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Financial Variables and Macroeconomic Forecast Errors

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Abstract: A large set of financial variables has only limited power to predict a latent factor common to the year-ahead forecast errors for real Gross Domestic Product (GDP) growth, the unemployment rate, and Consumer Price Index (CPI) inflation for three sets of professional forecasters: the Federal Reserve's Greenbook, the Survey of Professional Forecasters (SPF), and the Blue Chip Consensus Forecasts. Even when a financial variable appears to be fairly robust across sample periods in explaining the latent factor, from an economic standpoint its contribution appears modest. Still, several financial variables retain economic significance over certain subsamples; when non-linear effects are accounted for, these variables have an improved ability to consistently predict the latent factor over the business cycle.

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1 Introduction

Since the financial crisis of 2007-2009, a large amount of work has been devoted to the measurement and predictive power for macroeconomic activity of financial variables meant to capture different aspects of the macro-financial landscape, such as financial stability and credit availability (see among others, Brave and Butters 2012; Giglio, Kelly, and Pruitt 2016). This paper provides a related but somewhat different assessment of the nexus between finance and the macroeconomy by examining how a large battery of financial variables fares when used as predictors of macroeconomic forecast errors. In principle at least, if we were to find a single measure or class of measures that could robustly predict forecast errors, this could then inform researchers' and policymakers' resource allocation for developing financial indicators and macroeconomic models that capture the "missing" financial linkages important for macro forecasting.

To conduct this exercise, we first estimate a common latent factor that jointly captures the year-ahead forecast errors for real GDP growth, the unemployment rate, and CPI inflation for a panel of three forecasters: the Greenbook, the Survey of Professional Forecasters (SPF), and the Blue Chip Consensus Forecasts (hereafter, Blue Chip). If something is missing from the macro forecasting models, then it should affect the main macro variables of interest, and the missing factor should be missing from a variety of professional forecasters' forecasts. This paper shows that this missing or latent factor closely resembles the year-ahead unemployment rate forecast error for the SPF, and that its procyclical pattern implies that forecasters tend to underestimate the strength of expansions and depth of contractions.

Next we evaluate a battery of financial variables for their ability to forecast the missing factor, controlling for real- and price-side (non-financial) economic developments that could also affect the forecast error. Finding financial variables that robustly predict macroeconomic forecast errors across different samples can be challenging, as Stock and Watson (2003) showed in evaluating the predictive power of financial variables for economic activity. As this paper demonstrates, it is particularly challenging when controlling for a large set of other real- and price-side macro variables; even more so when the test is further strengthened by allowing for potential bias and inefficiency in the forecasts.

While many financial variables, most notably the Gilchrist and Zakrajšek (2012) excess bond premium (EBP), can be shown to be robust predictors of this missing factor across different samples of the data, none are found to be especially significant from an economic standpoint. Many of the variables have some statistical and economic significance some of the time, but not all of the time. Different types of variables may matter more at different points in time, either due to their particular roles in the macroeconomy at the time (such as expected real return on equity or mortgage credit) or due to the phase of the business cycle (such as credit spreads or non-financial leverage). Giglio, Kelly, and Pruitt (2016) show that their systemic risk variables, which are also considered in this paper's analysis, have little predictive power for median outcomes of future economic activity, but they do have predictive power for outcomes in the lowest quartile range.

To this end, we consider whether the relationship between the missing factor and the financial variable of interest is asymmetric over the business cycle, and benchmark its predictive power against that of the linear model using the EBP. The latter is shown to be the most robust predictor of this missing factor, and for this variable the linear null cannot be rejected against a threshold alternative.[1] This exercise shows that a broad set of variables, including variables capturing banks' nonperforming loans and the FDIC's problem banks, outperform the benchmark linear specification with the excess bond premium. Still, the importance of some of these variables for predicting the missing factor over the business cycle continues to be period-specific, even if the variables' improved predictive ability is evident over the entire sample.

The paper proceeds with a discussion of related literature in Section 2. Section 3 details the estimation of a common factor in the macro forecast errors. Section 4 evaluates the role of a large battery of financial variables in explaining the macroeconomic forecast errors as expressed by the common factor. It also presents the financial variables data and the hypothesis testing and estimation results and offers a discussion of these results, including their robustness. In Section 5, threshold estimates of the effect of financial variables on macro forecast errors is presented, and Section 6 concludes.

[1] Here, the threshold variable partitions the estimation sample according to whether the unemployment rate has been: (1) decreasing; or (2) staying the same or increasing.

2 Related Literature

In essence, this paper is an updated approach to evaluating whether there are certain financial indicators—specifically measures related to financial stability—that can robustly predict real and nominal macroeconomic forecast errors. Better forecasts are crucial for monetary policy, whose conduct features an important forward-looking component. Not surprisingly, previous work on evaluating macro forecasts and their relationship with financial variables has often been conducted in the context of assessing the role of certain financial variables in a monetary policy-reaction function. The finding that the financial variable of interest matters in a policy reaction function has different potential interpretations, and tests have been developed to distinguish among alternatives.[2] Our work is related to this literature, which we do not discuss here; we leave for future research the issue of whether monetary policy reacts to certain financial variables that we show are relevant for explaining the common factor in the forecast errors.

Work by Peek, Rosengren, and Tootell (PRT 1999) related to the analysis in this paper shows that in a panel of different forecasters' forecast errors for the unemployment rate and inflation, confidential supervisory information related to bank health can predict these forecast errors.[3] More recently, Chatterjee and Nowak (2016) uncover common factors related to uncertainty about U.S. macro-financial developments and global demand that explain errors due to overly optimistic macroeconomic forecasts for most advanced economies and G20 countries (the Group of Twenty).

The bulk of the work, however, has focused on evaluating the importance of financial variables, primarily asset prices, in forecasting real economic activity. Stock and Watson (2003) survey the literature and take an exhaustive approach to figuring out whether forward-looking information embedded in asset prices is helpful in predicting both inflation and output growth.

[2] These alternatives hinge on the relationship between the financial variable and the macroeconomic forecasts the policymaker is responding to in the reaction function (see Fuhrer and Tootell, 2008).

[3] In their study, they measure bank health by the percentage of bank assets held by banks deemed most likely to fail based on Capital, Asset, Management Earnings, and Liquidity (CAMEL) ratings. CAMEL ratings were intended to capture different degrees of bank health as assessed by bank examiners. In 1997 the measure was expanded to CAMELS to include Sensitivity to market risk.

They find that some asset prices have statistically significant marginal predictive content for output growth but less so for inflation. In addition, while forecasts based on individual data series are unstable, straightforward approaches to combining the information across many asset prices can ameliorate these instability problems.

More recently, Gilchrist and Zakrajšek (2012) (GZ) develop financial measures based on two things: (1) the secondary market prices of individual corporate bonds; and (2) the GZ credit spread and its decomposition. This decomposition is composed of a component reflecting countercyclical movements in expected defaults and the EBP, which proxies for the cyclical changes in the relationship between credit spreads and default risk. They show that the informational content of the GZ credit spread for economic activity can be accounted for by the deviations in corporate bond pricing relative to the issuer's default risk. Shocks to this EBP that are orthogonal to the current state of the economy lead to meaningful and significant changes to real-side macro variables and inflation. GZ argue that the EBP captures changes in the supply of credit and operates through the well-known financial accelerator mechanism (Bernanke and Gertler 1989; Kiyotaki and Moore 1997; Bernanke, Gertler, and Gilchrist 1999; Hall 2011).

López-Salido, Stein, and Zakrajšek (2017) take an approach steeped in the behavioral finance literature and argue that when credit market sentiment is high in period *t-2*, or when credit risk is aggressively priced, credit spreads will widen. This widening of spreads is associated with the beginning of a contraction in real activity. To measure credit market sentiment, they use lagged information on credit spreads and high yield bond issuance. Then they use predicted spread changes in a second stage regression and show that predicted widening in spreads is associated with declines in measures of real activity. Giglio, Kelly, and Pruitt (2016), meanwhile, evaluate the impact of changes in 19 different measures of systemic risk on the probability of a macroeconomic downturn.[4] They also construct indexes from this cross-section of systemic risk measures and show that they can robustly predict future macroeconomic shocks out of sample. In addition, Allen, Bali, and Tang (2012) develop a value-at-risk measure, CatFin, to measure aggregate systemic risk and show that it predicts

[4] Their data can be downloaded from www.sethpruitt.net/GKPwebdata.zip.

macroeconomic downturns six months into the future. The authors argue that elevated systemic risk in the banking sector affects the macroeconomy through aggregate lending activity.

The last relevant body of literature develops measures to monitor financial instability and systemic risk. Brave and Butters (2012), using an unbalanced panel of 100 mixed-frequency financial activity measures, develop a National Financial Conditions Index (NFCI) that they show is a strong and robust predictor of financial stress up to one year ahead. They emphasize that measures of leverage are important for this result and, for longer horizons, suggest employing a sub-index of the NFCI that is based on a relationship between nonfinancial leverage, financial stress, and economic activity measures.[5] They also develop three sub-indices of the NFCI: risk, credit, and leverage. Bisias, Flood, Lo, and Valavanis (2012) provide a survey of 30 systemic risk measures—constructed in Giglio, Kelly, and Pruitt (2016) for series with available data—that cover the general areas of institution-specific risk measures for banks including CoVaR and marginal expected shortfall (MES); the co-movement and contagion among financial institutions' equity returns; measures capturing the volatility and instability of the financial sector; and measures of liquidity and credit conditions in financial markets.

3 Estimation of a Common Factor in Macro Forecast Errors

The goal of this section is to infer a common factor in the forecast errors from the SPF, Blue Chip forecasts, and Greenbook. This common factor is meant to explain forecast errors for real GDP growth, the unemployment rate, and inflation over relevant forecast horizons; it can enter forecast errors differently depending on the forecaster and the variable in question. The estimation framework takes the following form:

$$\begin{aligned} e_t^{J,i} &= \beta^{J,i}\eta_t + \varepsilon_t^{J,i} \quad , \; J = SPF, BC, GB, \;\; i = \Delta y, ur, \pi \\ \eta_t &= \rho\eta_{t-1} + \upsilon_t \end{aligned} \qquad (1)$$

[5] These data are publicly available at https://www.chicagofed.org/publications/nfci/index.

The forecast errors e at each point in time t are indexed by forecaster *J*, with *SPF* denoting the SPF, *BC* the Blue Chip forecast, and *GB* the Federal Reserve Board's Greenbook forecast. The forecast errors are also indexed by variable *i*, with Δy denoting real GDP growth, ur the unemployment rate, and π inflation. The common unobserved component η is assumed to evolve as a simple autoregressive process of order 1. State-space methods can be used to infer the state variable η given the signals $e^{J,i}$.

We do not correct for potential biases in the forecasts. In the context of the signal equations in the system (1), one way of accounting for potential bias would be to write the signals in (1) as

$$A_t^i = \gamma_0^{i,J} + \gamma_1^{i,J} F_t^{i,J} + \beta^{J,i}\eta_t + \varepsilon_t^{J,i} \quad , \; J = SPF, BC, GB, \;\; i = \Delta y, ur, \pi \qquad (2)$$

where A^i is the actual value for variable i and $F^{i,J}$ is its forecast by forecaster *J*. Rather than constraining the parameters γ_0 and γ_1 to be 0 and 1, respectively, for all *i* and *J*, as we do in (1), the equations in (2) for the signals leave these parameters unconstrained. This specification, in addition to accounting for potential biasedness in the forecasts, also provides the best linear combination of F and η for explaining the actual value A. However, in this context where we are trying to infer an unobserved factor η, the specification in (2) is too unconstrained and turns out to be uninformative in practice. The reason is that in order to minimize the errors $\varepsilon_t^{J,i}$ given the assumed law of motion for η, the procedure will assign a zero weight to the GDP growth forecasts—that is, $\gamma_1^{\Delta y,J}$ is estimated to be zero for all J's—so that the factor η becomes for all practical purposes equal to the actual value of GDP growth. This, in addition to driving the errors in the signal equations for $A^{\Delta y}$ towards zero, also provides what is essentially ex-post information (in the form of realized GDP growth) to the other signal equations, thus also reducing the errors in those relationships substantially.

A viable alternative, which does not confound the issues of unbiasedness and efficient use of information in the forecasts, would be to first compute a bias-adjusted forecast error $\overline{e}_t^{J,i}$ from the individual regressions

$$A_t^i = \gamma_0^{i,J} + \gamma_1^{i,J} F_t^{i,J} + \nu_t^{J,i} \quad , \; J = SPF, BC, GB, \;\; i = \Delta y, ur, \pi \qquad (3)$$

and then estimate (1) with the bias-adjusted forecast error $\overline{e}_t^{J,i}$ instead of the forecast error $e_t^{J,i} \equiv A_t^i - F_t^{J,i}$. This approach yields an estimate of η that is very close to the estimate obtained under the assumption of forecast unbiasedness. Consequently, our results in terms of the inference about the latent factor do not appear sensitive to adjusting for bias in the forecasts. We note here that a considerable amount of work has been devoted to testing for biasedness in the forecasts made by private forecasters and by the Federal Reserve Board in the Greenbook. The results can be sensitive to the sample period being considered, and while unbiasedness often cannot be rejected,[6] it becomes more of an issue at the longer forecast horizons that we consider here, especially for the GDP growth and inflation forecasts.

The common factor is meant to capture a common element in the forecast errors of GDP growth, unemployment, and inflation. For this reason, the residuals $\varepsilon^{J,i}$ in (1) can still be correlated across forecasters for any given variable. There may be, for example, an error in the real GDP growth forecast driven by an erroneous assessment of import growth. Such an error, under certain circumstances, could have little impact on the forecast error for unemployment. Therefore, this error would not be captured by the common factor η but would be absorbed by the residual $\varepsilon^{J,\Delta y}$, and nothing prevents this residual from being correlated across forecasters. For this reason, we leave $\text{cov}(\varepsilon_t^{SPF,i}, \varepsilon_t^{BC,i})$, $\text{cov}(\varepsilon_t^{SPF,i}, \varepsilon_t^{GB,i})$, and $\text{cov}(\varepsilon_t^{BC,i}, \varepsilon_t^{GB,i})$ as free parameters to be estimated in (1) for each variable *i*. The other covariances in the state-space system (1) are instead set to zero. This implies that any correlation in forecast errors across variables is captured by the common factor η only. Following up with the same example, the error in imports that affect the GDP forecast but not the unemployment rate forecast could still affect the price forecast. Such a correlation will not be captured by our estimation. We make this choice of setting these other covariances to zero mainly to preserve degrees of freedom. We have experimented, however, with relaxing such an assumption, and the results do not appear to be affected materially.

[6] See, for example, the work by El-Shagi et al. (2014).

We make the normalization $\beta^{SPF,\Delta y} = 1$ in (1) as η is identified up to a multiplicative constant. In addition, we also constrain $\beta^{BC,i} = \beta^{SPF,i}$ for all variables *i* because there is significant overlap in the set of forecasters surveyed in the SPF and Blue Chip. It is possible to show that this constraint is not rejected by the data and that the point estimates that would result from estimating $\beta^{SPF,i}$ and $\beta^{BC,i}$ unconstrained are extremely close. The process for the common factor η turns out to be estimated with an autoregressive root ρ well within the unit circle. As a result, the estimated variance for the innovation σ_{υ}^{2} is not affected by the pileup problem described in Stock and Watson (1998) for state variables following a unit root process.

The forecasters that comprise the SPF are surveyed in the middle month of the quarter, and we use the median forecast. The Blue Chip survey occurs at a monthly frequency.[7] For each quarter, we take the middle month of the quarter "Consensus" forecast, which is the average of the forecasts made by each panel member for each variable.[8] The Federal Reserve Board forecasts (or Greenbook forecasts) were made eight times a year over the period we consider. We convert these forecasts to a quarterly frequency in order to align the forecasts as closely as possible with those of the SPF and Blue Chip. This typically means keeping the January, March, August and October Greenbook forecasts—that is, the forecast made early in the given quarter.

For real GDP growth, we consider the forecast error for the average quarterly growth expected to prevail over the next four quarters. Specifically, if the forecast is made at time *t*, the GDP growth forecast will cover the quarters $t+1$ to $t+4$. For the unemployment rate, we consider the forecast error for the level of the seasonally adjusted unemployment rate that, at time *t*, is expected to prevail at time $t+4$. For inflation, we take the forecast error involving the average level of inflation expected to prevail over the next quarters, as we do for GDP growth. Though we consider this four-quarter horizon because it is a relevant horizon for policy purposes, the setup in (1) can in principle be extended to include additional forecast horizons.

For the actual values of GDP, we use the vintage prevailing 15 months after the forecast was made, which corresponds to two years after the third release of the Bureau for Economic Analysis

[7] Typically, the Blue Chip survey is conducted the first and second business day of each month.

[8] Using the average SPF forecasts in place of the median SPF forecasts doesn't change our results.

(BEA). The BEA's estimate of GDP two years after the third release provides a comprehensive assessment of activity without being too distant from the forecasters' vantage point. For the unemployment rate, we simply take the most recent vintage of the data as actual values because the unemployment rate is not revised, aside from minor seasonal adjustments. We do the same for our measure of inflation, given by the quarterly change in the Consumer Price Index (CPI). The sample period considered in the estimation is 1973:Q1–2015:Q4. It is important to note that over this period forecasts are not available for all forecasters. In particular, the Blue Chip Forecasts are available only beginning in 1980. For the Greenbook, forecasts are made publicly available with a five-year lag. As a result, we consider Greenbook forecasts going up to only 2011. Moreover, the Greenbook started to forecast CPI inflation in 1980, and thus we do not have observations before then. The same is true for the SPF. In other words, the CPI inflation forecast error is available only from the early 1980s for all forecasters.

The system (1) is estimated via maximum likelihood using the Kalman filter. Estimation results are reported in Table 1. The table shows that a positive η is associated with an actual value of GDP growth that is higher than forecast, with a lower than forecast unemployment rate and higher than expected inflation. In other words, the common factor appears to capture amplification mechanisms over the forecast horizon that work similarly to a demand shock. There are some differences in the way the factor enters the Greenbook forecast errors relative to the SPF and the Blue Chip, especially for GDP growth and the unemployment rate. The estimated coefficients for the inflation forecast error are essentially the same.

The common factor typically explains about half of the variance of the GDP forecast error across forecasters. For the Greenbook, this fraction is lower when considering the period covering the 1970s and early 1980s. Aside from a sample starting in 1987, the value increases to about 50 percent, similar to the other forecasters. The portion of the inflation forecast error variance explained by the factor is substantially lower, hovering around 10 percent. Since the portion of inflation variance explained by activity on actual inflation data—for example, by means of a Phillips curve relationship—is typically small, this is not surprising. The fraction of the unemployment forecast error's variance explained by the common factor is about 95 percent for the SPF and Blue Chip, and about 70 percent for the Greenbook. In this regard, at the horizon considered here and over a comparable sample period, the variance of the unemployment rate forecast error is somewhat lower for the Greenbook than for the private forecasters.

In sum, the common factor in system (1) mostly captures the unemployment forecast error from the SPF and the Blue Chip. As such, it has a straightforward interpretation, and the factor is stable across different estimation periods. Its evolution is depicted in Figure 1, with recession periods shaded in grey. The timing of the factor is shifted forward four quarters, to match the horizon of the unemployment rate forecast. The cyclical nature of the factor is apparent, with negative values during recessions and early recovery periods (periods when the actual unemployment rate is high), and positive values during the more mature phases of the cycle. In other words, the factor captures the tendencies to over predict activity during recessions and under predict activity during expansions.

The fact that the common component mainly summarizes a miss in projected activity, as measured by the unemployment rate four quarters out, also makes it clear why it does not make much of a difference whether the forecast error is considered $e_t^{J,i}$, as we do in (1), or the bias-adjusted version $\overline{e}_t^{J,i}$ discussed earlier. The reason is that the bias in the SPF unemployment rate forecast is relatively small. Figure 2 compares the factor extracted from (1), and already depicted in Figure 1, with the factor extracted when $e_t^{J,i}$ is replaced by the bias-adjusted version $\overline{e}_t^{J,i}$. It is apparent from the figure that the two versions of the factor are very close, with just a few exceptions.

4 The Role of Financial Variables in Explaining Macro Forecast Errors

Given the estimated factor η, and exploring how much of its variation can be explained by financial variables, one issue is that financial variables can be correlated with other variables. For example, we will consider credit variables, and credit will be correlated with economic activity. For this reason, we control for nonfinancial macro factors in all of our analysis. In particular, we take the first principal component from roughly 60 real activity variables (GDP and its components, industrial production, labor market variables) and the first principal component from about 40 price and wage inflation indicators (different price indexes and deflators, different wage measures, disaggregated CPI and PPI data). The description of the data for activity and prices that goes into the construction of the principal components appears in the data appendix.

The empirical exercise entails estimating a relationship of the following form

$$\eta_t = \alpha_0 + \sum_{j=1}^{2}\sum_{i=1}^{2}\alpha_{j,i}X_{j,t-i} + \sum_{i=1}^{2}\alpha_{Z,i}Z_{t-i} + \xi_t, \qquad (4)$$

where X_1 and X_2 are the two first principal components for activity and prices, and Z denotes the financial variable whose ability to predict the factor η we are interested in assessing. Note that for a forecast made at time t, we consider information relevant for explaining η_t only up to $t-1$. While our exercise is not real-time, we consider only information from financial variables and the principal components that would be potentially available to forecasters when the forecasts were made. We consider two lags for the explanatory variables in (4) but note that the results are not especially sensitive to lag selection.

The test that we consider concerning a financial variable Z's predictive content for η is a simple Wald test of the hypothesis that the estimated coefficients $\alpha_{Z,1}$ and $\alpha_{Z,2}$ are jointly zero. Since the error term ξ in (4) will be serially correlated, we use standard errors for the coefficient estimates that are robust to serial correlation. In particular, given that η captures a large portion of the four-quarter-ahead unemployment rate, we consider standard errors that, in addition to being robust to heteroscedasticity, are robust to ξ following a moving average process of order three.

There is some value in controlling for the principal components X_1 and X_2 in (4). By themselves—that is, without the inclusion of any financial variable Z—these variables explain roughly 20 percent of the variation in η over the period 1973:Q1–2015:Q4. Stability tests (not shown) typically do not reject the hypothesis that the way the two principal components are related to η has not changed significantly over time.

4.1 Financial Variables Data

The data appendix features a list of all considered variables, with different groupings as described below. Although other criteria may be followed than the ones adopted here when grouping the variables, given the relatively large number of considered variables, it is nonetheless useful to describe results in terms of broader categories.

The first group of variables involves interest rates. We consider yields for both private and public sector instruments over the whole maturity spectrum. In addition to the level of the yields, we also consider term and risk spreads. The risk spread category will include, in addition to traditional spreads such as the paper-bill spread and the spread between a BBB-rated corporate bond yield index and the 10-year Treasury yield, the EBP and credit spread variables from Gilchrist and Zakrajšek (2012).

The second group of variables includes asset prices as captured by equity valuations, households' housing and non-housing net worth, and exchange rates. For equity prices and exchange rates, we take a log first difference transformation. We also consider measures of expected returns on equity, price-earnings ratios, and a measure of Tobin's Q.

The third group of variables considers the amount of credit extended to the private sector by depository institutions and finance companies. Credit is decomposed by type of borrower (household versus business) and type of loan. We consider both flow and stock measures of credit relative to potential GDP. For the stock variables, since we take two lags of Z in (4), these variables can still enter the relationship in first differences if the data so require.

The fourth group of variables considers a variety of measures related to financial market distress. Specifically, we consider the variables in Giglio, Kelly, and Pruitt that are not otherwise classified in our groupings. This set of variables includes measures of institution-specific risk, co-movement and contagion, volatility and instability, and liquidity. We complement the Giglio, Kelly, and Pruitt (2016) measures by also considering depository institutions' nonperforming loans and banks' willingness to lend, in addition to broader measures of volatility and uncertainty.

We do not take our list of variables as exhaustive, and we recognize that there has been considerable effort already in the literature to summarize the information in financial variables. For this reason, we also consider the explanatory power of summary measures of financial conditions. Specifically, we take the Federal Reserve Bank of Chicago's National Financial Conditions Index, which summarizes information from 105 indicators of financial activity. This index has been shown to be a robust indicator of future financial stress (Brave and Butters 2012). In addition to the aggregate index, we also consider the information in the sub-indices that classify variables according to risk, credit, and leverage.

4.2 Estimation Results

Stock and Watson (2003) emphasize that the role of asset prices in predicting output and inflation is typically not stable over time. While this paper deals with forecast errors rather than actual values, we are still concerned with the stability of our findings. Given the large number of variables being considered, we summarize our findings graphically for our different variable groupings.

Figure 3A plots *p*-values of the Wald test for the interest rate variables. The figure considers two periods, the full sample 1973–2015 against a "Great Moderation" subsample period 1987–2007. The reason for incorporating a Great Moderation subsample is that, as Figure 1 illustrates, the factor η takes large absolute values during the recessions of 1974–75, 1981–84, and 2008–09. While it is important to ascertain the financial variables' predictive power for these downturns, spurious results are also possible. In order to highlight the instances showing predictive power for η, in Figure 3A we focus on the *p*-values of the Wald test that are less than 0.20, and for simplicity set at 0.20 all *p*-values equal to or greater than this threshold. It is apparent from this figure that in the full sample several variables suggest explanatory power for η, most notably term and risk spreads. However, only one variable rejects the null hypothesis that the coefficients $\alpha_{Z,1}$ and $\alpha_{Z,2}$ are jointly zero at the 95 percent confidence level or better when considering the joint significance with the Great Moderation sample. For three other variables, the rejection over the Great Moderation period is at the 90 percent confidence level or better.

The issue of stability of results is also illustrated in Figure 3B, which depicts the *p*-values of the Wald test for the period 1987 to 2015, always against the Great Moderation sample. The 2008–09 Great Recession is associated with several variables becoming relevant in terms of explaining η. The significance of many interest rate variables during this period likely captures the fact the Great Recession resulted in a large shortfall in economic activity despite the easing of monetary policy; however, it would be difficult to generalize from this episode and argue for a significant explanatory power of interest rates for η. It is in fact possible to show that in the 1987–2015 sample, these variables lose their explanatory power after removal of the 2008–09 period.[9]

Overall, the results for the variables in this grouping indicate that only the credit spread variable from Gilchrist and Zakrajšek (2012), specifically the EBP component of the spread, provides explanatory power at better than the 95 percent confidence level in all the periods considered in Figures 3A and 3B. The hypothesis that this variable enters (4) in first differences is not rejected, with an increase in the premium associated with lower η —that is, with activity and inflation lower than expected. A Quandt-Andrews stability test (not shown) does not reject the hypothesis of stability of coefficients for this variable in (4) over the full sample. Other variables where significance is maintained across all three sample periods at the 90 percent confidence level or better are the BBB-rated corporate bond yield and its spread relative to the 10-year Treasury yield, and the spread of the 30-year Treasury yield over the federal funds rate. The BBB-rated corporate bond yield and its spread over the 10-year Treasury yield, which are estimated to enter (4) in first differences, share some similarities with the Gilchrist and Zakrajšek EBP variable, and thus their relevance is not too surprising. Moreover, an extensive literature documents the predictive power of term spreads for recession episodes, typically periods associated with large forecast errors and thus large absolute values for η.

The statistical significance of the Gilchrist and Zakrajšek EBP variable, nonetheless, translates into an economic relevance that we judge to be relatively modest. Figure 4 depicts η against its predicted value from just the principal components of activity and prices, X_1 and X_2, and from the augmented specification (4) which, in addition to these two principal components, includes the credit spread variable. Inclusion of this variable helps explain the behavior of η during the two most recent downturns, but only partly.

Next, we move to asset prices and exchange rates, summarizing the results of the Wald test as was done in Figures 5A and 5B. Broadly speaking, the results mimic previous results: the ability of a variable to explain η is generally not robust across different sample periods. The one

[9] It is also possible to show that the significance of the interest rate variables for the Great Recession episode is concentrated at the very short end of the maturity spectrum, where the effective zero-lower-bound on nominal interest rates was binding.

variable for which we can reject the null hypothesis that the coefficients $\alpha_{Z,1}$ and $\alpha_{Z,2}$ are jointly zero at the 95 percent confidence level or better across all three sample periods is the expected real return on equity. High values for this variable are associated with high values of η; economic activity and inflation are higher than forecast with a high expected return on equity and vice versa. The combined effect of the two lags of this variable, the sum of $\alpha_{Z,1}$ and $\alpha_{Z,2}$ in (4), is relatively stable over time. The only other variable in this group that shows statistical significance across different sample periods at least at the 90 percent confidence level is the Shiller cyclically adjusted price-to-earnings ratio. A high value for this variable is associated with a low η, with activity and inflation lower than expected.

The improvement from the inclusion of the expected real return on equity in (4) in explaining the dynamics of η, while statistically significant, appears modest from an economic standpoint. Figure 6 repeats the exercise in Figure 4 but uses the expected real return on equity as the financial variable in (4). Relative to a benchmark with only X_1 and X_2 in (4), the small improvement in fit appears to be associated mostly with the 1980s and the recession of the early 2000s.

Figures 7A and 7B show that the Wald test does not provide evidence of the credit variables group having a significant explanatory power for η over all three of the periods that we consider. Some in this group are stock variables (relative to potential GDP), but, as we have already noted, the presence of two lags in (4) allows them to enter as flows. Nevertheless, there could have been low-frequency changes in the growth rate of some of these variables that we would not be able to account for even when expressed in terms of flows. This issue should be partly mitigated when we consider the shorter sample periods, but even then we fail to find a significant role for these variables once controlling for the real and price principal components X_1 and X_2.

Figures 8A and 8B repeat this exercise for the last group of variables, which includes more diverse subsets of financial indicators. We label *GKP* the variables considered in Giglio, Kelly, and Pruitt (2016) and not already examined elsewhere, such as the term and risk spreads. Variables labelled *NFCI* are indices and sub-indices from the Federal Reserve Bank of Chicago's National Financial Conditions Index. The label "Bank" is for a subset of variables pertaining to depository institutions that includes banks' nonperforming loans, Federal Deposit Insurance Corporation (FDIC) problem banks, and the survey measure of banks' willingness to lend to consumers from the Senior Loan Officer Opinion Survey (SLOOS). The final set of variables includes broad uncertainty and volatility measures.

The figures reinforce a previously evident theme: few variables provide explanatory power for η consistently across different samples. In particular, the only variable for which we can reject the null hypothesis that the coefficients $\alpha_{Z,1}$ and $\alpha_{Z,2}$ are jointly zero at the 95 percent confidence level or better across all three sample periods is the nonfinancial leverage measure from the NFCI. This measure is the first principal component from several debt and equity indicators pertaining to the household and nonfinancial business sectors. A high value of this index signals a process of credit tightening, possibly associated with higher risk premia and declining asset valuations, which causes households and firms to deleverage. The sum of coefficients $\alpha_{Z,1}$ and $\alpha_{Z,2}$ for this variable is negative, implying that deleveraging is associated with a decline in η, or in activity being slower than expected. A Quandt-Andrews stability test (not shown) does not reject the hypothesis of stability of coefficients for this variable in (4) over the full sample.

The other variables for which we can reject the null hypothesis that the coefficients $\alpha_{Z,1}$ and $\alpha_{Z,2}$ are jointly zero at the 90 percent confidence level or better across all three sample periods are the International Spillover Index from Diebold and Yilmaz (2009), and the SLOOS measure of banks' willingness to lend to consumers.[10] As before, however, the improvement in explanatory power for η, while statistically significant, does not appear very relevant from an economic standpoint, as illustrated in Figure 9 for the nonfinancial leverage indicator. Relative to the case where η is explained only by the real and price principal components X_1 and X_2, the inclusion of nonfinancial leverage provides only a modest qualitative improvement, mostly in the latter part of the sample.

[10] The International Spillover Index measures the degree of macroeconomic connectedness across countries. It is a systemic risk indicator determined by the size concentration of the financial sector.

4.3 Discussion of Results

Our results echo earlier findings in Stock and Watson (2003), who document the instability of asset prices as indicators of future activity and inflation. The focus here, though, is on forecast errors and the interpretation of the findings is somewhat different. Our results on the role of stock market indicators in explaining forecast errors confirm previous findings by Fuhrer and Tootell (2008). We do not have the CAMEL ratings variable of Peek, Rosengren, and Tootell (1999), and the proxies for the ratings that we use in terms of nonperforming loans and problem banks are only marginally significant.[11] However, our exercise differs from the previous literature along relevant dimensions. We control for indicators of real activity and inflation. This makes our tests more stringent, but our principal components are estimated using the entire sample period, giving these variables a potential advantage over financial indicators that are more real-time in nature. In addition, we examine the explanatory power of financial variables for a common factor of the forecast error for GDP growth, the unemployment rate, and inflation across different forecasters. This common factor η captures a large portion of the forecast error for unemployment, but less so for the forecast errors for other variables, especially inflation.

In the literature, the assessment of whether some variables generate forecast improvements is often performed in the context of an equation such as (2), with η replaced by the variables of interest to the researcher. Our exercise restricts the coefficient γ_1 in (2) to be equal to 1. While placing such a constraint is necessary in our setup to identify η, it is possible to extend our exercise and relax the constraint by noting that η closely follows the SPF's four-quarter-ahead unemployment rate forecast error. We can account for the possibility that this forecast is biased and inefficient by including the SPF unemployment rate forecast as an additional control in (4). The next subsection includes a discussion of this exercise.

Interpreting our findings could lead to the conclusion that forecasters typically incorporate information from financial variables into their forecasts efficiently and, to the extent that they don't, the improvement in forecast performance, while statistically significant, is modest from an

[11] Peek, Rosengren, and Tootell already show that some of the publicly available proxies for CAMEL ratings do not perform as well as the CAMEL variable in explaining forecast errors.

economic standpoint. We see such a conclusion as premature. Financial variables may explain a nontrivial portion of the variation in η, but such an explanatory power is not robust across different samples. Also, some of the variables that we have considered may be more apt to explain forecast errors at particular stages of the business cycle. For example, Giglio, Kelly, and Pruitt (2016) have shown that their systemic risk variables (which we consider in our analysis) have little predictive power for median outcomes of future economic activity, but they do have predictive power for outcomes in the lowest quartile range. Considering that these variables are constructed to capture systemic risk, and thus may not provide much signal concerning the strength of future activity when systemic risk is not an issue, this is not necessarily surprising. Other financial variables that we consider here may be subject to some of the same issues. For example, when economic conditions are good, nonperforming loans may not respond strongly to further improvements in activity, but the relationship may become tighter as economic conditions worsen. For this reason, in section 5 we examine the possibility that the relationship between the financial variables and η differs across different stages of the business cycle.

4.4 Robustness

As a robustness exercise for the findings in this section, we estimate an augmented version of (4) which includes the SPF's unemployment rate forecast as an additional control

$$\eta_t = \alpha_0 + \sum_{j=1}^{2}\sum_{i=1}^{2}\alpha_{j,i}X_{j,t-i} + \sum_{i=1}^{2}\alpha_{Z,i}Z_{t-i} + \alpha_{ur}F_t^{ur,SPF} + \xi_t \;. \tag{5}$$

The reason for considering this augmented version (5) is that $\eta_t \approx (A_t^{ur} - F_t^{ur,SPF}) / \beta^{ur,SPF}$ —that is, the estimated common factor—is equal, up to a multiplicative constant, to the SPF's unemployment rate forecast error. Inclusion of the forecast as an additional explanatory variable in (5) allows controlling for potential bias in the forecast and for potential correlation of X_1, X_2, and Z with $F^{ur,SPF}$. Since the principal components X_1 and X_2 are likely to be correlated with $F^{ur,SPF}$, it is not clear in what direction the omission of $F^{ur,SPF}$ in (4) may bias the coefficients $\alpha_{Z,1}$ and $\alpha_{Z,2}$.

We estimate (5) and run the same Wald test over the three sample periods as in our baseline exercise, summarizing results and highlighting the differences from our benchmark findings. In a version of (5) with no financial variable Z included, the estimated coefficient α_{ur} is negative and significantly different from zero. Still, the principal components for real activity and prices, X_1 and X_2, continue to matter. The only interest rate variable for which we can reject the null hypothesis that the coefficients $\alpha_{Z,1}$ and $\alpha_{Z,2}$ are jointly zero at the 95 percent confidence level or better across all three sample periods is the EBP, as before. In contrast with our previous findings, no other variable produces Wald test results that are significant at the 90 percent confidence level or better across all three sample periods. For the asset prices group of variables, there is no variable for which we can reject the null hypothesis that the coefficients $\alpha_{Z,1}$ and $\alpha_{Z,2}$ are jointly zero at the 95 percent confidence level or better across all three sample periods. A 90 percent or better significance level for the Wald test is achieved by the households' net worth variable, which at the quarterly frequency exhibits a fairly high co-movement with broad measures of equity valuations and with the non-equity portion of households' net worth.

Whereas with (4) it is not possible to find explanatory power for η using any of the credit variables across all sample periods, with (5), mortgage credit is typically significant at the 90 percent level or better. Similar results arise for the remaining credit variable grouping, with evidence that the credit sub-index from the Chicago Federal Reserve NFCI is significant at the 95 percent confidence level or better, as is the share of nonperforming loans at small banks. The nonfinancial leverage sub-index from the NFCI remains significant, while the two variables from the Giglio, Kelly, and Pruitt (2016) list that mattered with (4), the credit and term premia, are not significant with (5).

Considering (5) instead of (4) generates somewhat different results, with variables related to credit availability providing more explanatory power for the common factor η. Still, for these variables as well, the additional explanatory power, while statistically significant, remains modest from an economic standpoint. Accordingly, choosing between (4) and (5) in terms of providing the appropriate benchmark is not crucial. While it's true that α_{ur} in (5) is estimated to be significantly different from zero, we see equation (5) as even less exploitable in real time than (4).

5 Threshold Estimates of the Effect of Financial Variables on Macro Forecast Errors

In principle, there are several ways to address whether the relationship between the common factor η and the financial variables changes over the course of the business cycle. Giglio, Kelly, and Pruitt (2016) consider quantile regressions and illustrate the predictive power of financial variables for future outcomes of real activity that are at the lower end of the distribution. While a similar exercise can be performed in our context, our dependent variable, the common factor η, summarizes forecast errors that become known to the forecasters four quarters after the forecasts are made. In order to develop a criterion for assessing the differential impact of financial variables on η that is more relevant in real-time, we consider a modified version of (4) that features a threshold effect for the financial variable

$$\eta_t = \alpha_0 + \sum_{j=1}^{2}\sum_{i=1}^{2}\alpha_{j,i}X_{j,t-i} + \sum_{i=1}^{2}\alpha_{Z,i}^{h}I\{ur_{t-1} - ur_{t-5} < 0\}Z_{t-i} + \sum_{i=1}^{2}\alpha_{Z,i}^{l}I\{ur_{t-1} - ur_{t-5} \geq 0\}Z_{t-i} + \xi_t \quad (6)$$

where $I\{.\}$ is an indicator function that takes the value of one if the condition inside the brackets is satisfied, and a value of zero if it is not satisfied. In our case, the condition is determined by the change in the unemployment rate over four quarters as of $t-1$, with the value of the threshold set at zero. Coefficients $\alpha_{Z,1}$ and $\alpha_{Z,2}$ take different values, as indicated by superscripts h and l, according to whether the unemployment rate is decreasing, $u_{t-1} - u_{t-5} < 0$, or whether it is flat or increasing, $u_{t-1} - u_{t-5} \geq 0$.

We consider the change in the unemployment rate as the threshold variable in order to separate periods when activity is slowing from periods when it is improving. The effects of financial variables on economic activity may be asymmetric over the business cycle. For example, bank health may matter less if economic conditions are improving, since firms may have an easier time finding alternative sources of credit. When economic conditions are deteriorating, however, bank health may become more important as other sources of credit dry up. This differential impact of financial variables on future activity could also affect the relationship between Z and common factor η.

The threshold specification in (6) increases the number of parameters to be estimated over a relatively short sample, with the sample partitioned between periods when the unemployment rate is declining and periods when it is increasing. Given the fairly limited number of degrees of freedom, we estimate (6) using all observations that are available for each financial variable Z over the sample period 1973–2015. In order to conduct an exercise comparable to the one in section (4), we consider the sum of squared residuals from (6) over different samples: the full sample 1973–2015, 1987–2015, and the Great Moderation sample 1987–2007, all computed using the estimated coefficients over the entire sample period. The sum of squared residuals is reported relative to the sum of squared residuals from estimating (4) when the variable Z is given by the EBP. The reasons to benchmark our findings against this variable are twofold. First, such a variable provides explanatory power for η consistently across different samples. This variable also tends to develop the strongest rejections for the Wald test of the hypothesis that the estimated coefficients $\alpha_{Z,1}$ and $\alpha_{Z,2}$ in (4) are jointly zero. In this regard, the EBP measure can be interpreted as the most reliable predictor of η that emerges from our previous analysis. Second, for this variable, we fail to develop significant evidence of a threshold effect per equation (6). As a result, considering the residuals from (4) rather than from (6) as the benchmark does not provide other financial variables with a significant advantage.

Figure 10A plots the ratio of sum of squared residuals for the interest rate variables, full sample, and Great Moderation period. A value less than unity indicates that for the variable in question, the sum of squared residual from (6) is less than the sum of squared residuals estimated from (4) with the EBP. In other words, the variable has more explanatory power for η than the EBP. The reverse holds when the ratio is greater than unity. Figure 10B features the same exercise, but as before it compares the period 1987–2015 with the Great Moderation sample. Evidence that the threshold in (6) is significant according to the likelihood ratio test in Hansen (2000) is obtained for only a small fraction of variables in this group, most notably for the term-premium variables. For two of these variables—the spread between the 10-year Treasury yield and the federal funds rate and the spread between the 30-year Treasury yield and the federal funds rate—the ratios are below one for all three sample periods. A Diebold-Mariano (1995) test shows, however, that the difference is not statistically significant.

Results for the asset prices variables are reported in Figures 11A and 11B. There is evidence (not reported) for a threshold effect in (6) for those variables that generate ratios below unity. These variables are the Shiller cyclically adjusted price-to-earnings ratio, the expected return on equity, and a measure of Tobin's Q. The first two of these variables had already been shown to matter in the context of the linear specification (4). At least for some of the samples considered here, the Diebold-Mariano test cannot reject that the forecasts generated from these variables outperform the benchmark linear specification with the EBP. The confidence level for this test is typically around 90 percent.

Results for the credit variable grouping, reported in Figures 12A and 12B, are notable in that the threshold specification (6) is almost always preferred to the linear specification (4). Still, despite the improvement in fit from the threshold specification, these variables only occasionally perform better than the EBP. In particular, the performance of these variables deteriorates almost uniformly during the Great Moderation period.

The final set of results concerns the more heterogeneous set of variables. Once again, for most of the variables it is not possible to reject the presence of a threshold effect as modeled in (6). For the GKP variables, Figures 13A and 13B show that improvement in fit as measured by the sum-of-squared residuals ratio is uneven across the three samples. There is instead a widespread improvement relative to the EBP for the "Bank" variables, specifically for the variables capturing banks' nonperforming loans and the FDIC's problem banks. A Diebold-Mariano test cannot reject that the predictions for η generated with these variables outperform the benchmark linear specification with the EBP, although the confidence level is typically around 90 percent. The same qualitative results hold for the Baker, Bloom, and Davis (2016) measures of economic policy uncertainty.

As a whole, these results indicate that a broader set of financial variables than the one found in section (4) matters for explaining the behavior of η. Importantly, the benchmark that we used to measure improvement was the EBP; the number of financial variables improving on such a specification would have been larger using a specification such as (4) with only the principal components X_1 and X_2 as the benchmark. Still, the usefulness of some of these variables for explaining the behavior of η continues to be period-specific, even if such an improvement will translate into better predictive ability over the whole sample. For instance, Figure 14 depicts η and its prediction from (4) using the EBP, plus a prediction from (6) using the number of FDIC's problem banks. The improvement in fit for this variable relative to the EBP comes mostly from the late 1980s and early 1990s, a period when banking failures curtailed the availability of credit.

6 Conclusion

A large battery of financial variables has difficulty robustly predicting a latent factor common to, or "missing" from, the joint year-ahead forecast errors for real GDP growth, the unemployment rate, and the CPI inflation rate for three sets of professional forecasters—the Greenbook, the SPF, and the Blue Chip. These findings do not imply that forecasters have been able to correctly assess the effect of financial variables on future economic activity. Indeed, financial variables can provide substantial explanatory power for the latent common factor at some times. What the results say is that the forecast miss cannot be robustly associated with a particular financial variable or indicator over the entire sample period that we consider. Even when robustness across different periods is met, for example, with a variable such as the Gilchrist and Zakrajšek (2012) EBP, its economic relevance is not especially large.

Still, the findings appear to speak more to the limitations of some of the econometric procedures than to the financial variables' modest predictive content for the latent factor. Empirical methods better suited to capturing the intermittent nature of the relationship can generate more positive findings. Indeed, the threshold effects explored in our analysis—one way of addressing the occasional correlation between the financial variables and the latent factor—suggest a more important role for several of the financial variables that we considered and reinforce previous results in the literature. The threshold effects are especially relevant because they imply that financial variables become more important for explaining forecast errors when the economy is deteriorating. In other words, financial variables help predict economic activity at times when a forecast error may be especially costly from a policy standpoint.

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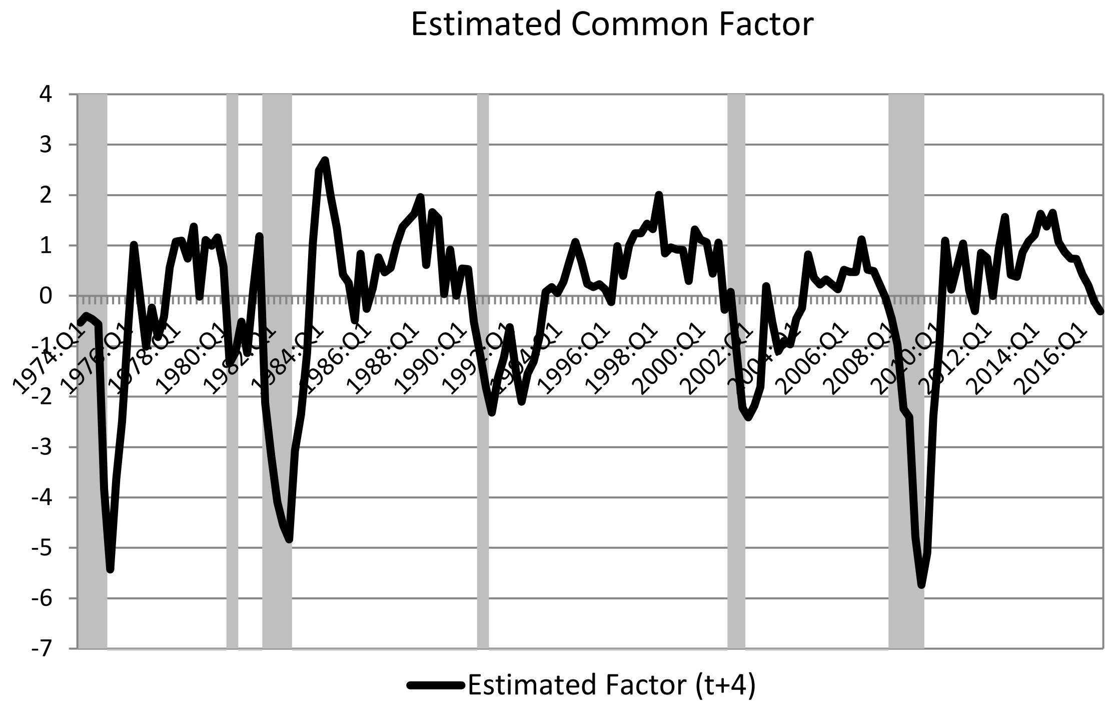
Table 1
Estimation of Common Factor η , 1973:Q1 to 2015:Q4

	Coefficient	Std. Error	z-Statistic	Prob.
$\beta^{GB,\Delta y}$	0.764744	0.078733	9.713188	0.0000
$\beta^{SPF,ur}$	-0.630003	0.072297	-8.714052	0.0000
$\beta^{GB,ur}$	-0.499180	0.072648	-6.871199	0.0000
$\beta^{SPF,\pi}$	0.324090	0.068639	4.721683	0.0000
$\beta^{GB,\pi}$	0.315658	0.086442	3.651688	0.0003
ρ	0.845976	0.048083	17.59396	0.0000

Log likelihood	-761.9296	Akaike info criterion	9.150344
Parameters	25	Schwarz criterion	9.607829
Diffuse priors	0	Hannang-Quinn criterion	9.335958

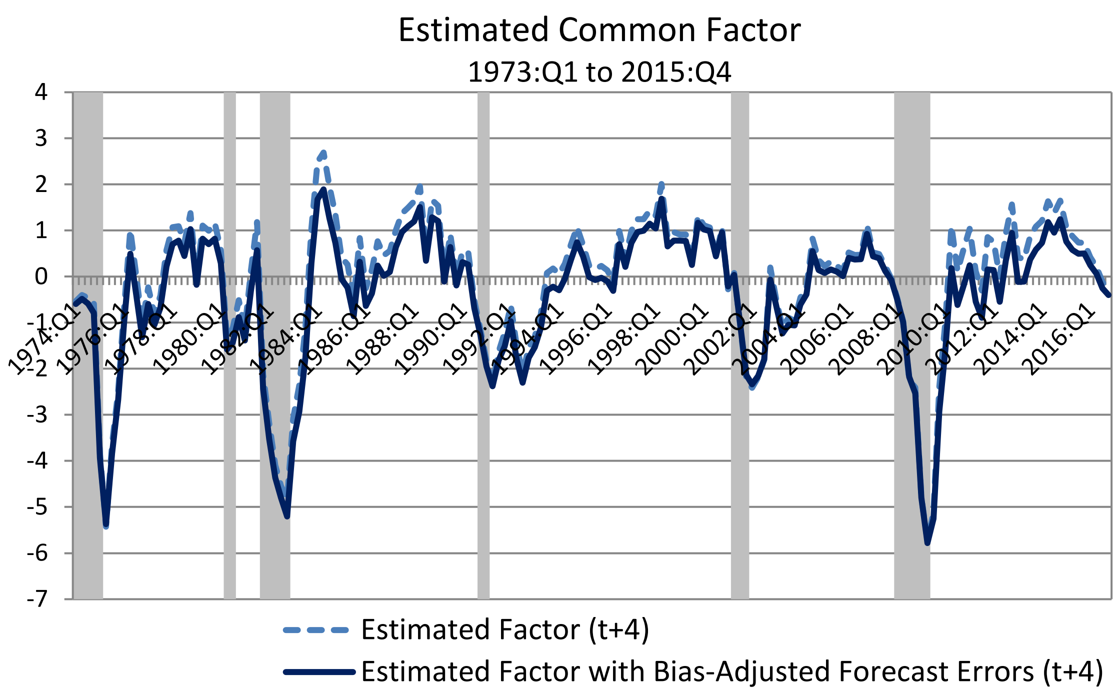
Source: Authors' calculations.

Figure 1



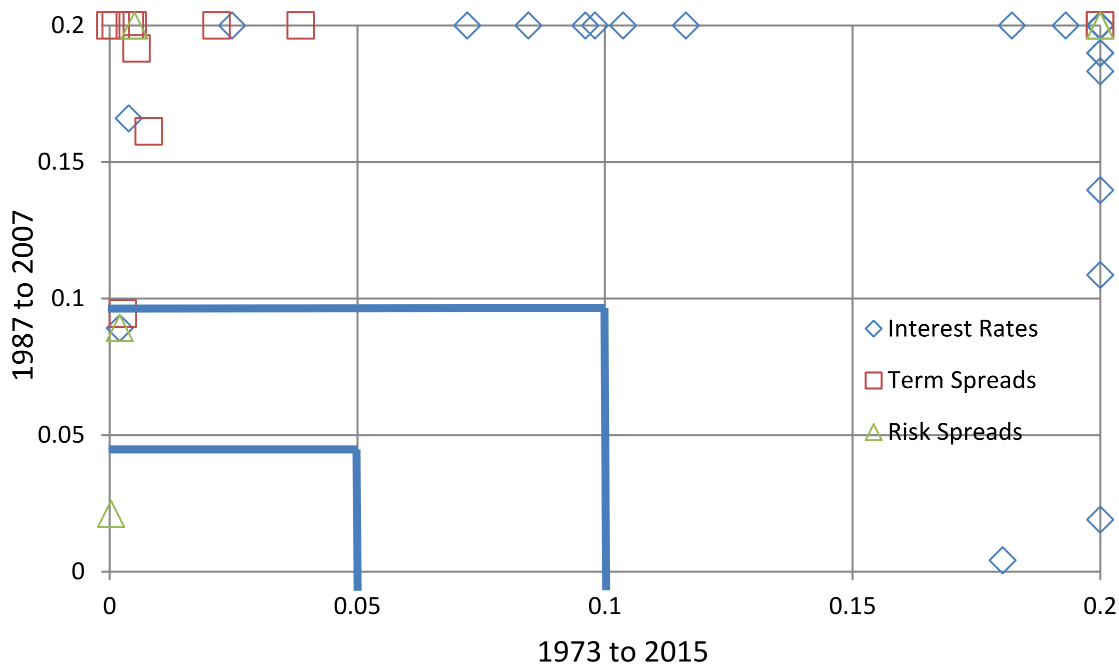
Source: Authors' calculations.

Figure 2



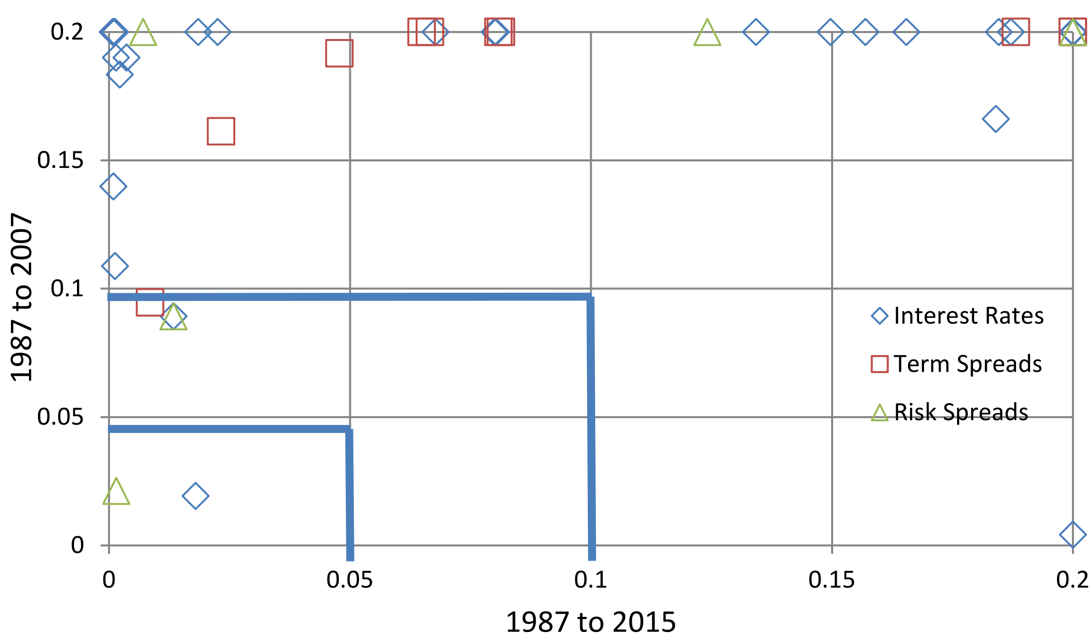
Source: Authors' calculations.

Figure 3A *P*-Values for Wald Test, Interest Rates Variables



Source: Authors' calculations.

Figure 3A *P*-Values for Wald Test, Interest Rates Variables, Post-1986 Sample



Source: Authors' calculations.

Figure 4 Common Factor η and Excess Bond Premium (EBP)

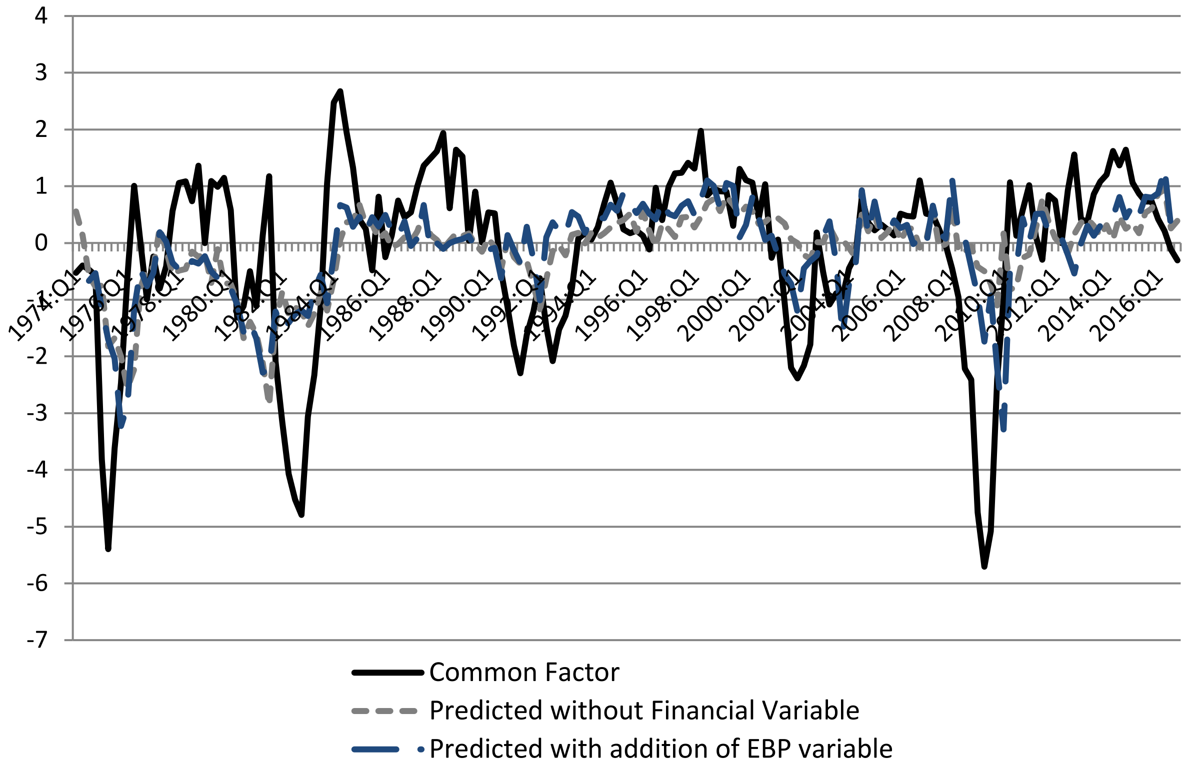


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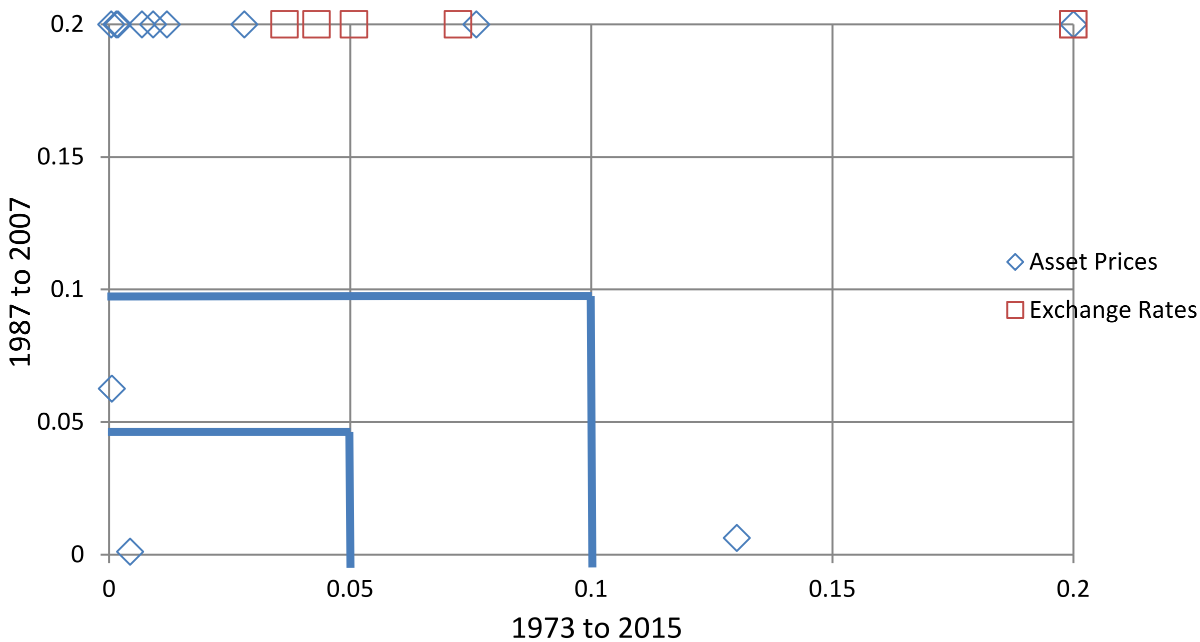
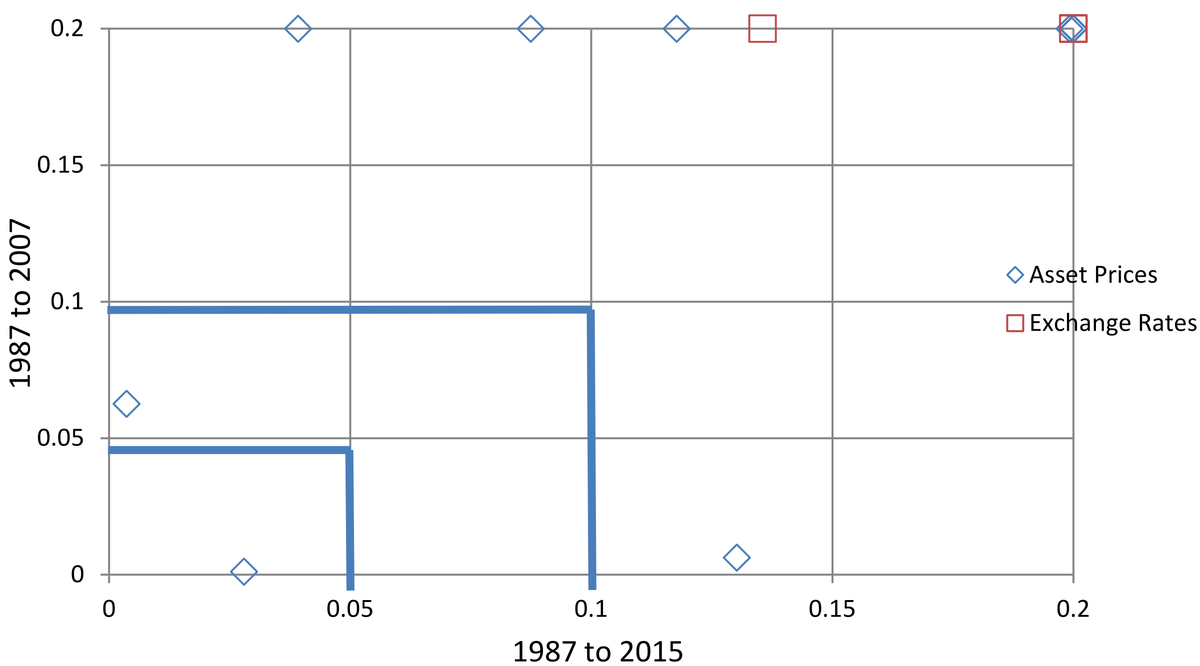
Figure 5A *P*-Values for Wald Test, Asset Prices Variables



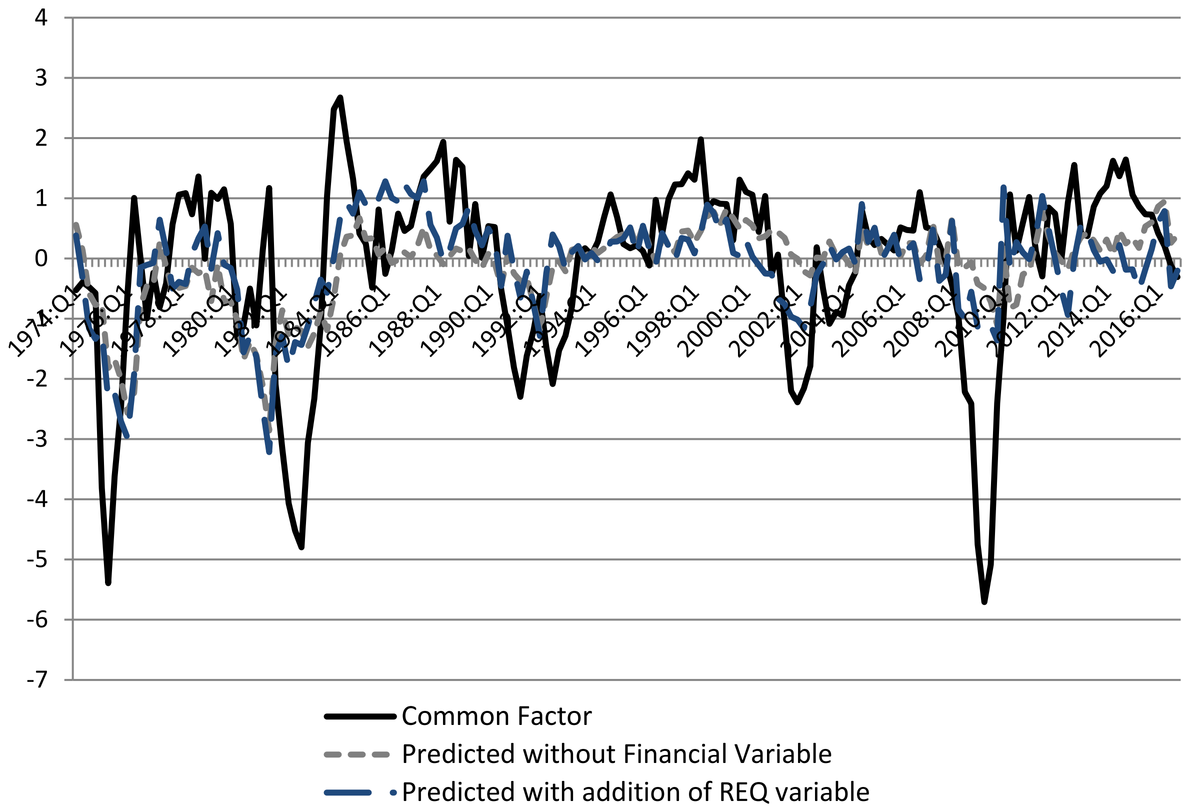
Source: Authors' calculations.

Figure 5B *P*-Values for Wald Test, Asset Prices Variables, Post-1986 Sample



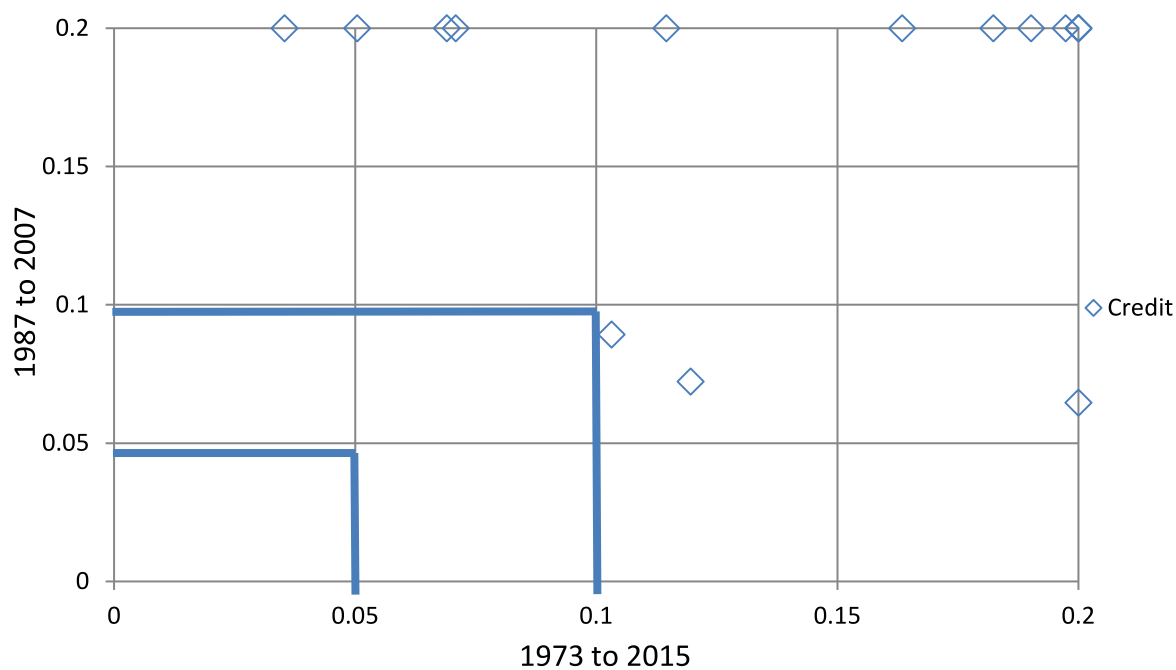
Source: Authors' calculations.

Figure 6   Common Factor η and Expected Return on Equity



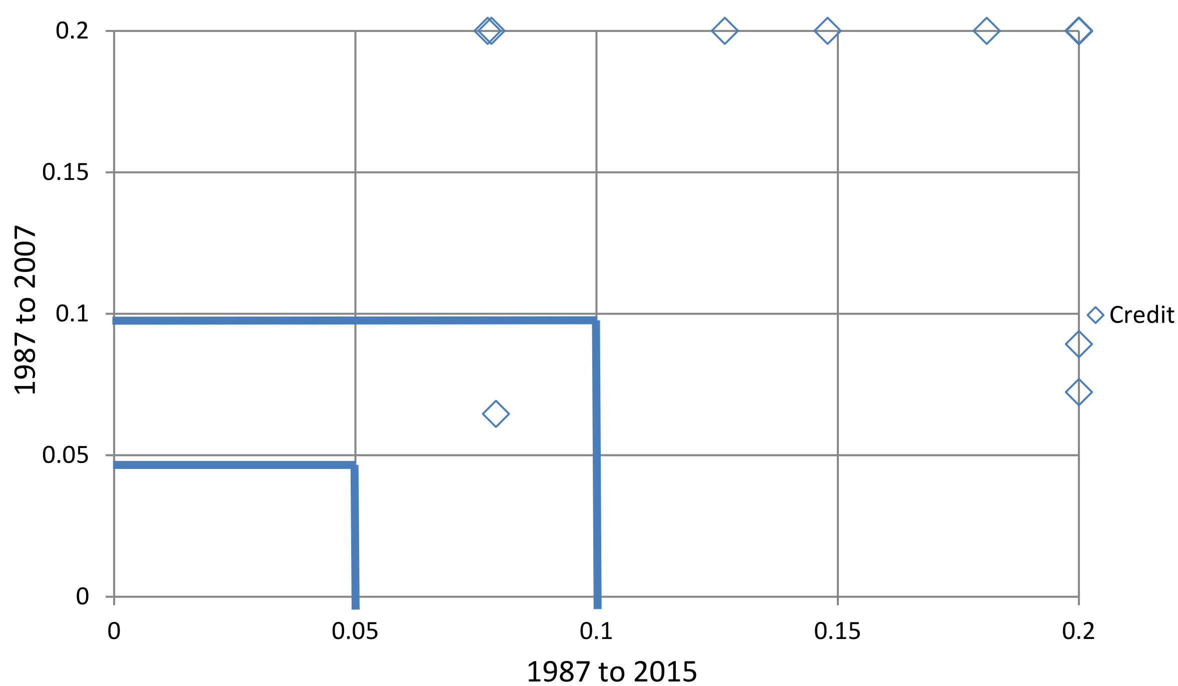
Source: Authors' calculations.

Figure 7A *P*-Values for Wald Test, Credit Variables



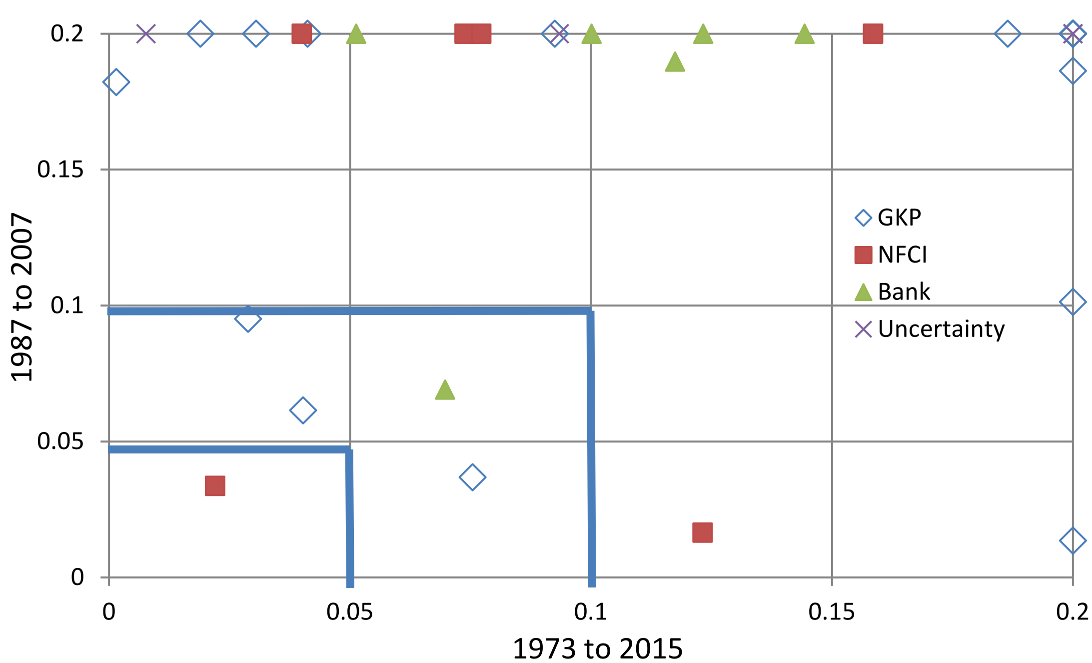
Source: Authors' calculations.

Figure 7B *P*-Values for Wald Test, Credit Variables, Post-1986 Sample



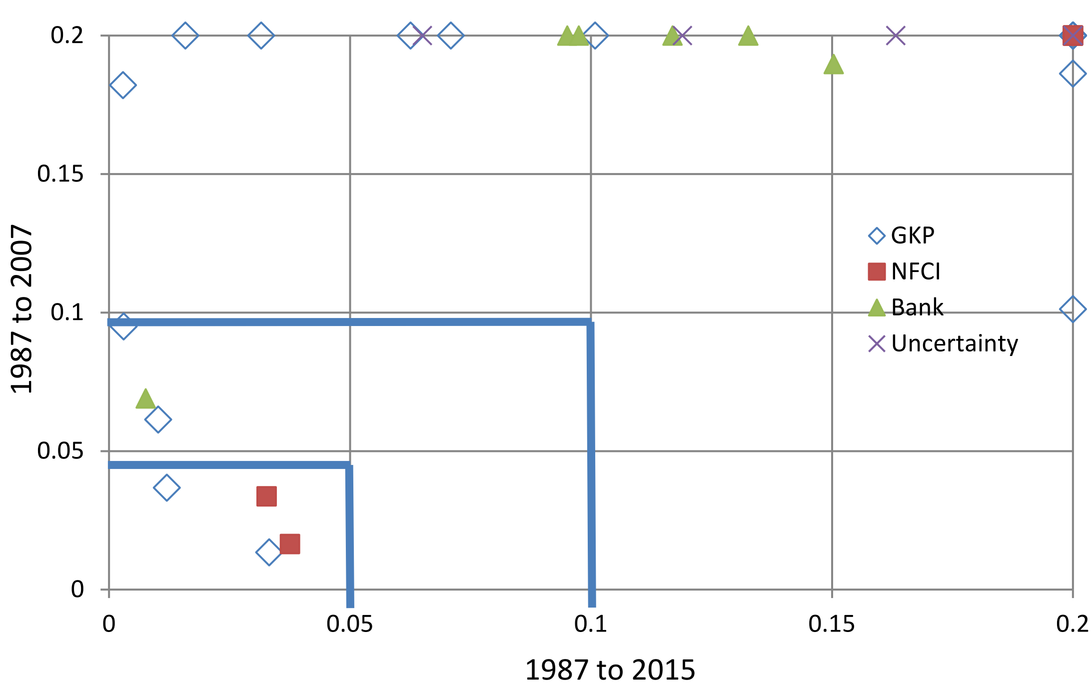
Source: Authors' calculations.

Figure 8A P-Values for Wald Test, Other Financial Variables



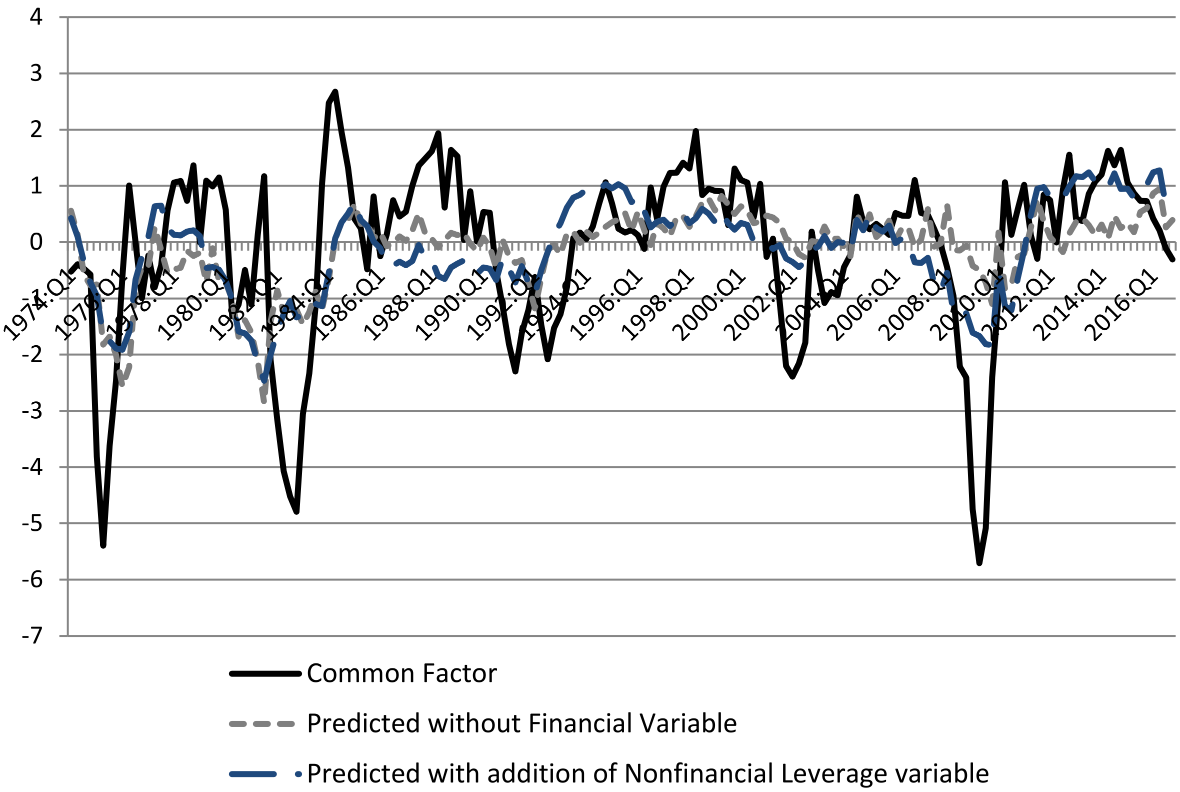
Source: Authors' calculations.

Figure 8B P-Values for Wald Test, Other Financial Variables, Post-1986 Sample



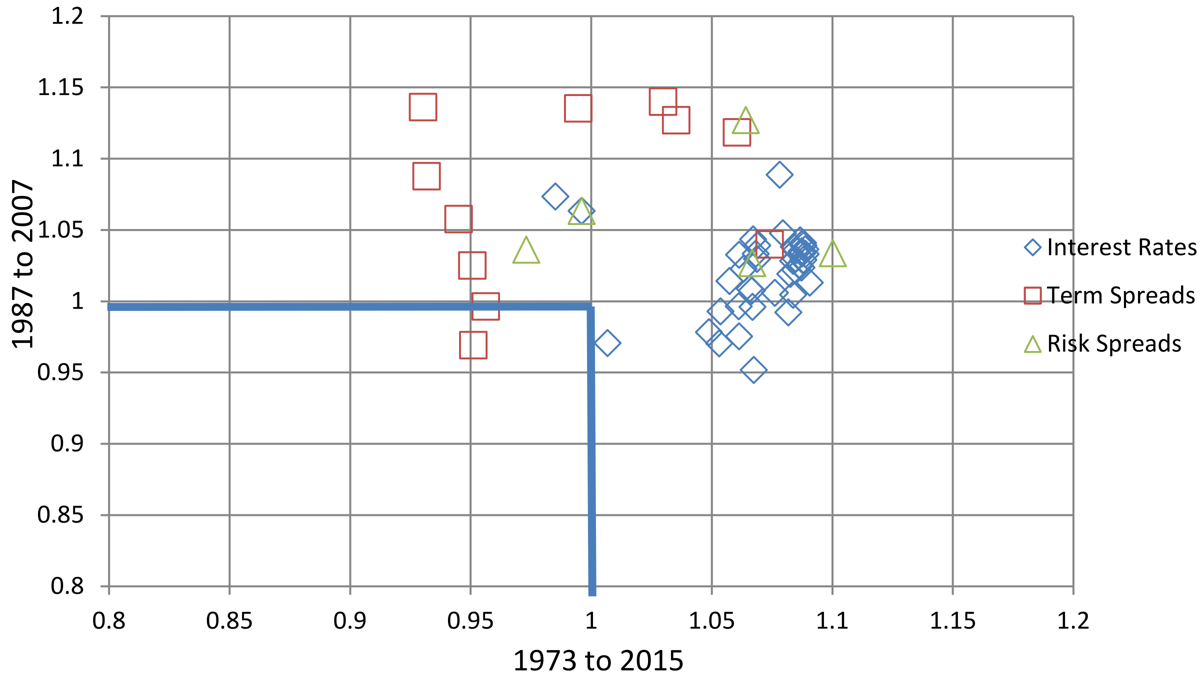
Source: Authors' calculations.

Figure 9 Common Factor η and Nonfinancial Leverage



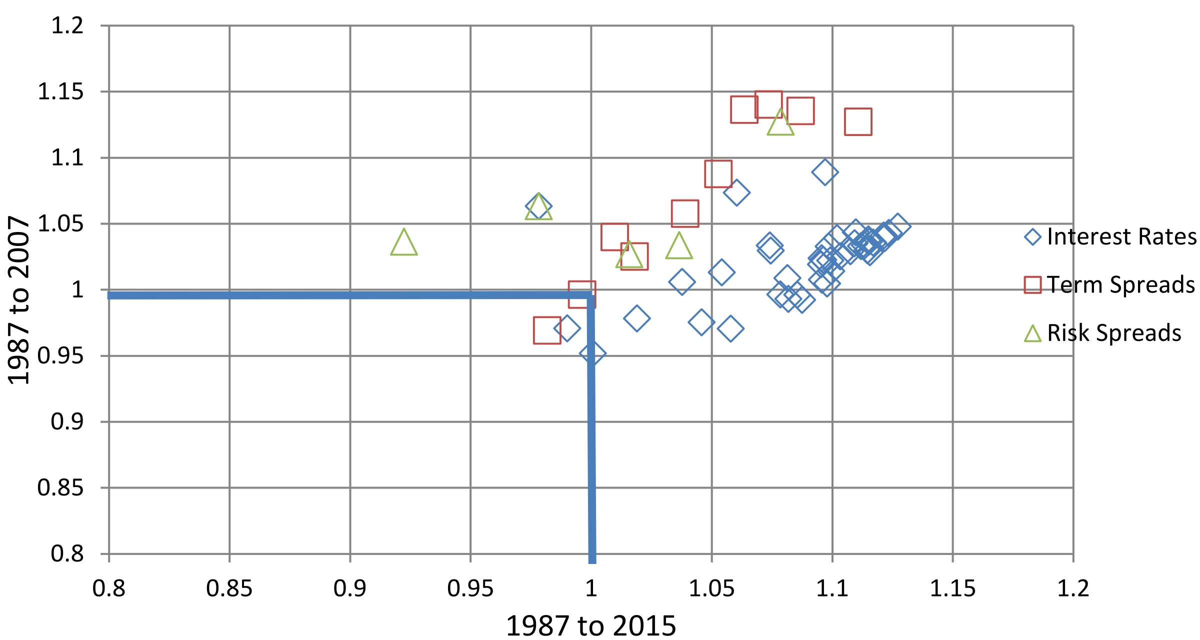
Source: Authors' calculations.

Figure 10A Sum of Square Residuals, Interest Rates Variables



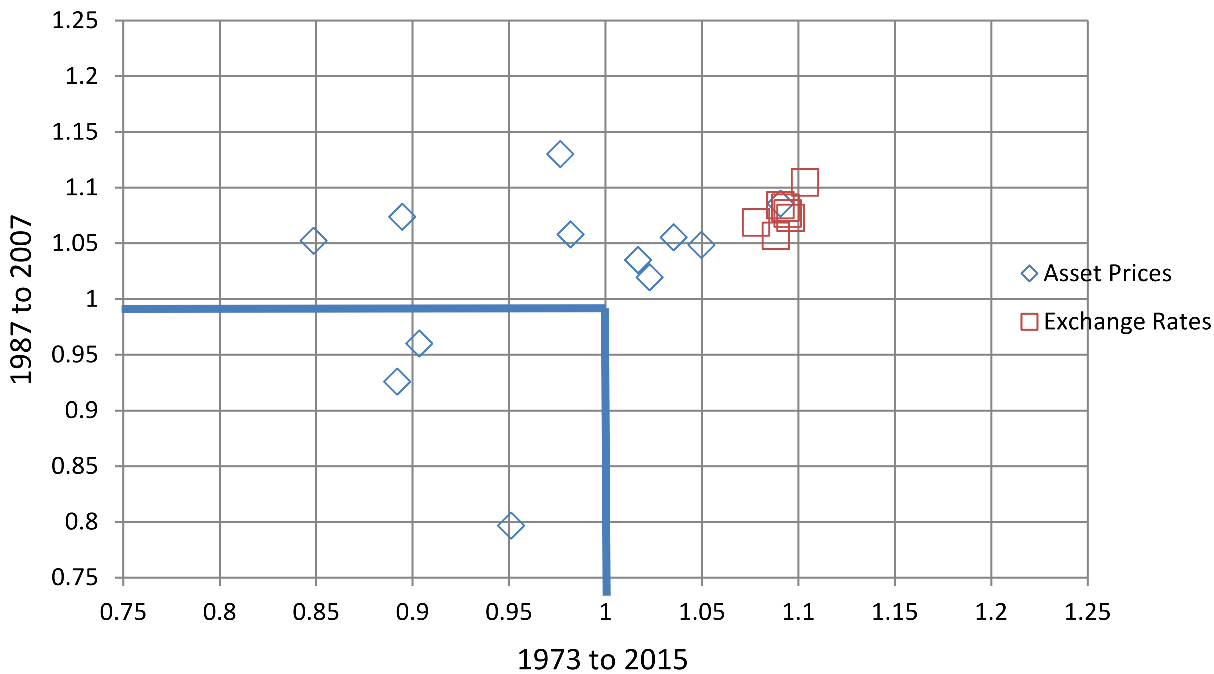
Source: Authors' calculations.

Figure 10B Sum of Square Residuals, Interest Rates Variables, Post-1986 Sample



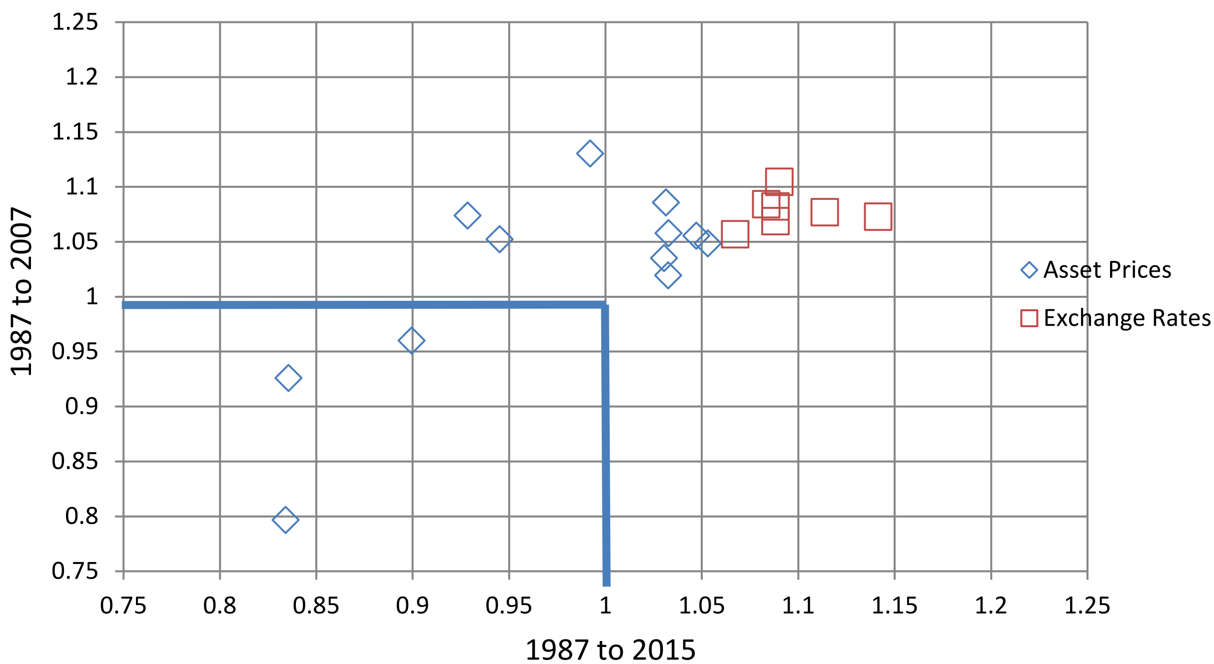
Source: Authors' calculations.

Figure 11A Sum of Square Residuals, Asset Prices Variables



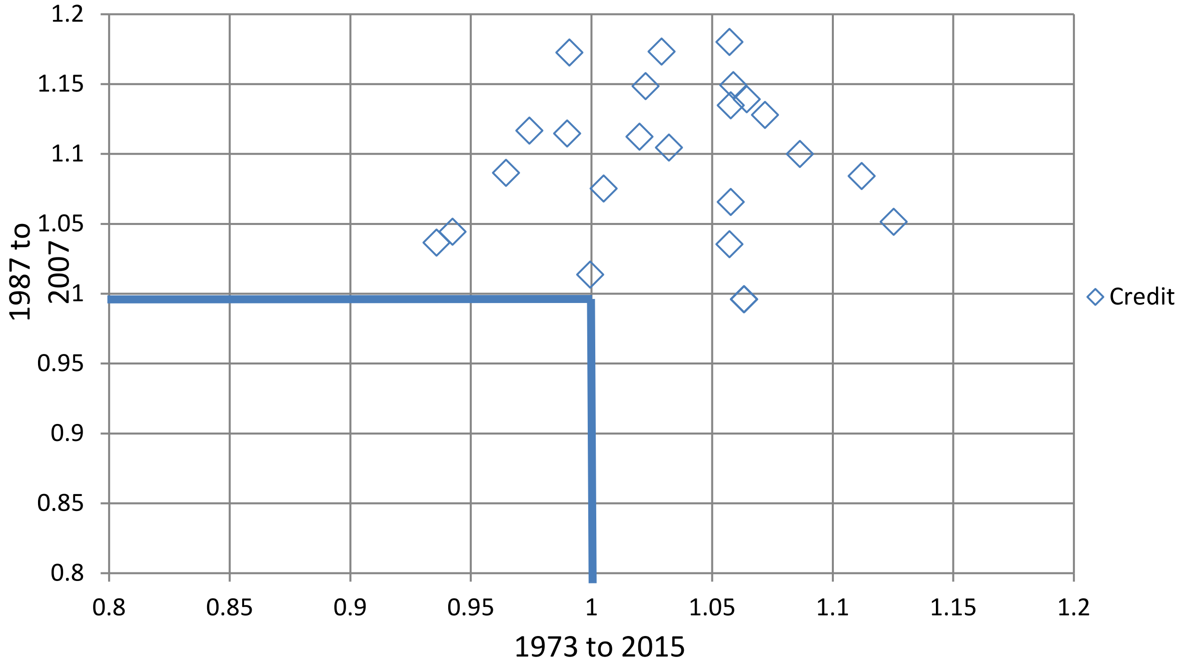
Source: Authors' calculations.

Figure 11B Sum of Square Residuals, Asset Prices Variables, Post-1986 Sample



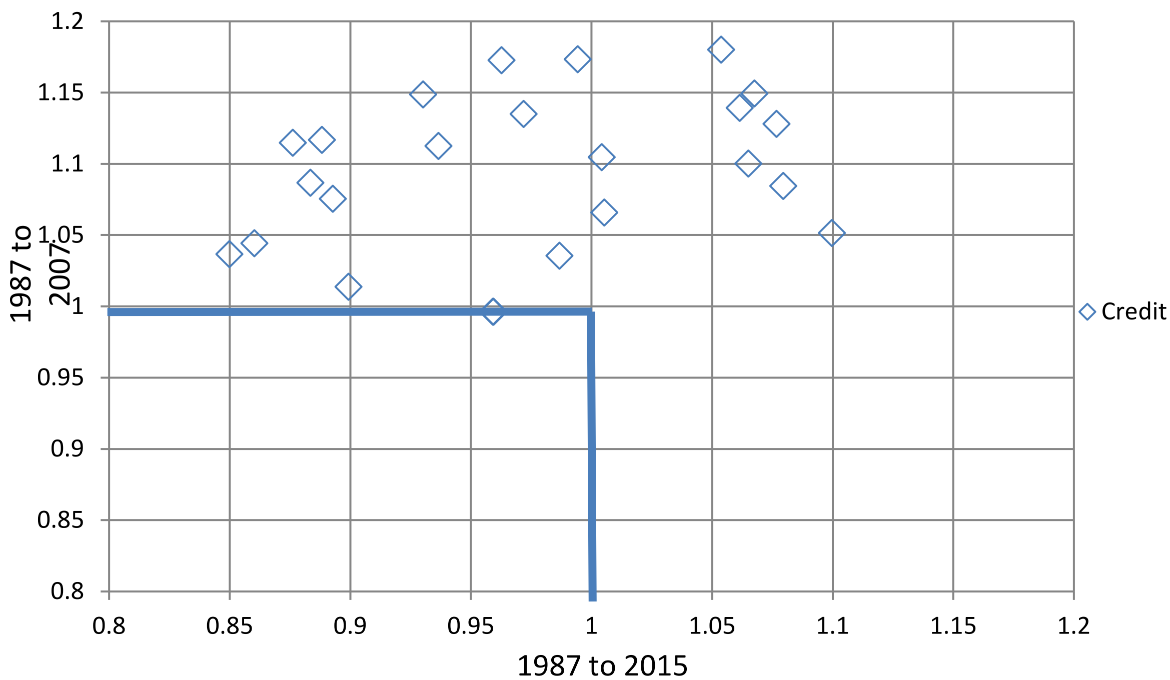
Source: Authors' calculations.

Figure 12A Sum of Square Residuals, Credit Variables



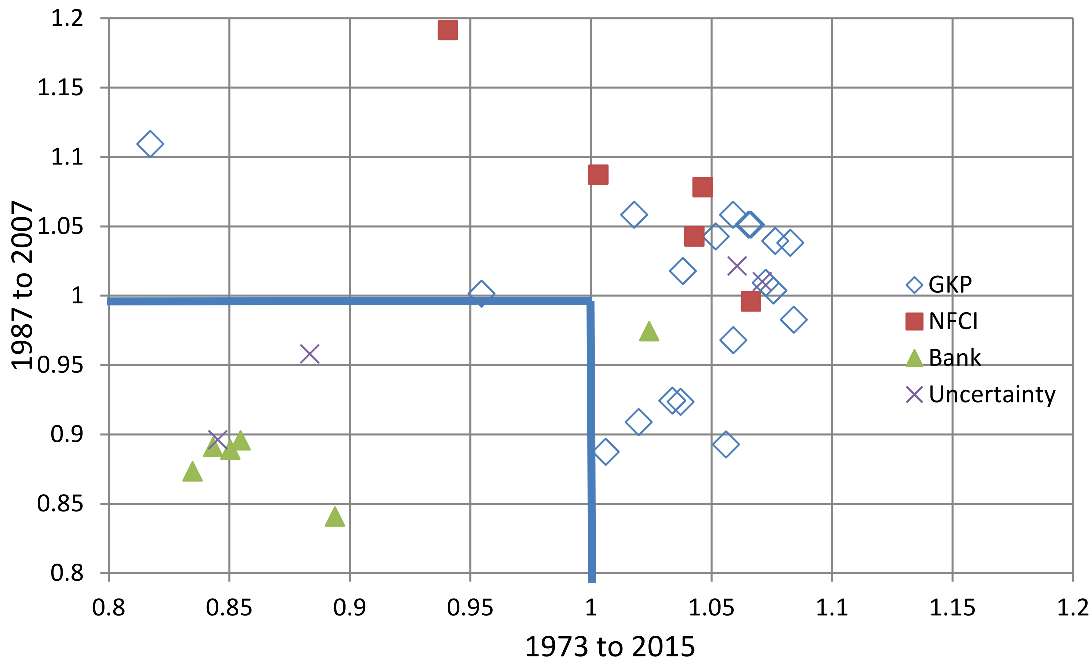
Source: Authors' calculations.

Figure 12B Sum of Square Residuals, Credit Variables, Post-1986 Sample



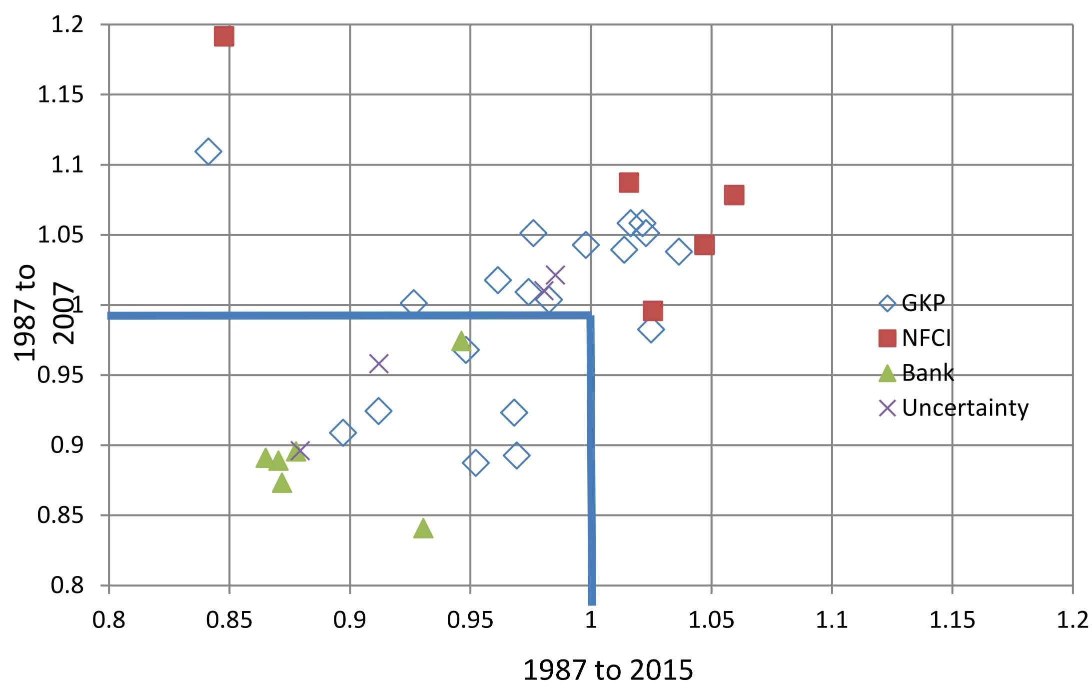
Source: Authors' calculations.

Figure 13A Sum of Square Residuals, Other Financial Variables



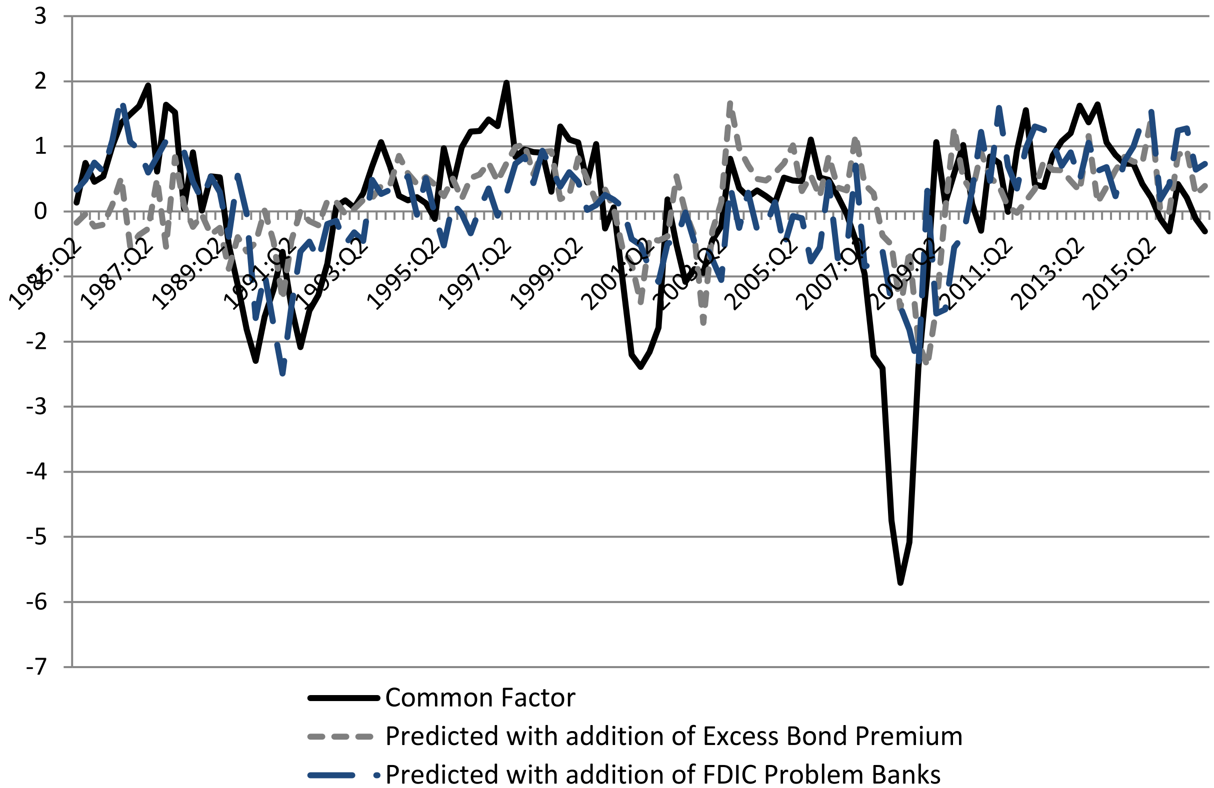
Source: Authors' calculations.

Figure 13B Sum of Square Residuals, Other Financial Variables, Post-1986 Sample



Source: Authors' calculations.

Figure 14 Common Factor η and FDIC's Problem Banks



Source: Authors' calculations.

Appendix 1

Macroeconomic and Financial Data

We compute principal components from a large set of macroeconomic data. The table below lists all variables used. We group principal components into two categories: (1) real activity data and (2) wage and price data. Before computing the principal component or using the financial variables, we transform the series; as such, the variables used in the construction of the two principal components and the financial variables are stationary as needed. Variables are listed below along with their mnemonics. The dataset is available from the authors upon request.

Real Variables

GDPPLUS	US GDPplus [Alternate Measure of Q/Q Rate of Growth of Real GDP] (SAAR, %Chg)
CUMFG	Capacity Utilization: Manufacturing [SIC] (SA, Percent of Capacity)
NAPMC	ISM Mfg: PMI Composite Index (SA, 50+ = Econ Expand)
NAPMOI	ISM Mfg: Production Index (SA, 50+ = Econ Expand)
YPSVR	Personal Saving Rate (SA, %)
PTVH	Change in Private Inventories: Contribution to Real GDP %Chg (SAAR, %Pt)
HSM	Manufacturers' Shipments of Mobile Homes (SAAR, Thous. Units)
GDPH	Real Gross Domestic Product (SAAR, Bil.Chn.2009$)
GDYH	Real Gross Domestic Income (SAAR, Bil.Chn.2009$)
GDPPOTHQ	Real Potential Gross Domestic Product [CBO] (SAAR, Bil.Chn.2009$)
IP	Industrial Production Index (SA, 2007=100)
LXNFA	Nonfarm Business Sector: Real Output Per Hour of All Persons (SA, 2009=100)
LXNCA	Nonfinancial Corporations: Real Output Per Hour, All Employees (SA,2009=100)
CH	Real Personal Consumption Expenditures (SAAR, Bil.Chn.2009$)
CSH	Real Personal Consumption Expenditures: Services (SAAR, Bil.Chn.2009$)
CNH	Real Personal Consumption Expenditures: Nondurable Goods (SAAR, Bil.Chn.2009$)
CDH	Real Personal Consumption Expenditures: Durable Goods (SAAR, Bil.Chn.2009$)
CDVH	Real PCE: Motor Vehicles & Parts (SAAR, Bil.Chn.2009$)
YPMH	Real Personal Income (SAAR, Bil.Chn.2009$)
YPXTPH	Real Personal Income excluding Current Transfer Receipts (SAAR, Bil.Chn.2009$)
YPWH	Wages & Salaries (SAAR, Bil. 2009$)
YCOMPRH	Compensation of Employees (SAAR, Bil. 2009$)
YPDH	Real Disposable Personal Income (SAAR, Bil.Chn.2009$)
Y_PRIV	Real Personal Income Ex-Govt. Transfers
FNEH	Real Private Nonresidential Fixed Investment: Equipment (SAAR, Bil.Chn.2009$)
FNENH	Real Pvt Nonres Fixed Investment: Info Processing Eqpt (SAAR, Bil.Chn.2009$)
FNEIH	Real Private Fixed Investment: Industrial Equipment (SAAR, Bil.Chn.2009$)
FNETH	Real Private Fixed Investment: Transportation Equipment (SAAR, Bil.Chn.2009$)
FNEOH	Real Private Fixed Invest: Other Equipment (SAAR, Bil.Chn.2009$)
FNPH	Real Pvt Nonres Investment: Intellectual Property Products (SAAR, Bil.Chn.2009$)
FNSH	Real Private Nonresidential Fixed Investment: Structures (SAAR, Bil.Chn.2009$)

FRH	Real Private Residential Fixed Investment (SAAR, Bil.Chn.2009$)
LRGAP	RA16-NAIRUQ
LUMD	Median Duration of Unemployment (SA, Weeks)
LUAD	Average [Mean] Duration of Unemployment (SA, Weeks)
LU0P	Unemployed for Less Than 5 Weeks: % of Civilians Unemployed (SA, %)
LU5P	Unemployed for 5-14 Weeks: % of Civilians Unemployed (SA, %)
LU15P	Unemployed for 15-26 Weeks: % of Civilians Unemployed (SA, %)
LUT27P	Unemployed for 27 Weeks and Over: % of Civilians Unemployed (SA, %)
NAPMEI	ISM Mfg: Employment Index (SA, 50+ = Econ Expand)
HWI	Help-Wanted Index (from Regis Barnichon)
RA16	Unemployment Rate (SA, %)
NAIRUQ	Natural Rate of Unemployment [CBO] (%)
RA15	Unemployment Rate: Unemployed 15 Weeks & Over [% of Civilian Labor Force](SA, %)
RA27	Unemployment Rate: Unemployed Less Than 27 Weeks (SA, %)
LICM	Initial Claims for Unemployment Insurance, State Programs, Wkly Avg (SA, Thous)
EA16	Civilian Employment (SA, Thous)
QA16	Employment-Population Ratio (SA, %)
FA16	Labor Force Participation Rate (SA, %)
LANAGRA	All Employees: Total Nonfarm (SA, Thous)
LAPRIVA	All Employees: Total Private Industries (SA, Thous)
LAGOVTA	All Employees: Government (SA, Thous)
LRPRIVA	Average Weekly Hours: Prod & Nonsupervisory: Private Industries (SA, Hrs)
LRGOODA	Avg Weekly Hours: Prod & Nonsupervisory: Goods-producing Industries (SA, Hrs)
LRPSRVA	Avg Wkly Hrs: Prod & Nonsupervisory: Pvt Service-providing Industries (SA, Hrs)
LOMANUA	Average Weekly Hours: Prod & Nonsupervisory: Overtime: Manufacturing (SA, Hrs)
LHTNAGRA	Aggregate Hours: Nonfarm Payrolls, Total (SAAR, Bil.Hrs)
CSENT	University of Michigan: Consumer Sentiment (NSA, Q1-66=100)
CEXP	University of Michigan: Consumer Expectations (NSA, Q1-66=100)
CCIN	Conference Board: Consumer Confidence (SA, 1985=100)
CCIEN	Conference Board: Consumer Expectations (SA, 1985=100)
HST	Housing Starts (SAAR, Thous.Units)
HPT	New Pvt Housing Units Authorized by Building Permit (SAAR, Thous.Units)

<u>Wage and Price Variables</u>

JGDP	Gross Domestic Product: Chain Price Index (SA, 2009=100)
JC	Personal Consumption Expenditures: Chain Price Index (SA, 2009=100)
JCXFE	PCE less Food & Energy: Chain Price Index (SA, 2009=100)
JCGSE	PCE: Energy Goods & Services: Chain Price Index (SA, 2009=100)
JCNFO	PCE: Food & Bev Purch for Off-Premises Consumptn: Chain Price Id x(SA, 2009=100)
JCXEGM	PCE excluding Energy Goods & Services: Chain Price Index (SA, 2009=100)
JCN	PCE: Nondurable Goods: Chain Price Index (SA, 2009=100)
JCD	PCE: Durable Goods: Chain Price Index (SA, 2009=100)
JCS	Personal Consumption Expenditures: Services: Chain Price Index (SA, 2009=100)
PCU	CPI-U: All Items (SA, 1982-84=100)
PCUSLFE	CPI-U: All Items Less Food and Energy (SA, 1982-84=100)
PCUSLE	CPI-U: All Items Less Energy (SA, 1982-84=100)

PCUSLF	CPI-U: All Items Less Food (SA, 1982-84=100)
PCUSLS	CPI-U: All Items Less Shelter (SA, 1982-84=100)
PCUSLM	CPI-U: All Items Less Medical Care (SA, 1982-84=100)
PCUCC	CPI-U: Commodities (SA, 1982-84=100)
PCUCS	CPI-U: Services (SA, 1982-84=100)
PCUCCDN	CPI-U: Durables (NSA, 1982-84=100)
PCUSND	CPI-U: Nondurables (SA, 1982-84=100)
UAXAF	CPI-U: Apparel Less Footwear (SA, 1982-84=100)
PCUT	CPI-U: Transportation (SA, 1982-84=100)
PCUM	CPI-U: Medical Care (SA, 1982-84=100)
PZALL	KR-CRB Spot Commodity Price Index: All Commodities (1967=100)
PZTEXP	Spot Oil Price: West Texas Intermediate [Prior'82=Posted Price] ($/Barrel)
SP3000	PPI: Finished Goods (SA, 1982=100)
SP2000	PPI: Intermediate Materials, Supplies and Components (SA, 1982=100)
SP1000	PPI: Crude Materials for Further Processing (SA, 1982=100)
SP3100	PPI: Finished Consumer Goods (SA, 1982=100)
LEPRIVA	Avg Hourly Earnings: Prod & Nonsupervisory: Total Private Industries (SA, $/Hour)
LEGOODA	Avg Hourly Earnings: Prod & Nonsupervisory: Goods-producing Industries (SA, $/Hr)
LEPSRVA	Avg Hrly Earn: Prod & Nonsupervisory: Private Svc-providing Industries (SA, $/Hr)
LXNFC	Nonfarm Business Sector: Compensation Per Hour (SA, 2009=100)
LXNCC	Nonfinancial Corporations: Compensation Per Hour (SA, 2009=100)
LSP	ECI: Compensation: Private Industry Workers (SA, Dec-05=100)
LXNFBL	Nonfarm Business: Labor Share, All Persons (SA)
LXNCBL	Nonfinancial Corporations: Labor Share, All Employees (SA)
PTR	10-year expected inflation (Hoey/Philadelphia survey)
ZPI10	Expected cons. price infl., for RCCH and RG10E eqs. (10-yr mat., weight: 1.0)
ZPIC30	Expected cons. price infl., for RCBE and WPSN eqs. (30-yr mat., weight: 1.0)
ZPI5	Expected cons. price infl., for RG5E eq. (5-yr mat., weight: 1.0)
ZPIC58	Expected consumer price inflation (5-8 qtrs mat.)

Financial Variables

SDY5COMM	S&P: Composite 500, Dividend Yield (%)
SPE5COMM	S&P: 500 Composite, Price/Earnings Ratio (Ratio)
SPECAPE	Shiller Cyclically Adjusted S&P Price to Earnings Ratio (Ratio)
REQ	Real expected rate of return on equity
PL10COG6	Nonfinancial Corporate Business: Market Value of Equities/Net Worth (%)
SPNY	Stock Price Index: NYSE Composite (Avg, Dec-31-02=5000)
SP500	Stock Price Index: Standard & Poor's 500 Composite (1941-43=10)
SPSPI	Stock Price Index: Standard & Poor's 500 Industrials (1941-43=10)
SPNYK	NYSE Financial Stock Price Index (Avg, 2003=100)
PA15CDA5_H	Households & Nonprofit Organizations: Net Worth (NSA, Bil.$)
WPS	Household stock market wealth, real
WPO	Household property wealth ex. stock market, real
FPX	Nominal exchange rate (G39, import/export trade weights)
FPXM	Nominal exchange rate (G39, bilateral import trade weights)
FPXR	Real exchange rate (G39, import/export trade weights)

FXUK	Foreign Exchange Rate: United Kingdom (US$/Pound)
FXSW	Foreign Exchange Rate: Switzerland (Franc/US$)
FXJAP	Foreign Exchange Rate: Japan (Yen/US$)
FXCAN	Foreign Exchange Rate: Canada (C$/US$)
FWILL	FRB Sr Officers Survey: Banks Willingness to Lend to Consumers (%)
FFED	Federal Funds [effective] Rate (% p.a.)
FBPR	Bank Prime Loan Rate (% p.a.)
FFP1	1-Month Financial Commercial Paper (% per annum)
FTB3	3-Month Treasury Bills (% p.a.)
FTB6	6-Month Treasury Bills (% p.a.)
FBDB1Y	Fama Bliss Discount Bond Yield, 1-year
FBDB2Y	Fama Bliss Discount Bond Yield, 2-year
FBDB3Y	Fama Bliss Discount Bond Yield, 3-year
FBDB4Y	Fama Bliss Discount Bond Yield, 4-year
FBDB5Y	Fama Bliss Discount Bond Yield, 5-year
TREAS1Y	Fama Bliss Treasury Yield, 1-year (fixed term index)
TREAS2Y	Fama Bliss Treasury Yield, 2-year (fixed term index)
TREAS5Y	Fama Bliss Treasury Yield, 5-year (fixed term index)
TREAS7Y	Fama Bliss Treasury Yield, 7-year (fixed term index)
TREAS10Y	Fama Bliss Treasury Yield, 10-year (fixed term index)
TREAS20Y	Fama Bliss Treasury Yield, 20-year (fixed term index)
TREAS30Y	Fama Bliss Treasury Yield, 30-year (fixed term index)
FYCCZ1E	US Treasury Yield: Continuously Compounded Zero-Coupon: 1-Yr (EOP, %)
FYCCZ2E	US Treasury Yield: Continuously Compounded Zero-Coupon: 2-Yrs (EOP, %)
FYCCZ3E	US Treasury Yield: Continuously Compounded Zero-Coupon: 3-Yrs (EOP, %)
FYCCZ4E	US Treasury Yield: Continuously Compounded Zero-Coupon: 4-Yrs (EOP, %)
FYCCZ5E	US Treasury Yield: Continuously Compounded Zero-Coupon: 5-Yrs (EOP, %)
FYCCZ6E	US Treasury Yield: Continuously Compounded Zero-Coupon: 6-Yrs (EOP, %)
FYCCZ7E	US Treasury Yield: Continuously Compounded Zero-Coupon: 7-Yrs (EOP, %)
RCAR	Commercial Real Estate: RCA-Based Top-10 MSA Retail Index DISC (NSA, Q4-00=1)
RME	Interest rate on conventional mortgages (effective ann. yield)
RG10E	10-year Treasury bond rate (effective ann. yield)
RG10P	10-year Treasury bond rate, term premium
RG5E	5-year Treasury note rate (effective ann. yield)
RG5P	5-year Treasury note rate, term premium
RG30E	30-year Treasury bond rate (effective ann. yield)
RG30P	30-year Treasury bond rate, term premium
RBBBE	S&P BBB corporate bond rate (effective ann. yield)
RBBBP	S&P BBB corporate bond rate, risk/term premium
RPD	After-tax real financial cost of capital for producers' durable equipment
RCCD	Cost of capital for consumer durables
RCCH	Cost of capital for residential investment
FK24P	Commercial Bank Interest Rates: 24-Month Personal Loans (NSA, %)
FCIR	C&I Loan Rate: All Loans, Actual (%)
FCIRS	C&I Loan Rate Spread Over Intended Fed Funds Rate: All Loans, Actual (%)
TP3M	FTB3 - FFED
TP6M	FTB6 - FFED
TP1Y	FTB1Y - FFED

TP3Y	FTB3Y - FFED
TP5Y	FTB5Y - FFED
TP7Y	FTB7Y - FFED
TP10Y	FTB10Y - FFED
TP30Y	FTB30Y - FFED
RP_BBB	RBBBE - RG10E
RP_RME	RME - RG10E
RP_CAR	RCAR - FBDB4Y
RP_24P	FK24P - FBDB2Y
FA70CNC5	Private Depository Institutions: Assets: Consumer Credit (SAAR, % of potential GDP)
FA70MOR5	Private Depository Institutions: Assets: Total Mortgages (SAAR, % of potential GDP)
FA70BLN5	Private Depository Institutions: Assets: Other Loans and Advances (SAAR, % of potential GDP)
FA76CNC0	U.S.-Chartered Depository Institutions: Assets: Consumer Credit (% of potential GDP)
FA76MOR5	U.S.-Chartered Depository Institutions: Assets: Total Mortgages (% of potential GDP)
FA76BLN5	U.S.-Chartered Dep Inst: Assets: Dep Institution Loans n.e.c. (% of potential GDP)
FA61CNC5	Finance and ABS Companies: Consumer Credit (% of potential GDP)
FA61MOR0	Finance and ABS Companies: Total Mortgages (% of potential GDP)
FA61FLB0	Finance Companies: Loans to Business (% of potential GDP)
FL14MOR5	Nonfinancial Business: Mortgages (% of potential GDP)
FL14BLN5	Nonfinancial Business: Bank Loans n.e.c. (% of potential GDP)
FL14OTL5	Nonfinancial Business: Other Loans and Advances (% of potential GDP)
FL15CNC0	Household Borrowing in Consumer Credit (% of potential GDP)
FL15OTL5	Households: Other Loans and Advances (% of potential GDP)
FL15HOM5	Household Borrowing in Home Mortgage (% of potential GDP)
FABWCA	Break-Adjusted C & I Loans in Bank Credit: All Comml Banks (% of potential GDP)
FABWRA	Break-Adjusted Real Estate Loans in Bank Credit: All Comml Banks (% of potential GDP)
FABWQA	Break-Adjusted Consumer Loans in Bank Credit: All Comml Banks (% of potential GDP)
FABWOA	Break-Adjusted Other Loans & Leases in Bank Credit: All Comml Banks (% of potential GDP)
FABWCDA	Break-Adjusted C & I Loans in Bank Credit: Domestic Comml Banks (% of potential GDP)
FABWRDA	Break-Adjusted Real Estate Loans in Bank Credit: Domestic Comml Banks (% of potential GDP)
FABWQDA	Break-Adjusted Consumer Loans in Bank Credit: Domestic Comml Banks (% of potential GDP)
FABWODA	Break-Adjusted Other Loans & Leases in Bank Credit: Domestic Comml Banks (% of potential GDP)
FONA	Break-Adjusted Nonrevolving Consumer Credit Outstanding (% of potential GDP)
FOTA	Break-Adjusted Consumer Credit Outstanding (% of Potential GDP)
NFCI	Chicago Fed National Financial Conditions Index
ANFCI	Chicago Fed Adjusted National Financial Conditions Index
LVRG	Chicago Fed National Financial Conditions Index – Leverage
NFLVR	Chicago Fed National Financial Conditions Index – Nonfinancial Leverage
RISK	Chicago Fed National Financial Conditions Index – Risk
CREDIT	Chicago Fed National Financial Conditions Index – Credit
SPVXO	Stock Market Volatility Index
EPU_HIST	Baker Bloom and Davis Historical News Based Uncertainty Index
EPU_Base	Baker, Bloom and Davis Baseline Overall Uncertainty Index

EPU_News	Baker, Bloom and Davis News Based Uncertainty Index
Agg_NPL_Ratio	Non Performing Loans – All Commercial & Savings Bank (less some banks based on rssd9425, i.e. credit card banks)
Lrg_NPL_Ratio	Non Performing Loans – All Commercial & Savings Banks – Assets Greater or Equal $50 billion
Sml_NPL_Ratio	Non Performing Loans – All Commercial & Savings Banks – Assets Less Than $50 billion
	PB_SHR_NUM Problem Bank share (count) end of year from the FDIC
PB_SHR_Assets	Problem Bank Assets share - end of year from the FDIC
EBP_OA	Gilchrist Zakrajšek Excess Bond Premium
GZ_SPR	Gilchrist Zakrajšek Spread
FFP3	3-Month Financial Commercial Paper (% per annum)
FCP3	3-Month Nonfinancial Commercial Paper (% per annum)
TPFCP3	FCP3-FFED
TPFFP3	FFP3-FFED
Absorption	Kritzman, Li, Page and Rigobon (2011) Absorption Ratio - Fraction of Financial System Variance Explained by First 3 Principal Components
AIM	Amihud (2002) Illiquidity Measure Aggregated Across Financial Firms
CoVar	Adrian and Brunnermeier (2011): Individual Banks' Sensitivity to Economy-wide Systemic Risk
DCoVar	Change in CoVar
MES	Acharya, Pederson, Phillipon and Richardson (2010): Individual Banks' Marginal Expected Shortfall Measure
MES-BE	Brownlees and Engle (2011): Individual Banks' Marginal Expected Shortfall Measure
BookLvr	Giglio, Kelly and Pruitt (2016): Aggregate Book Leverage for Largest 20 Financial Institutions
CatFin	Allen, Bali and Tang (2012): Value at Risk Measure Calculated Across the Cross Section of Financial Firms
DCI	Billio, Lo, Getmansky, and Pelizzon (2012): Dynamic Causality Index
DAbsorption	Change in Absorption
Int_Spill	Diebold and Yilmaz (2009): International Spillover Index
Size_Con	Giglio, Kelly and Pruitt (2016): Size Concentration in Financial Industry
Mkt_Lvg	Giglio, Kelly and Pruitt (2016): Aggregate Market Leverage for Largest 20 Financial Institutions
Volatility	Giglio, Kelly and Pruitt (2016): Average Equity Volatility for Largest 20 Financial Institutions, Averaged
TED_spr	LIBOR-T-bill
Turbulence	Kritzman and Li (2010): Returns' Recent Covariance Relative to Long-term Covariance Estimate
PQR	Giglio, Kelly and Pruitt (2016): Partial Quantile Regression Common Factor of 19 Systemic Risk Measures