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Charlotte Christiansen, Jonas Nygaard Eriksen and Stig V. Møller

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Department of Economics and Business
Aarhus University
Fuglesangs Allé 4
DK-8210 Aarhus V
Denmark

Email: oekonomi@au.dk
Tel: +45 8716 5515

Forecasting US Recessions: The Role of Sentiments*

Charlotte Christiansen† — CREATES, Aarhus University

Jonas Nygaard Eriksen‡ — CREATES, Aarhus University

Stig Vinther Møller§ — CREATES, Aarhus University

Abstract: We examine sentiment variables as new predictors for US recessions. We combine sentiment variables with either classical recession predictors or with common factors based on a large panel of macroeconomic and financial variables. Sentiment variables hold vast predictive power for US recessions in excess of both the classical recession predictors and the common factors. The strong importance of the sentiment variables is documented both in-sample and out-of-sample.

Keywords: Business cycles; Forecasting; Factor analysis; Probit model; Sentiment variables

JEL Classification: C22; C25; E32; E37; G17

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†CREATES, Department of Economics and Business, Aarhus University, Fuglesangs Alle 4, 8210 Aarhus V, Denmark. Phone: +45 8716 5576. Email: CChristiansen@creates.au.dk.

‡CREATES, Department of Economics and Business, Aarhus University, Fuglesangs Alle 4, 8210 Aarhus V, Denmark. Phone: +45 8716 6024. Email: JEriksen@creates.au.dk.

§CREATES, Department of Economics and Business, Aarhus University, Fuglesangs Alle 4, 8210 Aarhus V, Denmark. Phone: +45 8716 4825. Email: svm@asb.dk.

1 Introduction

The monthly releases of consumer and business sentiment surveys attract widespread attention from experts, investors, and the media, and are among the most watched indicators of future economic activity, especially during times of economic crisis. Chairman of the Board of Governors of the Federal Reserve System Ben S. Bernanke expresses the importance of confidence in the following way: "*As in all past crises, at the root of the problem is a loss of confidence by investors and the public in the strength of key financial institutions and markets.*"[1]

The purpose of this paper is to investigate how sentiment survey variables relate to future recessions and whether they contain information over and above traditional predictor variables and a large panel of control variables. The presumption that business and consumer sentiment variables are related to the state of the economy is substantiated by Figure 1 in which we plot indices of consumer and business sentiment (denoted PMI and CC, respectively) against NBER defined recession periods marked by grey shading. Around each recession period the sentiment variables drop. Thus, Figure 1 highlights the procyclical movements of both sentiment indices in relation to the business cycle.

[Insert Figure 1 about here]

The concept that sentiment variables contain information about future fluctuations in the level of real economic activity is not new. Matsusaka and Sbordone (1995) show that consumer sentiment adds significant information in predicting GNP even after controlling for other relevant predictors. Batchelor and Dua (1998) find that forecast of GDP during the 1991 recession could have been improved had forecasters taken consumer confidence into account. Carroll, Fuhrer, and Wilcox (1994), Bram and Ludvigson (1998), Howrey (2001), and Ludvigson (2004) show that measures of consumer sentiment contain information about consumer spending. Howrey (2001) also considers the relation between consumer confidence and recessions. Taylor and McNabb (2007) investigate the role of consumer and business confidence for four European economies and find that the sentiment variables indeed do play a role in the prediction of recessions.

Earlier empirical research documents that financial variables such as the term spread, the short rate, and the stock market return are good predictors of future recessions, e.g. Estrella and Mishkin (1998), Wright (2006), Kauppi and Saikkonen (2008), and Nyberg

[1] Quotation from speech by Bernanke (2008).

(2010). We find that sentiment-based variables contain considerable higher predictive power than these classical recession predictors. Moreover, combining the sentiment variables with the classical recession predictors provide strong predictive power for future recession periods, both in-sample and out-of-sample. In addition, we examine the predictive power of a large number of recession predictors individually; the sentiment variables, the classical recession predictors, as well as more than 150 macroeconomic and financial time series. We find that business sentiment (PMI) is by far the single best recession predictor in both in-sample and out-of-sample predictions.

Evidence of incremental predictive power of sentiment variables could, however, simply be a results of the exclusion of other relevant economic control variables. To account for this concern, we examine the ability of sentiment variables to predict future recessions when controlling for a large panel of more than 150 macroeconomic and financial time series. This is done in an efficient way using a common factor approach. We find that sentiment variables stand out as being strongly statistically significant and they contribute with important additional explanatory power over and above the common factors. Similarly, the sentiment variables contribute with additional explanatory power over and above the classical recession predictors. Overall, the sentiment variables are strong predictors for future recessions, and the predictive power is boosted by combining them with either the classical recession predictors or with the common factors.

The rest of the paper is structured as follows. Section 2 describe the econometric methodology. Section 3 introduces the data. Section 4 presents the empirical results, both in-sample and out-of-sample. Section 5 concludes. Various details are delegated to the Appendix.

2 Econometric Methodology

This section describes the econometric methodology. First, we describe the probit model. Second, we discuss the evaluation measures. Third, we describe how the explanatory factors are constructed.

2.1 The Model

The main interest in this paper is to assess the predictive power of sentiment-based variables with respect to future recessions when controlling for a large set of potential explanatory variables. That is, we want to forecast the time-series variable $\{y_t\}_{t=1}^{T}$, which is a binary-valued stochastic process that takes values in $y_t = \{0, 1\}$ depending on the state of the economy

$$y_t = \begin{cases} 1, & \text{if the economy is in a recession at time } t \\ 0, & \text{if the economy is in an expansion at time } t \end{cases} \tag{1}$$

The scalar recession indicator y_t has, conditional on the information set $\mathcal{F}_{t-1}$, a Bernoulli distribution with probability parameter p_t, i.e. $y_t|\mathcal{F}_{t-1} \sim \mathcal{B}(p_t)$. We are interested in modeling the conditional probability p_t of a future recession using information available in $\mathcal{F}_{t-1}$. To do so, we consider a standard static probit model. Define $\mathbb{E}_{t-1}[\cdot]$ as the expectations operator and $\mathbb{P}_{t-1}[\cdot]$ as the probability, respectively, conditional on the information set $\mathcal{F}_{t-1}$. Under these settings, the conditional recession probability $(y_t = 1)$ satisfies

$$\mathbb{E}_{t-1}[y_t] = \mathbb{P}_{t-1}[y_t = 1] = \Phi(\pi_t) = p_t \tag{2}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, which ensures that the conditional probability takes values in the unit interval $[0, 1]$, and π_t is a linear function of variables in $\mathcal{F}_{t-1}$. In particular, we consider nested specifications of π_t of the following form

$$\pi_t = \varpi + s'_{t-k}\alpha + z'_{t-k}\beta + f'_{t-k}\gamma \tag{3}$$

where s_{t-k} is a vector of sentiment variables, z_{t-k} is a vector containing the classical recession predictors (e.g. the term spread), and f_{t-k} is a vector of common factors representing information from a large panel of economic variables. Hence, with this specification, we control for a much richer information set compared to prior studies in which only a few observed variables are used as controls. This is important because by conditioning on a rich information set, it becomes possible to examine to what extent sentiment variables indeed do contain independent incremental explanatory power not captured by other economic indicators.

The parameters of the probit model can be estimated using maximum likelihood, that is by maximizing the log-likelihood function given as

$$\mathcal{L}(y, \pi) = \sum_{t=1}^{T} [y_t \log \Phi(\pi_t) + (1 - y_t) \log (1 - \Phi(\pi_t))] \tag{4}$$

The maximization problem in (4) is a highly nonlinear problem, but it can be estimated in a straightforward manner using standard numerical methods. Robust standard errors of the parameter estimates are computed as suggested in Kauppi and Saikkonen (2008).

In order to select the best model, we make a search over different lag orders k and different combinations of the explanatory variables. We allow k to vary between one and six, and we allow for combinations of up to five explanatory variables. In the earlier literature, it is custom to set k equal to the forecast horizon h. However, Estrella and Mishkin (1998) and Kauppi and Saikkonen (2008) show that the latest value of the explanatory variables is not necessarily the best in terms of predictive power. Thus, we allow the lag structure to be determined purely by model selection techniques. Given the large number of potential predictors, some standard pretesting is necessary in order to reduce the dimensionality of the set of potential model combinations, e.g. Ludvigson and Ng (2009) and Christiansen, Schmeling, and Schrimpf (2012).[2] We reduce the initial set of potential predictor variables by only considering variables with a t-statistic greater than two in absolute value in a univariate predictive probit model. In this way, we end up with a smaller set of predictors such that an analytical evaluation of all model combinations is computationally feasible. We compute the Schwarz-Bayesian Information Criterion (BIC) for each model combination and rank them accordingly for model selection. The BIC tends to favor models that provide a good fit while at the same time penalizing highly parameterized models.

2.2 Evaluation Measures

We estimate the selected models both in-sample and out-of-sample. The advantage of the in-sample results is that all available information is used to assess the fit of the model. We measure the in-sample fit using the pseudo-R^2 developed in Estrella (1998)

$$\text{pseudo-}R^2 = 1 - \left(\frac{\mathcal{L}(y,\pi)_{UR}}{\mathcal{L}(y,\pi)_R}\right)^{-(2/T)\mathcal{L}(y,\pi)_R} \tag{5}$$

where $\mathcal{L}(y,\pi)_{UR}$ is the loglikelihood value of the model of interest, $\mathcal{L}(y,\pi)_R$ is value of the loglikelihood function for a model in which all parameters, except the intercept, is set to zero, and T is the total number of observations.

However, a good in-sample fit does not necessarily translate into good out-of-sample performance, e.g. Hansen (2009). We therefore consider a pseudo out-of-sample setting to assess the true predictive power of the models. In particular, we divide the full sample

[2] In our case, with 15 common factors, two sentiment variables, and allowing for one to six lags and up to five explanatory variables gives us nearly 88 million different combinations.

into an initial estimation period and an out-of-sample period of T^* observations. We use a recursive estimation scheme with an expanding window to estimate the common factors as well as the selected models which gives us T^*out-of-sample forecasts of y_t. This ensures that only information available at time $t-1$ is used to construct the forecast $\hat{p}_t$ for each month in the out-of-sample period.

We employ a variety of evaluation measures to assess the models' ability to forecast recession periods out-of-sample. First, we evaluate the out-of-sample fit using the pseudo-R^2 from (5). The second measure is the quadratic probability score (QPS), which can be thought of as the probability-forecast analog to the commonly used mean squared error (MSE) accuracy measure, cf. Diebold and Rudebusch (1989). Let $\hat{p}_t$ be the recession probability forecast for month t, then the QPS is defined as

$$QPS = \frac{2}{T^*} \sum_{t=1}^{T^*} (\hat{p}_t - y_t)^2 \tag{6}$$

The QPS can take on values between 0 and 2, where a value of 0 corresponds to perfect forecast accuracy. The third forecast evaluation measure is the log probability score (LPS) defined as

$$LPS = -\frac{1}{T^*} \sum_{t=1}^{T^*} \left[y_t \log(\hat{p}_t) + (1 - y_t) \log(1 - \hat{p}_t) \right] \tag{7}$$

The value of LPS ranges between 0 and ∞, where 0 again implies perfect forecast accuracy. LPS penalizes larger mistakes more easily than QPS.

2.3 Estimation of Common Factors

We estimate the common factors from a large panel of macroeconomic and financial variables as in Stock and Watson (2002a,b, 2006, 2010) and Ludvigson and Ng (2009, 2010). In particular, we use a $T \times N$ panel of macroeconomic and financial data with elements x_{it}, where $i = 1, ..., N$ refers to the cross-sectional dimensionality of the panel and $t = 1, ..., T$ is the time index . We transform the panel of observed economic variables into stationary variables with zero mean and unit variance. We assume that x_{it} follows a factor model of the form

$$x_{it} = \Lambda_i' F_t + \xi_{it} \tag{8}$$

where F_t is an $r \times 1$ vector of common factors, Λ_i is an $r \times 1$ vector of factor loadings for the ith observed variable, and ξ_{it} is a zero-mean idiosyncratic error component. Essentially, (8) states that cross-sectional co-movements in the set of predictors in the panel are primarily governed by fluctuations in a relatively small number of common factors ($r \ll N$). The goal is to effectively reduce the dimension of the set of predictors while still being able to use and summarize the underlying information in the large panel. Specifically, we use the common factors in our specification of π_t in (3) where f_t is a subset of F_t.

The static factor model in (8) is estimated using the method of principal components, which is the solution to the nonlinear least-squares problem

$$\left(\hat{F}^{(r)}, \hat{\Lambda}^{(r)}\right) = \underset{F,\Lambda}{\arg\min} \quad V\left(F^{(r)}, \Lambda^{(r)}, x\right) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(x_{it} - \Lambda_i^{(r)\prime} F_t^{(r)}\right)^2 \tag{9}$$

subject to the identifying restriction that $F^{(r)\prime}F^{(r)}/T = I_r$, where I_r is the r-dimensional identity matrix, and that $\Lambda^{(r)\prime}\Lambda^{(r)}$ is diagonal. The superscript in $F^{(r)}$ and $\Lambda^{(r)}$ indicates the use of r factors in the estimation. $\hat{F}^{(r)}$ is then given as $\sqrt{T}$ times the eigenvectors corresponding to the r largest eigenvalues of the $T \times T$ matrix xx' and $\hat{\Lambda}^{(r)} = x'\hat{F}^{(r)}/T$. Consistency of the principal components estimator was first shown by Connor and Korajczyk (1986) for fixed T and $N \to \infty$ for the exact static factor model and extended to the approximate static factor model of Chamberlain and Rothschild (1983) by Stock and Watson (2002b), Bai (2003), and Bai and Ng (2006). Specifically, the estimated factors, $\hat{F}_t$, are consistent if $N \to \infty$, $T \to \infty$, and $\sqrt{T}/N \to 0$. This implies that parameter inference from the second-stage probit model needs not be affected by the effect of estimated (i.e. not observed) explanatory variables.

In order to determine the optimal number of factors, r, in the approximate static factor model, we follow the recent trend and make use of the panel information criterion, IC_2, developed in Bai and Ng (2002). This particular information criterion is defined as

$$IC_2\left(r\right) = \log\left(V\left(F, \Lambda, x\right)\right) + r\left(\frac{N+T}{NT}\right)\log\left(C_{NT}^2\right) \tag{10}$$

where $r\left(\frac{N+T}{NT}\right)\log\left(C_{NT}^2\right)$ is the penalty term, $C_{NT}^2 = \min\left\{N, T\right\}$, and r is the number of factors used in the estimation. We can then estimate the true number of factors, $\hat{r}$, by finding the minimum value of $IC_2\left(r\right)$ as $\hat{r} = \arg\min_{1\leq r\leq r_{\max}} IC_2\left(r\right)$, where $r_{\max}$ is an integer chosen by the econometrician. Note that $r_{\max}$ should be large enough to encompass the true number of common factors.

3 Data Description

We make use of three different sets of data: U.S. business cycle dates, sentiment survey variables, and macroeconomic and financial variables. All variables are measured at a monthly frequency. The sample period spans the period from $1978M01$ to $2011M12$, providing a total of $T = 407$ observations for the in-sample analysis.[3] The out-of-sample period covers $1998M01$ to $2011M12$, providing for a total of $T^* = 168$ predictions.

3.1 Business Cycle Dates

We use the NBER defined business cycle expansion and contraction dates to determine U.S. recessions, i.e. y_t from (1).[4] The NBER business cycle dates are publicly available and are standard in the business cycle literature. We use the same definition of recessions as Estrella and Trubin (2006). In particular, the first month following a peak month defines the first recession month and the last month of a through defines the last recession month.[5] A similar definition goes for expansion months.

Our in-sample sample period includes five recession periods. The out-of-sample period includes the two most recent recessions, the dot-com crisis in 2001 and the recent financial crisis in 2008 and 2009.

3.2 Sentiment Variables

The consumer sentiment survey data is based on the University of Michigan's Index of Consumer Sentiment. The index, denoted CC_t, is based on a monthly survey where a minimum of 500 households are interviewed by telephone. The households are asked questions about the household's own financial situation and the business conditions in the country as a whole. The results of the survey become publicly available either during the month of the survey or at the beginning of the following month.[6]

The business confidence data is based on the Institute of Supply Management's Purchasing Managers Index. The index, denoted PMI_t, is constructed from data collected through a survey of 400 industrial companies. The PMI_t is an equal-weighted average of five

[3] The availability of the sentiment variables determines the beginning of the sample period, whereas the availability of the variables in our panel determines the end of the sample period.

[4] The business cycle dates are available at `www.nber.org`.

[5] Hereby, the most recent recession is $2008M01$ through $2009M06$.

[6] We use the total index. We obtain similar results using the expectations component.

diffusion indexes: production level, new orders, speed of supplier deliveries, inventories, and employment level. The respondents answer questions that compare the current level of activity with that of the previous month. The results of the survey become available on the first business day of each month. Both the Index of Consumer Sentiment and the Purchasing Managers Index are available through the Federal Reserve Bank of St. Louis' economic research database.[7]

3.3 Additional Explanatory Variables

3.3.1 Classical Recession Predictors

To show how our results improve upon previous findings, we also consider three classical recession predictors: the term spread, the short rate, and a stock market return. The term spread, TS_t, is defined as the 10-year bond yield in excess of a 3-month Treasury bill rate. The short rate is taken to be the effective federal funds rate, which we denote FFR_t. Lastly, the stock market return, $SP500_t$, is defined as the simple return on the S&P500 index.

3.3.2 Common Factors

We use a standard panel of macroeconomic and financial series to estimate the common factors similar to Stock and Watson (2002a,b, 2006, 2010) and Ludvigson and Ng (2009, 2010). The total number of series is 176. The series represent the following categories of economic data: interest rates and spreads; stock market returns, risk factors and predictors; exchange rates; output and income; employment, hours and earnings; housing; money and credit; and prices. We provide detailed information about the series in the Appendix.

The Bai and Ng (2002) IC_2 criterion suggests that the optimal number of factors is 15. Figure $A.1$ in the Appendix illustrates that these 15 factors account for about 75% of the total variance in the panel, whereas the first five factors alone account for 54%. It is, however, important to note that principal component estimator does not take predictive ability of $x_{i,t-1}$ for y_t into account when estimating the factors, e.g. Bai and Ng (2008). Thus, there is no theoretical reason for the first factors being better predictors than the last factors.

[7] `research.stlouisfed.org/fred2/`.

A detailed economic interpretation of the latent factors is not viable. One reason is that the factors are only identified up to a rotation. Another reason is that a theoretically convincing economic interpretation would require correlated rather than orthogonal factors. Still, we believe that it is useful to briefly discuss how the factors load on the individual series in the panel. The appendix provides graphical illustrations of the loadings for each factor, where, as examples, we see that the first factor $\widehat{f}_{1,t}$ correlates 98% with the CRSP stock market return and is thus a stock market factor. The second factor $\widehat{f}_{2,t}$ is a real activity factor as it loads heavily on employment and somewhat on industrial production. The third factor $\widehat{f}_{3,t}$ is a return prediction factor as it loads on e.g. the dividend yield. The sixth factor $\widehat{f}_{6,t}$ is a term structure factor.

4 Empirical Findings

This section presents our empirical findings.[8] We first present in-sample results, which is then followed by the results from a pseudo out-of-sample exercise. We show that the sentiment variables add valuable information to the recession forecasts in both instances.

4.1 In-Sample Results

First, we consider the individual predictive ability of all variables in our data set by estimating the probit model for each variable one at a time at its preferred lag length, namely for the two sentiment variables, the 176 variables in the panel (which includes the classical recession predictors), and the 15 factors estimated using (9). In Table 1 we rank the 100 best models according to the BIC.

[Insert Table 1 about here]

Table 1 shows that the best univariate recession predictor is business confidence, PMI, for which the pseudo-R^2 is as large as 47%. The predictive ability of the PMI is far better than for the second best recession predictor, total private employment growth, which has a pseudo-R^2 of 30%. Consumer confidence, CC, is also a fairly good recession predictor on its own with a pseudo-R^2 of 26%. The best classical recession predictor is the term spread, but the term spread provides much worse predictions than the sentiment

[8] The estimation is conducted in Matlab.

variables, illustrated by a pseudo-R^2 of 9%. Thus, even these preliminary findings are highly supportive of our suggestion of using sentiment variables when predicting future recession periods.

4.1.1 Classical Recession Predictors

Table 2 shows the results from three specifications that rely solely on the three classical explanatory variables. The choices of explanatory variables are as follows: the six-month lagged term spread alone, the six-month lagged term spread and up to two different lags of the S&P500, and the six-month lagged term spread and up to two different lags of the short rate. The choice of variable combinations and lags is determined by the BIC.

[Insert Table 2 about here]

The predictive ability of the term spread alone is not very strong (the pseudo-R^2 only amounts to 9%). Combining the term spread with either the return on the S&P500 index (the Estrella and Mishkin (1998) specification) or the short rate gives about equivalent improvements in the explanatory power, so that the pseudo-R^2 values increase to 15%. Similar to previous papers, we show that the classical recession predictors are significant in predicting future recessions. However, their explanatory power is not that strong anymore and in particular weaker than in e.g. Estrella and Mishkin (1998). This is in accordance with Schrimpf and Wang (2010) who finds that the yield curve is loosing its predictive power for future economic activity.

4.1.2 Sentiment Variables

Table 3 shows the in-sample results that rely exclusively on the two sentiment variables. The optimal lag length of the sentiment variables is low (one lag according to the BIC).

[Insert Table 3 about here]

The PMI is a much more important variable for predicting future recessions than is the CC. Yet, the strongest predictive ability is accomplished by combining the two sentiment variables and thereby combining the business and consumer perceptions about the future.

In this manner, the pseudo-R^2 becomes as large as 54%. The sentiment variables are very strong candidates for predicting future recession periods. The coefficients to the sentiment variables are negative, which implies that low values of the sentiment indices imply a larger probability of future recessions. This is in line with the preliminary observations from Figure 1 in the Introduction.

4.1.3 Joint Specifications

We now consider joint specifications, where we directly compare the predictive content of the sentiment variables with that of the classical recession predictors and the estimated common factors. Table 4 allows for up to five explanatory variables at a time; in Panel A choosing from only the common factors, in Panel B choosing from classical recession predictors and the sentiment variables, and in Panel C choosing from the common factors and the sentiment variables. In each panel, we report the five best models according to the BIC.

[Insert Table 4 about here]

When we rely on common factors only, the best performing model has a pseudo-R^2 of 58% which is slightly better than the sentiment variable only specifications in Table 3. The five best performing models using only common factors are about equally good across all performance metrics. This implies that it is not overly important exactly which specific combination of common factors that is applied.

Combining sentiment and classical recession predictors improves the probit model's ability of forecasting future recession periods. The highest pseudo R^2 is 63%. The best models all include both sentiment variables at lag one in addition to the six month term spread and the S&P500 at lag two. So, by combining the sentiment variables with classical recession predictors we are able to improve the probit model's predictive ability to a large extent. It is worth noting that combining the classical recession predictors with the sentiment variables greatly improves the model's ability to correctly classify recessions at both the 50% and 25% threshold.

The predictive ability of the probit models also improves by adding the sentiment variables to the common factors. The pseudo-R^2 is as large as 66%. The five best models, which do about equally well, always include both sentiment variables. Using a combination of common factors and sentiment variables provides very high ratios of correctly classified recessions. The first lag of the PMI is included in the five best models as is either the first or second lag of the CC. The stock market factor $(\widehat{f}_{1,t})$ is also included in the best models, so when used in combination with the sentiment variables, the stock market plays an important role in predicting future recession periods even if it is unimportant when considered on its own. This is similar to the findings in Estrella and Mishkin (1998). The sixth or fifth lag of the term structure factor $(\widehat{f}_{6,t})$ enters into all of the preferred specifications. So, the preferred lag structure for the term structure factor is similar to that of the classical term spread variable. The return predictor factor $(\widehat{f}_{3,t})$ enters into three of the best models.

The results underscores that we gain predictive ability from combining the information in sentiment variables with either the information in the classical recession predictors or the information contained in the common factors.

4.1.4 Graphical Illustrations

The ability of the various specifications to predict recessions can be illustrated graphically by showing the recession probability forecast, $\widehat{p}_t$ together with the actual recession variable y_t. If the model predicts well, the estimated recession probability should exceed 0.5 when there is actually a recession, that is $\widehat{p}_t > 0.5$ for $y_t = 1$, and similarly it should be below 0.5 when there is actually an expansion, $\widehat{p}_t < 0.5$ for $y_t = 0$. This information is also summarized by the proportion of correct classifications for recessions and expansions that are tabulated for all the considered model specifications in Tables 2-4.

[Insert Figure 2 about here]

Figure 2.A shows the classical specification of Estrella and Mishkin (1998). The term spread together with the S&P500 predict the first couple of recessions well but seem to have lost their power as recession predictors in the last part of the sample. Figure 2.B shows that the sentiment variables do much better, although the identification of the latest recessions are slightly delayed. The PMI-CC specification gives 61% (86%) correct identification of recession dates when using the 50% (25%) threshold, see lower part of Table 3. Note that when using the 25% rather than 50% threshold sentiment variables are still very successful at identifying expansions. Figure 2.C shows the in-sample performance of the best model using common factors only. The factor specification results in 70% (89%) correct recession identification with the 50% (25%) threshold (Panel A in Table 4).

Figure 2.D illustrates the combined effort of the sentiment variables and the classical recession predictors. The identification of the recessions is improved and now the probit model correctly classifies 73% (93%) of the recession dates with the 50% (25%) threshold (panel B in Table 4). Figure 2.E illustrates the performance when using the best combination of common factors, which classifies 70% (89%) of the recession dates correctly with the 50% (25%) threshold (panel A in Table 4). Figure 2.E shows the estimated recession probabilities for the best specification that includes both sentiment and common factors. The proportion of correct recession predictions is now as high as 77% (98%) with the 50% (25%) threshold (panel C in Table 4). Moreover, almost all expansion periods are correctly identified so there are hardly any false recession signals.

In closing, the in-sample findings show that there is a lot of information about future business cycle to be gained from the new sources of recession predictors that we introduce here. Firstly, sentiment variables are strong predictors of future recession periods. Secondly, combining sentiment variables with either classical recession predictors or common factors provide further strength to predicting future recession periods.

4.2 Out-of-Sample Results

In general, the out-of-sample findings strongly support the conclusions drawn from the in-sample analysis.

[Insert Table 5 about here]

As a start, we consider the out-of-sample performance of all the potential predictor variables one by one in univariate probit models. Table 5 shows the results when sorting the models on the pseudo-R^2. The main point to take away is that PMI comes out as the best out-of-sample recession predictor. This result holds regardless of whether we sort by the pseudo-R^2, the QPS or the LPS.[9] Thus, the preliminary out-of-sample analysis confirms the related in-sample findings.

4.2.1 Joint Specifications

In the joint specifications, we estimate all possible model combinations of up to five variables and select the five best models based on the BIC. We restrict each variable to enter

[9]The QPS and LPS sorts are available upon request.

only at its preferred lag length chosen using information from the initial period only.[10] This procedure provides us with the best ex-post model combinations for forecasting US recession in an out-of-sample setting.

[Insert Table 6 about here]

Table 6 provides the main out-of-sample results. For each model, the table presents the three evaluation measures, pseudo-R^2 , QPS, and LPS. Moreover, we tabulate how often the models correctly identify the recessions at a 50% and a 25% threshold, respectively. The pseudo-R^2, the QPS, and the LPS evaluation measures all point towards the models allowing for both common factors and sentiment variables as the preferred model specification for predicting future recession periods. Thereafter follows the models allowing for common factors only. However, the models allowing for both classical recession predictors and sentiment variables are not far behind in terms of forecasting performance. It is worth noting that a pure sentiment model which only contains PMI and CC generates a pseudo-R^2 of 51% out-of-sample. We also stress that sentiment variables are always chosen to be part of best specifications when introducing classical variables and common factors (Panel C and D).

The combination of sentiment variables and common factors gives the best overall classification rate, which actually reaches up to 100% when using the 25% threshold. In addition, all the best models do very well in identifying expansion periods (all above 95%; not tabulated).

4.2.2 Graphical Illustrations

We illustrate graphically the out-of-sample performance of the competing specifications.

[Insert Figure 3 about here]

In Figure 3.A the classical specification using the term spreads and S&P500 is not able to identify the two recessions in the out-of-sample period using the 50% threshold. It does, however, obtain better results using the lower threshold of 25%. This again corresponds with the in-sample findings. Figure 3.B documents that the sentiment variables alone

[10] The lag restriction ensures that computing time remains feasible.

correctly identifies the two recent recession periods, but with a delay. Figure 3.C shows the best model using factors only. This model correctly identifies 77% (88%) of the recessions in the out-of-sample period using the 50% (25%) threshold, see Panel C in Table 6. Figure 3.D shows that combining the classical recession predictors with sentiment variables improve the out-of-sample fit substantially compared to either set of variables on their own. In fact, the joint specification is able to correctly identify 62% (88%) of the recessions. Finally, Figure 3.E shows that the combination of common factors and sentiment provides for 77% (100%) correctly classified recessions. It is clear from figure 3.D and 3.E that combining the sentiment with either classical recession predictors of common factors mitigates the classification delay substantially.

5 Conclusion

The financial press pays a lot of attention to the monthly announcements of consumer and business sentiment variables, especially during times of economic crisis. In this paper, we examine whether it is worthwhile monitoring sentiment surveys when it comes to forecasting business cycles. We provide comprehensive empirical evidence that sentiment variables hold vast predictive power for US recessions in excess of classical recession predictors and in excess of common factors estimated based on large panel of economic data. The best predictions for future recessions are obtained by combining the sentiment variables with either the classical recession predictors or with the common factors.

Understanding why consumer and business confidence variables do so well at predicting future recession periods is still a question that we leave open for future discussion. However, it would be possible to attribute the presence of recession predictability using sentiment variables either to animal spirits (Keynes (1936) and Akerlof and Shiller (2009)) or agents rationally and intelligently processing fundamental news. Barsky and Sims (2012) examine these two interpretations, but only considering consumer confidence. They conclude that it is not likely that the predictive power of consumer confidence reflects a causal effect of animal spirits on economic activity. Instead, they suggest that fundamental news is the driving force behind the predictive power of consumer confidence. We examine both consumer and business confidence and find that the latter is a substantially stronger recession predictor than the former. This finding points towards business professionals being better at processing fundamental news about the state of economy than individuals.

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Table 1: In-sample results: Top 100 Univariate Models

	Variable	pseudo-R^2	BIC	$\mathcal{L}(y,\pi)$		Variable	pseudo-R^2	BIC	$\mathcal{L}(y,\pi)$
1	PMI_{t-1}	0.47	0.40	-74.15	51	DY_{t-1}	0.06	0.78	-150.67
2	$AEPI_{t-1}$	0.30	0.55	-103.83	52	$IPNM_{t-1}$	0.06	0.78	-150.81
3	$AENF_{t-1}$	0.30	0.55	-104.67	52	$PITR_{t-1}$	0.06	0.78	-151.04
4	RHS_{t-1}	0.27	0.58	-109.74	54	$SBAAF_{t-6}$	0.06	0.78	-151.04
5	$AEGI_{t-1}$	0.27	0.58	-110.04	55	$FFMF_{t-4}$	0.06	0.78	-151.17
6	$AEPB_{t-1}$	0.27	0.58	-110.59	56	$IPCG_{t-1}$	0.05	0.78	-151.54
7	CC_{t-1}	0.26	0.58	-111.29	57	$SP500_{t-4}$	0.05	0.78	-151.71
8	$\hat{f}_{2,t-1}$	0.25	0.59	-112.81	58	$T3M_{t-1}$	0.05	0.78	-151.75
9	$AETU_{t-1}$	0.25	0.60	-114.13	59	$CPFE_{t-2}$	0.05	0.79	-151.84
10	AEM_{t-1}	0.25	0.60	-114.38	60	$FF18_{t-4}$	0.05	0.79	-151.87
11	$IPDM_{t-1}$	0.24	0.60	-114.96	61	$I5_{t-4}$	0.05	0.79	-151.88
12	$AEDG_{t-1}$	0.24	0.61	-116.35	62	$FF24_{t-4}$	0.05	0.79	-152.06
13	$SBAAA_{t-1}$	0.23	0.61	-117.52	63	$PPCE_{t-4}$	0.05	0.79	-152.28
14	$AESI_{t-1}$	0.21	0.63	-121.42	64	$DJCA_{t-4}$	0.05	0.79	-152.36
15	AEC_{t-1}	0.20	0.64	-122.31	65	$CRSP_{t-4}$	0.05	0.79	-152.50
16	$AEWT_{t-1}$	0.20	0.64	-122.36	66	$\hat{f}_{1,t-4}$	0.05	0.79	-152.57
17	$AERT_{t-1}$	0.19	0.66	-125.69	67	$FF19_{t-4}$	0.05	0.79	-152.62
18	IPT_{t-1}	0.18	0.66	-126.38	68	$I12_{t-4}$	0.05	0.79	-152.62
19	CUR_{t-1}	0.17	0.67	-129.42	69	$DJIA_{t-4}$	0.05	0.79	-152.82
20	$AENG_{t-1}$	0.16	0.68	-130.32	70	$FF23_{t-4}$	0.05	0.79	-152.94
21	UMP_{t-1}	0.16	0.68	-131.40	71	$I11_{t-4}$	0.05	0.79	-153.01
22	AWM_{t-1}	0.15	0.69	-132.07	72	$FF20_{t-4}$	0.05	0.79	-153.03
23	IPM_{t-1}	0.14	0.70	-133.95	73	BM_{t-1}	0.05	0.79	-153.12
24	$IPBE_{t-1}$	0.14	0.70	-134.01	74	$I9_{t-4}$	0.05	0.79	-153.24
25	$HSMW_{t-1}$	0.14	0.70	-134.27	75	$I24_{t-4}$	0.04	0.79	-153.32
26	AOM_{t-1}	0.14	0.70	-134.94	76	$FF5_{t-4}$	0.04	0.79	-153.34
27	$NPHA_{t-1}$	0.14	0.70	-135.21	77	$I13_{t-4}$	0.04	0.79	-153.46
28	AWG_{t-1}	0.14	0.70	-135.39	78	$FF14_{t-4}$	0.04	0.79	-153.72
29	$NOWH_{t-1}$	0.14	0.70	-135.56	79	DE_{t-1}	0.04	0.79	-153.79
30	$S3YF_{t-6}$	0.13	0.70	-135.61	80	$SVAR_{t-1}$	0.04	0.80	-154.13
31	$CU15_{t-1}$	0.13	0.70	-135.61	81	$3M_{t-1}$	0.04	0.80	-154.14
32	$S5YF_{t-6}$	0.13	0.71	-135.96	82	$FF17_{t-4}$	0.04	0.80	-154.19
33	$\hat{f}_{3,t-2}$	0.13	0.71	-136.59	83	PI_{t-1}	0.04	0.80	-154.20
34	HSW_{t-1}	0.12	0.72	-137.82	84	PSR_{t-1}	0.04	0.80	-154.22
35	$S10YF_{t-6}$	0.12	0.72	-138.09	85	$PEFE_{t-6}$	0.04	0.80	-154.30
36	CE_{t-1}	0.12	0.72	-138.17	86	$I15_{t-4}$	0.04	0.80	-154.38
37	$AWPI_{t-1}$	0.11	0.73	-140.41	87	$I30_{t-4}$	0.04	0.80	-154.40
38	$IPFP_{t-1}$	0.11	0.73	-140.59	88	$I25_{t-4}$	0.04	0.80	-154.48
39	$S1YF_{t-6}$	0.10	0.73	-141.66	89	CIL_{t-6}	0.04	0.80	-154.50
40	$AEFA_{t-1}$	0.09	0.74	-143.59	90	$DITA_{t-4}$	0.04	0.80	-154.62
41	$HSNE_{t-1}$	0.09	0.75	-144.97	91	AWC_{t-1}	0.04	0.80	-154.64
42	TS_{t-6}	0.09	0.75	-145.11	92	$CU14_{t-1}$	0.04	0.80	-154.65
43	HSS_{t-1}	0.08	0.76	-146.11	93	$\hat{f}_{6,t-6}$	0.04	0.80	-154.74
44	$IPDC_{t-1}$	0.08	0.76	-147.05	94	$I14_{t-4}$	0.04	0.80	-154.90
45	$CU26_{t-1}$	0.07	0.76	-147.35	95	BAA_{t-4}	0.04	0.80	-154.93
46	FFR_{t-6}	0.07	0.77	-148.50	96	$FF21_{t-4}$	0.04	0.80	-154.95
47	TCC_{t-1}	0.07	0.77	-148.87	97	$AHPI_{t-6}$	0.04	0.80	-154.95
48	DP_{t-1}	0.06	0.77	-149.38	98	$1Y_{t-1}$	0.04	0.80	-154.98
49	$I29_{t-4}$	0.06	0.78	-150.14	99	$6M_{t-1}$	0.04	0.80	-155.02
50	$CU27_{t-1}$	0.06	0.78	-150.21	100	$FF22_{t-4}$	0.04	0.80	-155.06

This table reports the in-sample results from estimating univariate probit models using monthly data from 1978M1 to 2011M12 for all variables in the panel along with factors and sentiment variables. Panel variables are identified using the short hand notation in the data appendix. Model fit is measured using the pseudo-R^2 measure developed in Estrella (1998) and $\mathcal{L}(y,\pi)$ is the value of the log-likelihood function. The univariate probit models are ranked by BIC.

Table 2: In-Sample Results: Classical Variables

Variable	TS	TS-SP500	TS-FED
TS_{t-6}	-0.35	-0.41	-0.31
	(-3.61)	(-4.23)	(-2.68)
$SP500_{t-4}$		-0.08	
		(-3.35)	
$SP500_{t-6}$		-0.07	
		(-2.45)	
FFR_{t-1}			-0.38
			(-2.13)
FFR_{t-3}			0.40
			(2.45)
$\mathcal{L}(y, \pi)$	-145.11	-131.77	-133.21
BIC	0.75	0.72	0.72
pseudo-R^2	0.09	0.15	0.15
$\mathrm{CR}^{50\%}$	0.14	0.16	0.14
$\mathrm{CR}^{25\%}$	0.41	0.52	0.41
$\mathrm{CE}^{50\%}$	0.99	0.99	0.97
$\mathrm{CE}^{25\%}$	0.93	0.86	0.91

This table reports the in-sample results from estimating probit models using monthly data from 1978M1 to 2011M12. t-statistics computed as in Kauppi & Saikkonen (2008) are presented in parentheses. $\mathcal{L}(y, \pi)$ is the log-likelihood value, pseudo-R^2 is the measure developed in Estrella (1998), and $\mathrm{CR}^{50\%}/\mathrm{CR}^{25\%}$ and $\mathrm{CE}^{50\%}/\mathrm{CE}^{25\%}$ denote, respectively, the proportion of correct recession and expansion predictions.

Table 3: In-Sample Results: Sentiment Variables

Variable	PMI	CC	PMI-CC
PMI_{t-1}	-0.24		-0.22
	(-7.38)		(-5.15)
CC_{t-1}		-0.07	-0.05
		(-4.90)	(-3.26)
$\mathcal{L}(y,\pi)$	-74.15	-111.29	-61.40
BIC	0.40	0.58	0.35
pseudo-R^2	0.47	0.26	0.54
$\mathrm{CR}^{50\%}$	0.66	0.30	0.61
$\mathrm{CR}^{25\%}$	0.77	0.75	0.86
$\mathrm{CE}^{50\%}$	0.98	0.97	0.98
$\mathrm{CE}^{25\%}$	0.93	0.86	0.94

This table reports the in-sample results from estimating probit models using monthly data from 1978M1 to 2011M12. t-statistics computed as in Kauppi & Saikkonen (2008) are presented in parentheses. $\mathcal{L}(y,\pi)$ is the log-likelihood value, pseudo-R^2 is the measure developed in Estrella (1998), and $\mathrm{CR}^{50\%}/\mathrm{CR}^{25\%}$ and $\mathrm{CE}^{50\%}/\mathrm{CE}^{25\%}$ denote, respectively, the proportion of correct recession and expansion predictions.

Table 4: In-sample results: Joint Specification

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Panel A: Factors					
$\hat{f}_{1,t-2}$	-0.64	-0.62	-0.58	-0.63	-0.63
	(-5.77)	(-5.24)	(-4.31)	(-5.11)	(-5.29)
$\hat{f}_{1,t-4}$	-0.46	-0.48	-0.48		
	(-3.27)	(-3.30)	(-3.54)		
$\hat{f}_{2,t-1}$	1.38	1.37	1.50	1.43	1.42
	(5.94)	(5.94)	(5.84)	(5.51)	(6.04)
$\hat{f}_{3,t-1}$		1.02	1.00	0.91	
		(6.71)	(5.85)	(5.74)	
$\hat{f}_{3,t-2}$	1.04				0.93
	(5.68)				(5.42)
$\hat{f}_{6,t-3}$			-0.63		
			(-3.52)		
$\hat{f}_{6,t-6}$	-0.73	-0.68		-0.70	-0.73
	(-3.79)	(-3.90)		(-3.61)	(-3.66)
$\hat{f}_{14,t-1}$				0.44	0.36
				(3.53)	(2.55)
$\mathcal{L}(y,\pi)$	-54.65	-55.47	-56.34	-56.85	-57.05
BIC	0.36	0.37	0.37	0.37	0.37
pseudo-R^2	0.58	0.58	0.57	0.57	0.57
$\mathrm{CR}^{50\%}$	0.70	0.68	0.68	0.66	0.66
$\mathrm{CR}^{25\%}$	0.89	0.84	0.89	0.93	0.89
$\mathrm{CE}^{50\%}$	0.98	0.97	0.97	0.97	0.97
$\mathrm{CE}^{25\%}$	0.94	0.95	0.94	0.94	0.93
Panel B: Sentiment and Classical Variables					
PMI_{t-1}	-0.21	-0.24	-0.24	-0.25	-0.23
	(-4.98)	(-5.20)	(-5.26)	(-5.49)	(-4.96)
PMI_{t-6}	-0.08				
	(-2.76)				
CC_{t-1}	-0.07	-0.06	-0.06	-0.06	-0.06
	(-3.86)	(-3.67)	(-3.53)	(-3.84)	(-3.84)
TS_{t-6}	-0.37	-0.33	-0.28	-0.29	-0.33
	(-2.74)	(-2.92)	(-2.37)	(-2.20)	(-2.78)
$SP500_{t-2}$	-0.16	-0.09	-0.12	-0.11	-0.11
	(-4.50)	(-3.22)	(-4.01)	(-3.73)	(-3.62)
$SP500_{t-3}$		-0.08			
		(-2.70)			
$SP500_{t-4}$					-0.08
					(-2.79)
$SP500_{t-6}$				-0.09	
				(-2.55)	
$\mathcal{L}(y,\pi)$	-46.81	-46.98	-50.19	-47.30	-47.44
BIC	0.32	0.32	0.32	0.32	0.33
pseudo-R^2	0.63	0.63	0.61	0.63	0.63
$\mathrm{CR}^{50\%}$	0.73	0.71	0.71	0.75	0.71
$\mathrm{CR}^{25\%}$	0.93	0.91	0.91	0.89	0.93
$\mathrm{CE}^{50\%}$	0.97	0.98	0.97	0.97	0.97
$\mathrm{CE}^{25\%}$	0.94	0.95	0.94	0.95	0.94

Continued on next page

Table 4 – continued from previous page

Panel C: Sentiment and Factors					
PMI_{t-1}	-0.29	-0.29	-0.30	-0.29	-0.30
	(-4.13)	(-4.35)	(-6.64)	(-6.19)	(-6.12)
CC_{t-1}		-0.08	-0.11	-0.10	-0.10
		(-3.49)	(-4.88)	(-4.85)	(-4.51)
CC_{t-2}	-0.08				
	(-3.39)				
$\hat{f}_{1,t-1}$	-0.48	-0.41	-0.50	-0.53	-0.57
	(-3.94)	(-3.63)	(-3.43)	(-4.04)	(-4.48)
$\hat{f}_{1,t-2}$	-0.51	-0.44			
	(-3.50)	(-3.27)			
$\hat{f}_{3,t-5}$			-0.43		-0.41
			(-2.10)		(-2.02)
$\hat{f}_{3,t-6}$				-0.39	
				(-2.01)	
$\hat{f}_{6,t-5}$					-0.66
					(-3.15)
$\hat{f}_{6,t-6}$	-0.65	-0.66	-0.67	-0.67	
	(-2.89)	(-3.17)	(-3.41)	(-3.51)	
$\mathcal{L}(y,\pi)$	-41.91	-41.97	-42.00	-42.23	-42.41
BIC	0.30	0.30	0.30	0.30	0.30
pseudo-R^2	0.66	0.66	0.66	0.66	0.66
$\text{CR}^{50\%}$	0.77	0.75	0.77	0.80	0.82
$\text{CR}^{25\%}$	0.98	0.96	0.95	0.96	0.93
$\text{CE}^{50\%}$	0.98	0.98	0.98	0.98	0.98
$\text{CE}^{25\%}$	0.95	0.96	0.94	0.95	0.95

This table reports the in-sample results from estimating probit models using monthly data from 1978M1 to 2011M12. t-statistics computed as in Kauppi & Saikkonen (2008) are presented in parentheses. $\mathcal{L}(y,\pi)$ is the log-likelihood value, pseudo-R^2 is the measure developed in Estrella (1998), and $\text{CR}^{50\%}/\text{CR}^{25\%}$ and $\text{CE}^{50\%}/\text{CE}^{25\%}$ denote, respectively, the proportion of correct recession and expansion predictions. Models are selected based on BIC.

Table 5: Out-of-Sample Results: Top 100 Univariate Models

No.	Variable	pseudo-R^2	QPS	LPS	No.	Variable	pseudo-R^2	QPS	LPS
1	PMI_{t-1}	0.40	0.14	0.23	51	$FF23_{t-4}$	0.04	0.24	0.40
2	$AEPI_{t-1}$	0.33	0.16	0.26	52	$I21_{t-5}$	0.04	0.24	0.40
3	$AEPB_{t-1}$	0.30	0.16	0.27	53	$FF18_{t-3}$	0.04	0.24	0.40
4	$AETU_{t-1}$	0.30	0.16	0.27	54	$FF20_{t-3}$	0.04	0.24	0.40
5	$AENF_{t-1}$	0.29	0.17	0.28	55	$I23_{t-2}$	0.04	0.24	0.40
6	$IPDM_{t-1}$	0.29	0.17	0.28	56	$FF22_{t-2}$	0.04	0.24	0.40
7	$\hat{f}_{2,t-1}$	0.29	0.17	0.28	57	$I12_{t-2}$	0.04	0.23	0.40
8	$AEGI_{t-1}$	0.28	0.17	0.28	58	$\hat{f}_{8,t-1}$	0.04	0.25	0.40
9	$AEWT_{t-1}$	0.28	0.17	0.28	59	PI_{t-1}	0.04	0.24	0.40
10	$AERT_{t-1}$	0.24	0.17	0.30	60	$CU27_{t-2}$	0.04	0.24	0.40
11	AEM_{t-1}	0.24	0.18	0.30	61	$I14_{t-4}$	0.04	0.24	0.40
12	$AEDG_{t-1}$	0.23	0.19	0.30	62	$FF21_{t-2}$	0.04	0.24	0.40
13	IPT_{t-1}	0.22	0.19	0.31	63	$FF19_{t-2}$	0.03	0.24	0.40
14	$AESI_{t-1}$	0.22	0.19	0.31	64	$T3M_{t-2}$	0.03	0.25	0.40
15	AEC_{t-1}	0.21	0.20	0.32	65	$I30_{t-4}$	0.03	0.24	0.40
16	$SBAAA_{t-1}$	0.19	0.18	0.32	66	$I16_{t-2}$	0.03	0.24	0.40
17	CUR_{t-1}	0.17	0.20	0.33	67	$CU14_{t-3}$	0.03	0.24	0.40
18	UMP_{t-2}	0.17	0.20	0.34	68	$M2_{t-1}$	0.03	0.24	0.40
19	$AENG_{t-1}$	0.16	0.19	0.34	69	$I15_{t-6}$	0.03	0.25	0.40
20	$IPBE_{t-1}$	0.16	0.20	0.34	70	$\hat{f}_{6,t-3}$	0.03	0.25	0.40
21	$IPFP_{t-1}$	0.15	0.21	0.34	71	$FF5_{t-4}$	0.03	0.24	0.40
22	$CU15_{t-1}$	0.15	0.21	0.35	72	$I24_{t-3}$	0.03	0.25	0.40
23	$AWPI_{t-1}$	0.14	0.21	0.35	73	$3M_{t-1}$	0.03	0.25	0.41
24	IPM_{t-2}	0.14	0.21	0.35	74	$I9_{t-4}$	0.02	0.24	0.41
25	CC_{t-1}	0.14	0.20	0.35	75	$FF16_{t-2}$	0.02	0.25	0.41
26	$AEFA_{t-1}$	0.13	0.21	0.35	76	$FF11_{t-2}$	0.02	0.25	0.41
27	CE_{t-2}	0.13	0.22	0.36	77	$I13_{t-2}$	0.02	0.24	0.41
28	$S3YF_{t-6}$	0.10	0.23	0.37	78	$FF12_{t-2}$	0.02	0.25	0.41
29	DE_{t-1}	0.09	0.22	0.37	79	$FF17_{t-2}$	0.02	0.24	0.41
30	$S1YF_{t-6}$	0.09	0.23	0.37	80	$DJUA_{t-2}$	0.02	0.25	0.41
31	$CU26_{t-1}$	0.08	0.23	0.38	81	$\hat{f}_{14,t-5}$	0.02	0.25	0.41
32	$IPNM_{t-4}$	0.08	0.22	0.38	82	$EXCU_{t-2}$	0.02	0.25	0.41
33	$SVAR_{t-1}$	0.07	0.23	0.38	83	$FF14_{t-3}$	0.02	0.25	0.41
34	$PITR_{t-1}$	0.07	0.23	0.38	84	$I25_{t-2}$	0.02	0.25	0.41
35	$S5YF_{t-6}$	0.07	0.24	0.38	85	$I26_{t-3}$	0.02	0.25	0.41
36	$IPCG_{t-2}$	0.07	0.24	0.38	86	$6M_{t-1}$	0.02	0.25	0.41
37	$IPDC_{t-4}$	0.07	0.24	0.38	87	$I20_{t-4}$	0.02	0.25	0.41
38	$I5_{t-4}$	0.07	0.23	0.39	88	$I22_{t-2}$	0.02	0.25	0.41
39	$I29_{t-4}$	0.06	0.23	0.39	89	$DITA_{t-2}$	0.02	0.25	0.41
40	CIL_{t-6}	0.06	0.24	0.39	90	$EXUU_{t-5}$	0.02	0.25	0.41
41	$SP500_{t-4}$	0.05	0.24	0.39	91	$1Y_{t-1}$	0.02	0.25	0.41
42	$FF24_{t-4}$	0.05	0.24	0.39	92	$FF6_{t-2}$	0.02	0.25	0.41
43	$FFMF_{t-2}$	0.05	0.24	0.39	93	RHS_{t-4}	0.01	0.18	0.41
44	AOM_{t-1}	0.05	0.24	0.40	94	$FF3_{t-4}$	0.01	0.25	0.41
45	$CRSP_{t-2}$	0.05	0.24	0.40	95	$FF1_{t-2}$	0.01	0.25	0.41
46	$DJIA_{t-2}$	0.05	0.24	0.40	96	$FF9_{t-2}$	0.01	0.25	0.41
47	$PPCM_{t-1}$	0.04	0.24	0.40	97	$S10YF_{t-6}$	0.01	0.25	0.41
48	$DJCA_{t-2}$	0.04	0.24	0.40	98	$I11_{t-4}$	0.01	0.25	0.41
49	$I4_{t-4}$	0.04	0.24	0.40	99	$I19_{t-2}$	0.01	0.25	0.41
50	$\hat{f}_{1,t-1}$	0.04	0.24	0.40	100	$I7_{t-4}$	0.01	0.25	0.41

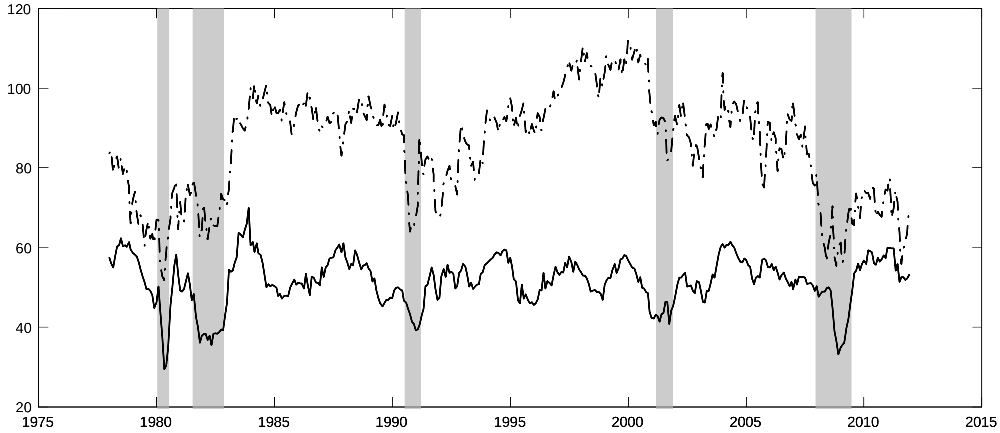
This table reports the out-of-sample results from estimating probit models using a recursive expanding window estimation scheme starting in 1998M1 for all variables in the panel along with the factors and sentiment variables. Panel variables are identified using the short hand notation in the data appendix. For each model, the table reports the pseudo-R^2 measure developed in Estrella (1998), the quadratic probability score (QPS), and the log probability score (LPS). Models are sorted according to the BIC.

Table 6: Out-of-Sample Results

Variables	QPS	LPS	pseudo-R^2	$CR^{50\%}$	$CR^{25\%}$
Panel A: Classical Variables					
TS_{t-6}	0.26	0.43	-0.03	0.00	0.15
TS_{t-6},$SP500_{t-4}$,$SP500_{t-6}$	0.23	0.36	0.11	0.08	0.42
TS_{t-6},FFR_{t-1},FFR_{t-3}	0.27	0.45	-0.07	0.00	0.00
Panel B: Sentiment Variables					
PMI_{t-1}	0.14	0.23	0.40	0.38	0.58
CC_{t-1}	0.20	0.35	0.14	0.46	0.62
PMI_{t-1},CC_{t-1}	0.12	0.18	0.51	0.38	0.65
Panel C: Factors					
$\hat{f}_{1,t-4}$,$\hat{f}_{2,t-1}$,$\hat{f}_{3,t-6}$,$\hat{f}_{5,t-6}$,$\hat{f}_{6,t-3}$	0.08	0.13	0.62	0.77	0.88
$\hat{f}_{2,t-1}$,$\hat{f}_{3,t-6}$,$\hat{f}_{5,t-6}$,$\hat{f}_{6,t-3}$,$\hat{f}_{8,t-1}$	0.08	0.13	0.62	0.77	0.88
$\hat{f}_{2,t-1}$,$\hat{f}_{3,t-6}$,$\hat{f}_{5,t-6}$,$\hat{f}_{6,t-3}$,$\hat{f}_{13,t-3}$	0.08	0.13	0.61	0.73	0.88
$\hat{f}_{2,t-1}$,$\hat{f}_{3,t-6}$,$\hat{f}_{5,t-6}$,$\hat{f}_{6,t-3}$,$\hat{f}_{10,t-3}$	0.08	0.14	0.61	0.73	0.85
$\hat{f}_{2,t-1}$,$\hat{f}_{3,t-6}$,$\hat{f}_{5,t-6}$,$\hat{f}_{6,t-3}$,$\hat{f}_{15,t-6}$	0.09	0.14	0.61	0.73	0.88
Panel D: Classical and Sentiment					
PMI_{t-1},CC_{t-1},TS_{t-6},FFR_{t-4},$SP500_{t-4}$	0.09	0.14	0.59	0.62	0.88
PMI_{t-1},CC_{t-1},TS_{t-6},FFR_{t-4}	0.10	0.15	0.58	0.46	0.81
PMI_{t-1},CC_{t-1},TS_{t-6},$SP500_{t-4}$	0.10	0.15	0.57	0.58	0.85
PMI_{t-1},CC_{t-1},$SP500_{t-4}$	0.11	0.17	0.53	0.58	0.88
PMI_{t-1},CC_{t-1},TS_{t-6}	0.12	0.17	0.53	0.38	0.73
Panel E: Factors and Sentiment					
PMI_{t-1},CC_{t-1},$\hat{f}_{2,t-1}$,$\hat{f}_{3,t-6}$,$\hat{f}_{5,t-6}$	0.06	0.10	0.70	0.77	1.00
PMI_{t-1},CC_{t-1},$\hat{f}_{3,t-6}$,$\hat{f}_{5,t-6}$,$\hat{f}_{6,t-3}$	0.06	0.10	0.69	0.77	0.85
PMI_{t-1},$\hat{f}_{2,t-1}$,$\hat{f}_{3,t-6}$,$\hat{f}_{5,t-6}$,$\hat{f}_{8,t-1}$	0.07	0.10	0.69	0.73	0.96
PMI_{t-1},CC_{t-1},$\hat{f}_{3,t-6}$,$\hat{f}_{5,t-6}$,$\hat{f}_{14,t-5}$	0.06	0.11	0.68	0.77	0.92
PMI_{t-1},CC_{t-1},$\hat{f}_{3,t-6}$,$\hat{f}_{5,t-6}$,$\hat{f}_{10,t-2}$	0.06	0.11	0.68	0.77	0.92

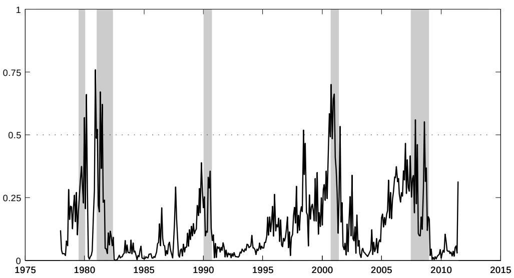
This table reports the out-of-sample results from estimating probit models using a recursively expanding window estimation scheme starting in 1998M1. Models tabulated are selected using the BIC. For each model, the table reports the quadratic probability score (QPS), the log probability score (LPS), the pseudo-R^2 developed in Estrella (1998), and $CR^{50\%}$ and $CR^{25\%}$, which denote the proportion of correct recession predictions for the given threshold.

Figure 1: Business and Consumer Confidence Indices

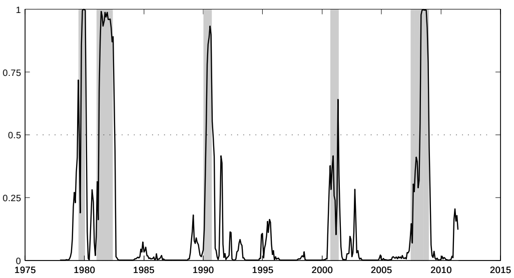


This figure plots the time series of business (PMI; solid line) and the consumer confidence (CC; broken line) against NBER defined recession dates (grey shaded areas). CC is the University of Michigan's Index of Consumer Sentiment, and PMI is the Institute of Supply Management's Purchasing Managers Index.

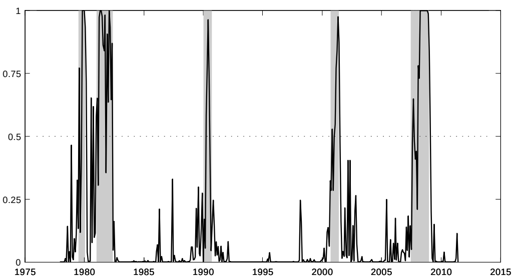
Figure 2: In-Sample Fit



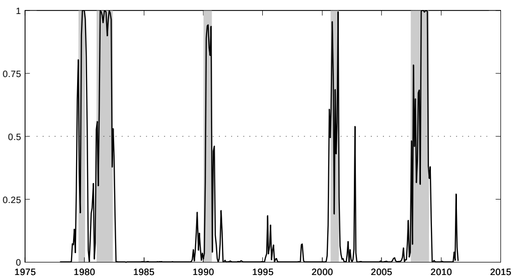
(A)



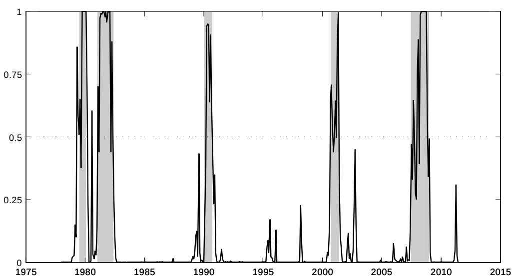
(B)



(C)



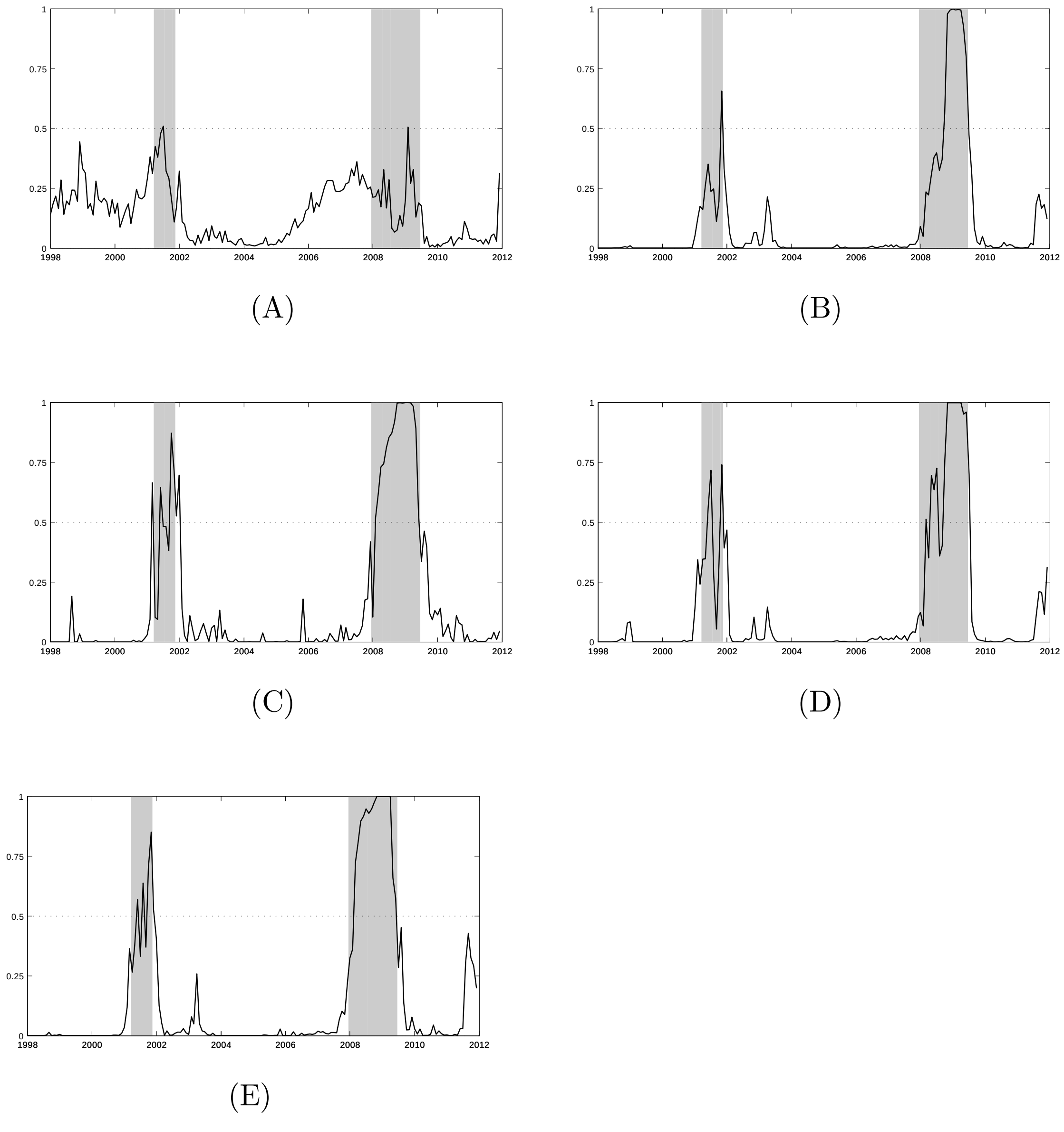
(D)



(E)

Panel (A) plots the estimated recession probabilities from the Estrella-Mishkin model against NBER recession dates in grey shading, Panel (B) the sentiment model containing PMI and CC, Panel (C) the best common factor model, Panel (D) the best joint specification of classical and sentiment variables, and Panel (E) the best joint specification of sentiment variables and factors.

Figure 3: Out-of-Sample Fit



Panel (A) plots the estimated recession probabilities from the Estrella-Mishkin model against NBER recession dates in grey shading, Panel (B) the sentiment model containing PMI and CC, Panel (C) the best common factor model, Panel (D) the best joint specification of classical and sentiment variables, and Panel (E) the best joint specification of sentiment variables and factors.

Appendix

This appendix provides additional details on the source and transformation of the variables contained in the panel used for estimating the common factors as well as additional details on their interpretation.

Panel Data Description

We list the series in the panel in the table below. The table shows the series number, source, transformation, and a description of the series. The transformation codes are: "lvl" means no transformation; "Δlvl" means first difference of the series; "ln" means log of the series; and "Δ ln" means log first difference of the series. We use the following sources: "FRED" refers to the St. Louis Fed's FRED database; "CRSP" refers to the Center for Research in Security Prices; "KF" refers to Kenneth French's data library which is available on his website; and "GW" refers to the Goyal and Welch (2008) data set available on Amit Goyal's website.

Interest Rates and Spreads

1	FRED	FFR	Δlvl	Effective Federal Funds Rate (FFR)
2	FRED	T3M	Δlvl	3-Month Treasury Bill: Secondary Market Rate (T3M)
3	FRED	3M	Δlvl	3-Month Certificate of Deposit: Secondary Market Rate (3M)
4	FRED	6M	Δlvl	6-Month Certificate of Deposit: Secondary Market Rate (6M)
5	FRED	1Y	Δlvl	1-Year Treasury Constant Maturity Rate (1Y)
6	FRED	3Y	Δlvl	3-Year Treasury Constant Maturity Rate (3Y)
7	FRED	5Y	Δlvl	5-Year Treasury Constant Maturity Rate (5Y)
8	FRED	10Y	Δlvl	10-Year Treasury Constant Maturity Rate (10Y
9	FRED	AAA	Δlvl	Moody's Seasoned Aaa Corporate Bond Yield (AAA)
10	FRED	BAA	Δlvl	Moody's Seasoned Baa Corporate Bond Yield (BAA)
11	FRED	S3MF	lvl	Spread: 3M-FFR
12	FRED	S6MF	lvl	Spread: 6M-FFR
13	FRED	S1YF	lvl	Spread: 1Y-FFR
14	FRED	S3YF	lvl	Spread: 3Y-FFR
15	FRED	S5YF	lvl	Spread: 5Y-FFR
16	FRED	S10YF	lvl	Spread: 10Y-FFR
17	FRED	S10YT3	lvl	Spread: 10Y-T3M
18	FRED	SBAAF	lvl	Spread: BAA-FFR
19	FRED	SBAAA	lvl	Spread: BAA-AAA

Stock Market Returns, Risk Factors and Predictors

20	FRED	SP500	Δlvl	The S&P 500 Index
21	CRSP	CRSP	Δlvl	The CRSP Value-Weighted Index (Including Dividends)
22	FRED	DJCA	Δlvl	Dow Jones Composite Average Index
23	FRED	DJIA	Δlvl	Dow Jones Industrial Average Index
24	FRED	DITA	Δlvl	Dow Jones Transportation Average Index
25	FRED	DJUA	Δlvl	Dow Jones Utility Average Index
26-50	KF	FF#	lvl	25 Fama-French Size and Value Portfolios (Value-Weighted Returns)
51-80	KF	I#	lvl	30 Industry-Sorted Portfolios (Value-Weighted Returns)
81	KF	FFMF	lvl	The Fama-French Market Risk Factor (Excess Market Return)
82	KF	SMB	lvl	The Fama-French SMB Risk Factor (Size Premium)
83	KF	HML	lvl	The Fama-French HML Risk Factor (Value Premium)
84	GW	DP	lvl	S&P Dividend-Price Ratio (sum of dividends in last 12 monhts divided by price)
85	GW	DY	lvl	S&P Dividend-Yield (sum of dividends in last 12 monhts divided by lagged price)
86	GW	EP	lvl	S&P Earnings-Price Ratio (sum of earnings in last 12 monhts divided by price)
87	GW	DE	lvl	Dividend-Payout Ratio (dividends relative to earnings)
88	GW	SVAR	lvl	Stock Variance (sum of squared daily returns on the S&P 500)
89	GW	BM	lvl	Book-to-Market Ratio (book value relative to market value for the DJIA)

Exchange Rates

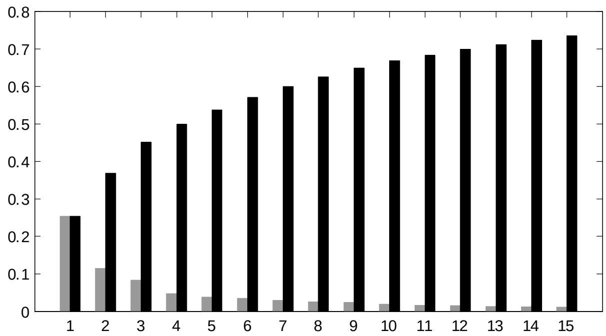
90	FRED	EXCU	Δ ln	Canada / U.S. Foreign Exchange Rate
91	FRED	EXDU	Δ ln	Denmark / U.S. Foreign Exchange Rate
92	FRED	EXIU	Δ ln	India / U.S. Foreign Exchange Rate
93	FRED	EXSU	Δ ln	Switzerland / U.S. Foreign Exchange Rate
94	FRED	EXJU	Δ ln	Japan / U.S. Foreign Exchange Rate
95	FRED	EXUA	Δ ln	U.S. / Australia Foreign Exchange Rate
96	FRED	EXUU	Δ ln	U.S. / U.K. Foreign Exchange Rate
97	FRED	TWUB	Δ ln	Trade Weighted U.S. Dollar Index (Broad)
98	FRED	RWUM	Δ ln	Trade Weighted U.S. Dollar Index (Major Currencies)

Output and Income				
99	FRED	PI	Δ ln	Personal Income (Chained 2005 Dollars, SA)
100	FRED	PDI	Δ ln	Disposable Personal Income (Chained 2005 Dollars, SA)
101	FRED	PITR	Δ ln	Personal Income Excluding Current Transfer Receipts (Chained 2005 Dollars, SA)
102	FRED	IPT	Δ ln	Industrial Production Index - Total Index (SA)
103	FRED	IPFP	Δ ln	Industrial Production Index - Final Products (SA)
104	FRED	IPCG	Δ ln	Industrial Production Index - Consumer Goods (SA)
105	FRED	IPDC	Δ ln	Industrial Production Index - Durable Consumer Goods (SA)
106	FRED	IPND	Δ ln	Industrial Production Index - Nondurable Consumer Goods (SA)
107	FRED	IPBE	Δ ln	Industrial Production Index - Business Equipment (SA)
108	FRED	IPM	Δ ln	Industrial Production Index - Materials (SA)
109	FRED	IPDM	Δ ln	Industrial Production Index - Durable Materials (SA)
110	FRED	IPNM	Δ ln	Industrial Production Index - Nondurable Materials (SA)
Employment, Hours and Earnings				
111	FRED	CLF	Δ ln	Civilian Labor Force (Thous., SA)
112	FRED	CUR	Δlvl	Civilian Unemployment Rate (%)
113	FRED	CE	Δ ln	Civilian Employment (Thous., SA)
114	FRED	UMP	Δlvl	Unemployed (Thous., SA)
115	FRED	ADE	Δlvl	Average Duration of Unemployment (Weeks, SA)
116	FRED	CU5	Δ ln	Civilians Unemployed - Less Than 5 Weeks (Thous., SA)
117	FRED	CU14	Δ ln	Civilians Unemployed for 5-14 Weeks (Thous., SA)
118	FRED	CU15	Δ ln	Civilians Unemployed - 15 Weeks & Over (Thous., SA)
119	FRED	CU26	Δ ln	Civilians Unemployed for 15-26 Weeks (Thous., SA)
120	FRED	CU27	Δ ln	Civilians Unemployed for 27 Weeks and Over (Thous., SA)
121	FRED	AENF	Δ ln	All Employees: Total Nonfarm (Thous., SA)
122	FRED	AEPI	Δ ln	All Employees: Total Private Industries (Thous., SA)
123	FRED	AEGI	Δ ln	All Employees: Goods-Producing Industries (Thous., SA)
124	FRED	AEML	Δ ln	All Employees: Mining and Logging (Thous., SA)
125	FRED	AEC	Δ ln	All Employees: Construction (Thous., SA)
126	FRED	AEM	Δ ln	All Employees: Manufacturing (Thous., SA)
127	FRED	AEDG	Δ ln	All Employees: Durable Goods (Thous., SA)
128	FRED	AENG	Δ ln	All Employees: Nondurable Goods (Thous., SA)
129	FRED	AESI	Δ ln	All Employees: Service-Providing Industries (Thous., SA)
130	FRED	AETU	Δ ln	All Employees: Trade, Transportation & Utilities (Thous., SA)
131	FRED	AEWT	Δ ln	All Employees: Wholesale Trade (Thous., SA)
132	FRED	AERT	Δ ln	All Employees: Retail Trade (Thous., SA)
133	FRED	AEFA	Δ ln	All Employees: Financial Activities (Thous., SA)
134	FRED	AEG	Δ ln	All Employees: Government (Thous., SA)
135	FRED	AEIS	Δ ln	All Employees: Information Services (Thous., SA)
136	FRED	AEPB	Δ ln	All Employees: Professional & Business Services (Thous., SA)
137	FRED	AWG	lvl	Average Weekly Hours of Production and Nonsupervisory Employees: Goods
138	FRED	AWC	lvl	Average Weekly Hours of Production and Nonsupervisory Employees: Construction
139	FRED	AWM	lvl	Aggregate Weekly Hours of Production and Nonsupervisory Employees: Manufactoring
140	FRED	AWPI	Δ ln	Aggregate Weekly Hours of Production and Nonsupervisory Employees: Total Private Industries
141	FRED	AHG	Δ ln	Average Hourly Earnings of Production and Nonsupervisory Employees: Goods
142	FRED	AHC	Δ ln	Average Hourly Earnings of Production and Nonsupervisory Employees: Construction
143	FRED	AHM	Δ ln	Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing
144	FRED	AHPI	Δ ln	Average Hourly Earnings of Production and Nonsupervisory Employees: Total Private
145	FRED	AOM	lvl	Average Weekly Overtime Hours of Production and Nonsupervisory Employees: Manufacturing
Housing				
146	FRED	HSMW	ln	Housing Starts in Midwest Census Region (Thous., SA)
147	FRED	HSNE	ln	Housing Starts in Northeast Census Region (Thous., SA)
148	FRED	HSS	ln	Housing Starts in South Census Region (Thous., SA)
149	FRED	HSW	ln	Housing Starts in West Census Region (Thous., SA)
150	FRED	NOWH	ln	New One Family Houses Sold: United States (Thous., SA)
151	FRED	NPHA	ln	New Private Housing Units Authorized by Building Permits (Thous., SA)
152	FRED	RHS	lvl	Ratio of Houses for Sale to Houses Sold (SA)
Money and Credit				
153	FRED	CIL	Δ ln	Commercial and Industrial Loans at All Commercial Banks (SA)
154	FRED	CLC	Δ ln	Consumer Loans at All Commercial Banks (SA)
155	FRED	CCM	Δ ln	Currency Component of M1 (SA)
156	FRED	M1	Δ ln	M1 Money Stock (SA)
157	FRED	M2	Δ ln	M2 Money Stock (SA)
158	FRED	REL	Δ ln	Real Estate Loans at All Commercial Banks (SA)
159	FRED	PSR	lvl	Personal Saving Rate (%)
160	FRED	TCC	Δ ln	Total Consumer Credit Outstanding (SA)
Prices				
161	FRED	PPCM	Δ ln	Producer Price Index: Crude Materials for Further Processing (1982=100, SA)
162	FRED	PPCF	Δ ln	Producer Price Index: Finished Consumer Foods (1982=100, SA)
163	FRED	PPFC	Δ ln	Producer Price Index: Finished Goods (1982=100, SA)
164	FRED	PPIM	Δ ln	Producer Price Index: Intermediate Materials: Supplies & Components (1982=100, SA)
165	FRED	PPCE	Δ ln	Producer Price Index:Finished Goods: Capital Equipment (1982=100, SA)
166	FRED	CPA	Δ ln	Cpi-U: All Items (82-84=100, SA)
167	FRED	CPFE	Δ ln	Cpi-U: All Items Less Food & Energy (82-84=100, SA)
168	FRED	CPT	Δ ln	Cpi-U: Transportation (82-84=100, SA)
169	FRED	CPC	Δ ln	Cpi-U: Commodities (82-84=100, SA)
170	FRED	CPD	Δ ln	Cpi-U: Durables (82-84=100, SA)
171	FRED	CPN	Δ ln	Cpi-U: Nondurables (82-84=100, SA)
172	FRED	CPF	Δ ln	Cpi-U: All Items Less Food (82-84=100, Sa)
173	FRED	CPS	Δ ln	Cpi-U: All Items Less Shelter (82-84=100, SA)
174	FRED	SOP	Δ ln	Spot Oil Price: West Texas Intermediate
175	FRED	PEC	Δ ln	Personal Consumption Expenditures: Chain-type Price Index (2005=100, SA)
176	FRED	PEFE	Δ ln	Personal Consumption Expenditures Excluding Food and Energy: Chain-type Price Index (2005=100, SA)

Relative Factor Importance

Figure A.1 presents summary statistics for the common factors estimated using the method of principal components in graphical form. In particular, Figure A.1 show the proportion, R_i^2, of the total variance explained by the ith factors as computed by the ith eigenvalue divided by the sum of eigenvalues. That is, denote by φ_i the ith eigenvalue, then $R_i^2 = \frac{\varphi_i}{\Sigma\varphi_i}$. The proportion of total variance explained by $\hat{f}_{i,t}$ is depicted in the grey bars in Figure A.1, and the cumulative proportion of total variance $\sum_{i=1}^{\hat{r}} R_i^2$ is depicted using the black bars.

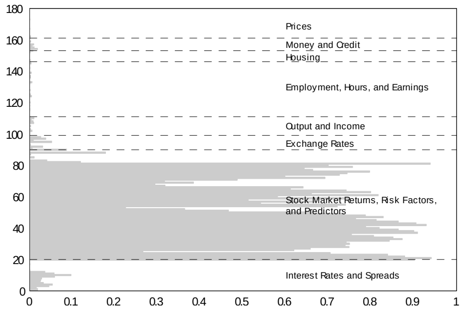
Figure A.1: Relative Factor Importance



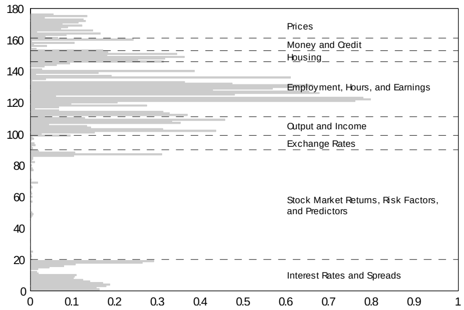
The first factor, $\hat{f}_{1,t}$, explains around 25% of the total variance in the panel, the second factor, $\hat{f}_{2,t}$, explains around 12% and so forth. The proportion of total variance explained by the ith factors is decreasing in i, but increasing in i on a cumulative basis. In fact, with 15 common factors as suggested by the panel information criteria developed in Bai and Ng (2002), nearly 75% of the total variation in the panel is accounted for. However, it is clear that a relatively small number of factors account for the largest fraction of the variance in our panel. For instance, the first four factors are able to explain 50% of the variance in the panel.

Economic Factor Interpretation

It is not possible to present a detailed economic interpretation of the estimated latent common factors as they are only identifiable up to an $r \times r$ matrix and, as pointed out by Ludvigson and Ng (2009), that any labeling of the factors will be imperfect as each factor is to some degree influenced by all panel variables and the orthogonalization implies that none of the factors will correspond exactly to a precise economic concept. However, a less detailed factor interpretation can be achieved by regressing each of the 176 panel variables onto each of the estimated common factors in turn. This procedure provides us with factor loadings such that an economic identification of the estimated common factors can be achieved. We present the results in bar chart format for all 15 factors below. The individual panel variables are grouped and aligned according to the grouping and numbering given in the Panel Data Description.



Factor 1



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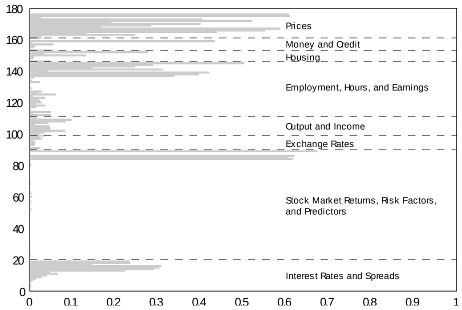

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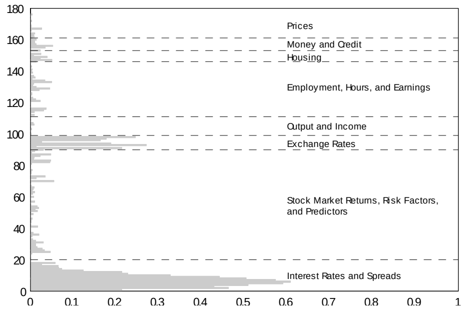

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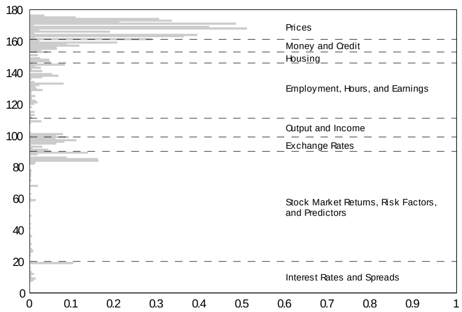

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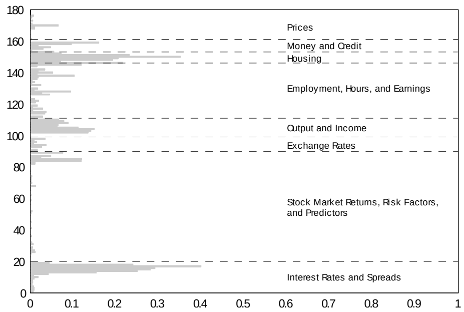

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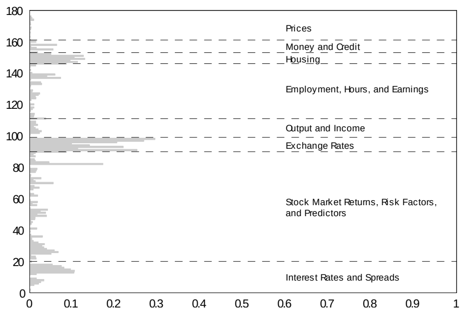

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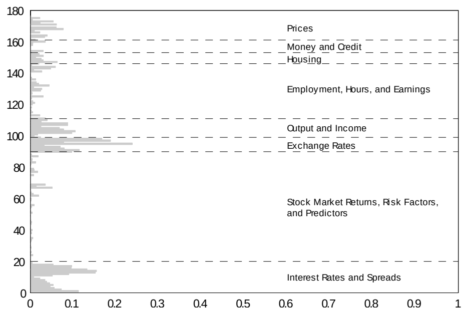

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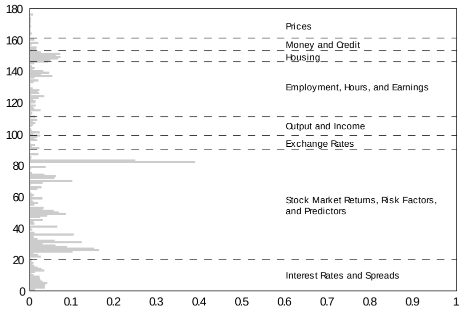

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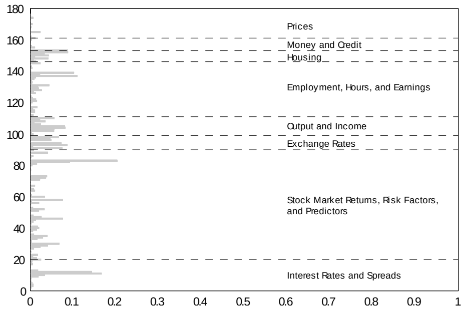

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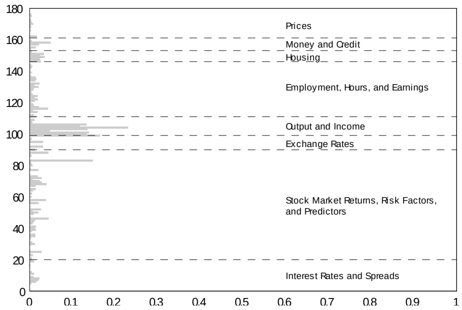

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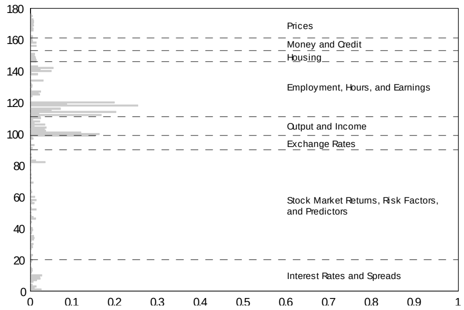

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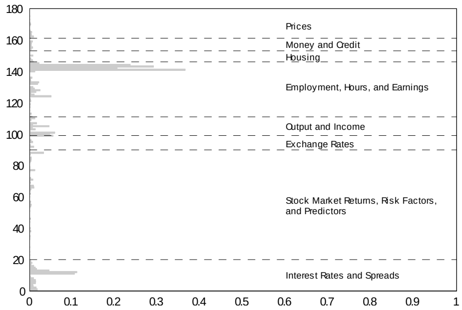

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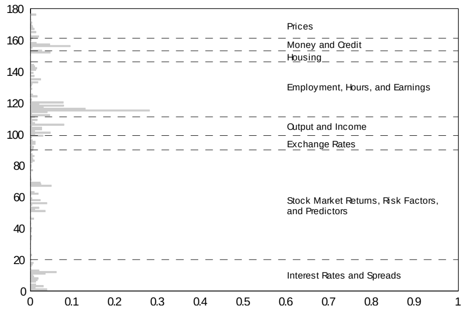
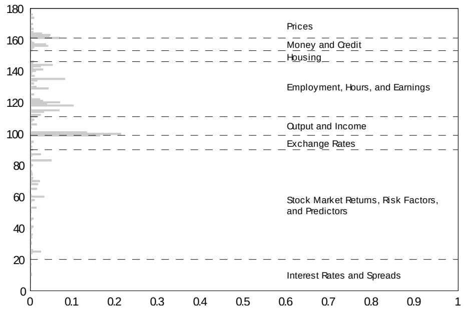


Factor 14



Factor 15

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