Exploring the Common Factors in the Term Structure of Credit Spreads

Abstract

This paper provides a factor analysis of the term structure of credit spreads. We show that credit spread innovations are subject to three common factors, two strong factors and one weak factor. A novelty is that our factors are extracted using canonical relations between credit spreads and a set of observable or estimated variables. This approach appears to estimate the factors in credit spreads better than the conventional principal component approach. The first strong factor is related to the contemporaneous state of the economy. The second strong factor represents investors' expectations about future economic conditions, and is shown to have predictive power for the state of the economy over a two-quarter horizon. The weak factor is mainly related to the error-correction processes in short-term spreads. While the weak factor is not a major determinant of credit spreads, it is needed to obtain a factor model representation of the data.

Keywords: Factor Analysis, Credit Risk, Common Factors, Generalized Method of Moments.

JEL Classification: C33, G12.

1 Introduction

The degree of comovements in asset prices is an important research subject in financial economics, see Cremers and Mei (2007) or Korajczek and Sadka (2008) for recent contributions. Term structure models begin with an assumption about the degree of economic variation in the corporate debt market, and whether the factors capturing the source of variation are of common or idiosyncratic nature. There appears to be little consensus about the number of common factors in the term structure of credit spreads, neither from the perspective of structural models, nor from the perspective of reduced-form models.[1] Knowing the correct number of common factors, however, is important to obtain reliable factors and risk premium estimates. Having too few factors obviously leads to the disadvantage that not all common variation possibly associated with a risk premium can be captured. A fact often overlooked in the literature is that factors and/or factor loadings estimated under the assumption of a larger than correct number of factors can be inconsistent.[2]

Our paper provides a factor analysis of credit spread innovations allowing us to explore the common factors in the term structure along several dimensions. Most fundamentally, what is the degree of comovements in credit spread innovations, and by how many latent factors can it be described? Our results show the existence of three latent factors. Two of them are *strong* factors and the third is a *weak* factor, since it only accounts for a small fraction of total common variation relative to the amount of idiosyncratic noise. The average explanatory power of the three factors is 49% of total variation, of which the two strong factors contribute 26% and 14%, respectively.

We test whether the *same* three factors can be identified with a parsimonious set of observable financial or macroeconomic variables. This is important, since a regression analysis would suggest that a strong common factor exists in the corporate bond market, that is not present in the equity market, the swap market, or the market for U.S. Treasury debt, see Collin-Dufresne et al. (2001). If this was the case, then we should be able to identify only one of

[1]Reduced-form models typically assume between one and six common factors, see for example Duffie and Singleton (1999), or Feldhuetter and Lando (2007) and references therein. Knez et al. (1994) suggest three-factor and four-factor models for money market returns, some of which are derived from instruments subject to default risk. Driessen (2005) proposes two common factors in credit spreads plus a common liquidity component, in addition to two factors that explain riskless bonds and also enter credit spreads.

[2]See Kan and Zhang (1999) for irrelevant factors mistakenly priced in estimation, or Hansen (1996) for estimation under too many factors resulting in nonstandard test results.

the two strong factors – but we find that both can be estimated using our factor analysis approach. Multiple regressions are not suited to detect this because the variables do not completely explain the factors, and leave unexplained components in the residuals. Such residuals are highly correlated across test assets since the variation to be explained is of systematic nature, and their principal components have high explanatory power. Our results are consistent with the notion that such high correlations are due to the use of imperfect measures of the true factors, and not due to the presence of omitted variables.

We show how to construct the factors using canonical correlation analysis (CCA), and find several advantages over the conventional factor extraction technique in a model-free environment, i.e. principal component analysis (PCA). As in the case of PCA, CCA factors are linear functions of the response variable. Conversely to PCA, CCA factors are extracted using the information from explanatory financial or macroeconomic variables such that economic interpretations are immediately available. We can investigate more precisely what the factors capture, or whether they are correlated with multiple economic channels. Furthermore, we find that irrelevant factors explain only the idiosyncratic noise of single test assets, while relevant ones explain all common variation in the term structure of credit spreads.

What are the three factors? The strongest factor is negatively correlated with all economic variables representing the riskless term structure, and the factor is also present in the equity market. The cyclical consistency of the term structure of credit spreads with these economic variables, plus the observation that the explanatory power of factor 1 increases with lower credit quality, allow us to interpret factor 1 as a systematic macro-default factor. Factor 1 also has a large positive correlation with the interest rate swap spread, which can be evidence of cyclical variation in the liquidity component of credit spreads, see Feldhuetter and Lando (2007), and is an affirmation of the predictions in Ericsson and Renault (2006). Our new finding here is that the common illiquidity component corresponds to the same factor that captures more general macroeconomic risk.

The second strong factor is mainly correlated with the variables representing the slope of the riskless term structure and the (implied) equity volatility given by VIX – both measures that have a forward-looking character. The slope of the riskless term structure, a traditional variable to capture changes in investors' expectations about real economic activity as shown by Harvey (1988) and Estrella and Hardouvelis (1991), has the predicted impact on credit spreads. VIX can be seen to capture investors' expectations through its correspondence with ex-ante risk premia.[3] Therefore, we interpret the second strong factor as one representing

[3]See for example Mele (2007) discussing the economic channels between ex-ante risk premia and equity volatility.

market participants' expectations, above and beyond those already captured by factor 1. The second strong factor is also confirmed to have predictive power out of sample: The strongest factor is most correlated with the contemporaneous realization of U.S. income data. The 'expectations factor', however, is most significant in explaining future realizations of U.S. income data over a six-month horizon.

Last but not least, we examine the cointegration relations among credit spreads of different credit quality and their error correction effects. Most of the previous studies using shorter time-series data have found that levels of credit spreads are non-stationary, see Pedrosa and Roll (1998) and Barnhill et al. (2000). It is beyond the scope of this paper to answer the question whether spread series should be non-stationary or not. Not much is known about the steady-state distribution of corporate debt from an equilibrium perspective, such that cointegration has little theoretical support at this point. However, our data shows evidence of cointegrated relations and we find the inclusion of error corrections leads to some significant adjustment coefficients. The third (and weak) factor, having explanatory power of 8% on average, is strongly correlated with the error correction series of credit spreads corresponding to short-term bonds. Somewhat surprisingly, error corrections also help to identify the second strong factor. Our results indicate that the error corrections in short maturities are not a major determinant of credit spreads, but a valid representation of the data.

Our paper proceeds as follows: We outline our method of estimating the number of factors in Section 2. We describe the data set in Section 3. Section 4 presents the analysis of credit spreads using multiple regressions and cointegration analysis. Section 5 presents the estimation results for the number of common factors. Section 6 shows the canonical correlation analysis, the development of the CCA factors and their economic interpretation. We conclude in Section 7, the Appendix contains Tables and Figures, and a digression on the properties of common factors constructed via canonical relations.

2 Factor Analysis Approach

Several procedures are available to estimate the number of common factors. For cases with a small number of cross sectional observations, Jöreskog (1967) developed a maximum likelihood (ML) method under strong distributional assumptions, which are not satisfied based on the dynamics of the term structure observable in our data set.[4] More recently, Bai and

[4] Cragg and Donald (1997) propose a methodology that requires weaker distributional assumptions and is based on the estimators of the ranks of matrices. However, as shown by Donald et al. (2005), it is computationally difficult to implement and might fail to locate a solution as it requires nonlinear optimization procedures.

Ng (2002) developed a general method for data with both large numbers of cross sectional and time series observations, but their method could produce inconsistent estimators if one dimension is small. Our estimation method is designed to consistently estimate the number of factors in panels with a large time series dimension and a small number of cross sectional observations, see Ahn and Perez (2007). We follow this procedure for three reasons: First, it fits the dimensionality and statistical properties of term structure data. Second, it allows us to estimate common factors from partially aggregated data. This has the advantage that idiosyncratic movements of individual bonds are averaged out, and we minimize the risk that a common factor extracts average idiosyncratic risk. Third, it allows for cross sectional and time series heteroskedasticity, autocorrelation, and requires no strict distributional assumptions. Another important feature of the method is that we can test how many of the latent factors can be captured by any set of observable variables.

2.1 Estimation of the Number of Factors in Credit Spreads

Assume a response variable follows the factor model given by

$$\Delta CS_{it} = \beta_i' f_t + \varepsilon_{it}, \tag{1}$$

where ΔCS_{it} is the change in credit spreads of the cross sectional unit i at time t, for $i \in \{1, 2...., N\}$ and $t \in \{1, 2...., T\}$, and f_t is the $L \times 1$ dimensional vector of common factors at time t; β_i is a $L \times 1$ dimensional vector of factor loadings, and ε_{it} the idiosyncratic component that is cross sectionally independent. The true number of factors, L_0, is unknown and will be estimated. We define $\Delta CS_{i\cdot}$ as the $T \times 1$ vector of time series observations of the cross sectional unit i, and $\Delta CS_{\cdot t}$ as the $N \times 1$ vector of cross sectional observations at time t. We also denote the matrix of factor loadings as $\beta = (\beta_1, \ \beta_2, \ ... \ \beta_N)'$.

We divide N cross sectional observations into two non-overlapping groups: the changes in credit spreads of group A are denoted by ΔCS_{it}^A, and those of group B by ΔCS_{it}^B. Groups A and B contain P and Q cross sectional series of credit spread changes, respectively, such that $P + Q = N$. Now consider the factor model for group A given by $\Delta CS_{\cdot t}^A = \beta^A f_t + \varepsilon_{\cdot t}^A$. Under the true number of factors L_0, there must exist a $P \times (P - L_0)$ matrix of *full column*, Φ, that is orthogonal to β^A. By premultiplying the model by Φ' we are able to remove the common components such that $\Phi' \Delta CS_{\cdot t}^A = \Phi' \varepsilon_{\cdot t}^A$. Thus, the following moment conditions should hold under the usual factor model assumption that idiosyncratic residuals of each group, $\varepsilon_{\cdot t}^A$ and $\varepsilon_{\cdot t}^B$, are uncorrelated:

$$E\left[\Phi' \varepsilon_{\cdot t}^A \otimes \varepsilon_{\cdot t}^B\right] = 0 \Leftrightarrow E\left[\Phi' \varepsilon_{\cdot t}^A \otimes \Delta CS_{\cdot t}^B\right] = 0 \Leftrightarrow E\left[\Phi' \Delta CS_{\cdot t}^A \otimes \Delta CS_{\cdot t}^B\right] = 0. \tag{2}$$

We can estimate the matrix Φ' by GMM. The usual identification requirement for GMM is that moment conditions should hold only at the true parameter values. Here, we also require that the number (L) of factors to construct the model is equal to the true number of factors, $L = L_0$. None of the $P \times (P - L)$ matrices of full column with $L < L_0$ can remove all common components, $\beta^A f_t$, from the model. The remaining common components will be absorbed into the residuals $\varepsilon^A_{\cdot t}$, which will therefore be correlated with $\Delta CS^B_{\cdot t}$. As a result the above moment conditions do not hold for any matrix Φ under $L < L_0$.

Ahn and Perez (2007) show that the moment conditions in equation (2) with some identifying restrictions imply the following multiple equations model:

$$Y = WH + \Xi, \quad \text{with a set of instruments given by } Z, \tag{3}$$

where

$$Y = \begin{bmatrix} \Delta CS^A_{1\cdot} \\ \Delta CS^A_{2\cdot} \\ \cdots \\ \Delta CS^A_{P-L\cdot} \end{bmatrix}, W = I_{(P-L)} \otimes \left[e, \Delta CS^A_{P-L+1\cdot}, \Delta CS^A_{P-L+2\cdot}, ..., \Delta CS^A_{P\cdot}\right],$$

$$H = [h'_1, h'_2, ..., h'_{(P-L)}]',\ Z = I_{(P-L)} \otimes \left[e, \Delta CS^B_{1\cdot}, \Delta CS^B_{2\cdot}, ..., \Delta CS^B_{Q\cdot}\right],$$

h_j is a $(L+1)\times 1$ vector of parameters to be estimated , e is a $T \times 1$ vector of ones, and Ξ is a vector of disturbances. The model implies $P-L$ equations for which the dependent variables of each equation are the first $P - L$ cross sectional series of group A. Every equation has the same regressors equal to the remaining L cross sectional series of group A, and a vector of ones. Every equation also has the same instruments, they are the entire cross sectional series of group B, and a vector of ones.

The optimal GMM estimator of H is the three-stage instrumental variables estimator (3SIV, Chamberlain (1984)) given by

$$\widehat{H} = (W'Z(T\widehat{V})^{-1}Z'W)^{-1}(W'Z(T\widehat{V})^{-1}Z'Y), \tag{4}$$

where $\widehat{V}$ is the optimal weighting matrix corresponding to the moment conditions given by (2). As usual, $\widehat{V}$ can be estimated following Newey and West (1987) or Andrews (1991) if we allow for time series autocorrelation of the disturbances, or by following White (1980) in the case of no autocorrelation. We can compute the J-statistic proposed by Hansen (1982) given by

$$J(\widehat{H}, L) = (Y - W\widehat{H})Z(T\widehat{V})^{-1}Z'(Y - W\widehat{H}). \tag{5}$$

One can show that the J-test statistic has asymptotic properties such that

$$\begin{aligned} \text{if } L &= L_0, \text{ then } J(\widehat{H}, L) \xrightarrow{d} \chi^2(df), \text{ and} \\ \text{if } L &< L_0, \text{ then } J(\widehat{H}, L) \xrightarrow{p} \infty, \end{aligned}$$

where the number of degrees of freedom is given by $df = (P-L)(Q-L)$. These properties of the J-test statistic allow us to draw inference about the true number of factors, and the following two procedures are proposed.

Sequential Hypothesis Testing. We first compute the J-statistic assuming the true number of factors is equal to one. We then test $H_0 : L_0 = 1$ against the alternative of $L_0 > 1$. If the true number of factors is larger than one the test statistic will converge to infinity in probability, leading to rejection of the null hypothesis. In case of rejection, we compute the statistic assuming the true number of factors is equal to two, testing $H_0 : L_0 = 2$ against the alternative of $L_0 > 2$, and so on. We continue this procedure until the null hypothesis is not rejected.

Model Selection Criterion. The estimated number of factors according to this procedure is the value of L that minimizes the criterion function

$$S(L) = TJ(\widehat{H}, L)f(T)^{-1} - g(L).$$

Several functional forms have been proposed for the choice of $f(T)$ and $g(L)$, see Cragg and Donald (1997) or Bai and Ng (2002). We use the Bayesian Information Criterion (BIC) given by

$$f(T) = log(T), g(L) = (P-L)(Q-L).$$

This choice satisfies the theoretical conditions leading to a consistent estimator, and simulations show good small sample properties.[5] An advantage of using the model selection criterion over the sequential testing method is that it does not require the use of the optimal weighting matrix $(\widehat{V})^{-1}$. Given the observed N cross sectional units of the response variable, groups A and B can be formed in $N!/P!(N-P)!$ different ways. Ahn and Perez (2007) show that if the response variables are functions of "strong" factors only – factors with a signal-to-noise ratio greater than 0.25 – then the estimation result is independent of the way the groups are formed. However, if data is generated by some "strong" and some "weak"

[5]We also utilized the functional forms given by $f(T) = log(T), g(L) = (P-L)(Q+1)$, and $f(T) = ln(T), g(L) = (P-L)(Q-L)$. Our choice of the BIC is better able to capture weaker factors, but the main conclusions of the paper do depend on this.

factors, then the estimated number of factors depends on grouping.[6] Utilizing this property, we propose to identify the presence of "weak" factors – factors with a signal-to-noise ratio smaller than 0.25 – by repeating the estimation under different group specifications.

2.2 Estimation of the Number of Factors with Macroeconomic and Financial Variables

The common factors are unobservable in the general factor model. Ideally, observable variables are used as proxies for the latent factors. But this raises questions, such as how good are the proxies explaining the response variables, do the observable variables proxy for all factors, or are we using too many or too few proxy variables. We attempt to answer these questions using the moment conditions defined above. We do not need to estimate the latent factors first in order to check if the proposed observable variables are correlated with them.

Simple observation of the moment conditions given in equation (2) reveals that any set of variables not correlated with the idiosyncratic components can be used as instruments instead of $\Delta CS^B_{\cdot t}$. The proposed moment conditions are then given by

$$E\left[\Phi' \varepsilon_{\cdot t} \otimes IN_{\cdot t}\right] = 0 \text{ or } E\left[\Phi' \Delta CS_{\cdot t} \otimes IN_{\cdot t}\right] = 0, \tag{6}$$

where $IN_{\cdot t}$ is a $K \times 1$ vector of instruments observed at time t including a vector of ones. Since we do not use $\Delta CS^B_{\cdot t}$ as instruments, we do not need to partition the response variables into groups, and the entire set of cross sectional observations $\Delta CS_{\cdot t}$ can be used for constructing moment conditions.

Suppose that $IN_{\cdot t}$ is highly correlated with all factors. While estimating the model using the true number of factors, the matrix Φ' will remove all L_0 factors and the idiosyncratic component will be "free" of factors, such that $E\left[\Phi' \varepsilon_{\cdot t} \otimes IN_{\cdot t}\right] = 0$. Suppose now that the true number of factors is three, and the vector of instruments is only correlated with two of them. Then we can claim that the moment conditions will hold when $L = 2$. Given $L = 2$, the corresponding matrix Φ will not remove all factors, and the third factor remains as part of the idiosyncratic component. But since $IN_{\cdot t}$ is not correlated with the missing factor the moment condition $E\left[\Phi' \varepsilon_{\cdot t} \otimes IN_{\cdot t}\right] = 0$ will still hold.

[6] Suppose the true data generating process includes two strong factors and one weak factor, then the procedure estimates mostly two factors and sometimes three factors, depending of the way groups A and B are formed. Ahn and Perez (2007) suggest to make inferences based on the estimation results of many different group specifications – they find that the number of factors most often estimated from 100 randomly selected group specifications is an accurate estimator.

In general, the moment conditions will hold for a value $\widetilde{L}$ equal to the number of common factors that are correlated with the proposed instruments. One can show that the J-test statistic has asymptotic properties such that

$$\begin{aligned} \text{if } L &= \widetilde{L}, \text{ then } J(\widehat{H}, L) \xrightarrow{d} \chi^2(df), \text{ and} \\ \text{if } L &< \widetilde{L}, \text{ then } J(\widehat{H}, L) \xrightarrow{p} \infty, \end{aligned}$$

where the number of degrees of freedom is given by $df = (N - L)(K - 1)$. Based on these properties we can estimate how many factors the proposed instruments are able to capture using the sequential hypothesis testing and the model selection criterion.

3 Data

This section describes the data used in our factor analysis, the data set for credit spreads, and the data set containing the additional macroeconomic and financial variables.

3.1 Credit Spreads

Our laboratory is a panel data set of constant maturity yield curves, following Feldhuetter and Lando (2007) among others, obtained from the Merrill Lynch bond index system.

In the cross section, we utilize yield curves sorted by rating category. The rating categorization is based on Merrill Lynch's composite rating of the Moody's, S&P and Fitch nomenclature.[7] We limit our attention to credit spreads from issues in the industrial sector, excluding issuers from the regulated financial and the utility sectors. Merrill Lynch reports the set of individual corporate bonds that are used to construct the respective yield curves for each rating category. For the time period of our study, the average number of bonds with time to maturity of less than 10 years in the joint set of AAA and AA bonds is 84 (minimum 66), reflecting the low number of highly rated issuers in recent times. In comparison, the average number of bonds with time to maturity of less than 10 years in the joint set of A and BBB bonds is 919 (minimum 556). As a result, we limit our data set to the nine rating categories with a high degree of bond coverage, ranging from A1 to BB3, thereby excluding AAA and AA bonds.

[7] In case of a split rating, the composite rating is based on the lower of the assigned ratings; for example, a Baa3/BB+ bond rating equals a BB1 composite rating. In case a bond is rated by one agency only, the composite rating will equal that individual rating.

The second cross sectional dimension of our data set is the term structure. For each point in time, we select 9 equally spaced points on the term structure, i.e. 2 to 10 years to maturity. We then define the credit spread as the difference between the corporate bond spot rate and the yield to maturity on a zero coupon government bond of the same maturity, see Elton et al. (2001) or Liu et al. (2006). The constant maturity yield curves are based on bond values stripped off any embedded call or put option, thereby making them comparable to portfolios of individual bullet bonds used in other studies. In each time series, we have 508 observations in levels generating 507 first differences, observed weekly each Friday and covering the time period between January 1997 and December 2006. Table 1 presents summary statistics for credit spread data in levels, and Table 2 for first differences, respectively. The average level of credit spreads in our data set is slightly larger than those reported by Elton et al. (2001) for a time period between 1987 and 1996. We cover a period with dramatic widening of spreads after the Russia/LTCM crisis in 1998, as well as a period of narrowing spreads to pre-1998 levels between 2002 and 2006. As an independent check on the data, we also compare the Merrill Lynch credit spreads to spreads obtained from the Bloomberg system, and find the two sources are generally consistent.[8]

In section 6, we study the explanatory power of our factor model in other market segments. Our laboratory for this is a second panel data set representing the term structure of credit spreads derived from of G.B.P. denominated corporate bonds. This data set has the same time series dimension as the U.S. dollar denominated yield curves but has a smaller cross sectional dimension. Again, to limit ourselves to a high degree of coverage we use the 3 rating classes ranging from AA to BBB, thereby excluding AAA and non-investment grade bonds. While our U.S. dollar denominated data set represents U.S. domestic issuers, the G.B.P. yield curves correspond to more than one country in terms of issuer origin. For example, as reported by Merrill Lynch as of Jan 1 2000, the portfolio of BBB-rated issues contains 86 individual bonds with maturities of less than 10 years to maturity, 71 are issued by U.K. domestic corporate issuers, the remaining 15 by non-domestic issuers. This ratio is representative for the entire sample period. Panel A of Table 3 presents summary statistics for U.K. credit spread data in levels, and Panel B for first differences, respectively.

[8]After performing a multiple regression analysis of changes in credit spreads on a set of explanatory macroeconomic and financial variables, as documented in the next section, our findings are quantitatively and qualitatively similar to previous studies based on averaged individual bond data. We find almost identical properties in estimated residuals while replicating Collin-Dufresne et al. (2001), which is another confirmation for the quality of our data.

3.2 Macroeconomic and Financial Variables

We use a set of macroeconomic and financial variables that previous literature has argued to be of importance in explaining common movements in credit spreads.

1. The Treasury debt market. A negative relation between the level of riskless interest rates and the credit spread has been documented for several data sets, see for example Duffee (1998). We use the 10-year yield to maturity obtained from U.S. Treasury zero coupon bonds as the riskless spot rate. Not only the level, but also slope of the term structure carries information about economic conditions - see Harvey (1988) and Estrella and Hardouvelis (1991). We use the difference between the 10 year spot rate and the one year spot rate as the diagnostic for the slope. While it has been documented that the shape of the riskless term structure itself can be explained by multiple factors, see Litterman and Scheinkman (1991) or Dai and Singleton (2002), it is unclear whether changes in the slope of the riskless term structure have explanatory power for changes in credit spreads above and beyond changes in the general level of interest rates.

2. The equity market. The volatility of firms' assets and degree of leverage are usual ingredients for structural models of credit risk. Since both are difficult to measure on aggregate, we usually rely on measures derived from observable liabilities like equity. Collin-Dufresne et al. (2001) find mixed evidence for the explanatory power of changes in leverage for changes in credit spreads; changes in equity volatility represented by VIX, however, show more consistent results. Changes in the value of equity obviously impact the degree of leverage and thereby the likelihood of default. But it has also been shown that macroeconomic conditions affect the amount of bondholder recovery *given* default, possibly through an industry channel, as in Acharya et al. (2007), or an economy-wide channel, as in Altman et al. (2005). Moreover, changes in the business climate might directly affect target capital structures as argued in Demchuk and Gibson (2006). We complement our data set with observations of the S&P 500 index.

3. The swap market. We should expect that credit spreads in our data set contain a reward for bearing illiquidity risk. One way to capture this empirically is to exploit an illiquidity factor already shown to exists in other fixed income market segments, see for example Liu et al. (2006) or Feldhuetter and Lando (2007) for liquidity factors in interest rate swap spreads. We add the term structure of swap spreads to our data set, such that credit spreads and swap spreads have congruent maturities.

4. Income data. In section 6, we interpret the CCA factors in their ability to predict economic conditions with an out-of-sample test, and based on a diagnostic that was not

used to construct the factors in the first place. For this purpose we utilize monthly real disposable U.S. personal income data, as reported in FRED. The trend in the monthly data is removed by a Hodrick/Prescott filter with lambda 14400, each observation is in chained year 2000 dollars.

4 Credit Spread Analysis

4.1 Cointegration and Credit Spreads

Other studies have documented non-stationary properties in levels of credit spreads, for example Pedrosa and Roll (1998) and Barnhill et al. (2000). Motivated by this finding, it is common to use a differentiated series instead, as the first differences usually appear to be stationary. However, using a differentiated series without a careful analysis of possible cointegration relations may lead to an incorrect specification of model. If a cointegration relation is not rejected, then a regression using the differentiated series as dependent variables should include error correction variables as regressors in order to be correctly specified. While it is not our main goal to determine whether cointegration relations indeed exist in the term structure of credit spreads, we investigate whether the error correction terms from the estimated cointegration relations have explanatory power.

We first test for stationarity in our data set using an Augmented Dickey Fuller (ADF) test. As expected, we can not reject the null hypothesis of a unit root for any of the series of levels of credit spreads. All ADF p-values are larger than 0.15, and most of them larger than 0.30. Hence, the time series of levels of credit spreads appear to be non-stationary, if not near non-stationary.[9]

Given these non-stationarity test results of the credit spread series, we investigate whether there is a cointegration in levels of credit spreads among different credit quality. Though not much is known about the steady-state distribution of corporate debt from an equilibrium perspective, it is possible that credit spreads of different credit qualities move together.[10]

[9]It seems implausible that any credit spreads series can actually explode, as a unit root process could. The power of the unit root test is low compared to near to unit root alternatives, nonetheless ignoring the data characteristics may lead to incorrect inferences. In contrast, the null hypothesis of non-stationarity is strongly rejected for differences in credit spreads – all p-values are smaller than .0001.

[10]A long-term relation could for example be due to target capital structures. If there is such a relation, then a temporary deviation from the long-term relation could be due to market frictions like adjustment costs, see Welch (2004) or Leary and Roberts (2005) for empirical evidence. While market frictions could affect the level of firm's borrowing rates as well as riskless interest rates, the use of a differentiated credit spread series alone would not allow us to detect importance of such a long-term relation.

Using the Johansen Rank statistic, we test how many cointegration relations are significant; the analysis is performed separately for each maturity, see Hall et al. (1992) for an example of cointegration analysis and the specification of an error correction model for U.S. riskless interest rates among different maturities. Results in Table 4 show that there are at most two cointegration relations for short-term credit spreads (MAT3 and MAT5) and at most one cointegration relation for longer-term credit spreads (MAT7 and MAT10.) We estimate the error correction series following Johansen (1988) and Johansen (1991) for each maturity bracket, given by the specification

$$ecm_t = CS_{t-1}^{A1} - \delta_0 - \delta_1 CS_{t-1}^{A2} - \delta_2 CS_{t-1}^{A3} ... + \delta_8 CS_{t-1}^{BB3}, \quad (7)$$

where the δ loadings represent the cointegration coefficients. The deviation from a long-run relation is corrected gradually through a series of partial short-run adjustments corresponding to the *ecm* term.

4.2 Multiple Regressions

Our motivation to undertake a multiple regression analysis prior to performing the factor estimation is threefold. First, we check whether our data yields quantitatively similar results with respect to common variation, as compared to data sets based on averaged individual bond data. Second, we test whether the inclusion of error correction terms leads to an improvement in explaining credit spreads. Third, we establish a benchmark case that can be used for comparison while constructing our own factor model in Section 6.

4.2.1 Standard Explanatory Variables

We first estimate the base case specification for which changes in credit spreads are linear functions of a subset of the explanatory variables introduced in section 3.2. The model is given by

$$\Delta CS_{it} = \beta_{0,i} + \beta_{1,i}\Delta r_t^{10} + \beta_{2,i}\left(\Delta r_t^{10}\right)^2 + \beta_{3,i}\Delta slo_t + \beta_{4,i}\Delta vix_t + \beta_{5,i} s\&p_t + \varepsilon_{it}. \quad (8)$$

Estimation results are summarized in Table 5. Average OLS estimates sorted by rating category are reported in Panel A, and sorted by time to maturity in Panel B. Associated t-statistics are given by the average of the absolute individual t-statistics, and are shown below the point estimates.

Changes in the risk free rate are statistically and economically significant in explaining changes in credit spreads, and the estimated sign is as expected – an increase in r_t^{10} leads to a reduction in credit spreads. Larger equity volatility, for example due to a larger degree of leverage or a larger degree of asset volatility or both, leads to an increase in credit spreads. The change in the slope of the riskless term structure adds explanatory power for some credit qualities. Panel B reveals that the slope impact is the strongest for short maturities. The estimated sign is surprising as we expected the cyclical behavior of *slope* to be negatively associated with changes in credit spreads. Our multiple regressions do not lead to coefficients that are significant or consistent in sign for the S&P index return.[11]

An analysis of estimated residuals is crucial for the objective of our study. First, does a multiple regression analysis applied to our data set also lead to relatively low explanatory power measured via R-square values? Second, does an inspection of estimated residuals reveal a strong common component as in Collin-Dufresne et al. (2001)? We find both facts to be true. Average adjusted R-square values vary between .06 and .40 – the explanatory power is the largest in lower rating categories.[12] Sorted by maturity, the average adjusted R-square values range from .16 to .18. Instead of interpreting the fraction of variation in the residuals explained by the principal components as in Collin-Dufresne et al. (2001) or Ericsson et al. (2007), we decide to extract the first principal component from residuals and add the extracted series to the set of explanatory variables. This has the advantage of avoiding a discussion as to how low the fraction of variation in the residuals explained by the first principal component needs to drop, to be able to infer with confidence whether a common component is left unexplained. Regression results are displayed in Table 6. The explanatory power of the multiple regression increases dramatically and adjusted R-square values double in all cases, now varying between .24 and .90 sorted by rating, and ranging from .39 to .45 sorted by maturity bracket. Hence, our data set has very similar properties as studies based on averaged individual bond data – average R-square values are low, and a strong common component appears to exists in residuals from a multiple regression analysis.

[11]This equity market effect, however, seems to be subsumed in other included variables, as (non-reported) univariate regression show that the S&P index return has a strongly negative, statistically and economically significant effect on changes in credit spreads.

[12]In comparison, Collin-Dufresne et al. (2001) find R-square values for comparable maturities between .20 and .34. Differences in estimates compared to other studies could be due to multiple reasons. For example, our data set and the Warga Database used in other studies overlap only in the year 1997, and a dramatic widening of spreads with increased volatility started to occur in 1998. Second, we do not exclude observations with less than 4 years to maturity. Third, our time series dimension has weekly instead of monthly observations, and we verified by restricting our data set to monthly changes that the explanatory power for high rating categories increases.

4.2.2 Explanatory Variables and Error Corrections

We now test whether the inclusion of error correction terms helps to explain changes in credit spreads. Changes in the dependent variable are a function of the same set of explanatory variables as above plus the (maturity-specific) error correction term given by

$$\Delta CS_{it} = \beta_{0,i} + \beta_{1,i}\Delta r_t^{10} + \beta_{2,i}\left(\Delta r_t^{10}\right)^2 + \beta_{3,i}\Delta slo_t + \beta_{4,i}\Delta vix_t + \beta_{5,i}s\&p_t + \beta_{6,i}ecm_t + \varepsilon_{it}. \quad (9)$$

Estimation results are summarized in Table 7. According to Panel A, and compared to the specification in equation (8), the inclusion of ecm_t increases explanatory power for 7 rating categories, and average coefficient estimates are significant for A1 to BBB1 rated bonds. According to Panel B, average coefficient estimates are significant for maturities 3, 5, and 7, and the statistical significance of the adjustment coefficients β_6 shows that the inclusion of ecm_t is a valid representation of our data.

We can conclude that deviations from a cointegration relation contain some information over and above what is already contained in a standard set of explanatory variables - in particular for credit spreads corresponding to shorter maturities. Credit spreads corresponding short-term bonds have a stronger (or faster) reaction to deviations from a cointegration relation as compared to spreads corresponding to longer maturities, not necessarily implying that short-term credit spreads adjust because they are in disequilibrium. The reported increases in R-square values, however, are by no means substantial. While they are statistically significant, their economic significance seems to be limited. We revisit this issue while employing ecm_t as an instrumental variable in the factor estimation study.

4.2.3 Robustness

The constant maturity yield curves in our data set are based on bond portfolios sorted by rating category. As reported by Merrill Lynch, these portfolios are rebalanced on the last business day of each month based on information about rating transitions up to the third business day prior to the last business day of the month. Since our data frequency is shorter than the rebalancing frequency, it might be possible that part of our empirical findings are driven by the mechanics of rebalancing. To address this issue, we test indicator variables corresponding to week-of-the-month effects interacted with the lagged performance of credit spread changes in several specifications. We find that our results about ecm_t are robust to all specifications and are not driven by the mechanics of rebalancing.

The average maturity (or duration) of individual bonds used to construct the constant maturity yield curves is not constant over time, as reported by Merrill Lynch. Hence, it might be the case that a yield curve estimation generates some term structure dynamics simply due to time-varying weights. We control for average maturity (duration) and find that our results are not affected by time-varying average maturities. The January effect, see Chang and Pinegar (1986), could also be present in our data set. Indeed, we find marginal evidence for the existence of the January effect in our time series. However, all our results are robust while controlling for the effect with indicator variables.

5 Factor Analysis

5.1 Estimation of Number of Factors in Credit Spreads

We now turn to the first main objective of our study and estimate the number of common factors. We perform our estimation for each maturity bracket separately. This allows us to draw more precise inference about the number of factors along the second cross sectional dimension. Though one can argue that common factors should be relevant for all maturities, specific market conditions could affect bonds with different maturities to a different extent. We present the estimation results based on the model selection criterion (upper graph) and the sequential hypothesis testing methods (lower graph) in Figure 1. The estimation is performed using 4 spreads as group A and 5 spreads as the instrument group B. We repeat the same tests for 100 randomly selected group specifications. We do so because the test results are sensitive to group specification, especially when some factors are weak. For the sequential testing method, we use 5% of significance level, and the method of Newey and West (1987) in order to estimate a weighting matrix with a bandwidth equal to 3. We selected bandwidth 3 since the level of autocorrelation in credit spread innovations is small.

The model selection criterion method estimates two factors more than 55% and three factors around 30% of the time for credit spreads with short maturities. For maturities larger than three years this relation is reversed, finding two factors 30-40% and three factors 45-60% of the time. Very similar results are obtained by applying the sequential testing method. For credit spreads corresponding to two and three years to maturity we can not reject the null hypothesis of two factors more that 55%, and three factors around 25% of the time. Again, for maturities larger than three this relation is reversed. We can not reject two factors 30-40%, and three factors 35-45% of the time.

Our results suggest that three common factors explain changes in the term structure of credit spreads. However, one of these three factors appears to be a "weak" factor – it might only account for a small degree of the total variance of the response variables, and we find it to be estimated only for some maturities. We will check after constructing the factors in Section

6, whether a signal-to-noise ratio smaller than 0.25 allows the identification of a weak factor. Two of the three factors, however, appear to be "strong" factors as their appearance is robust among all maturities and we rarely estimate only one factor. In addition to estimating the number of factors based on two testing techniques, we perform another robustness check. We expand our data set and include credit spreads from AA-rated bonds using the same data source despite lower bond coverage. If there exist three common factors that explain changes in credit spreads, then we should also expect to find three common factors in the data set based on an expanded cross-section. Estimation results are quantitatively very similar, and we can confirm the finding of three factors as before.

Two other studies have used the ML method and the likelihood ratio (LR) test to identify the number of factors in returns or credit spreads of corporate debt contracts. Knez et al. (1994) develop three-factor and four-factor models for money market returns, although a likelihood ratio test would indicate a much larger number of common factors for their data set. More recently, Driessen (2005) proposes two common factors in credit spreads also based on a likelihood ratio test plus a common liquidity component, in addition to two common factors that explain the variation in riskless bonds and also enter credit spreads, leading to five common factors in total.

In order to disentangle our factor estimation results from those studies, we apply a LR test to our data set of credit spreads. The null hypothesis of three factors is always rejected. If a conclusion about the number of factors was based solely on the likelihood ratio test – a test with strong distributional assumptions such as normality and stochastic independence of idiosyncratic errors over time – we would be tempted to suggest that credit spread innovations have four or more common factors. However, the null hypothesis of normality is strongly rejected for all credit spread series based on several test statistics.

5.2 Estimation of Number of Factors with Macroeconomic and Financial Variables

Our next objective is to test whether all common factors are captured by the macroeconomic and financial variables proposed above.

We first include as instruments the standard set of explanatory variables given by $IN(1) = \{\Delta r^{10}, (\Delta r^{10})^2, \Delta slo, \Delta vix, s\&p\}$. The results are presented in Figure 2. Under the model selection criterion (upper graph) and for credit spreads corresponding to shorter maturities ($< MAT5$) the estimation procedure finds one factor more than 50% of the time, two factors around 17%-34% of the time, and three factors 3%-15% of the times. For the case of longer maturities ($\geq MAT5$) the method estimates one factor around 30% of the time, two factors around 50% of the time, and three factors 17-27% of the time. Similar results are found using the sequential testing method (lower graph).

The $IN(1)$ variables appear to be correlated with three factors as the estimation procedure finds three factors with some positive frequency. The level of correlations with one or two of the three latent factors appears to be weak. We can infer this by comparing the estimation results using $IN(1)$ to the results of the previous subsection, where three factors were obtained 45-60% of the time for longer maturities. In the case of shorter maturities, we estimate three factors around 15% of the time using instrumental variables, compared to 25-30% obtained in the pervious subsection – such differences could be evidence of a weak correlation with one or two of the factors. To express results in a simple diagnostic we compute the average number of factors estimated with $IN(1)$ across all maturities, and compare it to the average number of factors estimated without instruments. Based on the model selection criterion, the average number of factors estimated with $IN(1)$ equals 1.75, compared to 2.37 factors without instruments.

We also notice that for maturities shorter than five years, the number of factors equal to one is estimated significantly more often compared to using credit spread changes as instruments. For example, we obtain one factor more than 50% of the time for maturities smaller than five, compared to less than 15% in the previous subsection. In summary, the variables $IN(1)$ are correlated with the three latent factors. However, our results suggest that their correlations with one of the factors are weak across all maturities. For shorter maturities there appears to be weak correlation with a second factor. Such weak correlations could be the cause of the strong explanatory power of the first principal component in the multiple regression found in Section 4.2, since the unexplained part of the *true* factors will remain part of the idiosyncratic component of the model.

We test some additional instrumental variables and check whether estimation results improve above and beyond what is already captured by $IN(1)$. Figure 3 shows estimation results adding the Fama and French factors *smb* and *hml* to the set of instruments, i.e. $IN(2) = \{IN(1), smb, hml\}$. The inclusion of *smb* and *hml* as instruments gives similar results compared to using $IN(1)$ only, the number of factors equal to one is estimated slightly more often. Based on the model selection criterion, the average number of factors estimated with $IN(2)$ decreases to 1.54, which is no improvement compared to 1.75 factors estimated with $IN(1)$. For robustness, we also test a set of instruments containing only *s&p*, *smb*, and *hml*, and find that both methods consistently estimate only one factor.

Figure 4 (upper graph) shows factor estimation results adding the variable $\Delta swap$ to the set of instruments, i.e. $IN(3) = \{IN(1), \Delta swap\}$. The inclusion of $\Delta swap$ does not change the results consistently across all maturities. An improvement occurs for credit spreads corresponding to maturities larger than seven years, as three factors are estimated with a larger frequency compared to $IN(1)$ alone. The set $IN(1)$ alone estimates three factors only 17% to 22% of the time for maturities between 7 and 10 years; $IN(1)$ plus $\Delta swap$, however, estimates three factors 25% to 35% of the time. Hence, if there exists a common factor linked to illiquid market conditions and it is not captured by $IN(1)$, then the addition of $\Delta swap$ seems to capture it for credit spreads corresponding to longer maturities.[13] The average number of factors estimated with $IN(3)$ increases to 1.78, which is a slight improvement over 1.75 factors estimated with $IN(1)$ only.

We also test the series *ecm* as an additional instrumental variable, i.e. $IN(4) = \{IN(3), ecm\}$. In this case *ecm* corresponds to maturity specific error correction terms. Figure 4 (lower graph) presents the results of the estimation of number of factors correlated with $IN(4)$. The results notably improve for spreads corresponding to shorter maturity bonds, as two factors are estimated more often compared to $IN(3)$ only. For spreads with maturities shorter than five years the model selection method now estimates one factor only 9% to 26% of the time, and two factors 43-54% of the time.[14] Based on the model selection criterion, the average number of factors estimated with $IN(4)$ increases to 2.12, a strong improvement over 1.78 factors estimated with $IN(3)$ only.

6 CCA Factors

Results from the previous section show that several economic variables are correlated with all three latent factors that explain changes in credit spreads. Using the information of those variables we attempt to construct "proxies" for the latent factors, which are more highly correlated with the latent factors than the observable explanatory variables are. Ideally, for the purpose of interpretation we like to know more precisely what the three factors capture or whether they are correlated with multiple economic channels.

[13] This result is consistent with Edwards et al. (2007), who find that percentage transaction costs increase with time to maturity of the underlying corporate bond. If transaction costs are a fundamental friction that correspond to bond market illiquidty, then we should expect a larger degree of bond market illiquidty for longer maturities compared to shorter maturities.

[14] This is also consistent with the multiple regression results presented in Section 4.2, where including the error correction term as a regressor improves adjusted R-square values for shorter maturity bonds.

6.1 Canonical Correlations

We propose the use of canonical correlation analysis (CCA) in order to construct the factors. This method is a generalization of multiple correlation analysis. In a multiple regression we use the coefficient of determination to find the linear combination that maximizes the correlation between one dependent variable and a set of predictor variables. In CCA this concept is generalized such that we find the linear combinations that maximize the correlation between a set of dependent variables and a set of independent variables.

Different methodologies have been proposed in the literature to construct latent factors. For example, Knez et al. (1994) construct latent factors using mimicking portfolios based on returns of financial securities in the money market, or Litterman and Scheinkman (1991) extract principal components from (riskless) bond returns. Reduced-form term structure models with specific distributional assumptions, for example Feldhuetter and Lando (2007), typically extract latent factors using filtering techniques. The advantages of using CCA is not only that we extract latent factors in a model-free environment, but also that we exploit the information of observable variables that are truly correlated with latent factors. Similarly to principal components, our CCA factors are linear functions of the response variables. However, the weights given to individual response variables are determined by canonical correlations between observable explanatory variables and the response variables. We base our decision about which observable variables to consider on the most promising factor estimation results, i.e. the set $IN(1) = \{\Delta r^{10}, (\Delta r^{10})^2, \Delta slo, \Delta vix, s\&p\}$, plus the variables $\Delta swap$ and ecm. Specifically, we include the error correction terms corresponding to three-year maturities because estimation results do not notably improve with error corrections in longer term credit spreads.

Formally, the first canonical coefficients are the vectors a_1 and b_1 that maximize the first canonical correlation, given by the objective

$$\rho_1 = \max_{a_1, c_1} \; corr(a_1' \Delta CS, c_1' IN), \tag{10}$$

subject to the restrictions $var(a_1' \Delta CS) = var(c_1' IN) = 1$. We denote $U_1 = a_1' \Delta CS$ and $V_1 = c_1' IN$ as the first pair of canonical variates. Similarly, the second canonical coefficients are the vectors a_2 and c_2 that maximize the correlation between ΔCS and IN, subject to the standard constraint that U_2 and V_2 are orthogonal to U_1 and V_1, respectively. Further canonical coefficients and variates are found according to the equivalent objective – the estimation can be reduced to an eigenvalue problem. We estimate the corresponding first three pairs of canonical coefficients and canonical variates, and propose U_1, U_2, and U_3 as the CCA factors. We refer the interested reader to the Appendix for a proof, showing that factors obtained from true covariances between credit spread changes and the instruments are consistent estimators of linear combinations of the true common factors.[15]

We hypothesize that all credit spread series are subject to the same factors, but expect different factor loadings. Therefore, we construct factors using canonical correlations with 36 cross sectional observations included in $a'\Delta CS$, and refer to them as "general" CCA factors. These 36 cross sectional observations include the 9 rating categories for maturities 3, 5, 7 and 10. We also consider "maturity-specific" CCA factors, for which only the 9 rating categories for each maturity are included in the canonical correlation analysis. We will use the "maturity-specific" CCA factors to gain additional insight into the economic meaning of the those factors and to check robustness of our results.[16]

6.2 CCA Factor Model

To investigate the explanatory power of the factor model we first perform a multiple regression analysis. The specification is given by

$$\Delta CS_{it} = \beta_{0,i} + \beta_{1,i} factor1_t + \beta_{2,i} factor2_t + \beta_{3,i} factor3_t + \varepsilon_{it}. \quad (11)$$

Estimation results in Table 8 show a large increase in explanatory power compared to the regressions in Section 4. The adjusted R-square value is now larger than 0.45 sorted by maturity, and between .20 and .76 sorted by rating class with an average of .48 across all ratings. The explanatory power of our factor model seems comparable to the 5-factor

[15]It is yet to be shown that the CCA factors from estimated covariances are also consistent. However, there are few reasons to doubt their consistency. The results of Chamberlain and Rothschild (1983) imply that factors estimated by applying principal component analysis (PCA) to a true variance-covariance matrix of a large number of response variables are consistent. Extending their results, Bai and Ng (2002) show that the PCA factors obtained from an estimated variance-covariance matrix of response variables are also consistent for the data containing both a large numbers of cross-sectional and time-series observations. The main difference between CCA and PCA is that the former estimates factors using covariances between response variables and instrumental variables, instead of the variance-covariance matrix of response variables. Similarly to PCA, CCA allows weak cross-sectional correlations among idiosyncratic errors. Both methods require the use of the data with large numbers of cross sectional and time series observations.

[16]Since the consistency of the CCA factors, see Appendix, would require a large number of credit spread changes, the maturity-specific factors are likely to contain some amount of noise. However, there is a simple way to check the quality of the CCA factors. If those factors capture true factors only poorly, some large common components should be left in the residuals from the regressions of credit spread changes on the CCA factors. If so, the first principal component from the residuals must have some power to explain credit spread changes. Thus, the average change in the goodness of fit (R-squared) of the time-series regressions by using the first principal component as an additional regressor could be used as a measure of the quality of the CCA factors.

reduced-form approach proposed by Driessen (2005), who reports an average R-square value of .387 based on a data set of investment grade bonds only – the average R-square value of our 6 investment grade bond portfolios equals .40.

As before, we extract the first principal component ($firstpc$) from residuals and add the extracted series as an explanatory variable, see Table 9. The increase in adjusted R-square values is minimal for the eight rating classes AA1 to BB2, i.e. less than .02 on average. Interestingly, the first principal component increases the explanatory power for the BB3 rating class to almost 100%, indicating that the first principal component represents the amount of idiosyncratic noise of the lowest rated credit spread series. The second principal component contains the idiosyncratic noise of another rating class. Based on this evidence we infer that all three factors can account for the common variation in credit spreads, and that the unexplained noise is of idiosyncratic nature. To close this argument, we return to the factor estimation procedure and test the set of instrumental variables equal to the explanatory variables of this regression, i.e. $IN(5) = \{factor1, factor2, factor3, firstpc\}$. The results are presented in Figure 5. Both estimation procedures lend strong support to three factors. Based on the model selection criterion, the average number of factors estimated with $IN(5)$ equals 2.67, a strong improvement over 2.12 estimated with $IN(4)$, and even slightly larger than the average number of 2.37 without instruments.[17]

We can compare the three CCA factors in their relative importance by studying the percentage of total variation explained by each factor, see Table 10. On average, factor 1 has explanatory power of 26.4%, followed by factor 3 with 14.1%, and by factor 2 with 7.5%.[18] We can confirm that factor 2 has a signal-to-noise ratio of 14% (as compared to 51% and 28% for factors 1 and 3), and thereby satisfies the definition of a weak factor. Factors 1 and 3 are strong factors based on a signal-to-noise ratio larger than .25. Sorted by rating, a trend appears not only in R-square values, but also in the percentage variation explained by factor 1 only. For credit spreads corresponding to BB2 and BB3 rated bonds, 90% of the total explanatory power is due to factor 1. While it is expected that lower rated corporate bonds carry a larger degree of systematic risk compared to higher credit quality bonds, see

[17]Testing for the number of factors with $IN(5)$ is important from another angle. The original factor estimation results in Section 5.1. were obtained maturity-specific, forgoing a restriction that the factors are the same across maturities. The results in Figure 5 show that three factors can be identified for *all* maturities with the same set of $IN(5)$.

[18]The explanatory power of CCA factors may not decrease in order, in that a preceding factor has higher explanatory power than the succeeding one. The order of CCA factors are determined by the canonical correlations between instruments and credit spread changes. It is possible that a CCA factor highly correlated with instruments can have weak correlations with individual credit spread changes. For an extreme example, suppose that a set of instrumental variables is highly and weakly correlated with the weakest and strongest factors, respectively. Then, the first CCA factor should be the weakest factor.

for example Elton et al. (2001) and Ericsson et al. (2007), we find it noteworthy that such a large fraction is explained by one of the three factors only.

To compare our CCA factors to an alternative methodology in a model-free environment, we estimate the number of factors using the model selection method of Bai and Ng (2002), although use of the 36 cross sectional observations may not be enough to obtain a reliable estimate. We try several different selection criteria proposed by Bai and Ng; the estimated number of factors are greater than three in all cases. We also extract the first three PCA factors from our credit spread series. We find that the three PCA factors lead to a similar explanatory power of the empirical model; however, an analysis of the residuals would indicate that more principal component factors are needed in total. Furthermore, the three principal component model does not have the appealing feature that an additional principal component explains the idiosyncratic noise of a specific rating class. Instead, an additional principal component explains idiosyncratic noises of many test assets.

6.3 Interpretation

We compute the pairwise correlations of the CCA factors with the set of explanatory variables that were used to construct them.[19] The results are shown in Table 11, Panel A. Factor 1 shows large pairwise correlations with all economic variables except *ecm*. Factor 1 is consistently negatively correlated with $\Delta r^{10}, (\Delta r^{10})^2$, and Δslo – changes in riskless rates are negatively associated with the term structure of credit spreads, first and second moment. While Δslo has a positive coefficient estimate in the multiple regression analysis with inconsistent statistical significance, see Section 4.2, the predicted economic channel becomes visible in our factor construction. In improved economic times, default will be less likely and an increase in slope associated with lower credit spreads. At the same time, the slope represents investor's expectations about future (riskless) interest rates, such that a decreasing credit spread can also be the result of expectations about increasing riskless interest rates while holding default activity constant.

Factor 1 also has a positive 31% correlation coefficient with equity volatility, and a negative 22% correlation coefficient with the equity market return. These consistent regularities with several economic variables, plus the observation that the explanatory power of factor 1 increases with lower credit quality, allow us to interpret factor 1 as a systematic macro-default factor. In addition, factor 1 has a positive 52% correlation coefficient with the interest rate

[19] Regression results capture partial effects of individual variables, holding other variables constant. Since structural models frequently do not make predictions on partial effects of economic variables, but rather on unrestricted correlations, we believe that interpretation of the pairwise correlations is more insightful.

swap spread. This can be evidence of cyclical variation in the liquidity component of credit spreads with the predicted sign. While it is an affirmation of the positive correlation between illiquidity and default components made by Ericsson and Renault (2006), the new finding is that the common illiquidity component corresponds to the *same* factor that captures the default component.

For factor 2 and factor 3, the largest pairwise correlations are given by the error correction terms with .25 and .38, changes in slope, .49, and equity volatility, .23. To disentangle these factors further we utilize the factor construction with maturity specific factors. Factor 2 shows the strongest correlation coefficient with *ecm*, ranging from .36 to .42, and therefore identifies as the common factor that relates to the adjustment of credit spreads to deviations from a cointegration relation. This interpretation is consistent with the monotone decreasing percentage of total variation explained by factor 2, see Table 10, with 11.4% for MAT3 to 4.1% for MAT10; our factor estimation results have shown that adding *ecm* to the set of instrumental variables helps to identify the number of factors for shorter maturity credit spreads.

The maturity-specific factors reveal that factor 3 is most related to Δslo and vix, with correlation coefficients between -.24 and -.08 for Δslo and between .13 and .19 for vix. Except for three rating categories, factor 3 also has a positive factor loading and therefore the predicted effect of Δslo and vix on credit spread innovations. The slope of the term structure as well as implied volatility have a forward-looking character – thereby representing market participants' expectations about real economic activity and stock return variability. A larger degree of vix can correspond to larger ex-ante risk premium, higher expected excess returns and increased credit spreads, see Mele (2007) for economic channels supporting this correspondence between risk premia and volatility. Therefore, we interpret factor 3 as a common factor representing market participants' expectations, above and beyond those already captured in factor 1.

To compare the CCA factor interpretation to the alternative principal component methodology, we check the pairwise correlations of the first three PCA factors with the set of explanatory variables that were *not* used to construct them. The interpretation of the first factor appears to be similar, due to a high time series correlation between the strongest CCA factor and the first PCA factor of 88%. However, the interpretation of the second and third PCA factor is diluted. For example, the largest pairwise correlations of the third PCA factor can be observed with the level of the riskless interest rate and swap spread with inconsistent signs. This is not surprising as the correlations between the second or third CCA factors and respective PCA factors are .35% and .50% only.[20]

[20] We find that it would require more than 10 principal component factors obtained from the same 36 cross

6.4 Out of sample tests

First, we split the data set into the estimation period covering 1997 to 2004 with 405 time series observations, and the test period covering 2005 to 2006 with 102 time series observations. We use the estimation period to find the canonical coefficients a and c, use these coefficients to construct factors for the test period, and repeat the multiple regression analysis *only* based on the test period. Estimation results are qualitatively and quantitatively similar to the results in Tables 8.[21]

The interpretation of a "common" factor depends on the set of assumptions placed on the degree of market integration, and we test to which extent our factors serve as common factors in an international context. Our factors are derived from the term structure of U.S. dollar denominated bonds of domestic issuers. We test the explanatory power on changes in credit spreads obtained from G.B.P denominated bonds primarily from U.K. issuers. We expect domestic-wide movements to be related to movements in the U.K. market due to market integration among developed economies. We can explain close to 20% of the variation in the U.K. data set, see Table 12. This explanatory power is driven by factor 1. The loading and the significance of factor 1 is at least 3 times as large as those of factors 2 and 3 - a pattern that is not observable in Table 8. After the inclusion of the first principal component, adjusted R-square values increase to values larger than .65. We also test the set of three factors as instrumental variables in the factor estimation procedure, and find that both methods consistently estimate one factor only. Therefore, the CCA factors have satisfactory performance in explaining credit spreads corresponding to G.B.P denominated corporate bonds, but at least one factor appears to be left unexplained in this exercise.

As a final test, we explore the predictive power of our factor model. It is useful to see if the factor interpretation remains valid based on a macroeconomic variable that was not used to construct them. We integrate the CCA factor first, and regress the time series of monthly real disposable U.S. personal income data on the two strong CCA factors. We employ contemporaneous as well as lagged values. If the second strong factor indeed represents

sectional observations to identify the same economic channels as our three CCA factors. After extracting 14 pc factors, and then generating the first three canonical relations between the 14 pc factors and the set $IN(1)$ plus the variables $\Delta swap$ and ecm, the correlations between the original and newly obtained CCA factors are between 78% and 94%.

[21] We then perform a cross-section out of sample test based on the credit spread series corresponding to AA-rated bonds. Compared to single A-rated bonds (i.e. the highest in our original data set), we expect this series to contain even less exposure to factor 1, but the second strong factor 3 to be relatively more important. The average explanatory power of the factor model for AA credit spreads is .20 R-square, and we can confirm that only .05 corresponds to factor 1, but .13 corresponds to factor 3.

mainly investors' expectations, then we should expect that it has predictive power for future realizations of the state of the economy. Test results are shown in Table 13, and a graphic visualization in Figure 6. The strongest factor is most correlated with the current realization of disposable income, lagged observations on matter marginally. This observation flips as we analyze the second strong factor. The 6-month lagged observation is the most significant lagged variable while predicting income. The contemporaneous realization is not important. Hence, we confirm the second strong factor has a component distinct from factor 1 while predicting the future state of the economy.

7 Conclusion

Several techniques are available to extract latent factors. Within a model-free environment, we find that using canonical relations to extract factors has advantages over using principal components. First, the factors are easier to interpret as they are obtained from canonical correlations between response variables and economic and/or financial variables. Second, the factors appear to have convincing properties even if the number of cross sectional units is small. The common variation in the term structure of credit spreads can be fully explained by three factors. There does not exist a strong factor that is not present in the equity market, the swap market, or the market for Treasury debt. The weakest of the three factors might be specific to the corporate bond market, but its' explanatory power is small. We identify the weak factor as one that is strongly related to deviations from a cointegration relation. The economic source for this relation, however, is unknown a this point. Whether credit spreads are stationary or not is a controversial issue. Studies using a longer time series might find that spreads are indeed stationary, and the existence of a weak factor to be a small sample artifact.

Our factor analysis is reduced-form in nature. But one might ask, how do our results speak to the future development of structural models? The existence of two strong factors lend to an environment in which two macro state variables drive the term structure of credit spreads. The interpretation of one of the two as an expectation factor would also be consistent with a one-factor model under stochastic volatility. Our results also generate insight into the hedging ability of common variation in the corporate bond market. Suppose an investor holds a portfolio of long-term BB corporate bonds. Then the correlations in Table 11, together with the factor loadings in Table 8, relate to the hedging coefficients with respect to tradable securities in the equity market, the swap market, or the market for Treasury debt. Based on this, the investor can control to which extent she wants to the exposed to systematic risk.

8 Appendix

8.1 Properties of the CCA Factors

In order to investigate what properties the canonical covariates would have, we need to define some notation first. Let y and x denote ΔCS and $IN = \{\Delta r^{10}, (\Delta r^{10})^2, \Delta slo, \Delta vix, s\&p, \Delta swap, ecm\}$, respectively. For simplicity, assume that the means of credit spread changes, instruments, and latent factors (f) are zeros: $E(y) = 0$, $E(x) = 0$, and $E(f) = 0$. This assumption can be easily relaxed at the cost of introducing more notation. Let $\Omega_{gh} = E(gh')$ for two random vectors g and h, such that Ω_{yy} and Ω_{xx} are the variance-covariance matrices of ΔCS and IN, respectively. Equation (1) can be written as a matrix equation, $y = Bf + \epsilon$. As factor analysis usually does, we normalize the factors such that $\Omega_{ff} = I_{L_0}$. Finally, we introduce a linear projection model $x = Gf + v$, where G is a matrix of coefficients, and f and v are uncorrelated. It is worth emphasizing that this model does not place any assumption on the causal relations between the instrumental variables and factors. Any two random vectors can be linearly linked by a projection model regardless of their causal relations. Thus, the projection model $x = Gf + v$ is not equivalent to an assumption that the instrumental variables in $x = IN$ are determined by the factors in f, or vice versa. Finally, we use $M^{1/2}$ to denote a root matrix of a symmetric matrix M such that $M^{1/2}M^{1/2} = M$.

With the notation and assumptions, we have $\Omega_{yx} = BG'$. Let us assume that $rank(B) = rank(G) = rank(BG') = L_0$. A necessary condition for this rank condition is that the number of instrumental variables in x should not be smaller than L_0. This condition generally holds if the instrumental variables in x are not perfectly correlated with each other. Under this condition, we have L_0 nonzero canonical correlations between y and x. Let $A = (a_1, a_2, ..., a_{L_0})$ and $C = (c_1, c_2, ..., c_{L_0})$ be the matrices of the canonical coefficient vectors such that a_j and c_j are the vectors corresponding to the j'th largest canonical correlation. The restriction that the U_j's (as well as the V_j's) are mutually orthogonal and have unitary variances implies that $A'\Omega_{yy}A = C'\Omega_{xx}C = I_{L_0}$. Define:

$$\begin{aligned} \Upsilon_B &\equiv (B'\Omega_{yy}B)^{1/2}(G'\Omega_{xx}G)(B'\Omega_{yy}B)^{1/2}; \\ \Upsilon_G &\equiv (G'\Omega_{xx}G)^{1/2}(B'\Omega_{yy}B)(G'\Omega_{xx}G)^{1/2} \end{aligned}$$

Let $\Xi = (\xi_1, \xi_2, ..., \xi_{L_0})$ be the orthonormal matrix such that ξ_j is the eigenvector corresponding to the j'th largest eigenvalue of Υ_B. Similarly, let $\Psi = (\psi_1, \psi_2, ..., \psi_{L_0})$ be the orthonormal matrix whose columns are the eigenvectors corresponding to the eigenvalues of Υ_G. Notice that the two matrices Υ_B and Υ_G share the same positive eigenvalues, say

$\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_{L_0}$. We now show that

$$A = \Omega_{yy}^{-1} B(B'\Omega_{yy}^{-1}B)^{-1/2}\Xi; C = \Omega_{xx}^{-1} G(G'\Omega_{xx}^{-1}G)^{-1/2}\Psi. \quad (12)$$

To show this, reconsider the maximization problem given in (10). With our notation and restrictions, $corr(a_1'y, c_1'x) = a_1'\Omega_{yx}c_1$. Thus, the first-order conditions for the problem are given by

$$BG'c_1 = (\theta/2)\Omega_{yy}a_1, \quad (13)$$

$$GB'a_1 = (\mu/2)\Omega_{xx}c_1, \quad (14)$$

where θ and μ are Lagrangian multipliers. Premultiplying (13) and (14) by a_1' and c_1', respectively, we can have $a_1'BG'c_1 = \theta/2 = \mu/2$ since $a_1'\Omega_{yy}a_1 = c_1'\Omega_{xx}c_1$. Thus, the value of $(\theta/2) = (\mu/2)$ is the first canonical correlation. Substituting (14) into (13) and premultiplying (13) by $(B'\Omega_{yy}^{-1}B)^{-1/2}B'$, we have

$$\Upsilon_A(B'\Omega_{yy}^{-1}B)^{-1/2}B'a_1 = (\theta/2)^2(B'\Omega_{yy}^{-1}B)^{-1/2}B'a_1,$$

which indicates that $(B'\Omega_{yy}^{-1}B)^{-1/2}B'a_1$ is an eigenvector of Υ_A and $(\theta/2)^2$ is a corresponding eigenvalue. Thus, the maximum value of $(\theta/2)^2$ must be equal to λ_1, and $(B'\Omega_{yy}^{-1}B)^{-1/2}B'a_1$ must be the corresponding vector. That is,

$$(B'\Omega_{yy}^{-1}B)^{-1/2}B'a_1 = \xi_1 \Leftrightarrow a_1 = \Omega_{yy}^{-1}B(B'\Omega_{yy}^{-1}B)^{-1/2}\xi_1.$$

Similarly, we can show that $c_1 = \Omega_{xx}^{-1}G(G'\Omega_{xx}^{-1}G)^{-1/2}\psi_1$. We now obtain the second canonical coefficient vectors a_2 and c_2 by maximizing $a_2'\Omega_{yx}c_2 = a_2'BG'c_2$, subject to $a_2'\Omega_{yy}a_2 = c_2'\Omega_{xx}c_2 = 1$ and $a_1'\Omega_{yy}a_2 = c_1'\Omega_{xx}c_2 = 0$. Using the Lagrangian multiplier method again, we can show that

$$\begin{aligned} a_2 &= \Omega_{yy}^{-1}B(B'\Omega_{yy}^{-1}B)^{-1/2}\xi_2; \\ c_2 &= \Omega_{xx}^{-1}G(G'\Omega_{xx}^{-1}G)^{-1/2}\psi_2 \end{aligned}$$

Continuing this maximization process L_0, we can obtain the results given in (12).

The results in (12) imply that

$$\begin{aligned} (B'\Omega_{yy}^{-1}B)^{-1/2}\Xi U &= f + (B'\Omega_{yy}^{-1}B)^{-1}B'\Omega_{yy}^{-1}\varepsilon; \\ (G'\Omega_{xx}^{-1}G)^{-1/2}\Psi V &= f + (G'\Omega_{xx}^{-1}G)^{-1}G'\Omega_{xx}^{-1}v, \end{aligned}$$

where $U = (U_1, U_2, ..., U_{L_0})' = A'y$ and $V = (V_1, V_2, ..., V_{L_0})' = C'x$. It is plausible to assume that all of the elements in B, G, Ω_{yy}, and Ω_{xx} are finite and bounded, if the changes in credit spreads and factors are stationary. Under this assumption,

$$\begin{aligned} p\lim_{N\to\infty}(B'\Omega_{yy}^{-1}B)^{-1}B'\Omega_{yy}^{-1}\varepsilon &= p\lim_{N\to\infty}\left(\frac{B'\Omega_{yy}^{-1}B}{N}\right)^{-1}\frac{B'\Omega_{yy}^{-1}\varepsilon}{N}=0_{L_0\times 1};\\ p\lim_{K\to\infty}(G'\Omega_{xx}^{-1}G)^{-1}G'\Omega_{xx}^{-1}v &= p\lim_{K\to\infty}\left(\frac{G'\Omega_{xx}^{-1}G}{K}\right)^{-1}\frac{G'\Omega_{xx}^{-1}v}{K}=0_{L_0\times 1}, \end{aligned}$$

where K is the number of instrumental variables. Thus, we have

$$\begin{aligned} p\lim_{N\to\infty}(B'\Omega_{yy}^{-1}B)^{-1/2}\Xi U &= f;\\ p\lim_{K\to\infty}(G'\Omega_{xx}^{-1}G)^{-1/2}\Psi V &= f. \end{aligned}$$

This result indicates that linear combinations of the canonical covariates are consistent estimators of the common factors in f, if the number of credit spread series or instrumental variables is large. Thus, if N or K is large, the canonical covariates U or V can be used as factors.

Given that the number of our instrumental variables is limited, the canonical covariates from this instrumental variables (V) may not produce good proxies for common factors. In our maturity-by-maturity analysis, the maturity-specific covariates from credit spreads might not be consistent either, because each maturity contains only nine credit spread series. However, if the factors are common to all maturities, the canonical covariates produced from all credit spreads would be reasonable proxies for the common factors.

8.2 Tables and Figures

series	min	max	mean	stdev
A1-MAT3	30.41	153.52	68.47	25.59
A1-MAT5	39.11	166.91	79.84	29.21
A1-MAT7	44.15	170.32	87.08	30.98
A1-MAT10	49.91	183.11	93.85	31.99
A2-MAT3	37.98	165.53	81.73	34.85
A2-MAT5	46.50	178.36	92.81	36.05
A2-MAT7	52.30	190.17	99.71	36.67
A2-MAT10	58.01	201.76	105.99	37.06
A3-MAT3	38.62	191.63	93.58	41.77
A3-MAT5	48.95	206.40	104.81	42.55
A3-MAT7	55.56	218.41	111.66	42.90
A3-MAT10	60.22	228.03	117.73	43.02
BBB1-MAT3	42.15	273.12	116.02	50.34
BBB1-MAT5	55.00	284.79	127.62	49.21
BBB1-MAT7	62.72	286.19	134.51	48.14
BBB1-MAT10	69.78	281.19	140.34	46.72
BBB2-MAT3	51.73	281.63	131.77	56.75
BBB2-MAT5	62.68	275.54	142.45	53.12
BBB2-MAT7	69.64	265.55	148.49	50.12
BBB2-MAT10	75.62	250.27	153.29	46.76
BBB3-MAT3	53.25	325.38	154.11	67.51
BBB3-MAT5	70.78	327.77	165.83	65.22
BBB3-MAT7	79.99	325.96	172.27	62.83
BBB3-MAT10	89.02	318.56	177.11	59.62
BB1-MAT3	82.08	576.26	239.48	105.98
BB1-MAT5	96.53	554.67	253.25	97.42
BB1-MAT7	105.84	532.93	260.88	91.75
BB1-MAT10	113.48	505.12	266.58	86.24
BB2-MAT3	118.38	612.74	290.11	107.59
BB2-MAT5	137.24	599.30	299.20	98.73
BB2-MAT7	146.32	589.18	303.67	93.31
BB2-MAT10	154.15	597.08	306.24	88.47
BB3-MAT3	138.24	745.44	335.60	141.04
BB3-MAT5	164.09	735.39	345.34	125.27
BB3-MAT7	180.66	725.24	350.01	115.50
BB3-MAT10	195.62	712.62	352.53	106.97

Table 1: **Data Set - Credit Spreads - Levels.** The table reports summary statistics for the indicated data series, 508 weekly observation between Jan 1997 and Dec 2006. Credit spreads are computed under semiannual compounding, expressed on an annual basis. All spreads are in basispoints.

series	min	max	mean	stdev
A1-MAT3	-18.78	19.38	0.025	3.57
A1-MAT5	-17.85	27.86	0.035	3.68
A1-MAT7	-16.17	32.63	0.043	3.88
A1-MAT10	-16.36	36.07	0.051	4.02
A2-MAT3	-24.98	22.18	0.011	3.74
A2-MAT5	-25.14	27.48	0.034	3.82
A2-MAT7	-24.80	30.61	0.050	3.92
A2-MAT10	-24.09	32.40	0.065	3.96
A3-MAT3	-12.99	29.22	0.028	3.86
A3-MAT5	-13.02	31.71	0.042	3.85
A3-MAT7	-12.90	33.46	0.052	3.94
A3-MAT10	-13.78	35.09	0.062	4.02
BBB1-MAT3	-18.72	35.10	0.032	5.21
BBB1-MAT5	-23.78	32.78	0.054	5.10
BBB1-MAT7	-31.36	33.05	0.071	5.15
BBB1-MAT10	-35.69	33.88	0.088	5.15
BBB2-MAT3	-16.18	40.16	0.028	4.73
BBB2-MAT5	-16.73	43.63	0.059	4.60
BBB2-MAT7	-16.35	45.65	0.080	4.66
BBB2-MAT10	-15.20	47.12	0.101	4.72
BBB3-MAT3	-23.99	42.69	0.049	6.21
BBB3-MAT5	-22.69	42.00	0.074	6.13
BBB3-MAT7	-24.38	40.89	0.091	6.24
BBB3-MAT10	-25.09	38.99	0.106	6.33
BB1-MAT3	-82.46	102.68	0.054	13.52
BB1-MAT5	-61.64	86.10	0.098	12.04
BB1-MAT7	-47.83	74.25	0.128	11.53
BB1-MAT10	-42.68	61.98	0.156	11.26
BB2-MAT3	-68.32	134.06	0.026	16.75
BB2-MAT5	-53.01	98.42	0.068	14.88
BB2-MAT7	-56.66	75.57	0.095	14.37
BB2-MAT10	-69.63	54.51	0.121	14.33
BB3-MAT3	-95.16	152.54	-0.034	22.89
BB3-MAT5	-79.91	117.81	-0.074	20.01
BB3-MAT7	-70.98	103.76	-0.105	19.10
BB3-MAT10	-72.22	85.65	-0.139	19.00

Table 2: **Data Set - Credit Spreads - First Differences.** The table reports summary statistics for the indicated data series, 507 weekly observation between Jan 1997 and Dec 2006. First differences are derived from credit spreads expressed on an annualized basis. All changes in spreads are in basispoints.

Panel A

series	min	max	mean	stdev
AA1-3-MAT3	17.40	119.00	55.50	18.80
AA1-3-MAT5	31.50	138.80	71.40	24.40
AA1-3-MAT7	41.80	151.70	81.90	28.60
AA1-3-MAT10	53.90	178.10	92.30	32.70
A1-3-MAT3	29.40	144.90	77.60	27.20
A1-3-MAT5	49.80	167.60	95.10	31.30
A1-3-MAT7	60.40	187.50	106.10	34.20
A1-3-MAT10	66.20	215.50	116.30	37.00
BBB1-3-MAT3	54.00	217.50	120.30	40.60
BBB1-3-MAT5	65.90	226.10	133.20	40.60
BBB1-3-MAT7	77.70	228.90	142.20	40.20
BBB1-3-MAT10	89.60	247.40	150.80	39.90

Panel B

series	min	max	mean	stdev
AA1-3-MAT3	-10.50	26.80	0.100	2.60
AA1-3-MAT5	-14.70	29.30	0.000	2.90
AA1-3-MAT7	-18.00	30.30	0.000	3.10
AA1-3-MAT10	-20.30	30.40	0.000	3.40
A1-3-MAT3	-13.40	27.10	0.100	3.20
A1-3-MAT5	-12.60	32.10	0.100	3.30
A1-3-MAT7	-16.00	34.40	0.000	3.50
A1-3-MAT10	-18.70	35.40	0.000	3.80
BBB1-3-MAT3	-39.90	46.00	0.000	7.30
BBB1-3-MAT5	-19.60	40.20	0.100	5.60
BBB1-3-MAT7	-18.30	37.70	0.000	5.00
BBB1-3-MAT10	-16.30	34.80	0.000	4.70

Table 3: **Data Set - U.K. Credit Spreads - Levels and First Differences.** Panels A (508 levels) and B (507 first differences) report summary statistics for the indicated U.K. data series between Jan 1997 and Dec 2006, used for the out-of-sample test of general CCA factors. First differences are derived from credit spreads expressed on an annualized basis. All changes in spreads are in basispoints.

Panel A - Mat3

no of ce(s)	eigenvalue	statistic	crit. value	prob.
None *	0.213	122.860	58.434	0.000
At most 1 *	0.136	75.090	52.363	0.000
At most 2 *	0.104	56.376	46.231	0.003
At most 3	0.063	33.117	40.078	0.246
At most 4	0.050	26.379	33.877	0.298

Panel B - Mat5

no of ce(s)	eigenvalue	statistic	crit. value	prob.
None *	0.207	118.945	58.434	0.000
At most 1 *	0.128	70.079	52.363	0.000
At most 2 *	0.103	55.644	46.231	0.004
At most 3	0.064	33.706	40.078	0.219
At most 4	0.049	25.943	33.877	0.324

Panel C - Mat7

no of ce(s)	eigenvalue	statistic	crit. value	prob.
None *	0.173	97.313	58.434	0.000
At most 1 *	0.106	57.400	52.363	0.014
At most 2	0.085	45.441	46.231	0.061
At most 3	0.063	33.180	40.078	0.243
At most 4	0.050	26.241	33.877	0.306

Panel D - Mat10

no of ce(s)	eigenvalue	statistic	crit. value	prob.
None *	0.160	89.127	58.434	0.000
At most 1 *	0.097	52.409	52.363	0.050
At most 2	0.066	35.205	46.231	0.447
At most 3	0.059	31.334	40.078	0.341
At most 4	0.044	23.137	33.877	0.520

Table 4: **Unrestricted Cointegration Rank Test (Maximum Eigenvalue).** Panels A and B indicate 3 cointegration equations, Panels C and D indicate 2 cointegration equations, (*) denotes rejection of the hypothesis at the 5% level. The last column shows MacKinnon-Haug-Michelis p-values.

Panel A

sorting	int.	Δr^{10}	$(\Delta r^{10})^2$	Δslo	Δvix	s&p	adj. R^2
A1	0.178	-2.292	-8.498	-1.601	0.528	0.009	0.085
	0.929	1.502	1.567	0.781	5.254	1.239	
A2	0.150	-3.223	-5.973	0.807	0.349	-0.005	0.058
	0.767	2.035	1.075	0.553	3.357	0.637	
A3	0.222	-5.451	-10.216	3.891	0.510	0.004	0.105
	1.150	3.486	1.865	1.838	4.969	0.618	
BBB1	0.196	-5.508	-8.188	0.367	0.840	0.007	0.128
	0.783	2.707	1.156	0.584	6.301	0.721	
BBB2	0.027	-7.416	0.830	0.381	0.551	0.007	0.094
	0.184	3.942	0.135	0.363	4.475	0.759	
BBB3	0.189	-12.941	-6.675	12.462	0.511	0.001	0.090
	0.611	5.154	0.763	3.648	3.105	0.485	
BB1	0.121	-43.260	-2.992	26.142	0.935	-0.031	0.227
	0.224	9.606	0.196	4.207	3.158	1.490	
BB2	-0.575	-74.047	27.454	23.451	1.129	-0.030	0.396
	0.944	14.920	1.594	3.379	3.467	1.340	
BB3	0.046	-81.525	-19.371	18.783	2.262	0.000	0.343
	0.108	11.833	0.801	1.884	4.942	0.177	

Panel B

sorting	int.	Δr^{10}	$(\Delta r^{10})^2$	Δslo	Δvix	s&p	adj. R^2
MAT3	0.010	-29.038	-1.937	16.881	0.954	-0.001	0.157
	0.406	6.256	0.706	3.075	4.338	0.986	
MAT5	0.056	-26.850	-3.596	10.903	0.878	-0.004	0.177
	0.603	6.409	1.013	2.170	4.552	0.843	
MAT7	0.079	-25.415	-4.359	6.839	0.815	-0.005	0.178
	0.706	6.226	1.135	1.451	4.396	0.763	
MAT10	0.102	-23.437	-5.055	3.015	0.738	-0.006	0.166
	0.819	5.637	1.214	0.965	4.060	0.726	

Table 5: **Multiple Regressions - Changes in Credit Spreads on Standard Set of Explanatory Variables.** Panel A shows average ols regression results sorted by rating category, Panel B sorted by maturity bracket. The averages of (absolute) t-statistics are shown below the parameter estimates. The (standard) set of explanatory variables includes the change in the 10 year riskfree spot rate, Δr^{10}, the squared change, $(\Delta r^{10})^2$, the change in the slope of the term structure, Δslo, the change in VIX, Δvix, and the return of the S&P 500 index, s&p.

Panel A

series	int.	Δr^{10}	$(\Delta r^{10})^2$	Δslo	Δvix	s&p	1st pc	adj. R^2
A1	0.178	-2.292	-8.498	-1.601	0.528	0.009	0.079	0.237
	1.026	1.644	1.731	0.848	5.767	1.350	10.044	
A2	0.150	-3.223	-5.973	0.807	0.349	-0.005	0.094	0.269
	0.876	2.312	1.229	0.621	3.819	0.727	12.084	
A3	0.222	-5.451	-10.216	3.891	0.510	0.004	0.087	0.283
	1.290	3.892	2.091	2.042	5.555	0.688	11.191	
BBB1	0.196	-5.508	-8.188	0.367	0.840	0.007	0.107	0.284
	0.869	2.989	1.279	0.639	6.963	0.789	10.502	
BBB2	0.027	-7.416	0.830	0.381	0.551	0.007	0.116	0.315
	0.213	4.541	0.153	0.412	5.161	0.871	12.792	
BBB3	0.189	-12.941	-6.675	12.462	0.511	0.001	0.145	0.286
	0.693	5.831	0.862	4.111	3.503	0.541	11.754	
BB1	0.121	-43.260	-2.992	26.142	0.935	-0.031	0.333	0.507
	0.279	12.075	0.244	5.310	3.975	1.874	16.954	
BB2	-0.575	-74.047	27.454	23.451	1.129	-0.030	0.449	0.723
	1.407	22.248	2.371	5.098	5.176	1.985	24.567	
BB3	0.046	-81.525	-19.371	18.783	2.262	0.000	0.785	0.902
	0.302	30.993	2.120	5.377	13.198	0.461	54.749	

Panel B

series	int.	Δr^{10}	$(\Delta r^{10})^2$	Δslo	Δvix	s&p	1st pc	adj. R^2
MAT3	0.010	-29.038	-1.937	16.881	0.954	-0.001	0.225	0.387
	0.528	10.086	1.008	4.507	6.176	1.174	18.425	
MAT5	0.056	-26.850	-3.596	10.903	0.878	-0.004	0.245	0.440
	0.750	10.407	1.377	3.177	6.326	1.060	19.226	
MAT7	0.079	-25.415	-4.359	6.839	0.815	-0.005	0.254	0.447
	0.847	9.650	1.479	2.006	5.892	0.972	18.517	
MAT10	0.102	-23.437	-5.055	3.015	0.738	-0.006	0.253	0.418
	0.967	8.313	1.505	1.180	5.213	0.921	17.004	

Table 6: **Multiple Regressions - Changes in Credit Spreads on Standard Set of Explanatory Variables and 1st Principal Component.** Panel A shows average ols regression results sorted by rating category, Panel B sorted by maturity bracket. The averages of (absolute) t-statistics are shown below the parameter estimates. The set of explanatory variables includes all the variables as in Table 5 plus the first principal component extracted from regression residuals.

Panel A

series	int.	Δr^{10}	$(\Delta r^{10})^2$	Δslo	Δvix	s&p	ecm	adj. R^2
A1	0.176	-1.855	-8.344	-2.177	0.506	0.008	0.003	0.104
	0.929	1.222	1.554	1.069	5.073	1.128	3.252	
A2	0.151	-3.002	-5.980	0.442	0.336	-0.005	0.002	0.067
	0.772	1.892	1.080	0.351	3.240	0.707	2.228	
A3	0.223	-4.562	-10.148	2.732	0.468	0.003	0.008	0.175
	1.199	3.030	1.923	1.346	4.739	0.418	6.442	
BBB1	0.200	-4.541	-8.301	-0.896	0.797	0.005	0.010	0.173
	0.819	2.281	1.200	0.494	6.124	0.572	5.160	
BBB2	0.030	-6.804	0.749	-0.463	0.523	0.006	0.006	0.118
	0.129	3.650	0.137	0.209	4.289	0.647	3.531	
BBB3	0.191	-12.039	-6.679	11.069	0.462	-0.001	0.008	0.137
	0.634	4.894	0.786	3.315	2.883	0.469	4.855	
BB1	0.127	-42.025	-3.197	24.557	0.882	-0.033	0.014	0.238
	0.234	9.364	0.205	3.969	2.994	1.595	2.885	
BB2	-0.583	-74.108	27.850	23.435	1.124	-0.030	-0.005	0.395
	0.956	14.858	1.616	3.354	3.440	1.353	0.774	
BB3	0.048	-81.540	-19.496	18.617	2.259	0.000	0.000	0.343
	0.115	11.784	0.803	1.862	4.924	0.192	0.661	

Panel B

series	int.	Δr^{10}	$(\Delta r^{10})^2$	Δslo	Δvix	s&p	ecm	adj. R^2
MAT3	0.040	-28.015	-3.555	15.337	0.920	-0.002	0.025	0.197
	0.498	5.861	0.874	2.689	4.210	0.953	4.285	
MAT5	0.041	-26.155	-2.688	9.788	0.832	-0.006	-0.007	0.209
	0.565	6.133	0.949	1.982	4.296	0.758	3.869	
MAT7	0.066	-24.926	-3.553	6.296	0.781	-0.007	0.001	0.201
	0.671	6.022	1.074	1.442	4.203	0.719	3.207	
MAT10	0.103	-23.337	-5.114	2.941	0.736	-0.006	0.002	0.172
	0.837	5.528	1.239	0.984	4.049	0.718	1.878	

Table 7: **Multiple Regressions - Changes in Credit Spreads: Test of ecm.** Panel A shows average ols regression results sorted by rating category, Panel B sorted by maturity bracket. The averages of (absolute) t-statistics are shown below the parameter estimates. In addition to the standard set of explanatory variables used in Table 5, we test the (maturity-specific) error correction terms stemming from the long-term relation, ecm.

Panel A

series	int.	factor 1	factor 2	factor 3	adj. R^2
A1	0.038	1.140	0.450	1.476	0.254
	0.263	7.839	3.074	10.142	
A2	0.040	1.128	0.693	1.127	0.202
	0.261	7.349	4.527	7.346	
A3	0.046	1.423	1.344	1.998	0.513
	0.376	11.716	11.190	16.463	
BBB1	0.061	1.948	1.416	2.901	0.536
	0.392	12.493	9.092	18.615	
BBB2	0.067	1.825	0.944	2.043	0.383
	0.415	11.200	5.780	12.560	
BBB3	0.080	2.067	2.672	2.747	0.489
	0.403	10.449	13.569	13.922	
BB1	0.109	7.115	4.394	2.599	0.532
	0.301	19.434	11.946	7.155	
BB2	0.078	12.661	2.501	-1.180	0.757
	0.235	39.347	8.034	4.679	
BB3	-0.088	15.776	2.355	1.289	0.640
	0.175	29.769	4.214	2.463	

Panel B

series	int.	factor 1	factor 2	factor 3	adj. R^2
MAT3	0.024	5.123	2.858	1.176	0.463
	0.152	15.570	10.477	9.800	
MAT5	0.043	5.068	2.088	1.625	0.503
	0.292	17.714	9.144	10.850	
MAT7	0.056	5.015	1.527	1.854	0.492
	0.373	17.433	7.046	10.545	
MAT10	0.068	4.830	0.981	2.012	0.454
	0.437	15.770	5.078	10.292	

Table 8: **Multiple Regressions - Changes in Credit Spreads on General CCA Factors.** Panel A shows average ols regression results sorted by rating category, Panel B sorted by maturity bracket. Explanatory variables are three factors constructed from a canonical correlation analysis using 36 cross-sectional observations, i.e. 9 rating categories and 3, 5, 7, and 10 years to maturity. The averages of (absolute) t-statistics are shown below the parameter estimates.

Panel A

series	int.	factor 1	factor 2	factor 3	1st pc	adj. R^2
A1	0.038	1.140	0.450	1.476	0.047	0.278
	0.267	7.967	3.120	10.305	4.066	
A2	0.040	1.128	0.693	1.127	0.083	0.271
	0.271	7.685	4.753	7.684	6.873	
A3	0.046	1.423	1.344	1.998	0.030	0.522
	0.380	11.821	11.296	16.611	3.056	
BBB1	0.061	1.948	1.416	2.901	0.018	0.537
	0.392	12.507	9.101	18.636	1.330	
BBB2	0.067	1.825	0.944	2.043	0.061	0.408
	0.423	11.443	5.910	12.830	4.669	
BBB3	0.080	2.067	2.672	2.747	0.044	0.495
	0.406	10.522	13.658	14.017	2.551	
BB1	0.109	7.115	4.394	2.599	0.042	0.537
	0.302	19.546	12.025	7.187	2.359	
BB2	0.078	12.661	2.501	-1.180	-0.023	0.766
	0.239	39.982	8.151	4.765	3.938	
BB3	-0.088	15.776	2.355	1.289	0.981	0.995
	1.471	272.603	44.952	22.211	209.011	

Panel B

series	int.	factor 1	factor 2	factor 3	1st pc	adj. R^2
MAT3	0.024	5.123	2.858	1.176	0.152	0.532
	0.217	45.424	21.086	11.980	34.599	
MAT5	0.043	5.068	2.088	1.625	0.166	0.564
	0.417	43.574	13.959	13.166	25.002	
MAT7	0.056	5.015	1.527	1.854	0.150	0.544
	0.606	51.862	9.714	13.680	28.387	
MAT10	0.068	4.830	0.981	2.012	0.103	0.498
	0.605	34.284	5.448	11.950	17.725	

Table 9: **Multiple Regressions - Changes in Credit Spreads on General CCA Factors and 1st Principal Component.** Panel A shows average ols regression results sorted by rating category, Panel B sorted by maturity bracket. Explanatory variables are three factors as in Table 8, plus the first principal component extracted from regression residuals. The averages of (absolute) t-statistics are shown below the parameter estimates.

Panel A

series	factor 1	factor 2	factor 3	R^2
MAT3	0.232	0.114	0.121	0.466
MAT5	0.275	0.085	0.146	0.505
MAT7	0.285	0.060	0.150	0.494
MAT10	0.266	0.041	0.149	0.456

Panel B

series	factor 1	factor 2	factor 3	R^2
A1	0.090	0.016	0.152	0.258
A2	0.086	0.034	0.086	0.206
A3	0.132	0.124	0.260	0.515
BBB1	0.143	0.078	0.317	0.538
BBB2	0.152	0.041	0.192	0.386
BBB3	0.110	0.186	0.195	0.491
BB1	0.346	0.135	0.053	0.534
BB2	0.705	0.038	0.013	0.757
BB3	0.615	0.021	0.004	0.641

Table 10: **Explanatory Power of CCA Factors.** The table shows the explanatory power of the three CCA factors as a fraction of the total variation of the response variable, sorted by maturity bracket in Panel A, and sorted by rating class in Panel B.

Panel A - Gen

series	Δr^{10}	$(\Delta r^{10})^2$	Δslo	Δvix	s&p	$\Delta swap$	ecm3
factor1	-0.71	-0.24	-0.36	0.31	-0.22	0.52	0.05
factor2	0.10	0.10	0.49	0.23	-0.14	-0.10	0.25
factor3	0.01	-0.19	-0.15	0.13	-0.05	-0.16	0.38

Panel B - Mat3

series	Δr^{10}	$(\Delta r^{10})^2$	Δslo	Δvix	s&p	$\Delta swap$	ecm3
factor1	-0.55	-0.14	-0.08	0.35	-0.24	0.39	0.14
factor2	0.15	-0.03	0.16	0.15	-0.05	-0.23	0.42
factor3	-0.07	-0.10	-0.24	0.14	0.01	0.05	-0.02

Panel C - Mat5

series	Δr^{10}	$(\Delta r^{10})^2$	Δslo	Δvix	s&p	$\Delta swap$	ecm3
factor1	-0.62	-0.17	-0.20	0.34	-0.24	0.44	0.12
factor2	0.12	-0.05	0.18	0.15	-0.08	-0.22	0.42
factor3	0.00	-0.10	-0.19	0.17	0.00	0.01	-0.03

Panel D - Mat7

series	Δr^{10}	$(\Delta r^{10})^2$	Δslo	Δvix	s&p	$\Delta swap$	ecm3
factor1	-0.64	-0.20	-0.28	0.33	-0.22	0.45	0.12
factor2	0.10	-0.04	0.18	0.13	-0.08	-0.20	0.40
factor3	0.05	-0.10	-0.13	0.18	-0.02	0.00	-0.03

Panel E - Mat10

series	Δr^{10}	$(\Delta r^{10})^2$	Δslo	Δvix	s&p	$\Delta swap$	ecm3
factor1	-0.65	-0.21	-0.33	0.30	-0.20	0.44	0.12
factor2	0.08	-0.02	0.17	0.12	-0.08	-0.17	0.36
factor3	0.07	-0.11	-0.08	0.19	-0.06	0.01	-0.04

Table 11: **Pairwise Correlations - CCA Factors and Explanatory Variables.** Panels show pairwise correlations between CCA factors and the set of observable explanatory variables. Panel A shows the results using the general CCA factors used in Table 8, Panels B-E are based on the maturity-specific CCA factors.

Panel A

series	int.	factor 1	factor 2	factor 3	1st pc	adj. R^2
AA	0.046	1.428	0.377	0.419		0.195
	0.337	10.387	2.743	2.992		
A	0.039	1.318	0.273	0.276		0.202
	0.338	10.994	2.267	2.276		
BBB	0.033	2.043	0.856	0.579		0.173
	0.151	9.213	3.888	2.686		
AA	0.046	1.428	0.378	0.419	0.212	0.683
	0.537	16.794	4.426	4.944	28.243	
A	0.039	1.318	0.273	0.276	0.188	0.702
	0.553	18.208	3.751	3.785	29.370	
BBB	0.033	2.043	0.855	0.579	0.402	0.820
	0.400	21.910	9.261	6.380	47.651	

Panel B

series	int.	factor 1	factor 2	factor 3	1st pc	adj. R^2
MAT3	0.041	1.440	0.447	0.240		0.136
	0.327	8.599	2.367	1.302		
MAT5	0.049	1.590	0.496	0.413		0.192
	0.337	10.345	2.922	2.613		
MAT7	0.042	1.673	0.523	0.498		0.217
	0.280	11.010	3.217	3.213		
MAT10	0.024	1.680	0.542	0.546		0.216
	0.158	10.838	3.357	3.478		
MAT3	0.041	1.440	0.450	0.240	0.287	0.649
	0.482	13.477	3.816	2.104	27.817	
MAT5	0.049	1.590	0.497	0.413	0.275	0.793
	0.689	22.329	6.935	5.761	43.778	
MAT7	0.042	1.673	0.520	0.498	0.262	0.790
	0.558	22.339	6.988	6.590	39.684	
MAT10	0.024	1.680	0.540	0.546	0.245	0.707
	0.258	17.737	5.512	5.690	29.072	

Table 12: **Multiple Regression - Changes in U.K. Credit Spreads on General CCA Factors.** Panel A shows average ols regression results sorted by rating category, Panel B sorted by maturity bracket, based on the data set of U.K. credit spreads. Explanatory variables are the three factors constructed from canonical correlation coefficients using all U.S. cross-sectional observations, plus the first principal component from estimated residuals. The averages of (absolute) t-statistics are shown below the parameter estimates.

Factor1

lag 0	lag 3	lag 6	lag 9	lag 12	adj. R^2
-7.74	0.18	-3.35	0.87	-3.12	0.126
-3.92	0.09	-1.62	0.41	-1.58	
-6.36					0.103
-3.83					

Factor3

lag 0	lag 3	lag 6	lag 9	lag 12	adj. R^2
-2.46	-1.15	-3.96	-2.44	0.37	0.096
-1.33	-0.55	-1.86	-1.17	0.20	
		-5.74			0.101
		-3.72			

Table 13: **Out of Sample Predictions of Income using the two strong CCA Factors between 1997 and 2006.** Income is the time series of monthly U.S. real disposable income. Factor 1 and Factor 3 are the extracted CCA factors, integrated to generate monthly observations. All series are filtered with a Hodrick/Prescott filter with lambda 14400. The upper panel shows the results of a multiple regression of income on contemporaneous (lag 0) and lagged observations (3, 6, 9, and 12 months) of Factor 1, the lower panel of Factor 3, respectively. T-statistic values are shown below the point estimate, and the estimated value of the constant is not shown in the table.

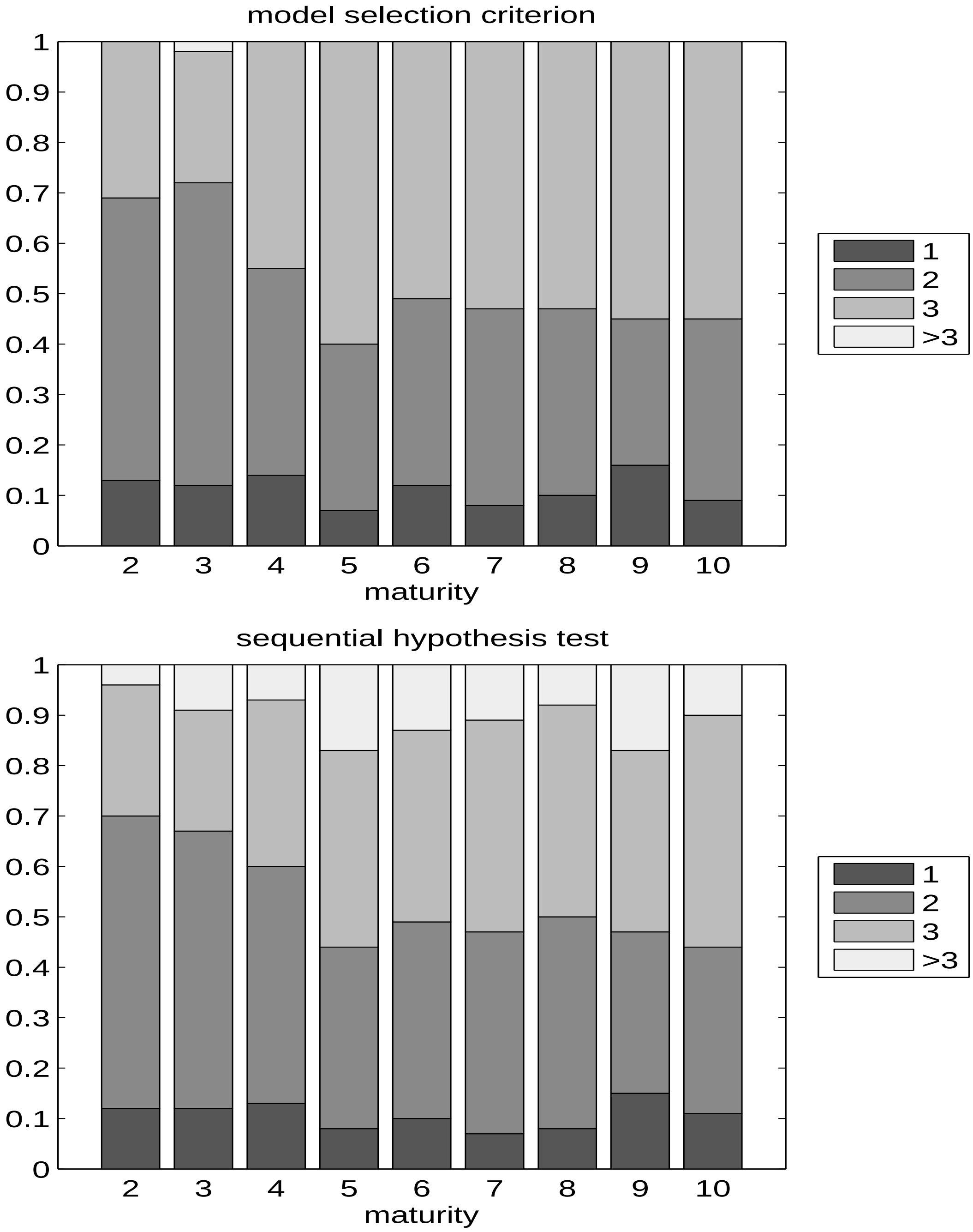


Figure 1: **Test of Number of Common Factors: Changes in Credit Spreads.** The upper graph shows results of the model selection criterion with BIC(1) penalty function, the lower graph shows results of the sequential hypothesis testing with confidence level of 95% and bandwidth 3. Percentages are stacked per maturity, displaying the proportion the respective number of factors is estimated.

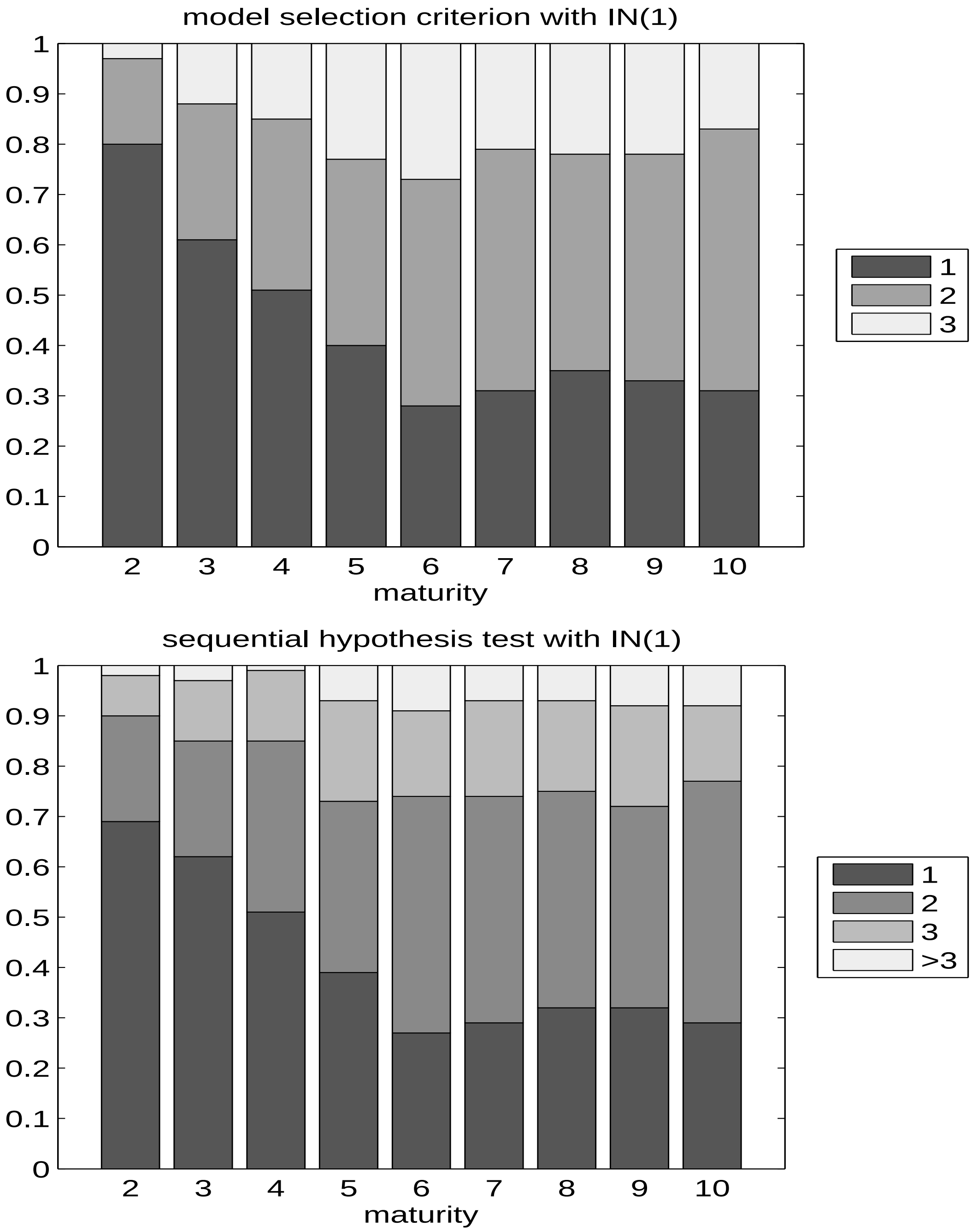


Figure 2: **Test of Number of Common Factors: Set of Instrumental Variables IN(1).** The upper graph shows results of the model selection criterion with BIC (1) penalty function, the lower graph shows results of the sequential hypothesis testing with confidence level of 95% and bandwidth 3. Instruments are Δr^{10}, $(\Delta r^{10})^2$, Δslo, Δvix, and s&p. Percentages are stacked per maturity, displaying the proportion the respective number of factors is estimated.

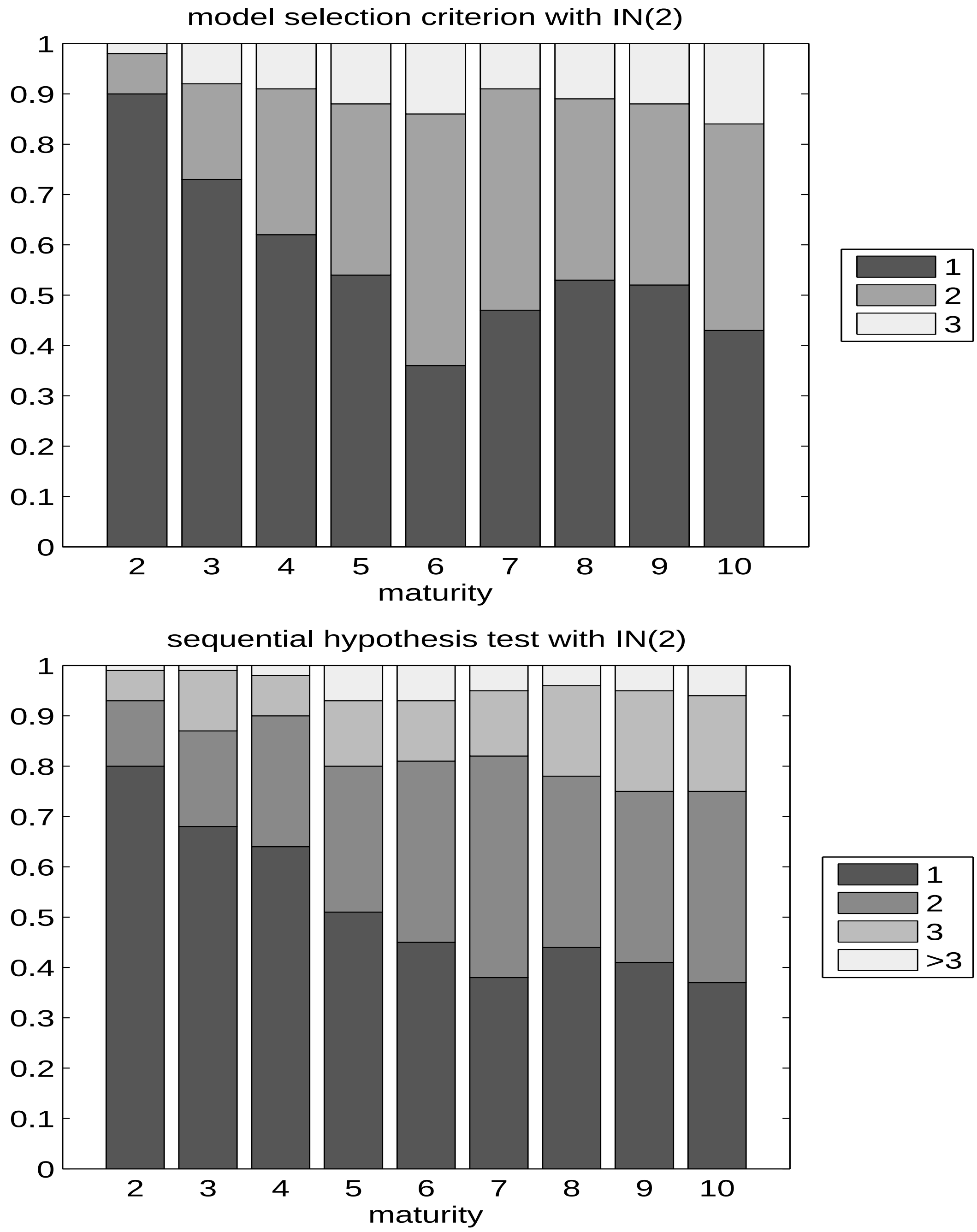


Figure 3: **Test of Number of Common Factors: Set of Instrumental Variables IN(2).** The upper graph shows results of the model selection criterion with BIC(1) penalty function, the lower graph shows results of the sequential hypothesis testing with confidence level of 95% and bandwidth 3. Instruments are Δr^{10}, $(\Delta r^{10})^2$, Δslo, Δvix, s&p, smb and hml. Percentages are stacked per maturity, displaying the proportion the respective number of factors is estimated.

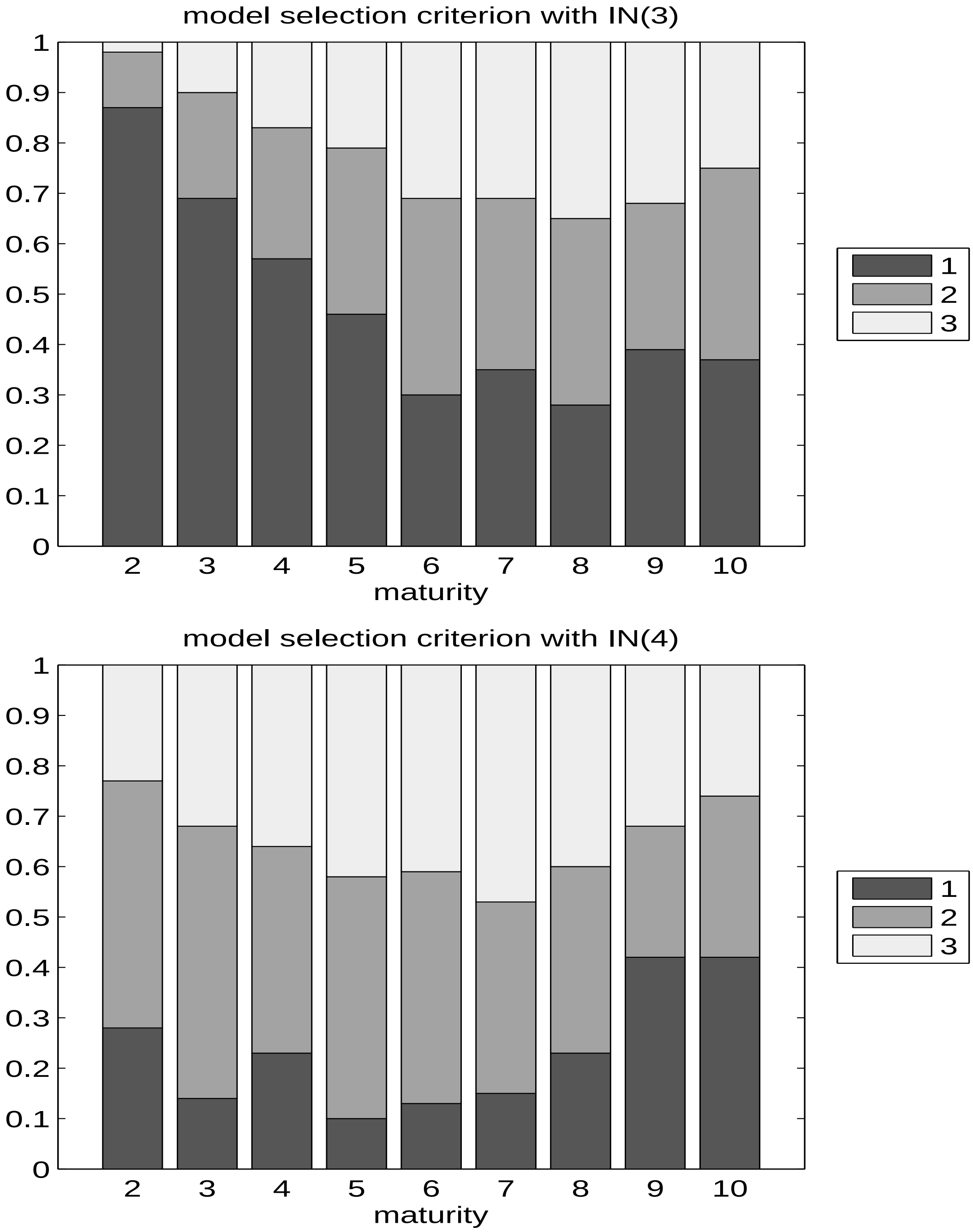


Figure 4: **Test of Number of Common Factors: Set of Instrumental Variables IN(3) and IN(4).** The upper graph shows results of the model selection criterion with BIC(1) penalty function, instruments are Δr^{10}, $(\Delta r^{10})^2$, Δslo, Δvix, s&p, and $\Delta swap$. The lower graph shows results of the model selection criterion with BIC(1) penalty function, instruments are Δr^{10}, $(\Delta r^{10})^2$, Δslo, Δvix, s&p, $\Delta swap$, and ecm. Percentages are stacked per maturity, displaying the proportion the respective number of factors is estimated.

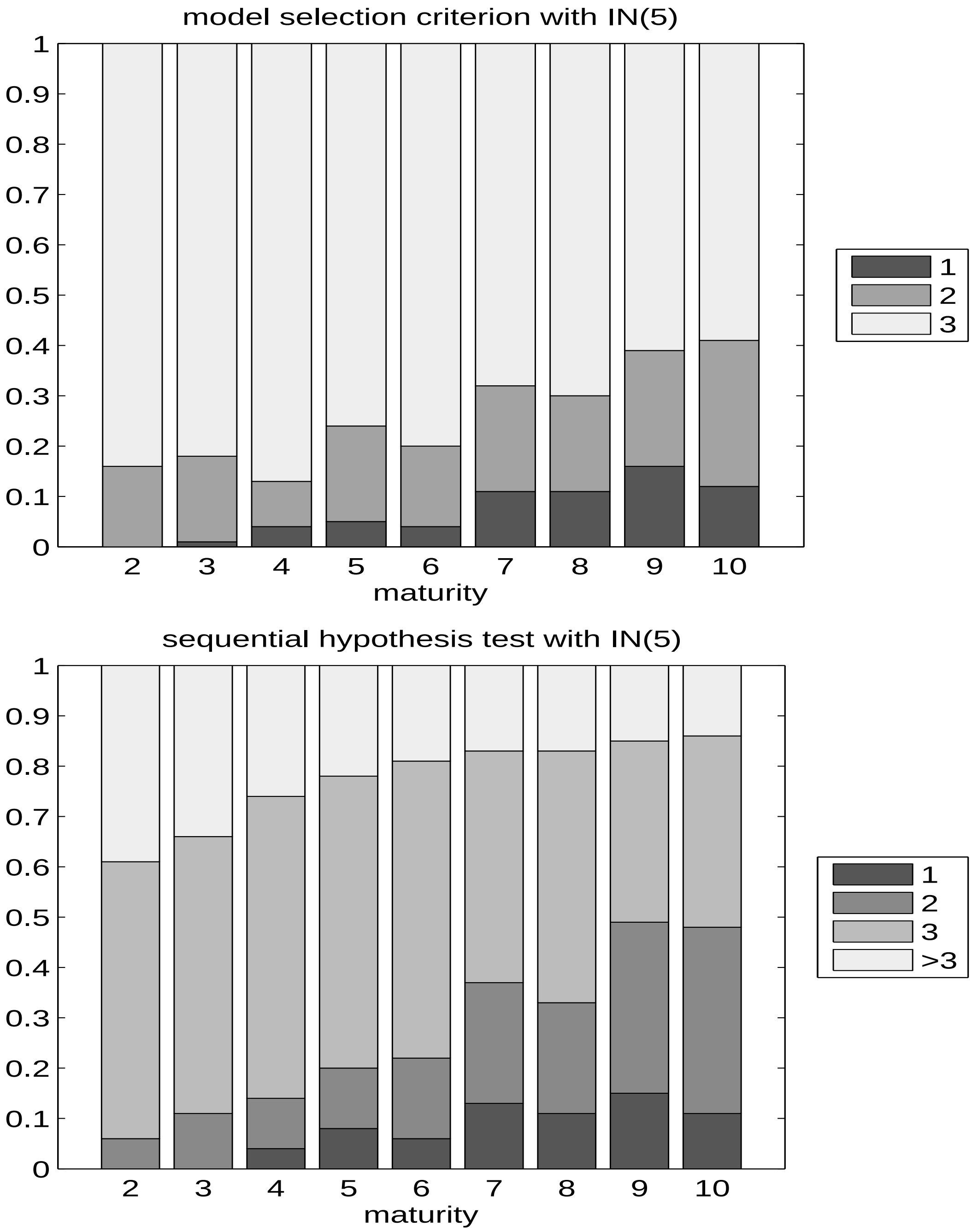
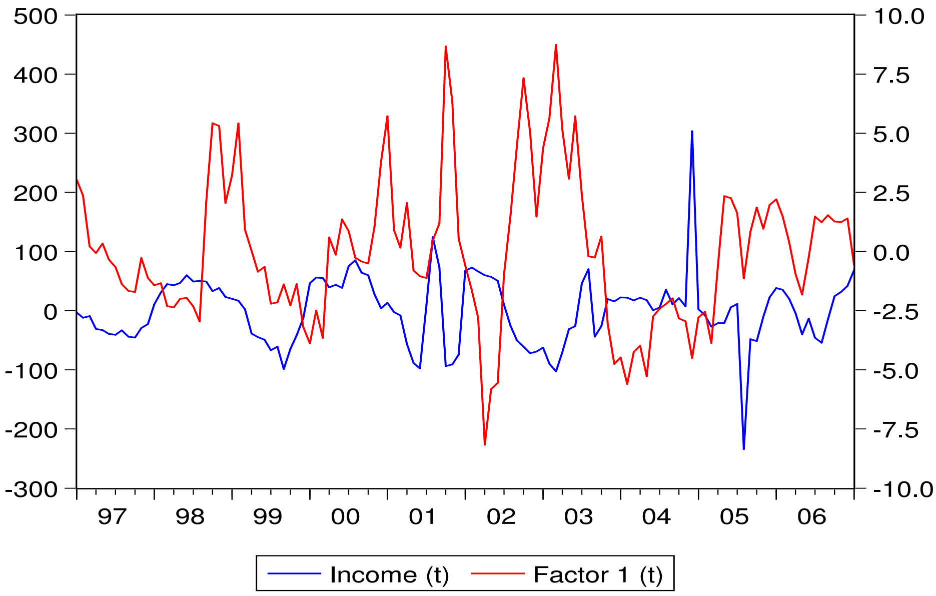


Figure 5: **Test of Number of Common Factors: Set of Instrumental Variables IN(5).** The upper graph shows results of the model selection criterion with BIC (1) penalty function, the lower graph shows results of the sequential hypothesis testing with confidence level of 95% and bandwidth 3. Instruments are $factor1$, $factor2$, $factor3$, and $firstpc$. Percentages are stacked per maturity, displaying the proportion the respective number of factors is estimated.



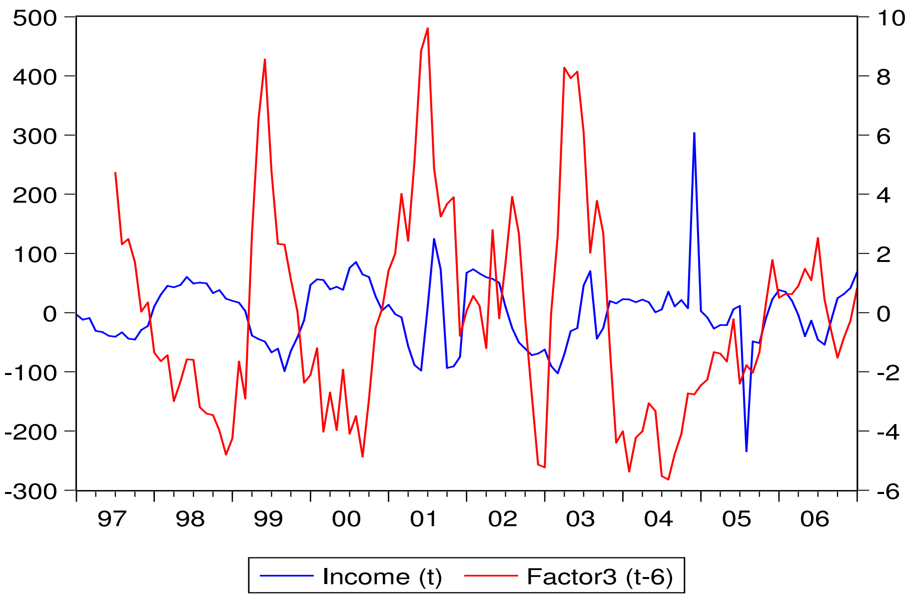


Figure 6: **Out of Sample Predictions of Income using the two strong CCA Factors between 1997 and 2006.** Income is the time series of monthly U.S. real disposable income. Factor 1 and Factor 3 are the extracted CCA factors, integrated to generate monthly observations. The upper graph shows the time series of Income and the contemporaneous observation of Factor 1 (the first strong factors). The lower graph shows the time series of Income and the 6-month lagged observation of Factor 3 (the second strong factors). The x-axis is the time of observation. All series are filtered with a Hodrick/Prescott filter, with lambda 14400.

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