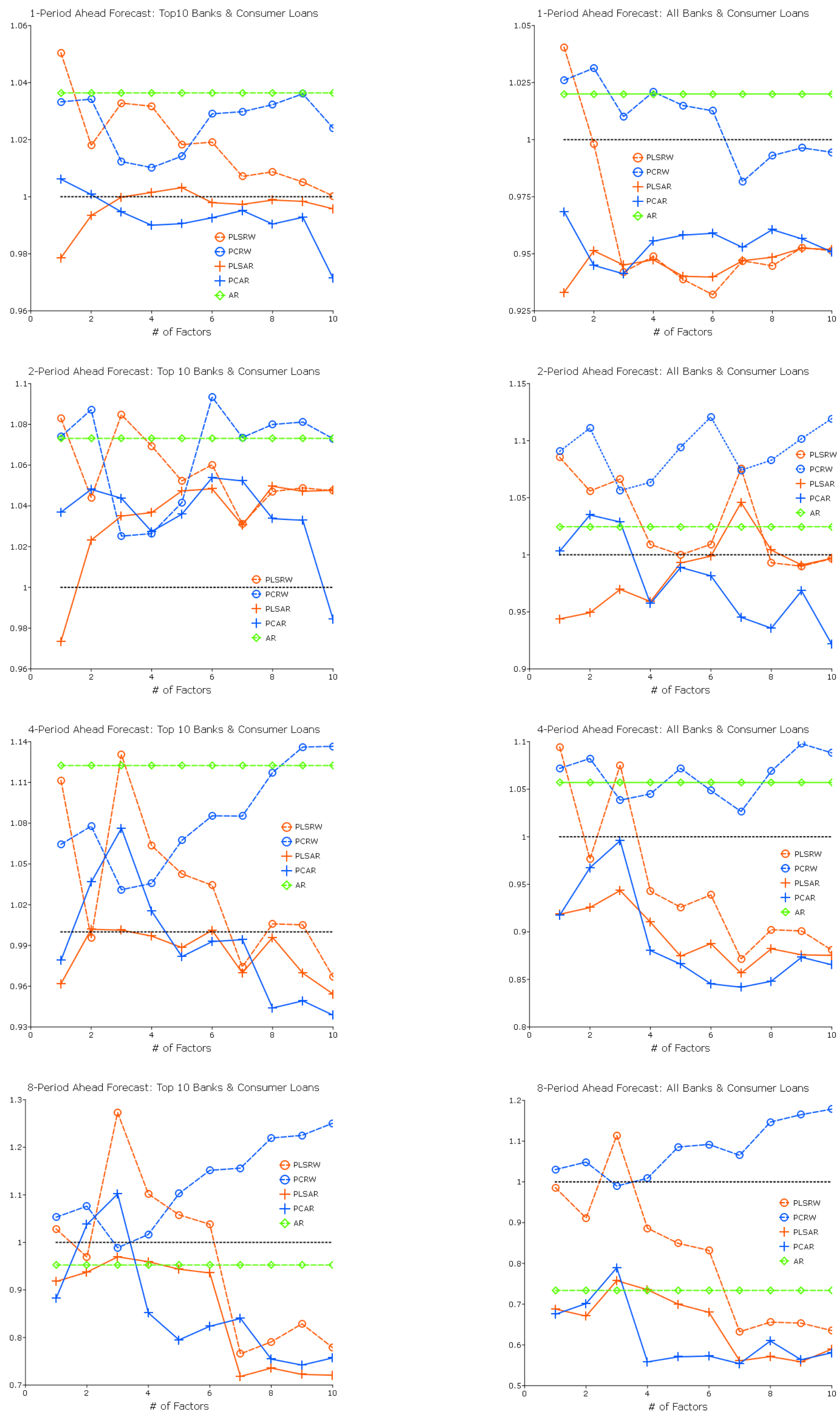
Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess the 8-quarter (2-year) ahead out-of-sample predictability of our factor models with up to 10 factors for all loan CORs of top 10 individual BHCs and the two aggregate CORs.

Figure 12. Out of Sample Forecast Performance: Aggregate CORs of Business Loans



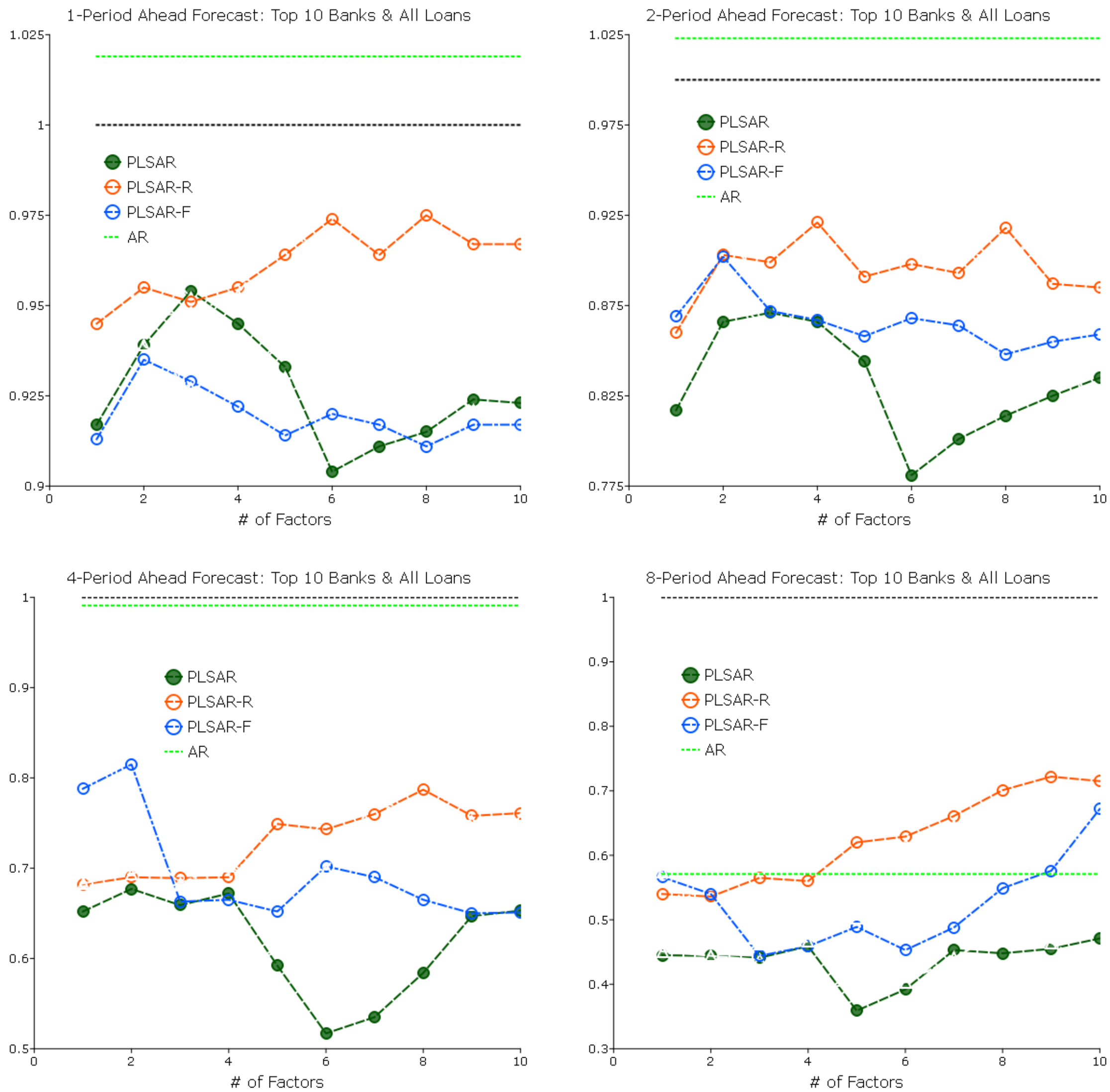
Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for the top 10 average COR and all banks average COR for business loans.

Figure 13. Out of Sample Forecast Performance: Aggregate CORs of Consumer Loans



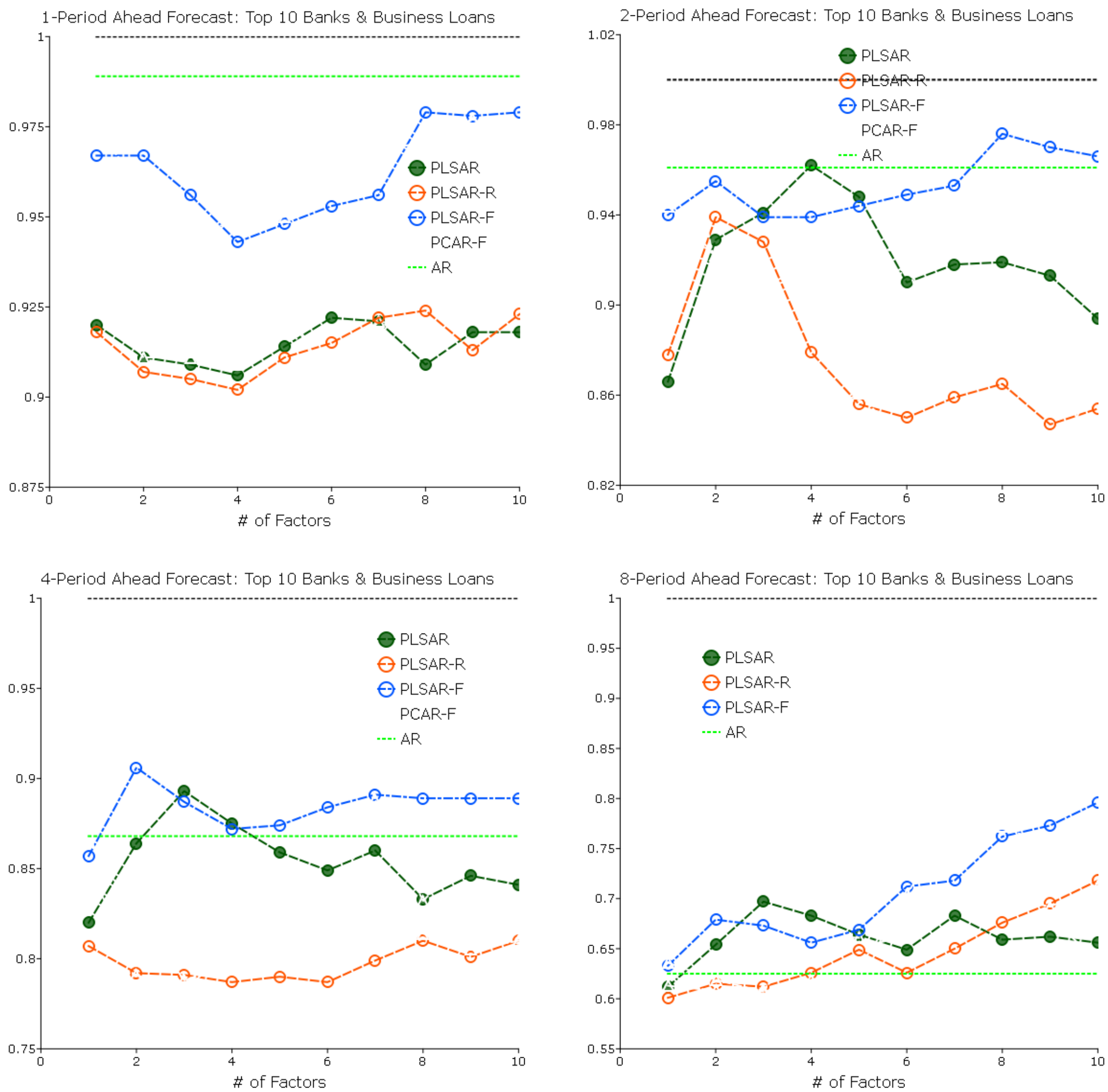
Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for the top 10 average COR and all banks average COR for consumer loans.

Figure 14. Real vs. Finance Factors: Top 10 Banks Average COR of All Loans



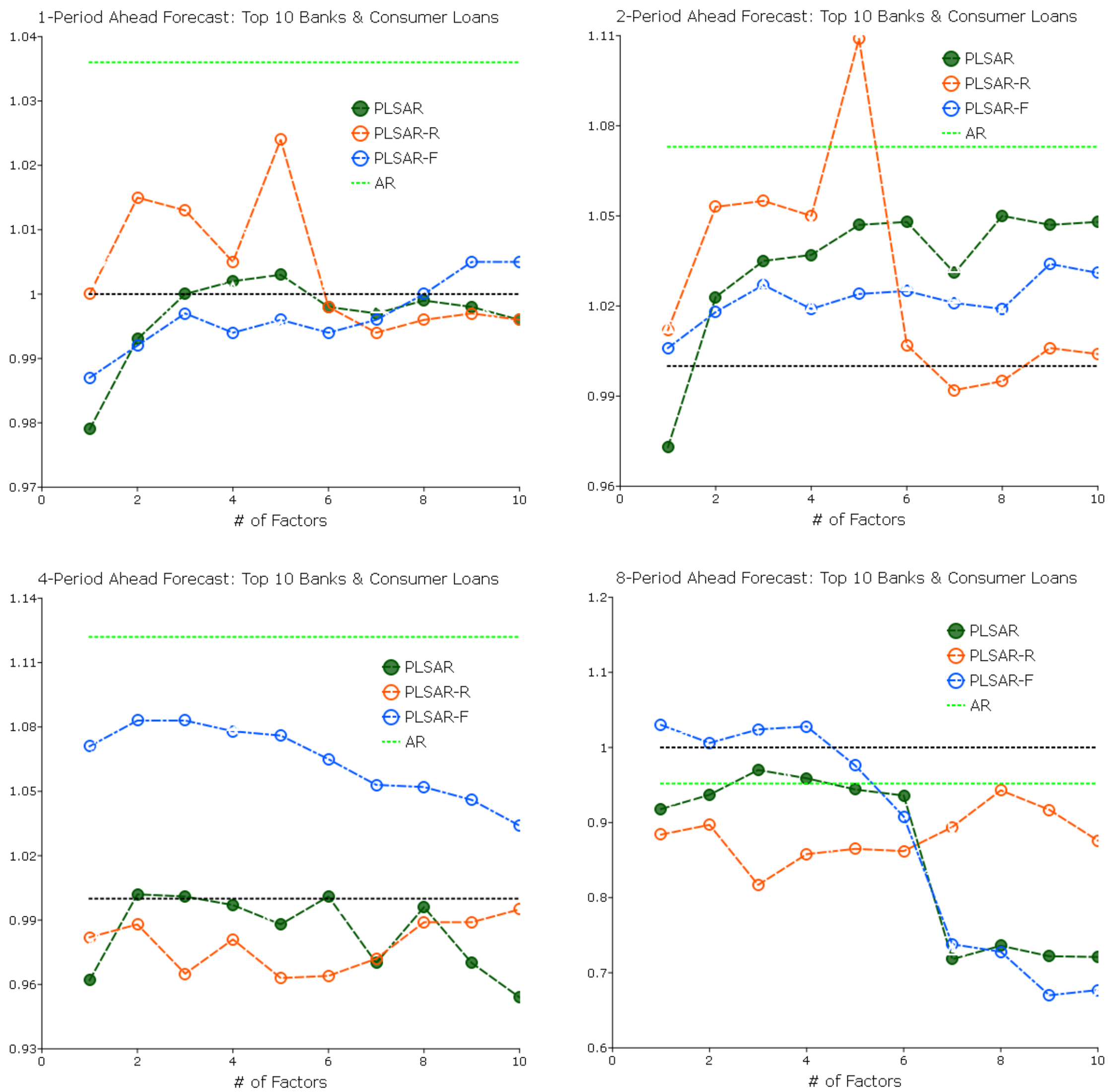
Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for the top 10 average all loan COR when factors are estimated via PLS utilizing real activity variables, financial sector variables, and all variables.

Figure 15. Real vs. Finance Factors: Top 10 Banks Average COR of Business Loans



Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for the top 10 average business loan COR when factors are estimated via PLS utilizing real activity variables, financial sector variables, and all variables.

Figure 16. Real vs. Finance Factors: Top 10 Banks Average COR of Consumer Loans



Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for the top 10 average consumer loan COR when factors are estimated via PLS utilizing real activity variables, financial sector variables, and all variables.

Appendix

Table A1. Macroeconomic Data Descriptions

Classifications	Group ID	Data ID	Data Descriptions
Real Activity	#1	1-22	NIPA
	#2	23-38	Industrial Production
	#3	39-87	Employment and Unemployment
	#4	88-99	Housing
	#5	100-107	Inventories, Orders, and Sales
	#6	108-118	Earnings and Productivity
Nominal/Financial	#7	119-166	Prices
	#8	167-186	Interest Rates
	#9	187-201	Money and Credit
	#10	202-206	Exchange Rates
	#11	207-213	Stock Markets
	#12	214-215	Others
	#13	216-224	Household Balance Sheets
	#14	225-237	Non-Household Balance Sheets

Note: We obtained all data from the FRED-QD (https://research.stlouisfed.org/econ/mccracken/fred-databases/). Quantity variables are log-transformed, while percent variables are divided by 100.

Table A2: Out-of-Sample Forecast Results: All Loans COR

		Top10 Banks RRMSPE					*All Banks RRMSPE*				
$\#H$	$\#F$	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR
1	1	1.041	1.020	0.917	0.960	1.019	1.041	1.026	0.933	0.968	1.020
	2	0.993	1.021	0.939	0.968	1.019	0.998	1.031	0.951	0.945	1.020
	3	1.012	0.986	0.954	0.952	1.019	0.942	1.010	0.945	0.941	1.020
	4	0.974	0.986	0.945	0.927	1.019	0.949	1.021	0.947	0.955	1.020
	5	0.941	1.009	0.933	0.941	1.019	0.939	1.015	0.940	0.958	1.020
	6	0.924	1.005	0.904	0.932	1.019	0.932	1.013	0.940	0.959	1.020
	7	0.920	1.014	0.911	0.931	1.019	0.947	0.982	0.947	0.953	1.020
	8	0.923	1.014	0.915	0.930	1.019	0.945	0.993	0.948	0.961	1.020
	9	0.935	1.005	0.924	0.921	1.019	0.953	0.996	0.952	0.957	1.020
	10	0.925	0.992	0.923	0.900	1.019	0.951	0.994	0.952	0.951	1.020
2	1	1.071	1.065	0.817	0.951	1.023	1.074	1.095	0.874	0.989	1.023
	2	1.030	1.081	0.866	0.963	1.023	1.057	1.117	0.961	0.991	1.023
	3	0.978	0.992	0.871	0.879	1.023	0.953	1.027	0.943	0.930	1.023
	4	0.908	1.001	0.866	0.804	1.023	0.980	1.108	0.972	0.959	1.023
	5	0.863	1.022	0.844	0.828	1.023	0.971	1.123	0.957	0.984	1.023
	6	0.801	1.069	0.781	0.829	1.023	0.910	1.165	0.914	0.998	1.023
	7	0.818	1.023	0.801	0.853	1.023	0.965	1.030	0.953	0.967	1.023
	8	0.823	1.027	0.814	0.862	1.023	0.966	1.023	0.962	0.960	1.023
	9	0.845	1.020	0.825	0.872	1.023	0.974	1.014	0.957	0.951	1.023
	10	0.855	0.999	0.835	0.798	1.023	0.968	0.999	0.953	0.909	1.023
4	1	1.093	1.036	0.652	0.735	0.991	1.062	1.041	0.766	0.805	0.952
	2	0.915	1.038	0.677	0.538	0.991	0.930	1.041	0.787	0.600	0.952
	3	0.792	0.922	0.659	0.529	0.991	0.800	0.904	0.789	0.601	0.952
	4	0.841	0.941	0.672	0.586	0.991	0.904	0.924	0.801	0.716	0.952
	5	0.656	0.962	0.592	0.611	0.991	0.759	0.971	0.732	0.781	0.952
	6	0.643	0.956	0.517	0.603	0.991	0.718	0.940	0.642	0.769	0.952
	7	0.644	0.940	0.535	0.639	0.991	0.713	0.925	0.668	0.781	0.952
	8	0.669	0.971	0.584	0.682	0.991	0.751	0.958	0.725	0.813	0.952
	9	0.742	0.976	0.647	0.659	0.991	0.819	0.964	0.768	0.798	0.952
	10	0.749	0.965	0.653	0.612	0.991	0.807	0.955	0.773	0.760	0.952
8	1	0.956	1.019	0.445	0.451	0.571	0.912	0.996	0.492	0.490	0.540
	2	0.773	1.019	0.444	0.444	0.571	0.736	0.996	0.487	0.423	0.540
	3	0.668	0.825	0.441	0.438	0.571	0.604	0.825	0.484	0.485	0.540
	4	0.794	0.874	0.459	0.385	0.571	0.701	0.856	0.480	0.484	0.540
	5	0.475	0.962	0.359	0.405	0.571	0.497	0.944	0.428	0.519	0.540
	6	0.485	0.897	0.392	0.403	0.571	0.472	0.881	0.436	0.527	0.540
	7	0.443	0.898	0.453	0.441	0.571	0.490	0.886	0.503	0.559	0.540
	8	0.494	0.985	0.448	0.482	0.571	0.555	0.943	0.527	0.544	0.540
	9	0.609	0.972	0.455	0.464	0.571	0.589	0.920	0.529	0.513	0.540
	10	0.552	0.967	0.471	0.426	0.571	0.549	0.907	0.522	0.455	0.540

Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess the 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for all loan average CORs of the top 10 BHCs and all banks in the U.S.

Table A3: Out-of-Sample Forecast Results: Business Loans COR

		Top10 Banks RRMSPE					*All Banks RRMSPE*				
$\#H$	$\#F$	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR
1	1	1.019	0.989	0.920	0.925	0.989	1.024	1.004	0.840	0.858	0.917
	2	0.958	0.987	0.911	0.925	0.989	0.942	1.008	0.843	0.889	0.917
	3	0.952	0.971	0.909	0.919	0.989	0.944	0.981	0.850	0.917	0.917
	4	0.938	0.970	0.906	0.909	0.989	0.938	1.009	0.855	0.858	0.917
	5	0.924	0.978	0.914	0.920	0.989	0.907	0.998	0.870	0.846	0.917
	6	0.940	0.966	0.922	0.905	0.989	0.906	1.011	0.871	0.847	0.917
	7	0.929	0.980	0.921	0.921	0.989	0.888	0.975	0.873	0.855	0.917
	8	0.925	0.986	0.909	0.919	0.989	0.891	1.043	0.860	0.887	0.917
	9	0.921	0.989	0.918	0.906	0.989	0.889	1.170	0.860	0.914	0.917
	10	0.928	0.974	0.918	0.890	0.989	0.903	1.159	0.878	0.908	0.917
2	1	1.040	1.050	0.866	0.955	0.961	1.045	1.075	0.883	0.977	0.920
	2	1.022	1.060	0.929	1.010	0.961	1.061	1.089	0.936	1.065	0.920
	3	0.992	0.978	0.941	0.921	0.961	1.009	1.012	0.953	0.933	0.920
	4	0.981	1.024	0.962	0.879	0.961	0.994	1.102	0.980	0.874	0.920
	5	0.972	1.030	0.948	0.886	0.961	1.008	1.140	0.991	0.911	0.920
	6	0.917	1.106	0.910	0.918	0.961	0.961	1.303	0.954	1.029	0.920
	7	0.929	0.997	0.918	0.859	0.961	0.952	1.063	0.944	0.900	0.920
	8	0.928	0.989	0.919	0.871	0.961	0.950	1.032	0.929	0.902	0.920
	9	0.925	0.979	0.913	0.870	0.961	0.959	1.032	0.929	0.889	0.920
	10	0.902	0.963	0.894	0.837	0.961	0.941	1.040	0.927	0.870	0.920
4	1	1.051	1.031	0.820	0.847	0.868	1.036	1.043	0.862	0.868	0.883
	2	0.939	1.028	0.864	0.803	0.868	0.937	1.039	0.890	0.815	0.883
	3	0.917	0.934	0.893	0.807	0.868	0.922	0.922	0.930	0.811	0.883
	4	0.927	0.941	0.875	0.807	0.868	0.926	0.917	0.892	0.814	0.883
	5	0.864	0.954	0.859	0.826	0.868	0.881	0.977	0.885	0.884	0.883
	6	0.855	0.918	0.849	0.794	0.868	0.872	0.946	0.868	0.859	0.883
	7	0.870	0.886	0.860	0.763	0.868	0.897	0.907	0.892	0.837	0.883
	8	0.854	0.908	0.833	0.784	0.868	0.896	0.928	0.871	0.852	0.883
	9	0.851	0.904	0.846	0.780	0.868	0.898	0.933	0.883	0.848	0.883
	10	0.844	0.882	0.841	0.751	0.868	0.908	0.925	0.906	0.834	0.883
8	1	0.946	1.048	0.612	0.629	0.625	0.905	1.013	0.688	0.680	0.687
	2	0.772	1.041	0.654	0.590	0.625	0.761	0.997	0.707	0.644	0.687
	3	0.738	0.878	0.697	0.622	0.625	0.749	0.879	0.756	0.698	0.687
	4	0.771	0.875	0.683	0.624	0.625	0.772	0.850	0.716	0.698	0.687
	5	0.698	0.910	0.664	0.651	0.625	0.721	0.898	0.708	0.751	0.687
	6	0.673	0.842	0.649	0.663	0.625	0.704	0.834	0.687	0.745	0.687
	7	0.706	0.896	0.683	0.703	0.625	0.775	0.869	0.771	0.809	0.687
	8	0.701	0.885	0.659	0.691	0.625	0.768	0.855	0.733	0.777	0.687
	9	0.663	0.869	0.662	0.682	0.625	0.772	0.852	0.759	0.775	0.687
	10	0.653	0.814	0.656	0.637	0.625	0.736	0.810	0.738	0.723	0.687

Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess the 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for business loan average CORs of the top 10 BHCs and all banks in the U.S.

Table A4: Out-of-Sample Forecast Results: Consumer Loans COR

		Top10 Banks RRMSPE					*All Banks RRMSPE*				
#H	#F	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR
1	1	1.050	1.033	0.979	1.006	1.036	1.049	1.036	0.954	0.977	1.012
	2	1.018	1.034	0.993	1.001	1.036	1.012	1.042	0.952	0.982	1.012
	3	1.033	1.012	1.000	0.995	1.036	1.005	1.038	0.958	1.004	1.012
	4	1.032	1.010	1.002	0.990	1.036	0.973	1.038	0.953	0.960	1.012
	5	1.018	1.014	1.003	0.991	1.036	0.964	1.028	0.960	0.962	1.012
	6	1.019	1.029	0.998	0.993	1.036	0.966	1.033	0.958	0.952	1.012
	7	1.007	1.030	0.997	0.995	1.036	0.962	1.017	0.948	0.945	1.012
	8	1.009	1.032	0.999	0.990	1.036	0.957	1.024	0.962	0.943	1.012
	9	1.005	1.036	0.998	0.993	1.036	0.963	1.031	0.968	0.955	1.012
	10	1.000	1.024	0.996	0.971	1.036	0.971	1.024	0.972	0.937	1.012
2	1	1.083	1.074	0.973	1.037	1.073	1.085	1.091	0.944	1.003	1.025
	2	1.044	1.087	1.023	1.048	1.073	1.056	1.111	0.949	1.035	1.025
	3	1.085	1.025	1.035	1.044	1.073	1.066	1.056	0.970	1.029	1.025
	4	1.069	1.026	1.037	1.027	1.073	1.009	1.063	0.959	0.957	1.025
	5	1.052	1.042	1.047	1.036	1.073	1.000	1.094	0.993	0.989	1.025
	6	1.060	1.093	1.048	1.054	1.073	1.009	1.121	0.999	0.982	1.025
	7	1.031	1.074	1.031	1.052	1.073	1.076	1.074	1.046	0.945	1.025
	8	1.047	1.080	1.050	1.034	1.073	0.993	1.083	1.004	0.936	1.025
	9	1.049	1.081	1.047	1.033	1.073	0.990	1.102	0.991	0.968	1.025
	10	1.047	1.073	1.048	0.984	1.073	0.997	1.119	0.997	0.921	1.025
4	1	1.111	1.064	0.962	0.979	1.122	1.094	1.072	0.919	0.917	1.057
	2	0.995	1.078	1.002	1.037	1.122	0.977	1.082	0.926	0.967	1.057
	3	1.130	1.031	1.001	1.076	1.122	1.075	1.038	0.944	0.996	1.057
	4	1.063	1.036	0.997	1.015	1.122	0.943	1.045	0.910	0.880	1.057
	5	1.043	1.067	0.988	0.982	1.122	0.926	1.072	0.874	0.866	1.057
	6	1.034	1.085	1.001	0.993	1.122	0.939	1.049	0.888	0.845	1.057
	7	0.974	1.085	0.970	0.994	1.122	0.872	1.027	0.856	0.842	1.057
	8	1.006	1.117	0.996	0.944	1.122	0.902	1.069	0.882	0.848	1.057
	9	1.005	1.136	0.970	0.949	1.122	0.901	1.098	0.876	0.873	1.057
	10	0.967	1.137	0.954	0.939	1.122	0.881	1.088	0.875	0.865	1.057
8	1	1.028	1.053	0.918	0.883	0.952	0.986	1.030	0.688	0.675	0.734
	2	0.969	1.076	0.937	1.038	0.952	0.911	1.049	0.671	0.701	0.734
	3	1.273	0.989	0.970	1.102	0.952	1.114	0.990	0.758	0.789	0.734
	4	1.102	1.017	0.959	0.852	0.952	0.886	1.009	0.735	0.558	0.734
	5	1.058	1.103	0.944	0.795	0.952	0.849	1.086	0.700	0.571	0.734
	6	1.038	1.151	0.936	0.824	0.952	0.832	1.092	0.680	0.573	0.734
	7	0.766	1.156	0.718	0.840	0.952	0.632	1.065	0.561	0.554	0.734
	8	0.791	1.219	0.736	0.755	0.952	0.656	1.147	0.571	0.610	0.734
	9	0.829	1.225	0.722	0.742	0.952	0.653	1.165	0.558	0.564	0.734
	10	0.779	1.251	0.721	0.757	0.952	0.635	1.178	0.590	0.581	0.734

Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess the 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for consumer loan average CORs of the top 10 BHCs and all banks in the U.S.

Table A5: Out-of-Sample Forecast Results: Real Factors for All Loans COR

		Top10 Banks RRMSPE					*All Banks RRMSPE*				
$\#H$	$\#F$	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR
1	1	1.030	1.018	0.945	0.969	1.019	1.035	1.029	0.950	0.970	1.020
	2	0.990	0.996	0.955	0.947	1.019	0.984	0.993	0.961	0.942	1.020
	3	0.976	1.001	0.951	0.948	1.019	0.965	0.991	0.956	0.946	1.020
	4	0.973	1.002	0.955	0.953	1.019	0.965	0.993	0.962	0.946	1.020
	5	0.979	1.012	0.964	0.974	1.019	0.976	0.987	0.972	0.937	1.020
	6	0.985	0.993	0.974	0.957	1.019	0.982	1.002	0.977	0.970	1.020
	7	0.987	0.981	0.964	0.952	1.019	0.981	0.998	0.976	0.974	1.020
	8	0.997	0.980	0.975	0.951	1.019	0.971	0.995	0.970	0.970	1.020
	9	0.993	0.977	0.967	0.948	1.019	0.970	0.986	0.957	0.965	1.020
	10	1.002	0.977	0.967	0.946	1.019	0.968	0.985	0.955	0.968	1.020
2	1	1.058	1.090	0.860	0.990	1.023	1.072	1.133	0.920	1.044	1.023
	2	1.040	1.014	0.903	0.886	1.023	1.077	1.036	1.007	0.934	1.023
	3	0.998	0.999	0.899	0.859	1.023	1.040	0.990	1.000	0.897	1.023
	4	1.060	1.013	0.921	0.882	1.023	1.024	0.998	0.951	0.915	1.023
	5	0.959	1.040	0.891	0.878	1.023	0.984	0.988	0.948	0.891	1.023
	6	0.962	1.018	0.898	0.868	1.023	0.988	1.010	0.970	0.939	1.023
	7	0.959	0.996	0.893	0.881	1.023	0.991	1.010	0.964	0.963	1.023
	8	0.979	0.990	0.918	0.874	1.023	0.980	0.991	0.959	0.936	1.023
	9	0.974	0.984	0.887	0.870	1.023	0.988	0.996	0.941	0.949	1.023
	10	0.980	0.988	0.885	0.865	1.023	0.978	1.014	0.924	0.967	1.023
4	1	1.085	1.032	0.682	0.683	0.991	1.072	1.050	0.790	0.769	0.952
	2	0.863	0.933	0.690	0.694	0.991	0.870	0.933	0.783	0.767	0.952
	3	0.895	0.949	0.689	0.704	0.991	0.909	0.968	0.759	0.795	0.952
	4	0.817	0.947	0.690	0.702	0.991	0.851	0.967	0.776	0.805	0.952
	5	0.889	0.952	0.749	0.673	0.991	0.948	0.962	0.856	0.758	0.952
	6	0.875	1.006	0.743	0.760	0.991	0.943	1.020	0.864	0.858	0.952
	7	0.870	0.986	0.760	0.777	0.991	0.959	1.003	0.894	0.866	0.952
	8	0.887	0.980	0.787	0.757	0.991	0.923	0.998	0.870	0.848	0.952
	9	0.886	0.972	0.758	0.752	0.991	0.931	0.986	0.842	0.845	0.952
	10	0.868	0.981	0.761	0.754	0.991	0.910	0.994	0.840	0.851	0.952
8	1	1.055	1.030	0.540	0.515	0.571	0.977	1.017	0.486	0.464	0.540
	2	0.802	0.902	0.536	0.554	0.571	0.710	0.845	0.496	0.478	0.540
	3	0.894	0.950	0.565	0.580	0.571	0.771	0.910	0.513	0.535	0.540
	4	0.784	0.952	0.560	0.596	0.571	0.695	0.909	0.513	0.563	0.540
	5	0.872	0.974	0.620	0.553	0.571	0.802	0.949	0.598	0.526	0.540
	6	0.841	1.053	0.629	0.616	0.571	0.776	1.070	0.595	0.601	0.540
	7	0.838	1.018	0.661	0.646	0.571	0.823	1.054	0.653	0.645	0.540
	8	0.873	1.011	0.701	0.592	0.571	0.800	1.052	0.632	0.607	0.540
	9	0.898	1.004	0.722	0.588	0.571	0.832	1.037	0.625	0.604	0.540
	10	0.835	1.028	0.715	0.589	0.571	0.782	1.058	0.628	0.618	0.540

Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess the 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for all loan average CORs of the top 10 BHCs and all banks in the U.S using real activity variables only.

Table A6: Out-of-Sample Forecast Results: Finance Factors for All Loans COR

		Top10 Banks RRMSPE					*All Banks RRMSPE*				
$\#H$	$\#F$	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR
1	1	1.048	1.021	0.913	1.001	1.019	1.032	1.013	0.968	1.009	1.020
	2	1.000	1.019	0.935	0.939	1.019	1.015	1.016	0.974	0.977	1.020
	3	0.968	0.999	0.929	0.927	1.019	0.971	1.016	0.956	0.958	1.020
	4	0.965	1.007	0.922	0.931	1.019	0.957	1.021	0.957	0.962	1.020
	5	0.929	1.006	0.914	0.930	1.019	0.963	1.029	0.961	0.963	1.020
	6	0.937	1.017	0.920	0.928	1.019	0.985	1.031	0.972	0.972	1.020
	7	0.933	1.016	0.917	0.926	1.019	0.984	1.022	0.975	0.980	1.020
	8	0.929	1.008	0.911	0.921	1.019	0.980	1.015	0.974	0.972	1.020
	9	0.935	1.015	0.917	0.929	1.019	0.980	1.014	0.973	0.976	1.020
	10	0.934	1.010	0.917	0.931	1.019	0.977	1.011	0.972	0.983	1.020
2	1	1.064	1.029	0.869	0.993	1.023	1.053	1.024	0.920	0.993	1.023
	2	0.996	1.030	0.902	0.915	1.023	1.007	1.027	0.935	0.893	1.023
	3	0.922	1.002	0.872	0.883	1.023	0.889	0.991	0.870	0.877	1.023
	4	0.899	1.013	0.867	0.888	1.023	0.872	1.005	0.867	0.890	1.023
	5	0.858	1.013	0.858	0.882	1.023	0.878	1.016	0.873	0.889	1.023
	6	0.879	1.024	0.868	0.884	1.023	0.920	1.017	0.892	0.899	1.023
	7	0.876	1.017	0.864	0.907	1.023	0.921	1.008	0.899	0.926	1.023
	8	0.869	1.010	0.848	0.897	1.023	0.913	0.995	0.893	0.906	1.023
	9	0.875	1.029	0.855	0.922	1.023	0.915	1.005	0.896	0.929	1.023
	10	0.879	1.020	0.859	0.936	1.023	0.906	1.002	0.894	0.956	1.023
4	1	1.065	1.043	0.788	0.963	0.991	1.023	1.026	0.868	0.929	0.952
	2	1.006	1.046	0.815	0.736	0.991	0.979	1.021	0.873	0.698	0.952
	3	0.795	0.984	0.663	0.683	0.991	0.727	0.916	0.682	0.688	0.952
	4	0.776	1.015	0.665	0.708	0.991	0.723	0.962	0.673	0.743	0.952
	5	0.700	1.041	0.652	0.690	0.991	0.708	1.001	0.693	0.776	0.952
	6	0.814	1.044	0.702	0.699	0.991	0.826	0.994	0.767	0.772	0.952
	7	0.803	1.028	0.690	0.774	0.991	0.831	0.977	0.788	0.812	0.952
	8	0.797	0.997	0.665	0.752	0.991	0.824	0.944	0.770	0.774	0.952
	9	0.794	1.053	0.650	0.806	0.991	0.821	0.982	0.773	0.810	0.952
	10	0.780	1.025	0.651	0.867	0.991	0.792	0.957	0.761	0.840	0.952
8	1	0.879	1.019	0.566	0.574	0.571	0.840	1.009	0.541	0.514	0.540
	2	0.878	1.020	0.540	0.467	0.571	0.805	0.978	0.529	0.510	0.540
	3	0.560	0.900	0.444	0.462	0.571	0.515	0.812	0.540	0.519	0.540
	4	0.557	0.927	0.459	0.466	0.571	0.515	0.836	0.601	0.513	0.540
	5	0.458	0.925	0.489	0.502	0.571	0.502	0.853	0.610	0.508	0.540
	6	0.537	0.854	0.453	0.605	0.571	0.534	0.777	0.606	0.671	0.540
	7	0.507	0.858	0.488	0.592	0.571	0.555	0.811	0.602	0.705	0.540
	8	0.511	0.823	0.549	0.627	0.571	0.551	0.768	0.625	0.745	0.540
	9	0.520	0.964	0.576	0.657	0.571	0.549	0.832	0.623	0.723	0.540
	10	0.544	0.972	0.672	0.609	0.571	0.614	0.850	0.706	0.668	0.540

Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess the 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for all loan average CORs of the top 10 BHCs and all banks in the U.S. using finance factors only.

Table A7: Out-of-Sample Forecast Results: Real Factors for Business Loans COR

		Top10 Banks RRMSPE					*All Banks RRMSPE*				
$\#H$	$\#F$	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR
1	1	1.009	0.989	0.918	0.928	0.989	1.020	1.010	0.856	0.883	0.917
	2	0.959	0.979	0.907	0.911	0.989	0.957	0.972	0.861	0.849	0.917
	3	0.940	0.972	0.905	0.911	0.989	0.923	0.968	0.859	0.837	0.917
	4	0.932	0.988	0.902	0.915	0.989	0.977	0.965	0.848	0.857	0.917
	5	0.926	0.994	0.911	0.927	0.989	0.883	0.957	0.838	0.844	0.917
	6	0.938	0.979	0.915	0.902	0.989	0.879	0.962	0.839	0.828	0.917
	7	0.942	0.952	0.922	0.883	0.989	0.876	0.963	0.843	0.849	0.917
	8	0.941	0.948	0.924	0.882	0.989	0.871	0.963	0.833	0.849	0.917
	9	0.935	0.943	0.913	0.877	0.989	0.871	0.960	0.834	0.847	0.917
	10	0.940	0.946	0.923	0.878	0.989	0.863	0.961	0.833	0.852	0.917
2	1	1.029	1.085	0.878	1.019	0.961	1.049	1.119	0.914	1.067	0.920
	2	1.070	1.026	0.939	0.916	0.961	1.142	1.077	0.976	0.908	0.920
	3	0.983	0.957	0.928	0.841	0.961	1.005	0.971	0.928	0.847	0.920
	4	0.992	0.970	0.879	0.847	0.961	0.936	1.043	0.851	0.880	0.920
	5	0.898	0.981	0.856	0.861	0.961	0.922	1.008	0.840	0.885	0.920
	6	0.897	0.968	0.850	0.837	0.961	0.911	1.016	0.831	0.879	0.920
	7	0.898	0.952	0.859	0.823	0.961	0.898	1.020	0.879	0.851	0.920
	8	0.895	0.947	0.865	0.827	0.961	0.929	0.996	0.882	0.838	0.920
	9	0.891	0.930	0.847	0.821	0.961	0.942	0.998	0.889	0.856	0.920
	10	0.892	0.970	0.854	0.873	0.961	0.937	1.000	0.884	0.874	0.920
4	1	1.054	1.029	0.807	0.798	0.868	1.053	1.052	0.864	0.850	0.883
	2	0.861	0.908	0.792	0.791	0.868	0.872	0.906	0.834	0.816	0.883
	3	0.862	0.887	0.791	0.782	0.868	0.879	0.905	0.827	0.820	0.883
	4	0.867	0.920	0.787	0.807	0.868	0.881	0.955	0.838	0.869	0.883
	5	0.857	0.934	0.790	0.799	0.868	0.878	0.952	0.841	0.860	0.883
	6	0.855	0.965	0.787	0.825	0.868	0.874	0.989	0.836	0.885	0.883
	7	0.837	0.938	0.799	0.818	0.868	0.894	0.970	0.869	0.883	0.883
	8	0.851	0.931	0.810	0.814	0.868	0.906	0.967	0.885	0.878	0.883
	9	0.846	0.914	0.801	0.805	0.868	0.910	0.949	0.880	0.868	0.883
	10	0.857	0.926	0.810	0.810	0.868	0.915	0.957	0.884	0.874	0.883
8	1	0.997	1.040	0.601	0.613	0.625	0.961	1.019	0.683	0.672	0.687
	2	0.753	0.842	0.615	0.608	0.625	0.747	0.813	0.681	0.642	0.687
	3	0.743	0.847	0.612	0.609	0.625	0.757	0.825	0.681	0.663	0.687
	4	0.749	0.887	0.626	0.662	0.625	0.768	0.890	0.704	0.745	0.687
	5	0.758	0.944	0.649	0.661	0.625	0.774	0.922	0.725	0.757	0.687
	6	0.751	1.019	0.626	0.700	0.625	0.767	0.994	0.705	0.796	0.687
	7	0.741	0.984	0.650	0.718	0.625	0.822	0.982	0.774	0.820	0.687
	8	0.746	0.981	0.676	0.702	0.625	0.818	0.972	0.784	0.805	0.687
	9	0.766	0.960	0.695	0.692	0.625	0.840	0.957	0.799	0.797	0.687
	10	0.796	0.993	0.718	0.713	0.625	0.871	0.980	0.823	0.822	0.687

Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess the 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for business loan average CORs of the top 10 BHCs and all banks in the U.S. using real activity variables only.

Table A8: Out-of-Sample Forecast Results: Finance Factors for Business Loans COR

		Top10 Banks RRMSPE					*All Banks RRMSPE*				
$\#H$	$\#F$	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR
1	1	1.022	1.000	0.967	0.974	0.989	1.010	1.009	0.889	0.902	0.917
	2	0.993	1.004	0.967	0.958	0.989	0.965	1.016	0.888	0.887	0.917
	3	0.981	0.990	0.956	0.945	0.989	0.943	1.026	0.888	0.898	0.917
	4	0.963	0.997	0.943	0.949	0.989	0.955	1.026	0.915	0.895	0.917
	5	0.967	1.000	0.948	0.950	0.989	0.972	1.049	0.941	0.910	0.917
	6	0.972	1.011	0.953	0.962	0.989	0.973	1.104	0.941	0.962	0.917
	7	0.972	1.014	0.956	0.968	0.989	0.989	1.101	0.952	0.982	0.917
	8	0.991	1.009	0.979	0.971	0.989	0.998	1.107	0.967	1.002	0.917
	9	0.988	1.012	0.978	0.977	0.989	0.994	1.078	0.964	0.986	0.917
	10	0.995	1.010	0.979	0.974	0.989	1.042	1.088	0.995	1.005	0.917
2	1	1.030	1.008	0.940	0.944	0.961	1.016	1.012	0.909	0.907	0.920
	2	0.983	1.018	0.955	0.922	0.961	0.993	1.023	0.929	0.898	0.920
	3	0.952	0.995	0.939	0.908	0.961	0.946	1.019	0.924	0.904	0.920
	4	0.940	1.001	0.939	0.913	0.961	0.934	1.041	0.931	0.921	0.920
	5	0.954	1.004	0.944	0.916	0.961	0.945	1.031	0.935	0.899	0.920
	6	0.962	1.015	0.949	0.929	0.961	0.939	1.042	0.929	0.913	0.920
	7	0.965	1.019	0.953	0.942	0.961	0.959	1.042	0.949	0.939	0.920
	8	0.981	0.994	0.976	0.936	0.961	0.970	1.029	0.962	0.939	0.920
	9	0.973	0.998	0.970	0.955	0.961	0.949	1.007	0.934	0.934	0.920
	10	0.978	0.992	0.966	0.954	0.961	0.946	1.014	0.930	0.946	0.920
4	1	1.007	1.028	0.857	0.865	0.868	0.992	1.025	0.877	0.877	0.883
	2	0.961	1.045	0.906	0.825	0.868	0.923	1.026	0.879	0.831	0.883
	3	0.901	0.955	0.887	0.788	0.868	0.861	0.916	0.847	0.770	0.883
	4	0.869	0.972	0.872	0.797	0.868	0.820	0.937	0.818	0.786	0.883
	5	0.869	0.977	0.874	0.802	0.868	0.822	0.959	0.823	0.808	0.883
	6	0.896	0.984	0.884	0.817	0.868	0.827	0.965	0.820	0.830	0.883
	7	0.902	1.033	0.891	0.888	0.868	0.843	0.964	0.831	0.861	0.883
	8	0.896	0.948	0.889	0.832	0.868	0.877	0.918	0.867	0.829	0.883
	9	0.897	0.973	0.889	0.860	0.868	0.880	0.929	0.866	0.843	0.883
	10	0.900	0.972	0.889	0.873	0.868	0.880	0.942	0.872	0.862	0.883
8	1	0.816	1.048	0.633	0.636	0.625	0.815	1.027	0.682	0.679	0.687
	2	0.795	1.068	0.679	0.619	0.625	0.774	0.999	0.704	0.682	0.687
	3	0.724	0.967	0.673	0.607	0.625	0.714	0.889	0.679	0.637	0.687
	4	0.695	0.957	0.656	0.619	0.625	0.695	0.873	0.664	0.642	0.687
	5	0.677	0.905	0.669	0.631	0.625	0.691	0.832	0.685	0.650	0.687
	6	0.719	0.873	0.712	0.704	0.625	0.713	0.833	0.707	0.781	0.687
	7	0.719	0.965	0.718	0.781	0.625	0.724	0.938	0.712	0.880	0.687
	8	0.766	0.900	0.762	0.772	0.625	0.778	0.892	0.764	0.874	0.687
	9	0.788	0.932	0.773	0.752	0.625	0.803	0.882	0.789	0.818	0.687
	10	0.809	0.980	0.796	0.762	0.625	0.800	0.932	0.791	0.840	0.687

Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess the 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for business loan average CORs of the top 10 BHCs and all banks in the U.S. using finance variables only.

Table A9: Out-of-Sample Forecast Results: Real Factors for Consumer Loans COR

		Top10 Banks RRMSPE					*All Banks RRMSPE*				
$\#H$	$\#F$	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR
1	1	1.042	1.034	1.000	1.014	1.036	1.046	1.041	0.965	0.982	1.012
	2	1.017	1.013	1.015	1.010	1.036	1.013	1.018	0.969	0.969	1.012
	3	1.031	1.008	1.013	1.005	1.036	1.010	1.012	0.974	0.964	1.012
	4	1.026	1.011	1.005	1.013	1.036	1.011	1.014	0.967	0.987	1.012
	5	1.025	1.019	1.024	0.999	1.036	0.982	1.008	0.967	0.995	1.012
	6	1.017	1.005	0.998	1.006	1.036	0.976	1.020	0.961	1.002	1.012
	7	1.006	1.003	0.994	1.003	1.036	0.981	1.023	0.959	0.996	1.012
	8	1.006	1.003	0.996	1.001	1.036	0.978	1.023	0.967	0.995	1.012
	9	1.005	1.003	0.997	1.000	1.036	0.975	1.017	0.966	0.984	1.012
	10	0.998	1.005	0.996	0.992	1.036	0.976	1.014	0.963	0.984	1.012
2	1	1.075	1.093	1.012	1.069	1.073	1.086	1.114	0.981	1.044	1.025
	2	1.063	1.036	1.053	1.032	1.073	1.079	1.065	0.982	0.974	1.025
	3	1.096	1.029	1.055	1.021	1.073	1.088	1.059	1.006	0.958	1.025
	4	1.093	1.044	1.050	1.047	1.073	1.105	1.076	0.986	1.047	1.025
	5	1.078	1.090	1.109	1.020	1.073	1.017	1.064	0.953	1.039	1.025
	6	1.039	1.066	1.007	1.021	1.073	0.995	1.066	0.938	1.067	1.025
	7	1.031	1.046	0.992	1.033	1.073	0.995	1.057	0.943	1.118	1.025
	8	1.034	1.039	0.995	1.023	1.073	0.975	1.056	0.944	1.088	1.025
	9	1.041	1.038	1.006	1.017	1.073	0.966	1.055	0.943	1.080	1.025
	10	1.023	1.026	1.004	1.011	1.073	0.988	1.046	0.955	1.076	1.025
4	1	1.106	1.064	0.982	0.977	1.122	1.096	1.074	0.901	0.896	1.057
	2	0.985	1.012	0.988	1.019	1.122	0.961	1.012	0.917	0.953	1.057
	3	1.087	1.049	0.965	1.061	1.122	1.052	1.029	0.930	0.973	1.057
	4	1.064	1.055	0.981	1.066	1.122	1.046	1.033	0.924	0.977	1.057
	5	1.027	1.070	0.963	1.074	1.122	1.000	1.021	0.909	0.996	1.057
	6	1.003	1.096	0.964	1.046	1.122	0.972	1.063	0.922	0.980	1.057
	7	1.028	1.098	0.972	0.981	1.122	0.996	1.071	0.925	0.926	1.057
	8	1.044	1.100	0.989	0.964	1.122	1.016	1.075	0.951	0.916	1.057
	9	1.025	1.096	0.989	0.947	1.122	0.967	1.068	0.928	0.905	1.057
	10	1.026	1.102	0.995	0.948	1.122	0.952	1.077	0.925	0.908	1.057
8	1	1.061	1.067	0.884	0.864	0.952	1.019	1.045	0.664	0.647	0.734
	2	0.943	0.973	0.897	0.968	0.952	0.874	0.935	0.681	0.777	0.734
	3	1.165	1.092	0.817	1.113	0.952	1.082	0.999	0.725	0.840	0.734
	4	1.125	1.095	0.858	1.108	0.952	1.069	1.003	0.690	0.840	0.734
	5	1.106	1.118	0.865	1.128	0.952	1.010	0.997	0.690	0.821	0.734
	6	1.031	1.205	0.862	1.067	0.952	0.957	1.101	0.711	0.810	0.734
	7	1.119	1.196	0.894	0.885	0.952	1.008	1.104	0.713	0.690	0.734
	8	1.154	1.207	0.943	0.867	0.952	1.017	1.121	0.745	0.687	0.734
	9	1.074	1.203	0.917	0.825	0.952	0.907	1.114	0.705	0.676	0.734
	10	0.979	1.232	0.876	0.853	0.952	0.852	1.147	0.703	0.696	0.734

Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess the 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for consuer loan average CORs of the top 10 BHCs and all banks in the U.S. using real activity variables only.

Table A10: Out-of-Sample Forecast Results: Finance Factors for Consumer Loans COR

		Top10 Banks RRMSPE					*All Banks RRMSPE*				
$\#H$	$\#F$	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR	PLS_{RW}	PC_{RW}	PLS_{AR}	PC_{AR}	AR
1	1	1.049	1.021	0.987	1.002	1.036	1.036	1.017	0.982	0.989	1.012
	2	1.016	1.023	0.992	1.011	1.036	1.018	1.021	0.977	0.995	1.012
	3	1.036	1.021	0.997	1.005	1.036	1.010	1.024	0.980	0.991	1.012
	4	1.020	1.020	0.994	1.001	1.036	0.992	1.021	0.977	0.983	1.012
	5	1.016	1.021	0.996	0.995	1.036	0.986	1.030	0.978	0.968	1.012
	6	1.010	1.040	0.994	1.002	1.036	0.984	1.046	0.973	0.979	1.012
	7	1.012	1.038	0.996	0.998	1.036	0.982	1.040	0.973	0.982	1.012
	8	1.013	1.034	1.000	0.994	1.036	0.983	1.036	0.978	0.982	1.012
	9	1.017	1.035	1.005	0.991	1.036	0.979	1.030	0.972	0.980	1.012
	10	1.017	1.030	1.005	0.985	1.036	0.992	1.029	0.982	0.975	1.012
2	1	1.073	1.032	1.006	1.013	1.073	1.064	1.033	0.976	0.979	1.025
	2	1.010	1.038	1.018	1.036	1.073	1.023	1.046	0.960	0.999	1.025
	3	1.055	1.019	1.027	1.027	1.073	1.025	1.029	0.965	0.983	1.025
	4	1.025	1.025	1.019	1.020	1.073	0.981	1.049	0.953	0.967	1.025
	5	1.024	1.024	1.024	1.015	1.073	0.980	1.051	0.962	0.935	1.025
	6	1.022	1.049	1.025	1.027	1.073	0.993	1.078	0.964	0.951	1.025
	7	1.019	1.046	1.021	1.023	1.073	0.953	1.075	0.936	0.970	1.025
	8	1.017	1.047	1.019	1.018	1.073	0.944	1.079	0.928	0.974	1.025
	9	1.027	1.053	1.034	1.013	1.073	0.946	1.064	0.928	0.959	1.025
	10	1.022	1.048	1.031	1.012	1.073	0.960	1.057	0.940	0.950	1.025
4	1	1.086	1.046	1.071	1.065	1.122	1.058	1.036	1.033	1.031	1.057
	2	1.058	1.060	1.083	1.135	1.122	1.070	1.055	1.034	1.066	1.057
	3	1.144	1.017	1.083	1.113	1.122	1.079	1.000	1.026	1.019	1.057
	4	1.079	1.045	1.078	1.081	1.122	0.987	1.031	0.989	0.987	1.057
	5	1.070	1.068	1.076	1.039	1.122	1.001	1.066	1.002	0.937	1.057
	6	1.072	1.086	1.065	1.042	1.122	1.013	1.081	0.985	0.920	1.057
	7	1.055	1.082	1.053	1.037	1.122	1.008	1.067	0.987	0.943	1.057
	8	1.060	1.079	1.052	1.028	1.122	1.005	1.041	0.984	0.927	1.057
	9	1.065	1.100	1.046	0.980	1.122	0.975	1.049	0.931	0.902	1.057
	10	1.028	1.090	1.034	0.982	1.122	0.937	1.035	0.913	0.924	1.057
8	1	1.004	1.044	1.030	1.009	0.952	0.979	1.037	0.750	0.763	0.734
	2	1.050	1.075	1.006	1.034	0.952	0.987	1.067	0.761	0.731	0.734
	3	1.109	0.980	1.024	1.008	0.952	0.925	0.963	0.761	0.693	0.734
	4	1.055	1.013	1.028	0.937	0.952	0.850	1.002	0.735	0.657	0.734
	5	0.956	1.030	0.976	0.793	0.952	0.775	1.026	0.729	0.572	0.734
	6	0.964	1.013	0.908	0.709	0.952	0.809	1.012	0.678	0.468	0.734
	7	0.797	1.023	0.738	0.731	0.952	0.652	1.022	0.553	0.572	0.734
	8	0.780	1.010	0.728	0.700	0.952	0.656	0.980	0.561	0.549	0.734
	9	0.773	1.065	0.670	0.628	0.952	0.619	1.012	0.481	0.554	0.734
	10	0.734	1.085	0.677	0.673	0.952	0.653	1.048	0.567	0.593	0.734

Note: We report the RRMSPE statistics with the random walk benchmark model. Therefore, lower values than 1 imply that competing models outperform the benchmark. We assess the 1-quarter to 8-quarter ahead out-of-sample predictability of our factor models with up to 10 factors for consumer loan average CORs of the top 10 BHCs and all banks in the U.S. using finance variables only.