Dynamic Comovement among Banks, Systemic Risk, and the Macroeconomy *

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June 15, 2017

Abstract

This paper develops a new measure of comovement in the banking sector that takes into account the dynamic nature of interlinkages among different bank holding corporations at different stages of business cycles. For this purpose, we use a dynamic factor model with time-varying parameters and stochastic volatility that decomposes the panel data for the return on assets (ROA) and net chargeoffs (NCO) into a common component and an institution-specific idiosyncratic components. We find that the relative contribution of the common factor in explaining the variation in ROA and NCO peaked during the financial crisis, suggesting a significant increase in systemic stress in the banking sector. Using the least absolute shrinkage and selection operator (LASSO) approach, we show that the estimated common components and their stochastic volatilities from our approach perform well when compared to other widely used measures of systemic risk in explaining real economic activity. Furthermore, we find that these measures have better in-sample fit with real economic activity measures than the industry averages of ROA and NCO that are frequently used in the banking literature. Finally, we provide economic interpretation for the idiosyncratic components as banking balance sheet characteristics.

JEL Classification: E32, G21

Keywords: Business Cycles, Systemic risk, Banks, Dynamic Factor Model, Return on Assets, Chargeoffs

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*We would like to thank A.J. Michelli and Shibani Putatunda for excellent research assistance with the banking data and the participants at the Fall 2016 Midwest Macro Meetings and FDIC seminar, as well as Grant Everett, Christoffer Koch, and Julieta Yung for feedback on an earlier draft of the paper circulated under the title "Dynamic Comovement Among Banks' Returns and Chargeoffs in the U.S.". The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

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1 Introduction

The Great Recession of 2008-2009 has renewed the academic interest in the role of the banking sector in the overall macroeconomy. A significant amount of recent research in the banking literature has focused on systemic risk, stress testing, and contagion. One lesson learned during the financial crisis of 2008-09 was that each financial intermediary, such as a bank holding corporation (BHC), should not be considered in isolation while evaluating its impact on the aggregate macroeconomy, as it may impose negative externalities on other financial institutions and may create systemic risk for the overall macroeconomy as was clearly evident from the collapse of Lehman Brothers in 2008. At the same time, focusing only on the very largest banks' contribution to the risk originating in the banking sector may not be sufficient, as it is possible that they contribute a relatively small share of the comovement in the banking sector. There is also a consensus in the literature that the degree of comovement among financial institutions, while time-varying, is highest during the crisis periods.[1] It is surprising, therefore, that relatively little work has been done on examining the time-variation in the degree of comovement across different banking institutions in the U.S.

To take into account the dynamic nature of the comovement in the banking system and its implications for the real economy, we use a time-varying dynamic factor model with stochastic volatility (DFM-TV-SV) developed by Del Negro and Otrok (2008). This model decomposes panels of BHC income statement variables (return on assets, ROA, and net chargeoffs, NCO) into two components: common (to all BHCs) factor and institution-specific idiosyncratic factors.[2] This approach also allows the volatility of both the components to be time-varying via stochastic volatility in innovations. The factor loadings on the common factor may vary over time, which, together with time-varying stochastic volatilities, allow for the relative shares of common and idiosyncratic contributions to explaining total variation of a given variable to vary over time as well. The estimated common and idiosyncratic components from the DFM-TV-SV model have important policy impli-

[1] See for example Acharya et al. (2016) and Billio et al. (2012), Hale (2012) among others.

[2] We use the return on assets (ROA) and net chargeoffs (NCO) data from the Call Reports of the U.S. insured depository institutions aggregated to the BHC level with at least $10 billion in assets, because the Dodd-Frank Act mandates the participation of banks with assets over that lower threshold. The choice of the variables is given by the least granular banking variables whose evolution directly affects capital under macroeconomic stress. See Kapinos and Mitnik (2016) for an overview of the top-down stress testing literature that employs similar portfolio-level variables. Section 4 provides a detailed description of our data.

cations, since the dynamic evolution of the common component is likely to represent the systemic behavior in the banking sector, whereas the idiosyncratic component may capture the individual characteristics specific to each BHC. Similarly, stochastic volatility of the common factors reflects systemic uncertainty in the banking sector. We also employ the time-varying feature of our model to examine the hypothesis that during recessions the comovement among BHCs tends to increase. Insofar as the common movement in ROA and NCO reflects the aggregate banking sector cycle, the relative contribution of the common component to a particular BHC income statement will show the extent to which that BHC is exposed to the sector-wide risk.[3] Another attractive feature of our approach is that it allows us to examine whether different BHCs have become alike or different in terms of their responses to common shocks. In other words, our framework examines the cross-sectional dispersion in volatility of the BHC's ROA and NCO, tracks its changes over time, and assesses which factor's volatility—common or idiosyncratic—drives the overall cross-sectional dispersion in volatility.

The results from the DFM-TV-SV model show that the relative contribution of the common factor in explaining the variation in ROA and NCO increased significantly during the financial crisis.[4] Importantly, the peak in the relative contribution of the common factor as well as the peak (trough) in the estimated level of common component of ROA (NCO) occurred much earlier than the collapse of Bear Sterns and Lehman Brothers implying the forward-looking nature of this measure. This is consistent with the findings of Gorton et al. (2015) who find that the stress in the financial system was building much before the crisis and Lehman collapse in 2008 was the tipping point. Decomposition of the total cross-sectional dispersion in volatility shows that the BHCs became more heterogeneous in their response to common shocks and the BHC-specific cycles also became different during the crisis.

Our paper also contributes to the literature on the relationship between systemic risk in the banking sector and macroeconomy by examining the predictive ability of the measure of comove-

[3]This may shed further light on the recent findings by Gandhi and Lustig (2015) that large banks tend to have lower risk and lower return on average because of the implicit bailout guarantee by the government and smaller banks have higher beta and therefore is more exposed to systemic risk.

[4]Relative contribution of each component is derived from the variance decomposition of ROA and NCO. This share is determined by time-varying factor loadings, persistence of the component and also stochastic volatility of each component.

ment obtained from our approach for real economic activity. We find a strong relationship between estimated common components and stochastic volatility of ROA and NCO with four measures of real economic activity considered in our exercise: real GDP growth, percentage change in industrial production, jobs growth and change in unemployment rate. Using the least absolute shrinkage and selection operator (LASSO) approach, we show that comovement and uncertainty measures derived from the DFM-TV-SV model perform well relative to the other popular measures of systemic risk as has been outlined in Giglio et al. (2016). One interesting finding of the LASSO analysis is that none of the measures of comovement, contagion and volatility reported in Giglio et al. (2016) consistently survive shrinkage in explaining all the measures of real economic activity.

We also perform a direct comparison of predictive power of the widely used industry averages of ROA and NCO with the measures estimated in our exercise and find that the latter significantly outperform the former. This is not surprising since these aggregate measures are likely to be influenced by outliers and fail to account for the dynamics within the cross-section of institutions in the sample. Our approach, on the other hand, exploits the heterogeneity in the variation of income statement variables across time and across firms and provides a common component measure that does not suffer from aggregation issues.This result is consistent with the broader literature on the role of financial sector in predicting and amplifying business cycle fluctuations.[5]

Finally, we investigate the potential drivers of the remaining byproduct of our model's decomposition and study whether the shares of idiosyncratic shock contribution to the total volatility in the ROA and NCO, as well as the levels of BHC-specific idiosyncratic factors, can be explained by the BHC balance sheet characteristics. We find that they are strongly correlated with lags of several balance sheet variables that are frequently used in the literature to characterize banking profiles and business models. Therefore, while measures of sectoral comovement and uncertainty appear to be strongly related to the business cycles, idiosyncratic factors of income statement variables appear to be driven by the BHC-specific balance sheet characteristics.

The remainder of the paper is organized as follows. Section 2 briefly summarizes the related literature. Section 3 presents the time-varying dynamic factor model. Section 4 discusses the data.

[5]See Bernanke et al. (1996), Asea and Blomberg (1998) and Shularick and Taylor (2012) among others.

Section 5 presents estimation results for the different decomposition components from our model. Section 6 discusses the relationship between the macroeconomy and different measures of systemic risk and financial stress, including the ones obtained from our model. Section 7 describes the relationship between BHCs' idiosyncratic factors and their balance sheet variables. Finally, Section 8 concludes.

2 Related Literature

Our paper lies at the intersection of the literature on the estimation of systemic risk in the banking sector and its impact on the macroeconomy. The earlier literature on the estimation of systemic risk was mainly based on examining banks' interlinkages through autocorrelation of their defaults and returns. Notable studies in this vein include De Bandt and Hartmann (2000), Jorion (2005), and Bartram, Brown and Hund (2007) among others. Building on the seminal study by Mandelbrot (1963), researchers have also tried to incorporate tail dependence in the systemic risk literature. Longin and Solnik (2001) use extreme value theory to show that large negative returns are much more highly correlated than positive returns. Bae, Karolyi and Stulz (2003) propose a new approach to evaluate contagion in financial markets using coincidence of extreme return shocks. More recently, extreme tail dependence has been incorporated into the development of systemic risk measures. One example of the strand of the literature is due to Adrian and Brunnermeier (2014) who use quantile regression approach to develop a modified value at risk model that they call CoVar. There is also strong evidence in the literature that the degree of comovement among financial institutions, while time-varying, is highest during the crisis periods. Notable studies to document this feature of comovement include Acharya et al. (2016), Billio et al. (2012), and Hale (2012) among others. Overall, the consensus from the recent developments in this strand of the literature is that systemic risk measures do have a strong impact on real activity, although its precise scope varies from one variable to another.

The other strand of literature that has focused on the impact of systemic risk on the overall macroeconomy, possibly amplifying the effect of adverse economic shocks. Bernanke et al. (1996)

were among the first to provide evidence for the so-called *financial accelerator* whereby relatively small adverse macroeconomic (especially contractionary monetary policy) shocks could yield large macroeconomic effects because of the asymmetries in the financial sector lending driven by the flight to quality.[6] Gertler and Lown (1999) also find support for the financial accelerator and emphasize that the firms most susceptible to the relevant financial frictions have "traditionally relied heavily on commercial banks for external finance". Asea and Blomberg (1998) demonstrate that bank lending was responsible for the amplification of the U.S. business cycle using a Markov-switching panel model. Shularick and Taylor (2012) expand the historical and international scope of investigating the role of financial leverage, particularly obtained through bank lending, in amplifying business cycle fluctuations and confirm the intuition behind the financial accelerator.[7] The financial crisis that triggered the Great Recession of 2008-2009 has provided an impetus for the more rigorous study of the effect of different measures of systemic risk on the macroeconomy. Using a wide selection of the recently proposed measures of systemic risk, Giglio et al. (2016) studies how systemic risk and financial market distress affect the distribution of shocks to real economic activity and find that several such measures predict changes in real activity well.[8]

The overarching theme from the current state of the literature in banking suggests that empirical models of dynamic relationships among different BHCs should account for the inherent time-varying nature in how different BHCs are related to each other. To model time-variation in the comovement of the BHC ROA and NCO, we use a dynamic factor model with time-varying loadings and stochastic volatility (DFM-TV-SV). The attractive feature of this class of models is that it decomposes the movements in longitudinal panels into common and idiosyncratic components and also allows the relative contributions of these common and idiosyncratic components to

[6]Bernanke et al. (1999) launched a large literature on the role of the financial accelerator in the dynamic stochastic general equilibrium (DSGE) setting, which has emerged as one of the primary models for the analysis of the role of the financial sector in the transmission of macroeconomic shocks. Kashyap and Stein (2000) provide an early comprehensive review of the channels of transmission of monetary policy using a panel dataset of all commercially insured banks in the U.S.

[7]The literature has also addressed the more specific structural details for the channels of transmission of macroeconomic and policy shocks. For instance, Black and Rosen (2007) separate the bank lending channel from the balance sheet channel, while Egert and Southerland (2014) distinguish between the bank lending channel and the broad lending or financial accelerator channel. Re-investigating these structural details is outside the scope of the present paper.

[8]In section 6, we examine the relative usefulness of our measure of comovement and stochastic volatility with all the measures studied in Giglio et al. (2016) in detail.

vary with time. The latter aspect is driven by the time-varying loadings on common component and stochastic volatility in both of these components. Dynamic factor models with time-variation have been mainly used in macroeconomics. Often these model are used to explain comovement in economic fundamentals across countries (Forni et al., 2000; Stock and Watson, 1998). Mumtaz and Surico (2012) incorporate time-varying coefficients and stochastic volatility in the dynamic factor framework to study inflation dynamics in industrialized countries. Recently, Stock and Watson (2016) use this method to understand the time-varying role of disaggregated components of price level in the determination of trend inflation. Methodologically, our paper follows Del Negro and Otrok (2008) who develop a dynamic factor model with time-varying factor loadings and stochastic volatility in the latent factors, as well as idiosyncratic components of a time series. Our paper, therefore, contributes to the existing literature on systemic risk and the dynamic relationship between banking and the macroeconomy by using an econometric approach that allows us to model the time-variation in the extent of comovement among the biggest BHCs in the U.S.

3 Methodology

To examine the time-varying importance of the common and idiosyncratic factors, we extend the standard constant parameter Dynamic Factor Model (DFM) to a DFM with time-varying loading parameters and stochastic volatility (denoted by DFM-TV-SV), following closely the approach as proposed by Del Negro and Otrok (2008). While time-varying dynamic factor models have a long tradition in the data-rich environment of stock returns (see Bekaert and Harvey (1995) for an early contribution and Bakaert et al (2005) for extending that framework to the study of international contagion), we believe that our paper is the first to extend this type of an empirical framework to the banking data. The DFM-TV-SV decomposes the variations of the variable of interest (NCO or ROA in our case) into two components: the common factor, which applies to all BHCs, and each BHC's idiosyncratic factor. Specifically, the model is given by:

$$y_{i,t} = \lambda_{i,t} \cdot g_t + \epsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ denotes NCO or ROA for each BHC i at time t; g_t is the common factor that affects all BHCs' NCO or ROA at time t; $\lambda_{i,t}$ is the time-varying loading parameters for the common factor; and, finally, $\epsilon_{i,t}$ represents the idiosyncratic bank-specific factor.

To capture the potentially time-varying co-movement among bank variables over time, we allow the loading parameters to vary over time. Specifically, we assume that the time-varying loading parameter for the common factor follows a random walk process[9]:

$$\lambda_{i,t} = \lambda_{i,t-1} + \eta_{i,t};\ \eta_{i,t} \sim\ i.i.d.N(0, \Sigma_\eta). \tag{2}$$

Following Del Negro and Otrok (2008), we assume that the shocks to loading parameters are independent across i's, implying independence among these time-varying loadings.[10] Following the broader literature on the DFM, we also assume that the shocks to the common and idiosyncratic components are orthogonal to each other. Time variation in the loading parameters, as well as factor volatility, permits contributions of various factors to evolve dynamically. As a result, the variance decomposition of the ROA or NCO for each BHC (conditional on knowing $\lambda_{i,t}$) is given by:

$$Var(y_{i,t}) = \lambda_{i,t}^2 \cdot Var(g_t) + Var(\epsilon_{i,t}). \tag{3}$$

The common factor follows a stationary AR(p) process with a stochastic volatility:

$$g_t = \sum_{p=1}^{P} \phi_p^g g_{t-p} + \sqrt{\exp(h_t^g)} \cdot \nu_t^g, \tag{4}$$

where $\nu_t^g \sim\ i.i.d.N(0, \sigma_g^2)$. The common factor stochastic volatility follows a random walk process:

[9]It is conceivable that the loadings and volatility, to be presented below, may follow a more discrete or Markov-switching type of time variation in lieu of the gradual time variation assumed in our approach. However, the Markov-switching specification is infeasible due to the curse of dimensionality when the number of series to be dealt with is large, which is certainly the case in our study. Moreover, the usual test of time variation has a low power against the alternative, that is, it is usually difficult to distinguish between different forms of time variations. Therefore, the specification we choose to employ is a feasible way to document potential time variations of the co-movement among BHCs' NCO or ROA even though the random walk specification does tend to smooth out these time variations.

[10]Note that this may not be a very restrictive assumption, since the introduction of the stochastic volatility of the common factor can capture potential common movements in the time-varying contributions of the common factor.

$$h_t^g = h_{t-1}^g + \sigma_g^h \cdot \omega_t^g, \quad \omega_t^g \sim \ i.i.d.N(0,1). \tag{5}$$

Each idiosyncratic or BHC-specific factor also follows a stationary AR(q) process:

$$\epsilon_{i,t} = \sum_{q=1}^{Q} \phi_{i,q}\epsilon_{i,t-q} + \sqrt{\exp(h_{i,t})} \cdot \nu_{i,t}, \tag{6}$$

where $\nu_{i,t} \sim \ i.i.d.N(0, \sigma_i^2)$. Finally, similar to (5) the idiosyncratic stochastic volatility follows a random walk process:

$$h_{i,t} = h_{i,t-1} + \sigma_i^h \cdot \omega_{i,t}, \quad \omega_{i,t} \sim \ i.i.d.N(0,1). \tag{7}$$

Volatility shocks, $\omega_{i,t}$, are assumed to be orthogonal to each other.

Note that the loading parameters and the common factor's shock variance are not separately identifiable. Normalizing the common factor shock, we set $\sigma_g^2 = 1$. Moreover, the whole path of time-varying stochastic volatility can be shifted up or down to yield observationally equivalent results, as long as the factor loading parameters are re-scaled accordingly. To address this issue, we follow Del Negro and Otrok (2008) and impose the restriction that the time-varying volatilities in equations (5) and (7) all have zero as their initial values, i.e., $h_0^g = h_{i,0} = 0$ for $i = 1, 2, \ldots, N$. Finally, since the means of factors are not separately identifiable, we follow the past literature and demean the series before the estimation. Due to its large scale, this model is typically estimated using a Bayesian Markov Chain Monte Carlo (MCMC) estimation algorithm. Specifically, we employ the Gibbs-sampling algorithm that involves breaking the model into smaller blocks and making draws of parameters and states from the posterior conditional distributions. Most of the Gibbs-sampling steps are standard, as outlined in Kim and Nelson (1999), except for the time-varying stochastic volatility. To make stochastic volatility draws, we rely on the approximation method developed by Kim, Shephard and Chib (1998), which has been shown to perform well and widely used in the recent literature, see e.g., Stock and Watson (2007, 2016) and Primiceri (2005). Throughout the estimation process, we impose diffuse priors to introduce little prior information.

Interested readers are referred to Del Negro and Otrok (2008) or Bhatt, Kishor and Ma (2015) for further estimation details.

4 Data

Our banking data are from the Call Reports of individual banks aggregated to the bank holding company (BHC) level as of 2014Q4. We keep only the BHCs that had $10 billion or more in assets at least once during our sample. We have also excluded the following institutions: foreign-owned; located in Puerto Rico; ones that do not provide traditional banking services. Because the DFM-TV-SV decomposition requires a relatively long time-series dimension, we have also excluded banks that were formed after 2008. The ROA data cover 1984Q1—2014Q4 and include 68 BHCs. ROA is calculated as quarterly net income divided by total assets (NETINCQ/ASSET). The NCO data cover 1990Q2—2014Q4 and include 61 BHCs, with 7 institutions dropped because of the low number of non-zero observations that prevented the algorithm from converging. NCO is calculated as net chargeoffs on residential real estate for 1-4 family housing divided by total loans secured by 1-4 family residential properties held in domestic offices (NTRERESQ/LNRERES). The full list of included and excluded institutions is available in Table A.1.

Figure 1 displays the dynamic evolution of the ROA and NCO panels and motivates the use of the DFM-TV-SV decomposition. First, there is significant variation in the moments of the cross-sectional distribution of BHCs over time, with particularly dramatic changes during the Great Recession. This feature calls for the use of time-varying parameters in the decomposition as well as stochastic volatility to absorb spikes in variation. Second, this figure clearly indicates that the *average* measures of NCO(ROA), while different from their values during expansions, are not nearly as high(low) as the upper(lower) percentiles of the cross-sectional distribution. Note that the figure may very well understate the scope of the individual BHC movement within the cross-section over time, since the visual tracing of all individual paths is graphically challenging.

In addition to the two primary income statement variables of interest, we also use several balance sheet variables frequently employed in the literature to characterize banks.[11] Asset growth

[11] We use these variables in the second part of our analysis where we provide economic interpretation of the estimated

(percentage change in ASSET expressed in fractions) describes growth; log asset is the standard proxy for size; shares of commercial real estate, credit card, and construction and industry loans in total assets characterize banks' lending profiles; ratio of non-accrual loans and leases to total assets is a measure of loan quality; ratio of brokered deposits to total assets and the ratio of securities, federal funds sold and reverse repurchase agreements (collectively referred to as liquid assets) to total assets are both measures of liquidity; Tier 1 leverage is calculated as the share of risk-based tier 1 capital in total assets.[12] All balance sheet variables are standardized making the comparison of their coefficients in Section 7 possible.[13]

Our macroeconomic variables and industry averages are from the FRED2 database maintained by the Federal Reserve Bank of St. Louis. The dynamic evolution of our measures of real activity is displayed in Figure 2. These series provide a parsimonious descriptions of the evolution of the business cycles in the U.S. and a reference point for comparison with the dynamics of the BHC common factors. Finally, to provide context for the analysis undertaken in the post-decomposition stages of our project, Table 1 provides the descriptive statistics for all of our variables from the Call Reports and FRED2. For the descriptive statistics of the systemic risk measures from Giglio et al. (2016), see their paper and references therein.

5 Empirical Results

In this section, we present the estimation results from our dynamic factor model outlined in Section 3.[14] We begin by documenting the time variation in the relative importance of each factor in explaining the observed variation in the BHC ROA and NCO. We then discuss the cross-BHC correlations implied by our dynamic factor model. Finally, we present the estimated time-varying stochastic volatility along with its cross-sectional dispersion over time.

factors.

[12]Tier 1 capital is only available starting in 1996Q1.

[13]Since log assets are trending over time, we remove its effects by running a pooled OLS regression of stacked log assets on stacked time variables and standardize the resulting residuals.

[14]We set lag order P=Q=2 in the estimation for the sake of parsimony.

5.1 Evolution of the Common Factor in ROA and NCO

Figure 3 presents the visual summary of the evidence in support one central message of this paper—that the use of banking aggregates that do not take into account the movements of individual BHCs within the cross-section or periods of elevated stochastic volatility is likely to yield different results than from the common factor that does account for these considerations. The median estimated common factors for NCO(ROA), given by (4), reach their peak(trough) during the Great Recession sooner than the industry averages and exhibit less volatility during expansions, suggesting that the latter is primarily driven by idiosyncratic factors. The comparison of our estimated common component with the aggregate measure leads to further observations of interest. First, average ROA and average NCO measures are much more volatile than the estimated common ROA and NCO. Second, average ROA and ROA common factor are highly correlated (0.93), whereas the estimated NCO common factor's correlation with average NCO is low (0.18). Third and more importantly, we find that our estimated common components (both ROA and NCO) Granger cause average ROA and average NCO at all levels of significance, whereas we do not reject the null of no Granger causality from the average ROA and NCO to these estimated common factors at conventional levels of significance. This clearly suggests that the estimated common factors contain information about the future movements in aggregate banking variables. We also compare the predictive ability of these industry averages with the estimated common component for real economic activity in the next section

Figure 4 provides a sense of the estimation uncertainty for the two median common factors by means of the 90% confidence bands. The confidence bands are large for the estimated common component of the NCO for the BHCs in our sample before the beginning of the financial crisis, as there is not much variation in its estimated level. Notably, during the normal times, there are many BHCs that have zero net chargeoffs for extended periods of time prior to the financial crisis. This poses computational problems preventing the convergence of the estimation algorithm. Arguably, however, during the normal times there was no economy-wide factor that led to variation in the NCO that was common across different BHCs. It is only during the periods of high volatility in the financial markets that there is a common movement in the NCO across different BHCs. In theory, therefore, our DFM-TV-SV model is able to capture these dynamics better than a simpler DFM models that do not allow for time-variation in volatility as well as the loadings. Our results show that the degree of time-variation in loadings on common factor is higher than the time-variation in factor itself for the pre-crisis period. This behavior changed dramatically during the financial crisis. The common factor in the NCO witnessed a sizable jump in the last quarter of 2007. Note that this increase in the common component of the NCO took place after the big decline in the common component of the ROA. This increase in the common component was short-lived, as it peaked in 2009Q2. Since then, the common component has declined and stayed around the same level after 2010.

The ROA common factor started declining in the third quarter of 2005, much before the Bear Sterns crisis in March 2008 and the Lehman Brothers collapse in September 2008 suggesting forward looking nature of this component. Insofar as the inverse of the ROA common component proxies for the systemic risk in the U.S. banking sector, this measure started increasing much before the Bear Sterns and Lehman events. Our results show that the trough of the common factor was in the last quarter of 2008, which coincided with the peak of the financial crisis. They are consistent with the findings in the shadow banking literature where Gorton et al. (2014), among others, find that the stress in the financial system was building much before the crisis and the Lehman collapse in September 2008 was the tipping point. It should be noted that different measures of real economic activity kept declining in 2009 and it was not until the end of 2009 that the real GDP growth became positive again. This finding provides preliminary evidence that our estimated common component of ROA that reflects information about the the extent of comovement in the banking sector leads the real economic activity measures. We examine the predictive power of the estimated common factor for real economic activity measures in more detail in the next section.

5.2 Stochastic Volatility of the Common Factors

Unlike the conventional DFM model, our DFM-TV-SV model also allows volatility to be time-varying. Figure 5 describes the estimated stochastic volatility of the common component of the BHC NCO and ROA given by (5). Our results suggest that the stochastic volatility of the common component of NCO declined until 1998Q1. There was a slight increase during the time period 1998Q2-2000Q1 that preceded the recession of 2001. This volatility started increasing in 2006Q1, reaching its maximum in 2009Q3 and slowly declining thereafter. Having peaked in 2008Q4 during the Great Recession, the ROA common factor stochastic volatility began declining at the beginning of 2009. Comparing the stochastic volatility of the common factor of ROA and NCO, we find that the increase in volatility of NCO during the financial crisis was much more long-lasting than the increase in volatility of ROA. Since stochastic volatility captures the time-variation in volatility, it can also be argued that this measure is capturing the sector-wide uncertainty among banks.[15] These results provide further evidence on the justification for allowing time-variation in volatility as it allows us to capture economically meaningful relationship between volatility and macroeconomic outcomes that would not be possible if one assumes constant volatility.

5.3 Idiosyncratic Factors

Figure 6 describes the dynamic evolution of the panel of idiosyncratic factors for individual BHCs given by (6). The top panel indicates that the dispersion of the NCO idiosyncratic factors during the recession was quite symmetric, with large positive and negative values in the 90th and 10th percentiles respectively. The bottom panel, on the other hand, suggests that for ROA idiosyncratic factors were important in explaining the downside realization but not the upside. In section 7, we examine the possibility that the idiosyncratic factors may be explained by the BHCs balance sheet characteristics. Figure 6 plots the variance contribution of idiosyncratic factors. The black line represents the median of the variance contribution. The results show that the the variance contribution of the idiosyncratic factor declined during the financial crisis and this decline started before the Lehman collapse. This is consistent with the increase in the variance contribution of common factors during the financial crisis.

[15] While the full investigation of the effect of this measure of uncertainty is outside the scope of this paper, we find that it has a negative relationship with aggregate loan growth: its correlation coefficient is -0.51 with NCO stochastic volatility and -0.41 with the ROA one. Digging deeper, we also find significant heterogeneity in the the relationship between common factor stochastic volatility and different types of loans. In particular, we find that real estate loans are more sensitive to changes in volatility, whereas consumer and credit card loans are relatively insensitive. To conserve space we do not report detailed results in the paper; they are available upon request.

5.4 Time-Varying Comovement and Cross-sectional Dispersion in Volatility

As compared to a traditional dynamic factor model, our approach allows for time-variation in the relative contribution of the common and idiosyncratic components. The time-varying nature of their relative contributions provides us with a measure of BHC sensitivity to a common shock, and whether that sensitivity peaks at a particular point of time in the business cycle. Our results as displayed in Figure4 shows that the contribution of the common factor in explaining the overall variation in the NCO and ROA experienced a decline at the beginning of the sample for most of the BHCs. There was a significant increase in its contribution before and during the financial crisis. This increase in the contribution of the common factor is consistent with overall increase in the economy-wide systemic risk and both of their declines at the end of the financial crisis are largely coincident.

We also report the implied pairwise correlation in NCO and ROA for our sample. Specifically, the factor model (1) and the orthogonality assumption imply that for $i \neq j$, we have $Cov(y_{i,t}, y_{j,t}) = \lambda_{i,t}\lambda_{j,t} \cdot Var(g_t)$, where the right-hand-side values are given by (3). As a result we compute all pairwise correlations implied by the factor model at each point in time and for each MCMC draw. Figure 8 plots the unweighted average cross bank correlation for all the BHC in our sample. The figure plots the median and the 90% bands of this average. The results for the pairwise correlation are consistent with the role of the common factor for ROA and NCO. The results suggest that the cross-correlation started increasing much before the crisis. Interestingly for NCO, the increase in correlation was gradual before the crisis, but the decline in correlation after the crisis was very rapid. On average, the cross-sectional correlation for ROA was higher than NCO implying a higher degree of comovement in ROA than NCO for the BHCs in our sample.

Finally, we present the results for the cross-sectional dispersion in volatility of BHCs, which refers to the standard deviation of the volatility of all series within a panel at each time point. This measure takes into account the time-varying heterogeneity in the volatility of different BHCs. Cross-sectional dispersion in volatility indicates whether the convergence in volatility is due to the common factor or due to the BHC-specific factor. Figure 9 shows the estimated time-varying standard deviation of total cross-sectional volatility and decomposition of this volatility into common and idiosyncratic volatility. The figure plots the median across the MCMC draws and the 90% confidence bands. We find that there was a gradual decline in cross-sectional volatility before 2006 for both the ROA and the NCO. Not surprisingly, there was a big spike in dispersion during the crisis period. The total cross-sectional dispersion in volatility declined after the financial crisis. Decomposition of the total cross-sectional dispersion shows the large increase during the crisis period was attributed to both the common and idiosyncratic factors. This implies that the degree of heterogeneity in the response to common shock across different BHCs increased during the crisis period. Moreover, the BHC-specific cycles also became more different during the crisis period.

6 Economic Interpretation of the Common Factors and Stochastic Volatility

Since the model presented in this paper allows us to estimate the time-variation in comovement of income statement variables as well as volatility of common component, we can exploit the time-varying feature of these variables and examine its relationship with different measures of real economic activity in the U.S. A casual look at the evolution of these variables undertaken in the previous section suggested a link with the U.S. macroeconomy. In this section, we examine this relationship in more detail. First, we compare the explanatory power of a wide class of systemic risk measures for real economic activity using the LASSO method and perform a preliminary check on the relative usefulness of the measures developed in this paper. Second, we perform a comparison of the predictive power of the common components and stochastic volatilities of ROA and NCO with simple industry averages of ROA and NCO. We find that our common factors outperform several standard measures of systemic risk and explain the evolution of real activity better than the industry averages.

6.1 LASSO Analysis of Relationship Between Systemic Risk and Real Economic Activity

Although there is a consensus on the impact of systemic risk on macroeconomy, the literature is divided over which measure of systemic risk is the most dominant in explaining real economic activity. In a comprehensive study, Giglio et al. (2016) investigate how systemic risk and financial market distress affect the distribution of shocks to real economic activity by using 19 different measures of systemic risk. They separate 18 of these measures into four groups—institution-specific, comovement and contagion, volatility and instability, liquidity and credit—and develop an additional one that combines the other variables for optimize prediction of downturns.[16] Even though our estimated common components and stochastic volatility measures use information from only the BHC income-statement variables, and therefore, has information set that is vastly limited in scope than the popular measures of systemic risk, it would still be instructive to examine the relative strength of the estimated common components and stochastic volatilities with these widely used measures of systemic risk. In addition to the 19 different measures of systemic risk used by Giglio et al. (2016), we also use VIX, percentage change in all transaction house price index in the U.S. (USSTHPIpch), national financial condition index (NFCI) developed by the Chicago Fed, economic policy uncertainty index (USEPUI) developed by Baker et al. (2016) and the real S&P500 stock return from Robert Shiller's website. These variables, that can be grouped under "aggregate risk", are added to broaden the measures of real economic activity and financial stress. Inclusion of industry averages

[16]The institution-specific risk group comprises of the following measures: CoVar (as well as ΔCoVar) is the value-at risk measure developed by Adrian and Brunnermeier (2016); marginal expected shortfall (MES) due to Acharya et al. (2016); and MES-BE (also known as SRISK) by Brownlees and Engle (2016) measure capital shortfalls of financial institutions in a severe downturn. The contagion and comovement group consists of the following: the absorption ratio (ABSOR, as well as its change, ΔABSOR) described by Kritzman et al. (2011) measures the fraction of the financial system variance explained by the first K principal components (K = 3); the Dynamic Causality Index (DCI) from Billio et al. (2012) counts the number of significant Granger-causal relationships among bank equity returns; ISI is international spillover index by Diebold and Yilmaz (2009). The volatility and instability group includes: REAL_VOL is the average equity volatility of 20 largest financial institutions; Turbulence (TURB) is constructed by Kritzman and Li (2010) who consider returns' recent covariance relative to a longer-term covariance estimate; CATFIN is the systemic risk measure from Allen, Bali and Young (2012); Book leverage and Market leverage are the aggregate book leverage and market leverage for the largest 20 financial institutions created by Giglio et al. (2016); Size concentration calculates size concentration in financial industry. Finally, the liquidity and credit group comprises of: Amihud's (2002) illiquidity measure, AIM; the TED spread (LIBOR minus the T-bill rate); the default spread (BAA bond yield minus AAA bond yield); the Gilchrist and Zakrajsek (2012) credit spread measure (GZ); and the term spread (the slope of the Treasury yield curve). PQR is the index-of-indexes measure developed by Giglio et al. (2016) to optimize the prediction of the 20th percentile of industrial production growth.

of ROA and NCO is instructive because they are directly comparable to the measures developed in our paper, as they are based on similar information sets. Including two measures of common component and two measures of stochastic volatility, we have 31 variables in total as explanatory variables. The variables that we are interested in explaining are four measures of real economic activity: real GDP growth, percentage change in index of industrial production, non-farm payroll employment growth and change in unemployment rate. These four measures capture the health of real economic activity as well as the strength of the labor market. Given high number of regressors (0-4 lags of each variable to address the potential variation in transmission lags) and limited data size, we use the least absolute shrinkage and selection operator (LASSO) to examine the relative usefulness of these 31 variables and their lags in explaining real economic activity.

For a detailed exposition describing the LASSO methodology, see the seminal contribution of Tibshirani (1996). Here, we lay out this framework keeping the technical details to the necessary minimum. LASSO solves the following optimization problem:

$$\min_{\gamma} \left\{ (y_t - \sum_{k=1}^{K} \sum_{l=0}^{4} \gamma_{k,l} x_{k,t-l})^2 + \lambda \sum_{k} \sum_{l} |\gamma_{k,l}| \right\}, \tag{8}$$

where y is the real activity variable of interest, x are the measures of systemic risk and financial stress, K is the total number of independent variables indexed by k and l is the lag index.[17] The parameter λ imposes a penalty factor on reducing the residual sum of squares through additional regressors k. Note that for $\lambda = 0$, the problem reduces to ordinary least squares. Increasing λ leads to dropping of the regressors that are least useful in explaining the variation in y. [18] To summarize LASSO survivorship of individual x, we add up all survival incidences of each candidate variable and its lags for $\lambda \geq \lambda^*$. Therefore, given the selection non-reversal at higher levels of the penalty parameter, if a variable is selected at least once, it is selected at λ^*, while additional selections occur at higher values of that parameter. Since our sample has a relatively short longitudinal dimension, imposing the 10-fold cross-validation leads to a minor variation in the selection outcomes at λ^*

[17] All variables are standardized for LASSO, so that selection is not driven by differences in relative variances.

[18] We use a standard geometric grid from an arbitrarily low value of λ to the maximum that keeps only one regressor to minimize the mean square error based on cross validation with the conventional fold size of 10 and designate the resulting value of the penalty parameter as λ^*. We use the default grid search settings of the `lasso()` function in MATLAB. While there are selection reversal at the low values of $\lambda < \lambda^*$, there are none for $\lambda > \lambda^*$.

with random draws that define the 10-fold cutoffs. Therefore, the results that we present below are averaged over 100 replications of the 10-fold cutoff draws.

Figures 10 through 13 provide a visual summary of this variable selection exercise. For the real GDP growth, the LASSO selects variables primarily from the aggregate risk, volatility and instability, and liquidity and credit groups but virtually none from the institution-specific and comovement and contagion groups. It also selects the NCO common factor at λ^*, whose LASSO survival is only bested by the stock returns, policy uncertainty, turbulence, market leverage, and the GZ spread. Similar results obtain for industrial production growth, with the NCO common factor having better survival rates than the vast majority of other systemic risk variables. For total non-farm payroll growth, ROA stochastic volatility and industry average ROA are selected at λ^* and the NCO common factor is not. This is the only time when a banking industry average measure is selected at λ^*, although its survival rates for higher values of the penalty parameter are quite low. Finally, for unemployment rate change, the only product of the DNO decomposition that is selected at λ^* is, again, the NCO common factor, which survives LASSO at least as well as any measure from the institution-specific risk, comovement and contagion, and volatility and instability groups.

To summarize the results from the LASSO exercise, we find that in almost every case (with only one exception), the industry averages of ROA and NCO do not survive the shinkage at different levels of the tuning parameter, which is at least equal to the optimal level based on 10-fold cross validation. In contrast, we find that NCO common factor survives in case of real GDP growth and industrial production and stochastic volatility measures are important in the context of the labor market indicators. These results clearly suggest that comovement and uncertainty measure derived from the DFM-TV-SV model is competitive with the other measures of systemic risk even if it only uses information from the income statement of BHCs. The only set of variables that survive the higher values of λ are several aggregate risk measures not considered in Giglio et al. (2016), with the NCFI, stock returns, and policy uncertainty performing particularly well, and their liquidity and credit group where it is difficult to single out a variable that consistently demonstrates superior survival. This clearly suggests that our measure of comovement as measured by the common factors and uncertainty in the common factor as measured by stochastic volatility do have meaningful explanatory power for the variations in different measures of real economic activity and is competitive with the other widely used measures of systemic risk.

6.2 Comovement, Stochastic Volatility and Real Economic Activity

Our findings from the LASSO exercise suggest that the estimated common NCO factor and stochastic volatilities of ROA and NCO survive the shrinkage for optimal value of regularization parameter for different measures of real economic activity. On the other hand, the coefficients on the industry averages are shrunk to zero in the LASSO model for real GDP growth, industrial production and unemployment rate change. The LASSO analysis, however, does not provide us information about quantitative estimate of the explanatory power of different variables. Therefore, it would be interesting to perform a direct comparison of these industry averages with the measures estimated from our approach. Importantly, the purpose of the exercise below is to provide a first-pass description of the dynamic relationships between our estimates of ROA and NCO common factors and real economic activity, rather than to establish causal links using alternative methods for isolating exogenous variation.[19] This type of an empirical investigation is outside the scope of the present paper but could provide an interesting avenue for future research.

Table 2 reports the regression results for the in-sample predictive relationship between banking variables and the four measures of real economic activity that we consider in our exercise. The results reported in Table 2 show how much variation in real economic activity measures can be explained by the past movements in banking variables. All the four measures of real economic activity are regressed on lagged values of common component, stochastic volatility and industry averages of ROA and NCO separately. The number of lags are chosen based on the BIC selection criteria.[20] The dependent variables are organized along the columns and regressors are organized

[19]There are two methods for identifying exogenous variation to study the transmission of shocks from the banking sector to the macro economy and vice versa. One is to impose structural, for instance dynamic stochastic general equilibrium, models; for a recent example, that studies the transmission of macroeconomic shocks on banking aggregates, see Christiano and Ikeda (2013), and for the opposite direction, see Chen and Zha (2016). Another approach is to impose minimal structural assumptions to isolate exogenous variation in the first stage and then study its effects in the second stage. Bleudorn et al (2017) use this technique to study the transmission of monetary shocks on bank lending and Bassett et al (2014) use it to study the effect of credit shocks on the macroeconomy.

[20]The reported coefficients are the sum of coefficients on all lags and reported p-values are the p-values of the test

along the rows. The Newey-West HAC p-values are in parentheses and R-squared values are in brackets. Note that we regress the dependent variable on each regressor separately. For expository purposes, we report the results in the same column. The first column shows that 30 percent of the variation in next quarter's GDP growth can be explained by lags of ROA common component (CF_ROA), whereas the corresponding R-squared for the industry average ROA (IA_ROA) is 21 percent and the lagged industry average ROA is significant at only 10 percent level. We find similar results for the lagged NCO common factor (CF_NCO) and industry average NCO (IA_NCO) as regressors. 16 percent of the variation in next quarter's GDP growth can be explained by using lagged CF_NCO, whereas the corresponding number is only 3 percent for IA_NCO. If lags of stochastic volatility of ROA are used as regressors, it can explain 34 percent of the variation in next quarter's real GDP growth, whereas the corresponding number is 31 percent for the SV_NCO.

The second column with the percentage change in index of industrial production as the dependent variable performs a similar exercise. The results presented in this column also show that both the ROA and the NCO common component significantly outperform the industry average ROA and NCO. In fact, the coefficients on lagged values of industry average ROA and NCO are insignificant. The stochastic volatility of ROA (SV_ROA) has the highest explanatory among all the explanatory variables listed in the table. The lags of SV_ROA itself explain 37 percent of the variation in next quarter's movement in the percentage change in IPI.

The other two measures of real economic activity are related to the state of the labor market. The third column reports the results for jobs growth (non-farm payroll employment growth). The results in this column are again consistent with the previous two measures of real economic activity. One interesting finding from this regression is that the common factor of NCO as well as the stochastic volatility of NCO have higher explanatory power for the next quarter's variation in jobs growth than the common factor and stochastic volatility of ROA. Stochastic volatility of NCO is estimated to explain 52 percent of the variation in next quarter's jobs growth. The results for change in unemployment rate as the dependent variable are presented in the last column. These results are consistent with the other measures of real economic activity where we find the industry averages of

of significance of the sum of coefficients for all lags. The maximum number of lags for all the regression equations is 4.

ROA and NCO are dominated by the measures developed in this paper. Among all the variables, SV_ROA has the highest explanatory power for next quarter's movement in unemployment rate changes with R-squared of 0.58.

The sign of the coefficients for all the models reported in Table 2 are intuitive. Increase in ROA across all the BHCs captured by an increase in common component may boost real economic activity through financial accelerator channel. Similar logic can be applied for the common component of NCO. We find that the ROA common factor is positively associated with next quarter's real economic activity, whereas this correlation is negative for NCO. We also find similar signs for industry averages though in quite a few specifications, the coefficients are insignificant. Similarly, one would expect an increase in sector wide volatility to have negative effect on real economic activity and positive effect on level of unemployment. Our results for stochastic volatility of ROA and NCO are consistent with this intuition.

To summarize, the results from a simple regression analysis suggest that the estimated common component and stochastic volatilities of ROA and NCO from our DFM-TV-SV model strongly dominates industry averages in explaining the movements in next quarter real economic activity. These results are consistent with the lasso model where the comovement and volatility measures obtained from our approach dominates the industry averages.

7 Relationship between Balance Sheet Variables and Idiosyncratic Factors

In the previous section, we showed that the estimated common component of both the NCO and ROA exhibit strong dynamic relationship with real economic activity measures. The next natural step is to examine the determinants of the BHC-specific factor. In particular, we investigate whether BHC-specific balance sheet variables can help explain the variations in the idiosyncratic component. To do so, we investigate whether balance sheet characteristics affect changes in NCO and ROA primarily through idiosyncratic factors or their effect on the common factor. We run panel Granger causality regressions of the form:

$$Y_{it} = \alpha_i + \sum_{p=1}^{P} \beta_p Y_{it-p} + \sum_{q=1}^{Q} \gamma_q X_{it} + e_{it}, \tag{9}$$

where Y_{it} is either NCO or ROA, the respective idiosyncratic factors ϵ_{it} in (6), or the contribution of idiosyncratic volatility to total volatility, $Var(\epsilon_{it})/Var(y_{it})$, in (3). The last two measures provide alternative ways to identify the effect of idiosyncratic factors: the factors themselves can identify the sign of the effect whereas the variance contributed by idiosyncratic component (VCI) (Figure 6) shows the relative variation in ROA and NCO that can be explained by the idiosyncratic factor. X_{it} are the balance sheet characteristics: asset growth, log assets, different loan type shares in the loan portfolio, a measure of loan quality (share of loans and leases in non-accrual status in total assets), and two measures of liquidity (ratio of brokered deposits to total assets and a ratio of liquid assets to total assets). If the sum of γ_q's is significant in the regression for NCO(ROA) and insignificant for idiosyncratic measures, i.e. X_{it} Granger-cause NCO(ROA) but not the two idiosyncratic measures, then balance sheet characteristics primarily affect NCO(ROA) through the common factor. Conversely, if X_{it} Granger-cause the idiosyncratic measures but not NCO(ROA), then they affect the departures of individuals BHCs from the common factor but have no systematic relationship with it. If X_{it} Granger-causes both NCO(ROA) and idiosyncratic measures, balance sheet characteristics are important for both departures from the common factor and its evolution. Finally, if X_{it} do not Granger-cause any of the three types of measures, then balance sheet characteristics are unimportant for either the common factor or BHCs departures therefrom. The total number of lags P and Q is selected by the Schwarz criterion with the maximum set to 8 for both. Below, we present three statistics for each regression: the p-value for the null hypothesis of Granger-noncausality that all γ_q's are zero; the sum of these coefficients to determine the sign of the cumulative effect of a balance sheet variable on the outcome variable, and the p-value associated with the null that this cumulative effect is zero.

Table 3 presents the results of our Granger-causality regressions for NCO and related idiosyncratic measures. All variables Granger-cause NCO at the 1% level of significance except C&I loans and Tier 1 Leverage. The signs of the estimated coefficients are also intuitive: NCO decreases with asset growth (which primarily happens during expansions), credit card loan share, and liquidity (higher brokered deposit share signals lower liquidity, whereas higher liquid asset share the opposite); it increases with size, as well as CRE loan share and the share of loans in non-accrual status that signal portfolio risk. For idiosyncratic factors, asset growth, log assets, C&I loan share, bad loan share, and Tier 1 leverage remain significant, suggesting that the other balance sheet characteristics primarily operate through the common factor and its link with the business cycle fluctuations. For VCI, only C&I loan share is insignificant with a strong effect coming from size (increasing idiosyncratic volatility) and the strongest from capital (decreasing idiosyncratic volatility).

Table 4 displays analogous results for ROA and related idiosyncratic measures. Asset growth and C&I loan shares are insignificant for ROA, whereas the other balance sheet variables are significant at the 1% level. Importantly, size and CRE loan share reduce profitability whereas liquidity improves it. Although several of the balance sheet characteristics Granger-cause median idiosyncratic factors, their cumulative impact appears to be small. However, size, CRE loan share, and bad loans appear to reduce volatility contributions of idiosyncratic factors whereas liquidity increases it. In sum, these findings suggest that balance sheet characteristics are an important determinant of the idiosyncratic contributions to the evolution of NCO and ROA.

8 Conclusion

In this paper, we have proposed applying a dynamic factor model with time-varying factor loadings and stochastic volatility to decompose panels of income statement variables for the U.S. bank holding companies (BHC) into a common factor and BHC-specific idiosyncratic factor. This method allows us to estimate the time-variation in the degree of comovement in ROA and NCO of BHCs and can be used to measure the extent of the interconnectedness in the banking sector. The estimated common component for both ROA and NCO from this approach is forward looking in nature and started showing stress much before the Lehman collapse. Even though this procedure is entirely agnostic of the possible effect of the macroeconomic variables on the banking variables of interest, we do find that the estimated common factor and stochastic volatility for the BHC ROA and NCO is highly predictive of the real macroeconomic activity and have coefficients in the directions consistent with the standard economic intuition. We also compare the measures derived from our approach with wide class of systemic risk measures using the LASSO approach and find that they either meet or beat the explanatory power of different measures systemic risk. Furthermore, we find that the variation in the idiosyncratic component is closely correlated with several balance sheet characteristics.

The results obtained in our paper have significant policy implications. We confirm the recent findings in the literature regarding interconnectedness of the banking system and the hypothesis that the comovement among the BHCs tend to increase during the crisis periods. Our findings also have some implications for the testing the exposure of each BHC to the common shock in the banking system. Comovement captured by the common factors and uncertainty captured by stochastic volatility appear to capture systemic risk better than some of the recently proposed alternatives and have a stronger effect on real activity than simple, industry-wide average measures.

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A Graphs and Tables

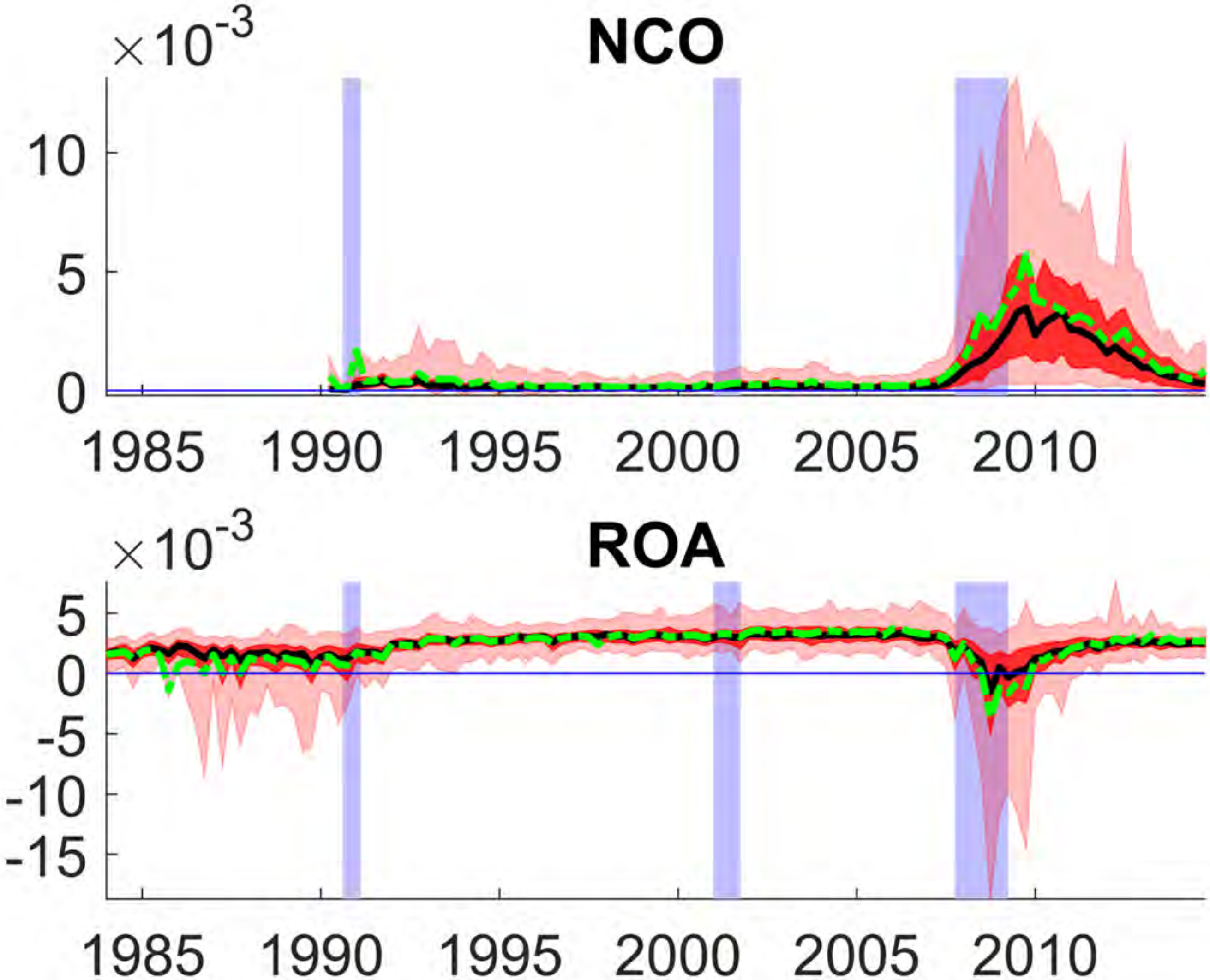

Figure 1: Evolution of the distribution of dependent variables: Pale red shade—5th to 95th percentiles; dark red shade—interquartile range; black solid line—median; dashed green line—mean. NBER-defined recessions in blue-shaded boxes.

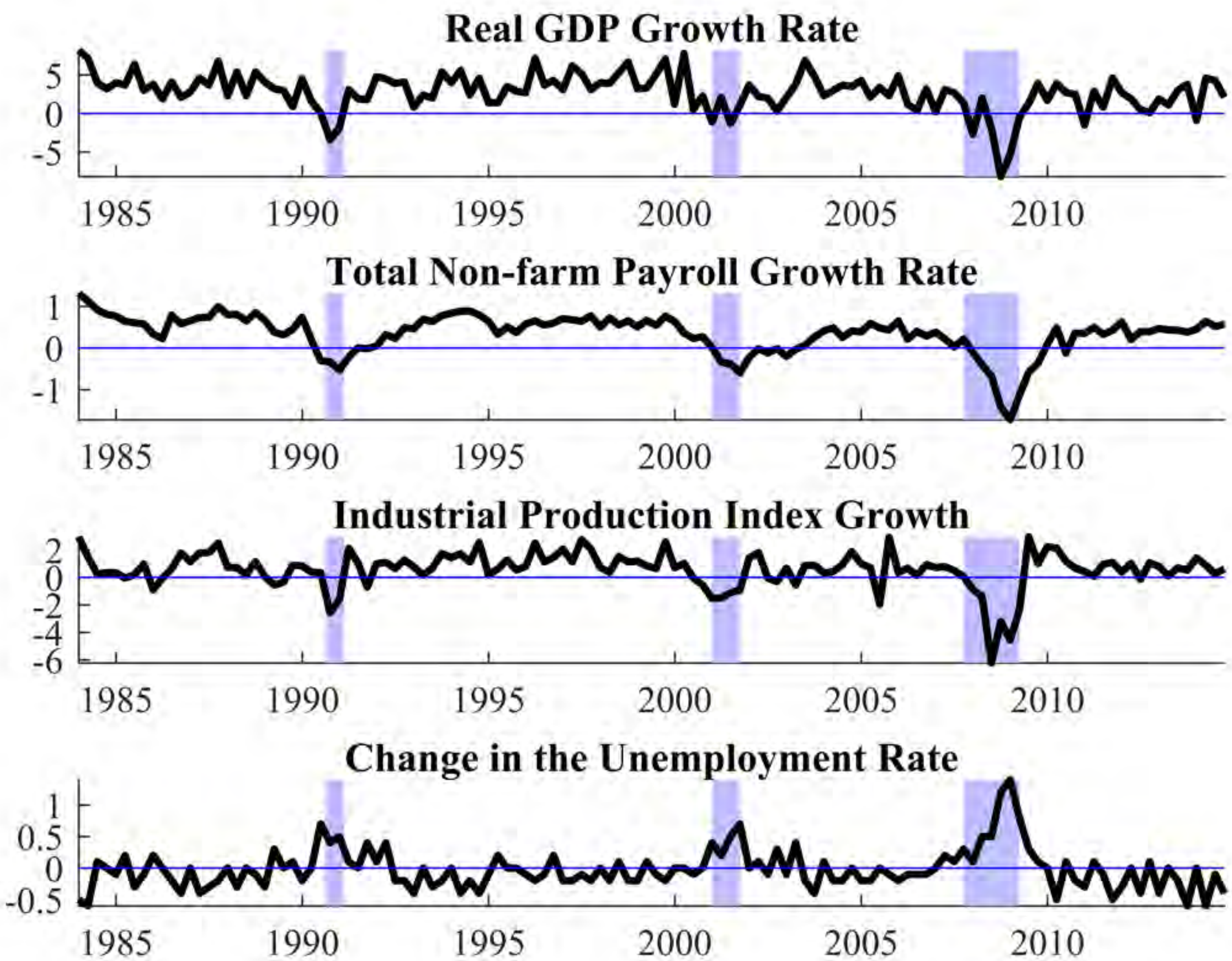

Figure 2: Measures of real activity. NBER-defined recessions in blue-shaded boxes.

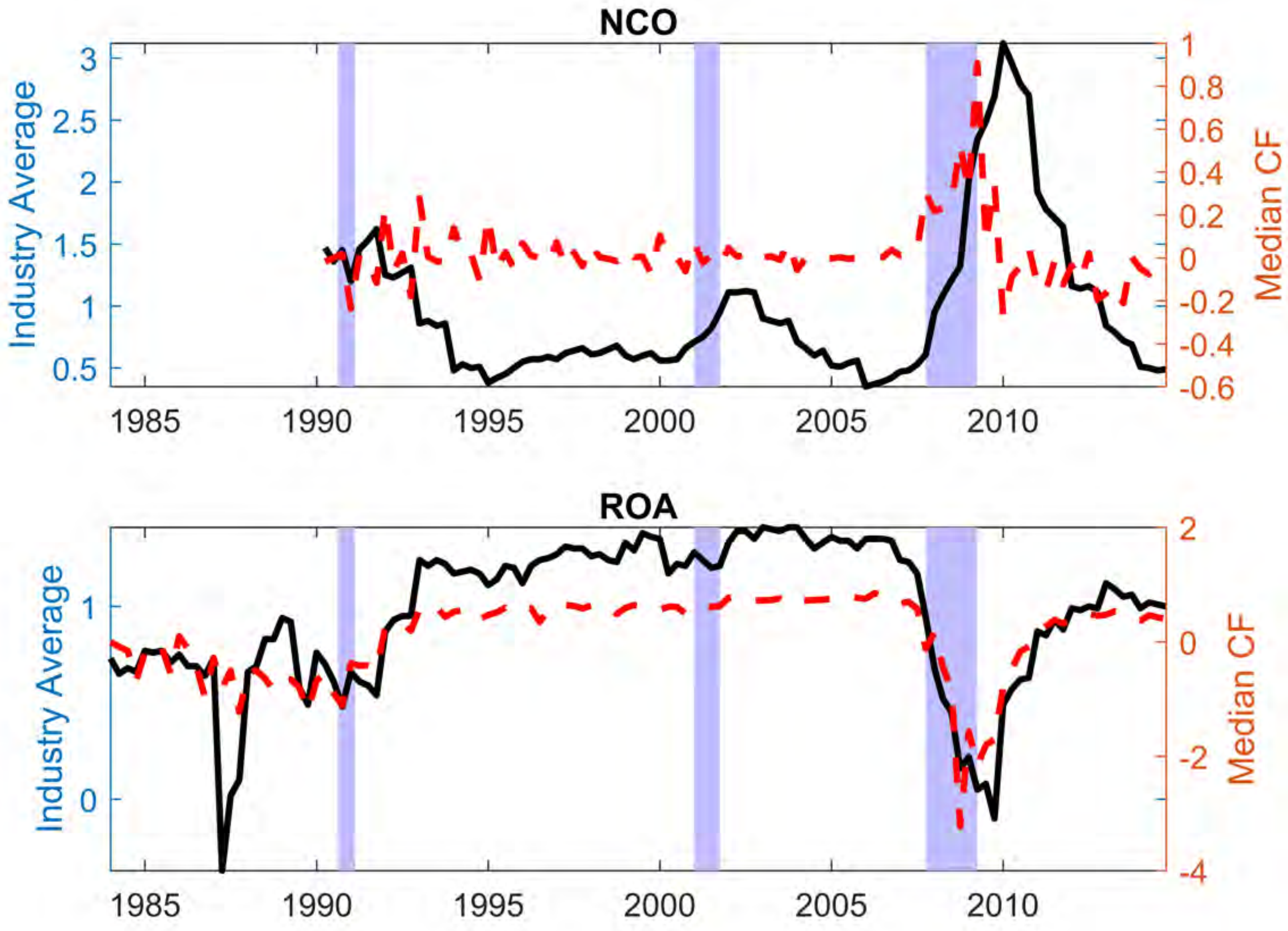

Figure 3: Industry averages for ROA and NCO (left scale, black solid line) vs respective common factors (right scale, red dashed line). NBER-defined recessions in blue-shaded boxes.

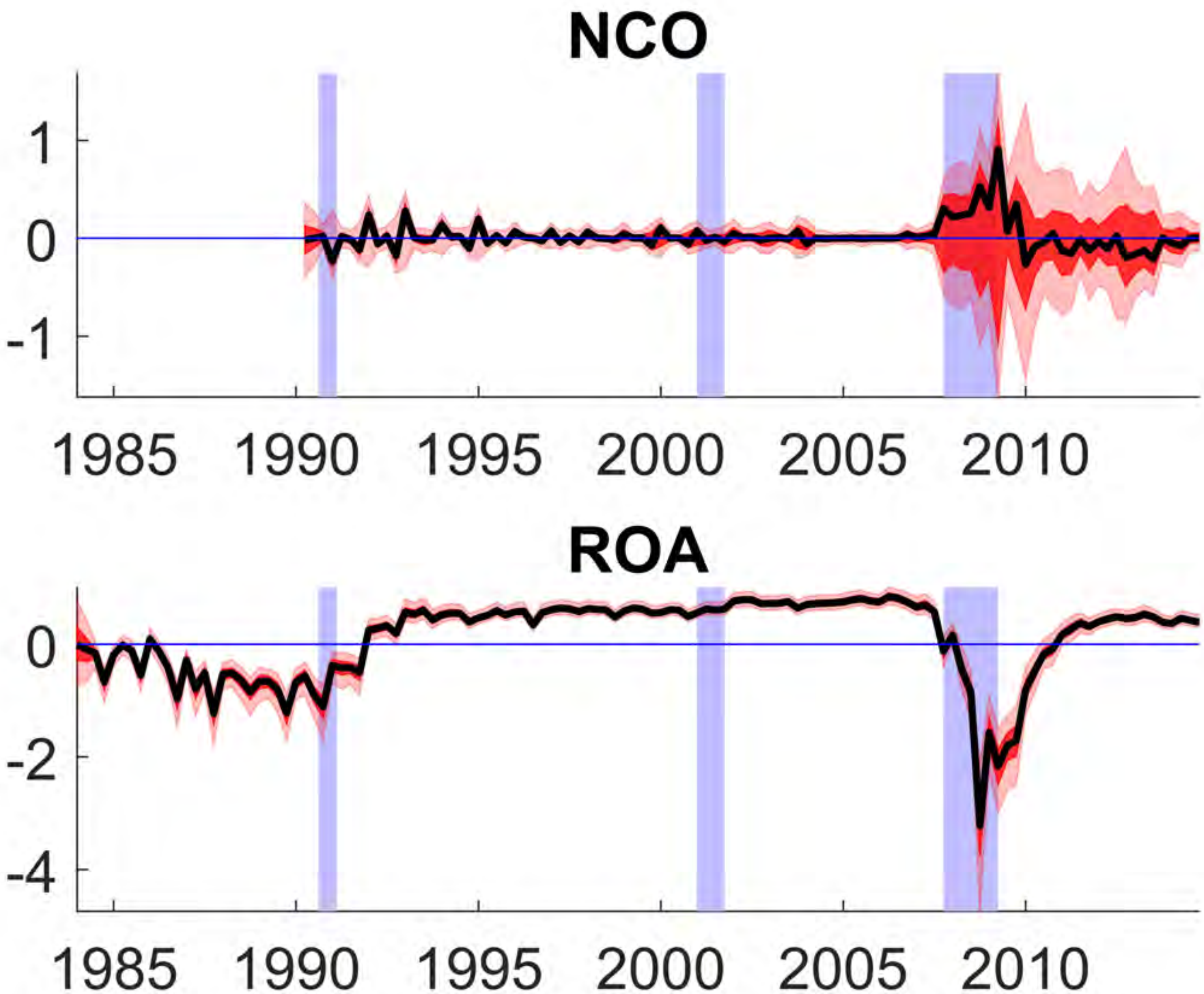

Figure 4: Estimated common factors: Pale red shade—5th to 95th percentiles; dark red shade—interquartile range; black line—median. NBER-defined recessions in blue-shaded boxes. .

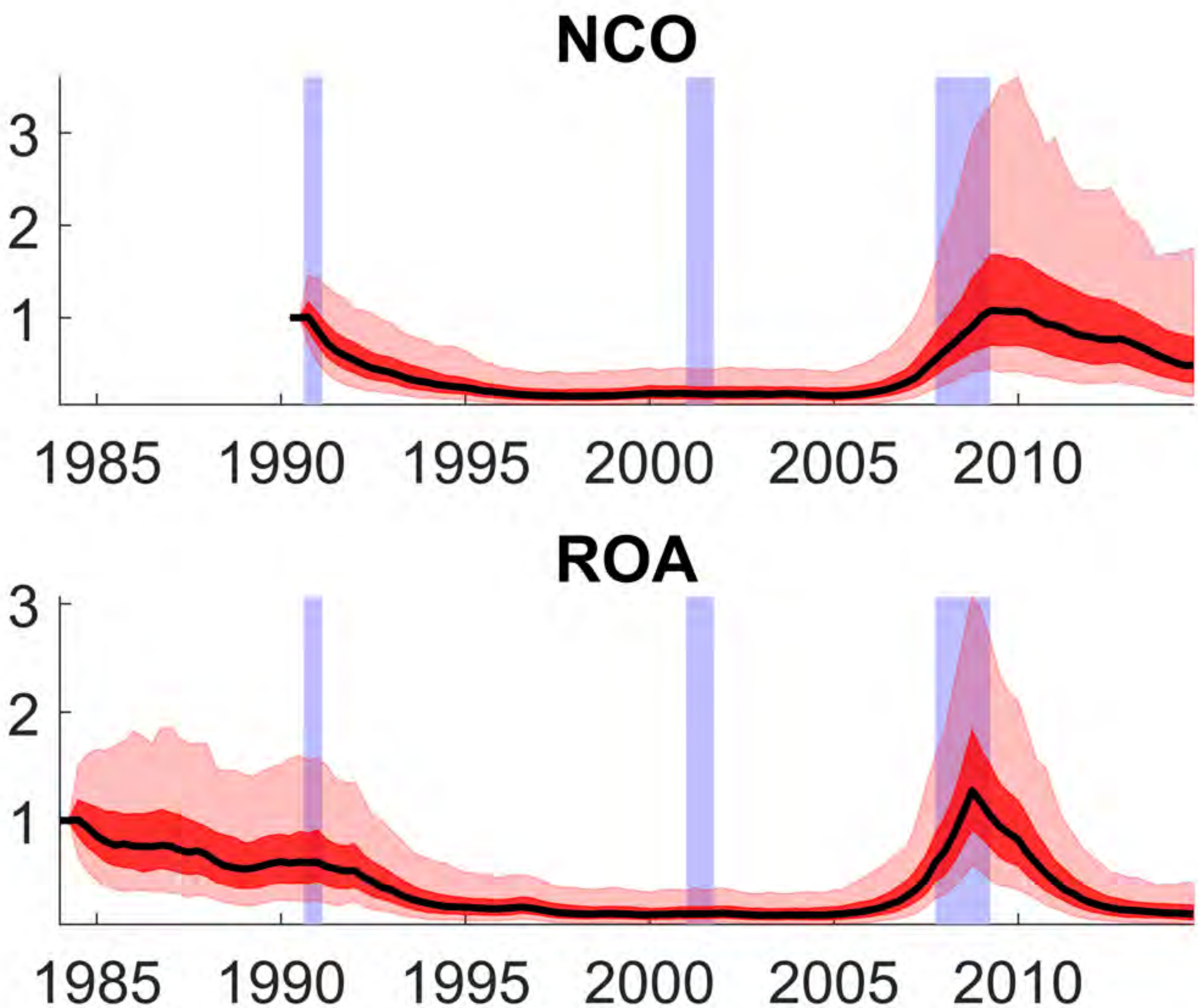

Figure 5: Estimated stochastic volatility of the common factors: Pale red shade—5th to 95th percentiles; dark interval—interquartile range; black line—median. NBER-defined recessions in blue-shaded boxes.

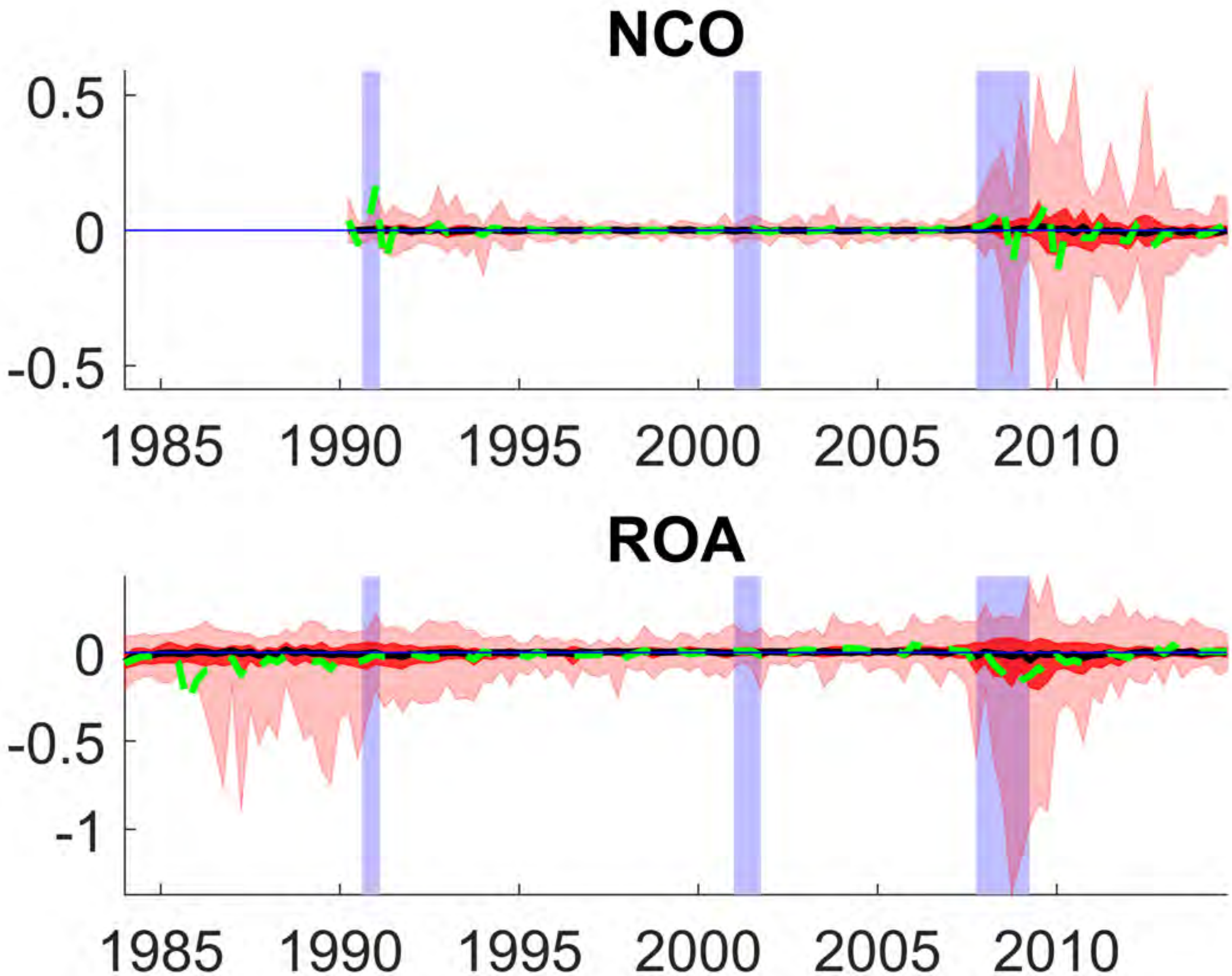

Figure 6: Estimated idiosyncratic factor distributions: Pale red shade—5th to 95th percentiles; bright red shade—interquartile range; black solid line—median; dashed green line—mean. NBER-defined recessions in blue-shaded boxes.

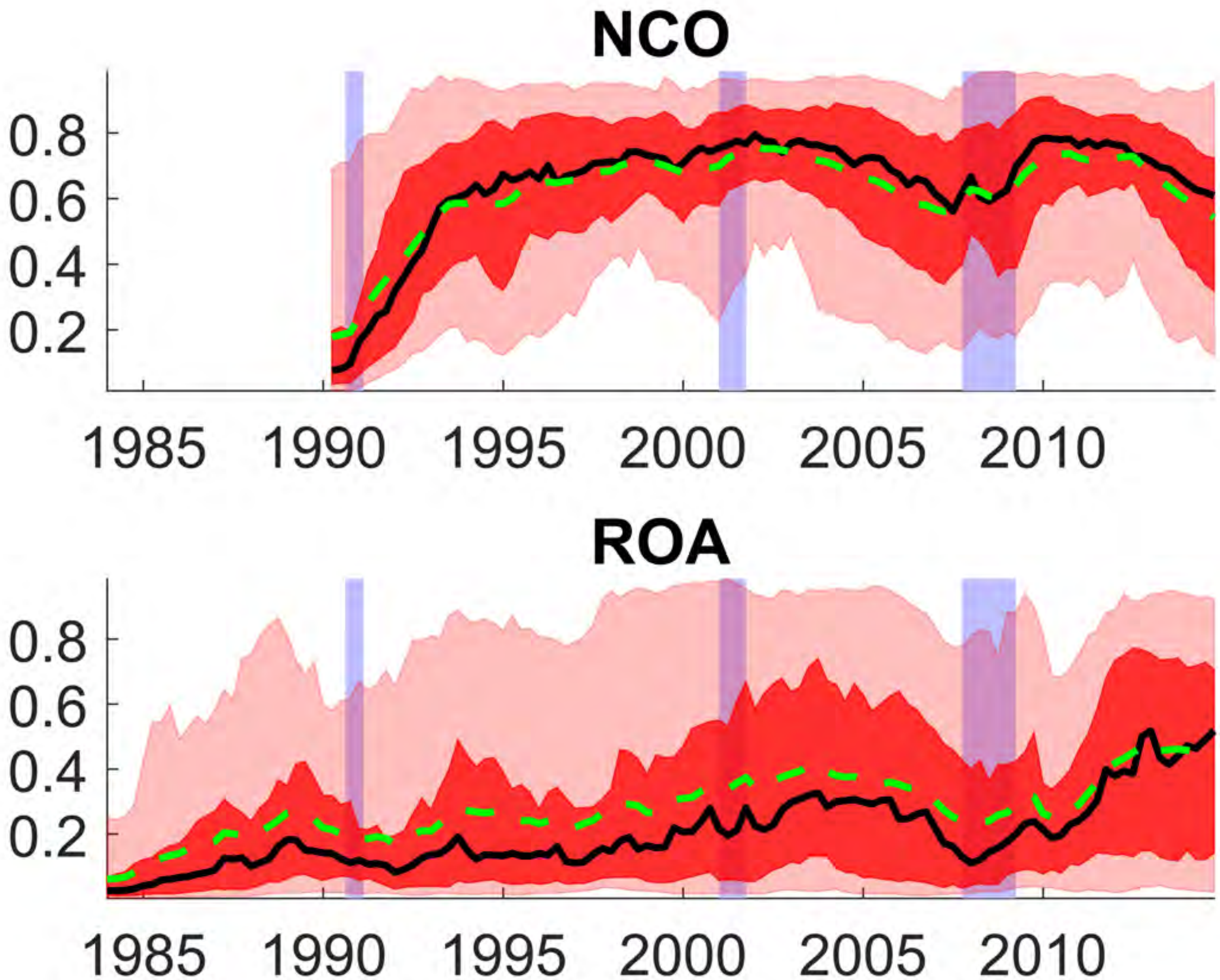

Figure 7: (Total) Variance Contribution of Idiosyncratic Factors (VCI): Pale red shade—5th to 95th percentiles; dark red shade—interquartile range; black line—median. NBER-defined recessions in blue-shaded boxes.

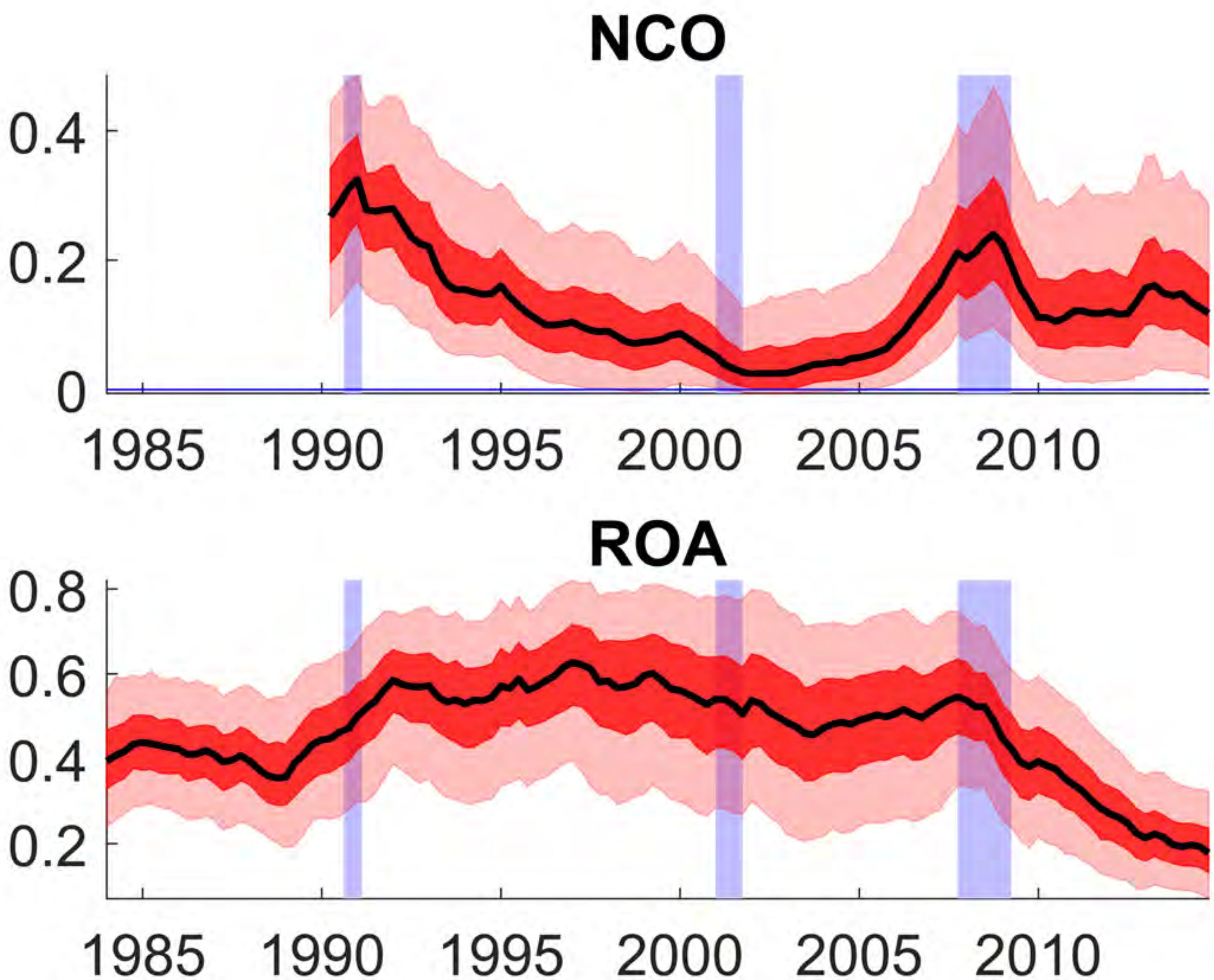

Figure 8: Estimated average cross-BHC correlations of idiosyncratic factors: Pale red shade—5th to 95th percentiles; dark red shade—interquartile range; black line—median. NBER-defined recessions in blue-shaded boxes.

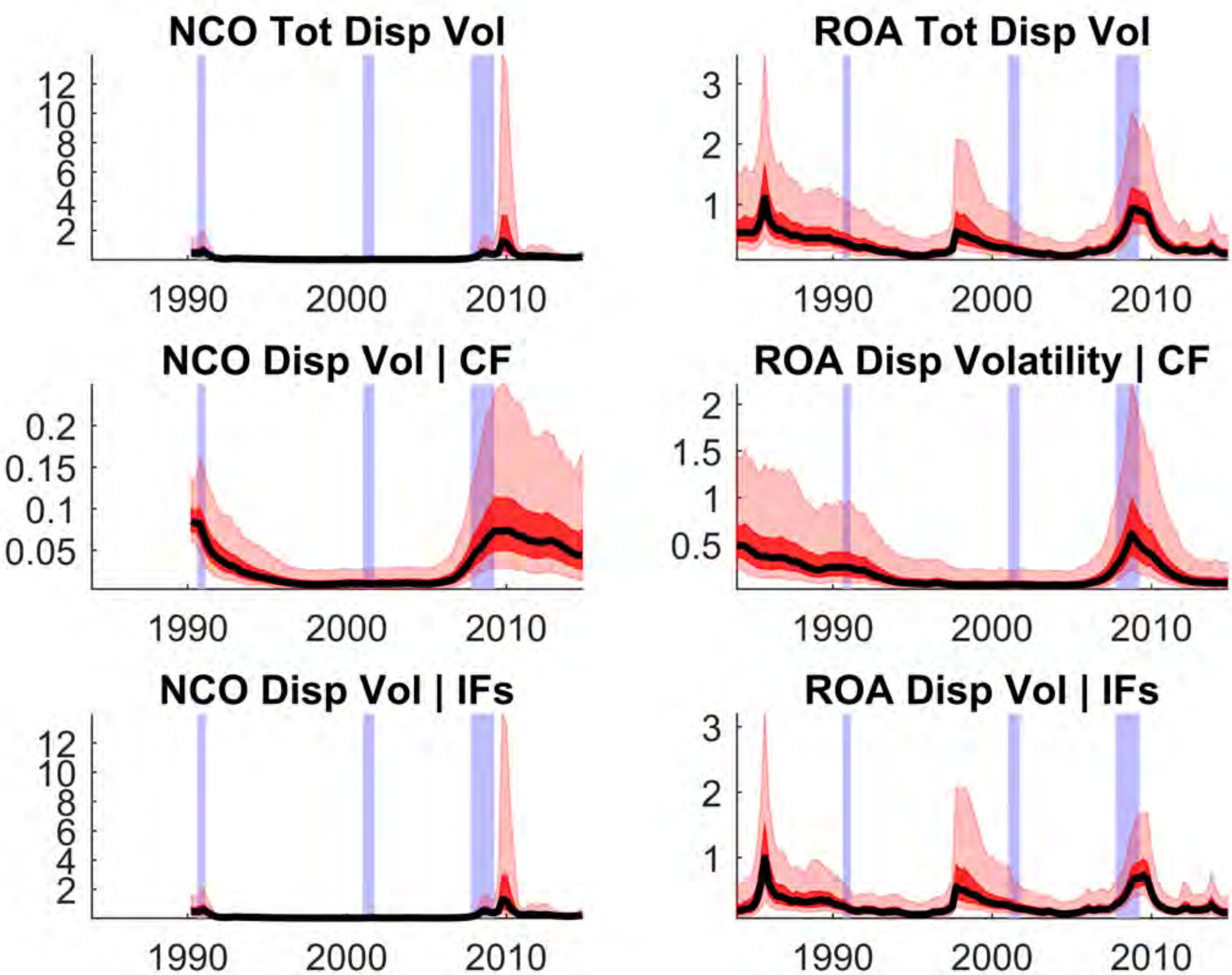

Figure 9: Dispersion Decomposition: Left column—NCO; right column—ROA; light interval—5th to 95th percentiles; dark interval—interquartile range; black line—median. NBER-defined recessions in blue-shaded boxes.

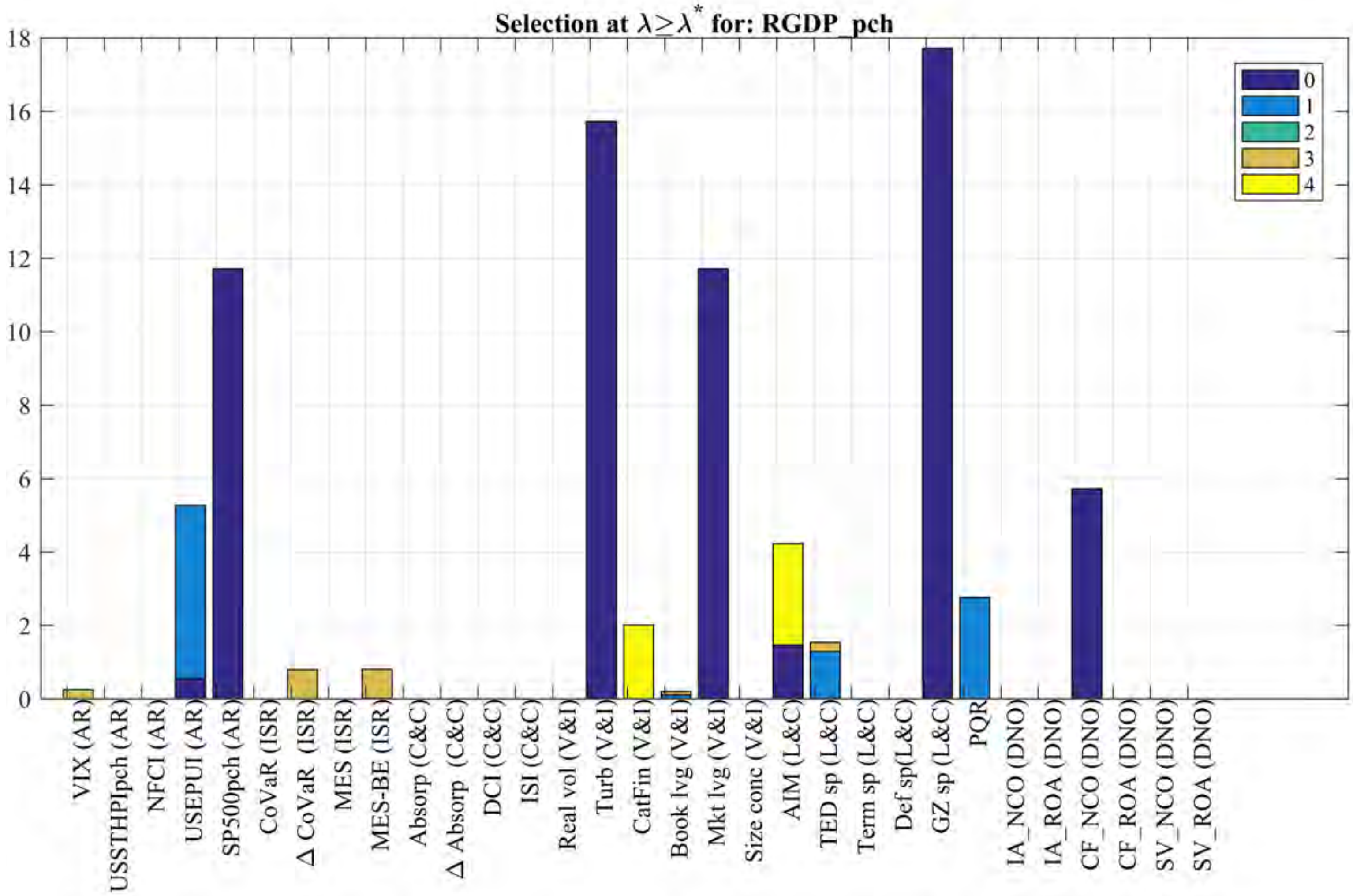

Figure 10: LASSO results for real GDP growth: Selected lag order from 0 to 4 in the legend.

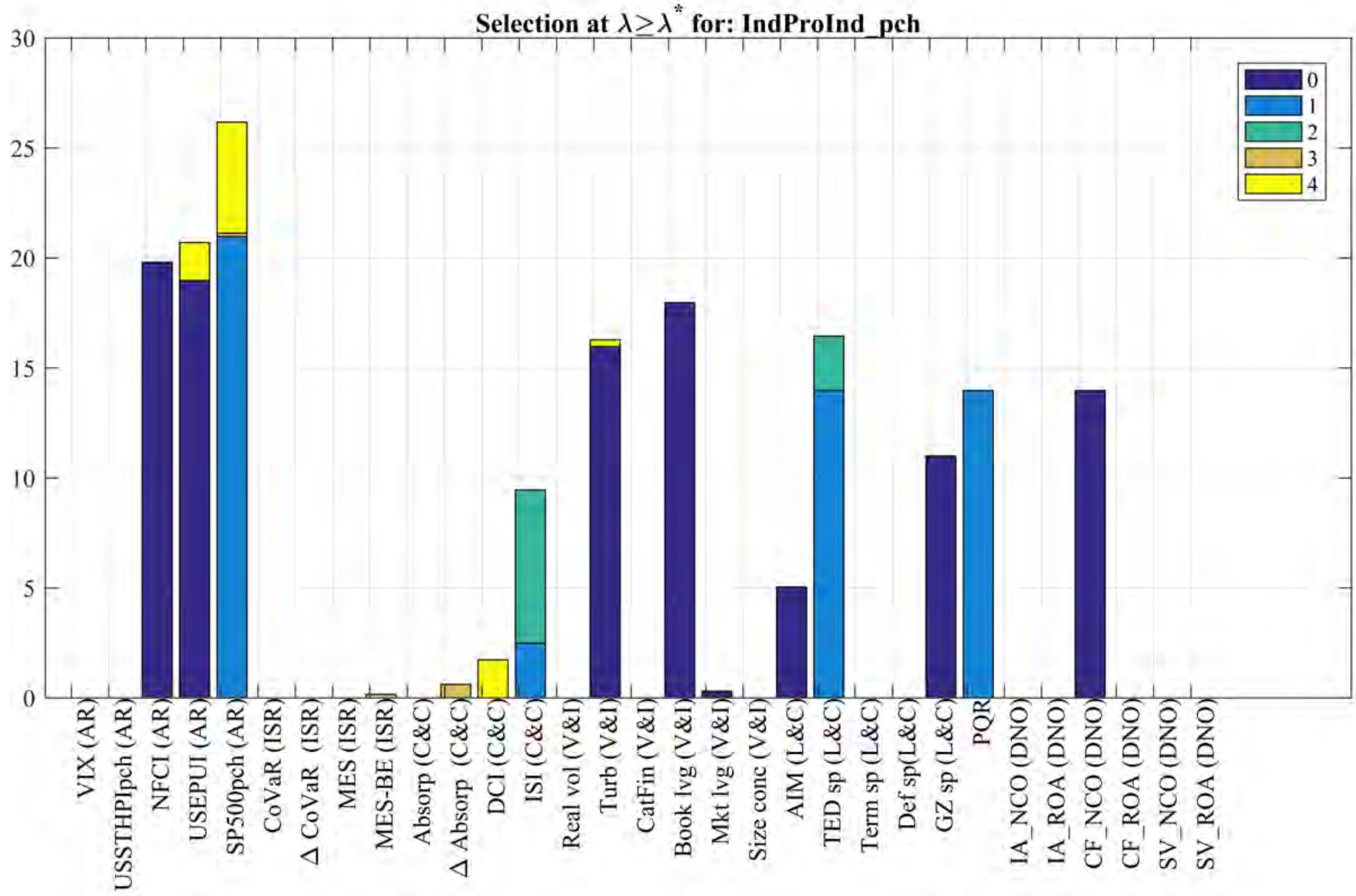

Figure 11: LASSO results for industrial production index: Selected lag order from 0 to 4 in the legend.

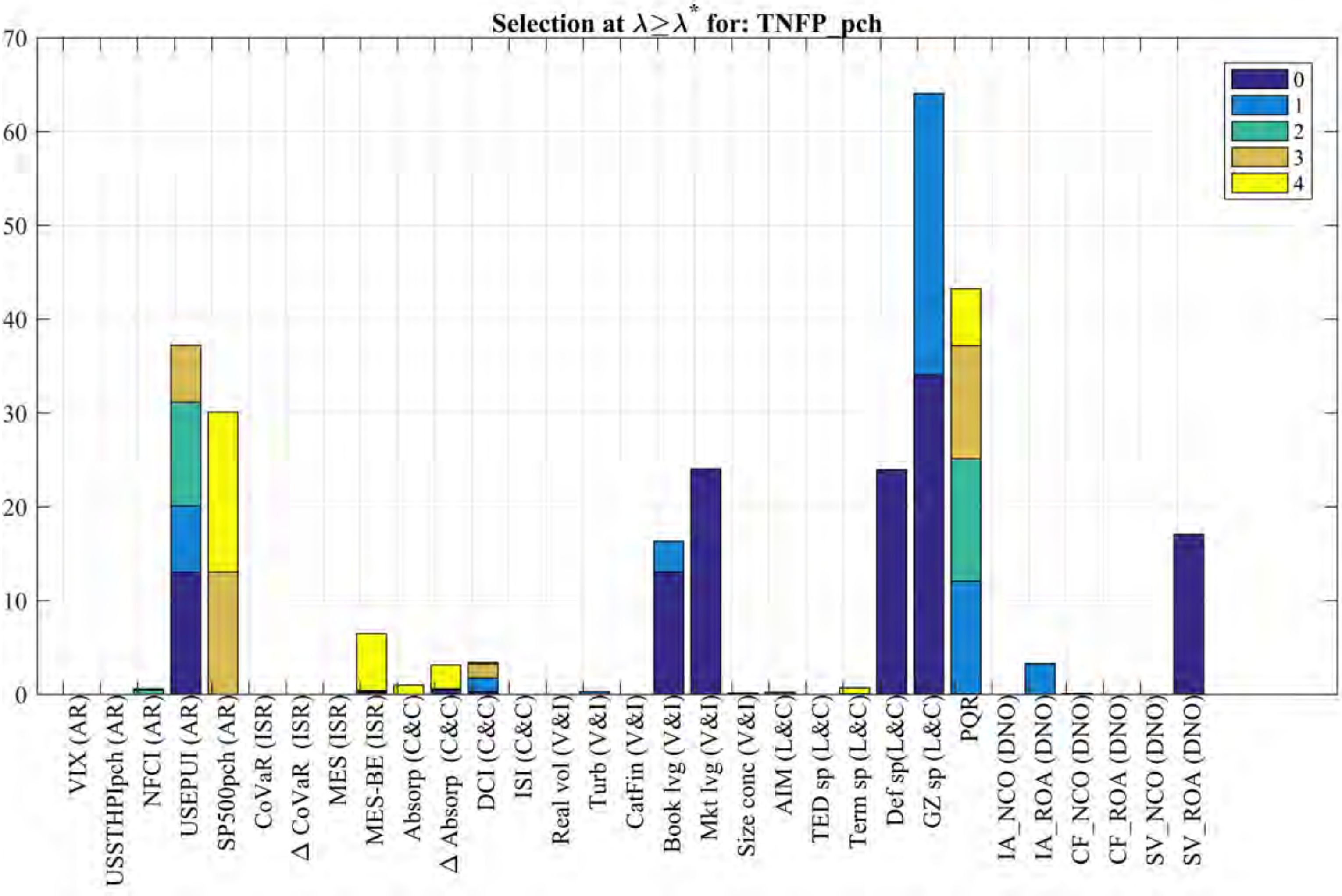

Figure 12: LASSO results for total non-farm payroll growth: Selected lag order from 0 to 4 in the legend.

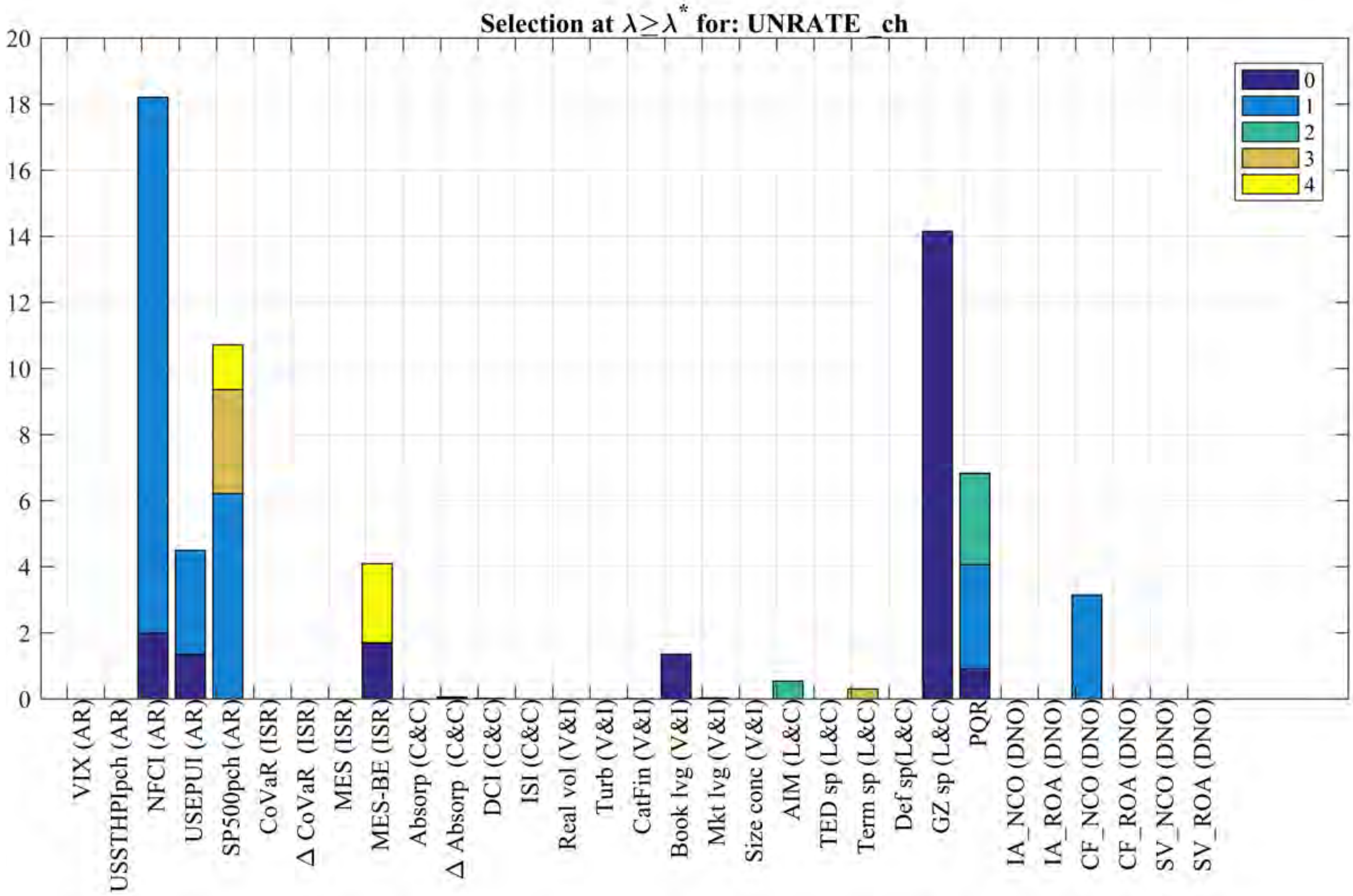

Figure 13: LASSO results for unemployment rate: Selected lag order from 0 to 4 in the legend.

Table 1: Descriptive Statistics

Variable	Mean	Median	Min	Max	St Dev
Return on Assets (ROA)	0.002	0.003	-0.176	0.032	0.004
ROA Common Factor	0.118	0.443	-3.229	0.839	0.710
ROA Median Idiosyncratic Factors	-0.024	0.000	-17.721	2.994	0.315
Variance Contribution of ROA IFs	0.281	0.170	0.001	0.999	0.279
Net Charge-offs (NCO)	0.001	0.000	-0.002	0.116	0.003
NCO Common Factor	0.011	-0.002	-0.285	0.903	0.154
NCO Median Idiosyncratic Factors	-0.001	-0.000	-11.389	9.919	0.154
Variance Contribution of NCO IFs	0.625	0.677	0.009	1.000	0.253
Asset growth	9.795	9.433	2.099	14.609	1.601
log Asset (log $ mln)	0.000	0.000	-0.036	0.037	0.001
CRE Loan Share	0.268	0.242	0.000	0.886	0.150
Cred Card Loan Share	0.047	0.008	0.000	0.999	0.149
C and I Loan Share	0.200	0.186	0.000	0.871	0.122
Non-accrual LL to TA	0.008	0.005	0.000	0.151	0.009
Brokered Dep to TA	0.027	0.007	0.000	0.761	0.067
Liquid Assets to TA	0.263	0.251	0.000	0.858	0.110
Tier 1 Leverage	0.082	0.079	0.033	0.796	0.025
Change in Unemployment	0.678	0.741	-2.113	1.987	0.614
Real GDP Growth	-0.018	-0.100	-0.600	1.400	0.314
Industry Average ROA	0.968	1.055	-0.370	1.410	0.374
Industry Average NCO	0.974	0.805	0.350	3.120	0.594

Table 2: Explaining Real Economic Activity

Regressors	Real GDP Growth	IPI Growth	Jobs growth	Unemployment Change
CF_ROA	1.13 (0.00) [0.30]	0.23 (0.00) [0.35]	0.19 (0.35) [0.24]	-0.20 (0.00) [0.53]
IA_ROA	2.58 (0.07) [0.21]	0.54 (0.42) [0.03]	0.32 (0.39) [0.06]	-0.31 (0.00) [0.36]
CF_NCO	-6.33 (0.00) [0.16]	-2.93 (0.00) [0.12]	-2.67 (0.00) [0.45]	1.47 (0.00) [0.37]
IA_NCO	-0.71 (0.24) [0.03]	-0.04 (0.87) [0.01]	-0.15 (0.14) [0.36]	0.01 (0.99) [0.31]
SV_ROA	-4.19 (0.00) [0.34]	-1.13 (0.00) [0.43]	-0.45 (0.25) [0.45]	0.59 (0.00) [0.58]
SV_NCO	-3.33 (0.00) [0.31]	-1.12 (0.00) [0.29]	-0.47 (0.05) [0.52]	0.23 (0.16) [0.27]

Note: Newey–West P-values are in parentheses. R-squared values are in brackets. CF_ROA, CF_NCO, SV_ROA, SV_NCO are estimated common factors and stochastic volatility of common factors of ROA and NCO from our approach. IA_ variables are industry averages. Lagged values of regressors are used as explanatory variables. Results in each row represent a different regression model, i.e., the first row and the first column represents the results for regression of real GDP growth on lagged CF_ROA. Number of lags are chosen based on BIC. Sample period is 1990Q2-2015Q1

Table 3: Granger Causality and Sum-of-coefficients Results

	NCO			NCO Median Idiosyn Factors			NCO VCI		
	GC p-value	SoC Estimate	SoC p-value	GC p-value	SoC Estimate	SoC p-value	GC p-value	SoC Estimate	SoC p-value
Asset growth	0.01	-0.03	0.00	0.05	0.01	0.05	0.12	0.02	0.11
log Asset	0.02	0.24	0.00	0.01	0.08	0.00	0.00	0.86	0.00
CRE Loan Share	0.00	0.09	0.00	0.29	0.01	0.21	0.00	0.04	0.02
Cred Card Loan Share	0.00	-0.05	0.00	0.30	0.01	0.18	0.04	-0.05	0.01
C and I Loan Share	0.83	0.00	0.81	0.07	0.01	0.05	0.58	-0.01	0.54
Non-accrual LL to TA	0.00	0.24	0.00	0.00	0.02	0.00	0.00	-0.07	0.00
Brokered Dep to TA	0.00	0.07	0.00	0.75	0.00	0.73	0.00	0.05	0.00
Liquid Assets to TA	0.00	-0.08	0.00	0.82	-0.00	0.80	0.03	-0.04	0.01
Tier 1 Leverage	0.46	0.89	0.00	0.01	-0.96	0.00	0.00	-8.33	0.00

Table 4: Granger Causality and Sum-of-coefficients Results

	ROA			ROA Median Idiosyn Factors			ROA VCI		
	GC p-value	SoC Estimate	SoC p-value	GC p-value	SoC Estimate	SoC p-value	GC p-value	SoC Estimate	SoC p-value
Asset growth	0.51	0.01	0.50	0.48	0.00	0.47	0.02	0.04	0.02
log Asset	0.00	-0.39	0.00	0.04	-0.07	0.00	0.00	-0.48	0.00
CRE Loan Share	0.00	-0.13	0.00	0.05	-0.01	0.01	0.00	-0.12	0.00
Cred Card Loan Share	0.00	0.09	0.00	0.58	-0.00	0.43	0.00	0.08	0.00
C and I Loan Share	0.67	0.01	0.61	0.20	0.01	0.13	0.15	0.03	0.09
Non-accrual LL to TA	0.00	-0.11	0.00	0.00	0.01	0.00	0.00	-0.16	0.00
Brokered Dep to TA	0.00	-0.09	0.00	0.56	0.00	0.51	0.00	-0.08	0.00
Liquid Assets to TA	0.00	0.11	0.00	0.85	0.00	0.81	0.00	0.09	0.00
Tier 1 Leverage	0.00	0.00	0.97	0.00	0.02	0.00	0.00	0.01	0.74

Table A.1: List of BHC Companies in the Sample

Top Holder RSSDID No.	Top Holding Co. Name	Top Holder State Code	NCO Drop
1025309	BANK OF HAWAII CORPORATION	HI	
1027004	ZIONS BANCORPORATION	UT	
1031449	SVB FINANCIAL GROUP	CA	X
1037003	M&T BANK CORPORATION	NY	
1039502	JPMORGAN CHASE & CO.	NY	
1048773	VALLEY NATIONAL BANCORP	NJ	
1049341	COMMERCE BANCSHARES, INC.	MO	
1049828	UMB FINANCIAL CORPORATION	MO	
1060627	FIRSTBANK HOLDING COMPANY	CO	
1066209	LAURITZEN CORPORATION	NE	
1068025	KEYCORP	OH	
1068191	HUNTINGTON BANCSHARES INC	OH	
1069778	PNC FINANCIAL SERVICES GROUP, INC	PA	
1070345	FIFTH THIRD BANCORP	OH	
1070804	FIRSTMERIT CORPORATION	OH	
1071276	FIRST FINANCIAL BANCORP	OH	
1073757	BANK OF AMERICA CORPORATION	NC	
1074156	BB&T CORPORATION	NC	
1075612	FIRST CITIZENS BANCSHARES, INC.	NC	
1076217	UNITED BANKSHARES, INC.	WV	
1078846	SYNOVUS FINANCIAL CORP.	GA	
1079562	TRUSTMARK CORPORATION	MS	
1086533	HANCOCK HOLDING COMPANY	MS	
1090987	MB FINANCIAL, INC.	IL	
1094314	CENTRAL BANCOMPANY, INC	MO	
1094640	FIRST HORIZON NATIONAL CORP	TN	
1095674	ARVEST BANK GROUP, INC.	AR	
1097089	BANK OF THE OZARKS INC	AR	
1097614	BANCORPSOUTH, INC.	MS	
1098303	OLD NATIONAL BANCORP	IN	
1102367	CULLEN/FROST BANKERS, INC.	TX	
1104231	INTERNATIONAL BANCSHARES CORP	TX	
1109599	PROSPERITY BANCSHARES, INC.	TX	
1111435	STATE STREET CORPORATION	MA	X
1117026	NATIONAL PENN BANCSHARES, INC.	PA	
1117129	FULTON FINANCIAL CORPORATION	PA	
1118797	FIRST BANKS, INC.	MO	
1119794	U.S. BANCORP	MN	
1120754	WELLS FARGO & COMPANY	CA	
1121340	OTTO BREMER TRUST	MN	
1131787	SUNTRUST BANKS, INC.	GA	
1132449	CITIZENS FINANCIAL GROUP, INC.	RI	
1133437	SOUTH STATE CORPORATION	SC	
1145476	WEBSTER FINANCIAL CORPORATION	CT	
1199563	ASSOCIATED BANC-CORP	WI	
1199611	NORTHERN TRUST CORPORATION	IL	
1199844	COMERICA INCORPORATED	TX	
1208184	FIRST MIDWEST BANCORP, INC.	IL	
1249347	UNITED COMMUNITY BANKS, INC.	GA	
1275216	AMERICAN EXPRESS COMPANY	NY	X
1562859	ALLY FINANCIAL INC.	MI	
1839319	PRIVATEBANCORP, INC.	IL	X
1843080	CATHAY GENERAL BANCORP	CA	X
1883693	BOK FINANCIAL CORPORATION	OK	
1951350	CITIGROUP INC.	NY	
2126977	BANNER CORPORATION	WA	
2132932	NEW YORK COMMUNITY BANCORP, INC.	NY	
2260406	WINTRUST FINANCIAL CORPORATION	IL	
2277860	CAPITAL ONE FINANCIAL CORPORATION	VA	
2291914	IBERIABANK CORPORATION	LA	
2349815	WESTERN ALLIANCE BANCORP	AZ	
2389941	TCF FINANCIAL CORP	MN	
2477754	INVESTORS BANCORP, INC.	NJ	
2706735	TEXAS CAPITAL BANCSHARES, INC.	TX	X
2734233	EAST WEST BANCORP, INC.	CA	
2747644	UMPQUA HOLDINGS CORPORATION	OR	
3005332	N.B. CORPORATION	PA	
3083291	STERLING BANCORP	NY	
3212091	NEW YORK PRIVATE BANK & TRUST CORP	NY	
3242838	REGIONS FINANCIAL CORP	AL	
3587146	BANK OF NEW YORK MELLON CORP	NY	
3650152	PEOPLE'S UNITED FINANCIAL, INC.	CT	
3838811	DIAMOND A FINANCIAL, LP	TX	
3846375	DISCOVER FINANCIAL SERVICES	IL	X