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Modeling the yields on noninvestment grade bond indexes Credit risk and macroeconomic factors

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Abstract

To accurately price credit derivatives, it is necessary to understand the underlying factors that determine credit spreads and the influence that external shocks can have on required yields. We model the factors that influence the yield on the most volatile segment of the corporate bond market, noninvestment grade bonds. A long-run equilibrium is found between the yield on BB- and B-rated bonds and Treasury yields, Moody's default rate, and the leading economic indicator. In the short run, changes in Treasury yields, Moody's default rates, and mutual fund flow continue to affect the movements in noninvestment yields. We also find that the resulting error correction models are useful in forecasting the yields. External shocks have a greater effect on the more volatile B-rated bonds. We find that the Iraq invasion of Kuwait, the Russian and Asian financial crises, and Long-Term Capital Management collapse all have influence on noninvestment grade yields. Evidence is also found suggesting a significant flight to quality for BB- and B-rated bonds during the Russian financial crisis.

JEL classification: C31; C52; G10

Keywords: Noninvestment grade; Forecasting; Derivative pricing; High yield; Yield spread; Market segmentation; Cointegration

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1. Introduction

In this paper, we examine the risk factors that move the yields on the most volatile segment of the bond market, noninvestment grade. By determining the risk factors and the magnitude of these risk factors on noninvestment grade yields, an equilibrium model can be built to determine the relative pricing of current credit derivative instrument(s), to understand the effect of shocks to the market, and to forecast future changes in the index level(s) or credit derivative price(s). We develop separate models for noninvestment yields on BB and B assets.

Pricing credit derivatives accurately requires an understanding of the underlying factors that determine yields and correspondingly credit spreads. Analyzing individual credits focuses on interest rate risk, default risk, and liquidity risk. In addition, for credit derivatives on individual assets, it is necessary to understand the determinants of the firm-specific risk and the credit spreads for that individual issue. There has been a great deal of work done in this area (see Boardman & McEnally, 1981; Fisher, 1959; Silvers, 1973). However, banks and financial institutions are also concerned with macro movements in the credit markets. The risks created by these movements have important consequences on the pricing of the firm's assets and derivatives and on the currently developing markets for credit derivatives, which can be purchased to minimize these risks.

Understanding the factors that influence yields on corporate bonds is not new. There have been three generations of yield premium and yield spread models. The first generation focused (Altman & Bencivenga, 1995; Fons, 1987) on the market yield premium for holding risky debt (the average yield spread between risky debt securities and the risk-free security). This break-even type approach is a long-run analysis that calculates whether there is a net return (yield premium minus default rate) for holding risky bonds over a long period. A second generation of yield spread models developed by Fridson and Jonsson (1995). These models focus on the short-run dynamics of the credit spreads and include liquidity risk measures and a broad definition of default risk. A third-generation model was developed by Barnhill, Joutz, and Maxwell (2000). The later model augments the first-generation model by adjusting for default risk in the long run and merges this information with the second-generation yield premium models focusing on the short-run dynamics.

We attempt to further extend the third-generation model by testing additional macroeconomic variables in the long-run "equilibrium" relation in an effort to better understand the underlying process moving yields and spreads. We test for the stability of the model(s) over the extremely volatile 1998 and 1999 period through recursive estimation and forecasting. We find that the models are reasonably stable over time and suggest that they can provide value in the pricing of these credit derivatives.

The paper is organized into six sections. First, we review some of the previous literature and examine the risk factors and macroeconomic variables that can influence the risk of holding high-yield securities. Second, the time series properties of the yields, risk factors, and macroeconomic factors are presented. Third, we test for and identify the long-run equilibrium correction relations between the risk factors and the two yields using cointegration analysis. Then, we formulate a short-run error correction model (ECM) of the risk factors influencing the yield and, correspondingly, the "equilibrium" spread of noninvestment grade bonds. The advantage of this approach is that it merges information gained from the long-run equilibrium analysis. Fifth, we perform a forecasting exercise using dynamic unconditional and conditional versions of the ECMs. Finally, we summarize the discussion of risk factors and macroeconomic determinants of yields and the use of the model in credit derivative pricing.

2. Brief review of the literature on noninvestment grade yields, risk factors, and macroeconomic determinants

Noninvestment yields depend on interest rate movements of risk-free assets (Treasuries) and factors similar to those of investment grade assets. However, given the nature of noninvestment assets, they are more sensitive to default risk, equity markets, future expectations about the economy, and uncertainty related to them.

Interest rate risk is the dominant factor affecting the value of investment grade bonds. However, as credit quality decreases, default risk begins to dominate interest rate risk in bond valuation. By analyzing yield as compared to yield spread, the strength and significance of changes in Treasury rates on the yield of noninvestment grade bonds can be studied. To assess the appropriate Treasury yield to utilize in this study, a correlation analysis was done on 5-, 7-, and 10-year notes. The results indicate that the appropriate Treasury yield to utilize is the 7-year Treasury note.

Default risk is also found to influence credit yields and spreads. Fridson and Jonsson (1995) find Moody's trailing-12-month default rate and an index of lagging economic indicators to have a statistically significant effect on (changes in) yield spreads. An index of leading economic indicators was found to have no statistical significance. Barnhill et al. (2000) also find Moody's trailing-12-month default rate to be significant in the long and short run. The default risk and economic indicator measures found in the previous research is perplexing. It is expected that investors would price bonds based on the future probability of default not on the past. The prior research results suggest that investors place a great deal of emphasis on past information in the current pricing of risky debt. Institutional factors like fund covenants require fund managers to allocate their portfolios according to fixed or maximum percentages of non-investment grade instruments. In this study, we include these measures of default risk, but we incorporate them in different ways and come to a different conclusion.

Bookstaber and Jacob (1986), Ramaswami (1991), and Shane (1994) demonstrate that noninvestment grade bonds move with equity indexes. This relationship is consistent with the Black and Scholes (1973) model of firm capital structure—contingent claims analysis (CCA). The bondholders' payoff is the value of the bonds (on the upside) or the value of the firm on the downside. In this framework, the closer the value of the bonds is to the total firm value (high leverage), the more highly correlated changes in bond value and changes in equity value will become. The greater the positive difference in the value of the firm compared to the value of the bonds (low leverage), the more highly correlated changes in bond value and changes in risk free bond values will become.

Warther (1995) finds that mutual fund investment flow influenced stock and bond returns. Since mutual funds make up a large segment of the market,[1] the change in mutual fund flow and the liquidity position of the mutual funds could have a significant effect on market yield. Barnhill et al. (2000) and Fridson and Jonsson (1995) find fund flow into high-yield mutual funds, as a percentage, to be associated with a narrowing of the yield spread and an increase in the price of noninvestment grade securities. Net inflows of funds are thought to affect the short-run pricing of securities, but not the fundamentals.

Firms issuing noninvestment grade instruments are very sensitive to liquidity in the high-yield market. Firms with noninvestment rated debt have limited ability to access the more stable bank financing. Hence, they face greater problems raising capital. Their performance and investment spending depend greatly on cash flow, the ability to leverage, and other balance sheet factors. Hence, they are very susceptible to current and future expectations about the business cycle and changes in monetary policy by the Federal Reserve. (For a discussion of macro determinants and their effect on capital markets, see Gertler & Gilchrist, 1994; Hoshi, Kashyap, & Scharfstein, 1991; Jones, Lamont, & Lumsdaine, 1998; Lamont, 1997; Morck, Schleifer, & Vishny, 1990).

There is a well-documented January effect in bond returns (see Chang & Huang, 1990; Chang & Pinegar, 1986, 1988; Cooper & Shulman, 1994; Fama & French, 1993; Maxwell, 1998). The January effect is thought to be a function of year tax-loss selling and "window dressing" by institutional investors.

3. Examination of the data on yields, risk factors, and macroeconomic indicator(s)

In this section, the data series are presented and the time series properties of the variables are tested. The sample period under investigation is January 1987 to December 1999.

In this study, we use CS First Boston's BB and B bond indexes to track the yield on the two largest segments of the high-yield market. While there are bonds rated CCC/CC/C, they are typically very few bonds in this category and they trade at distressed security levels. There is an active market for distressed securities and debtor-in-possession financing, but they are typically considered as separate markets with separate dynamic risk factors. In addition, nonrated bonds are typically considered to be noninvestment grade, but they are usually small or foreign issues, which are a small fraction of the high-yield market. We use monthly data from January 1987 through December 1999. To be included in the CS First Boston indexes,

[1] Chase Securities estimates high-yield mutual funds comprise 22% of the market in 1995 (DeRosa-Farag, 1996). Though statistics are not available, conversation with investment banker suggests that the BB segment of the noninvestment grade market is dominated by insurance companies, pension funds, and investment grade mutual funds (typically investment grade mutual funds are allowed to hold between 5% and 10% of their portfolio in noninvestment grade bonds). The single B category is dominated by noninvestment grade mutual funds as most insurance companies, pension funds, and investment grade mutual funds avoid the most volatile section of the market.

the bonds must have at least US$40 million outstanding and be rated BB or B by either Moody's or Standard & Poor's.

Our analysis focuses on five series in particular: BB yields, B yields, the Moody's default rate, 7-year Treasury Bond (T-Bond) yields, and the Conference Board's Leading Economic Indicator. The variables are plotted, the autocorrelation functions are examined, and augmented Dickey–Fuller (ADF) statistics are evaluated for the levels and the first differences of the variables.

Fig. 1 shows the yields on BB, B, and 7-year T-Bonds. Prior to 1990, BB and B yields averaged about 11% and 13%, respectively. Treasuries began a slow descent from about 9% in 1989, but the noninvestment yields held firm and then rose dramatically in 1990 and 1991. Single B yields peaked above 18%. This was caused by the collapse of Drexel–Burnham and the spike in oil prices following the Iraqi invasion of Kuwait. The latter contributed to the economic downturn and recession. Since 1992, yields on BB and B assets have fallen about 200 basis points with Treasuries. The financial crises in the summer and fall of 1998 and concern about the sustainability of the economic boom caused rates first to jump up about 100 basis points and then remain there.

Fig. 2 shows the Moody's 12-month dollar-denominated default rate series and the yield spreads on noninvestment grade bonds. The BB premium has fluctuated between 2% and 4+%. Naturally, the single B's has been more volatile; they have ranged between 4% and 10%. The premiums appear to move closely with the Moody's dollar-denominated default

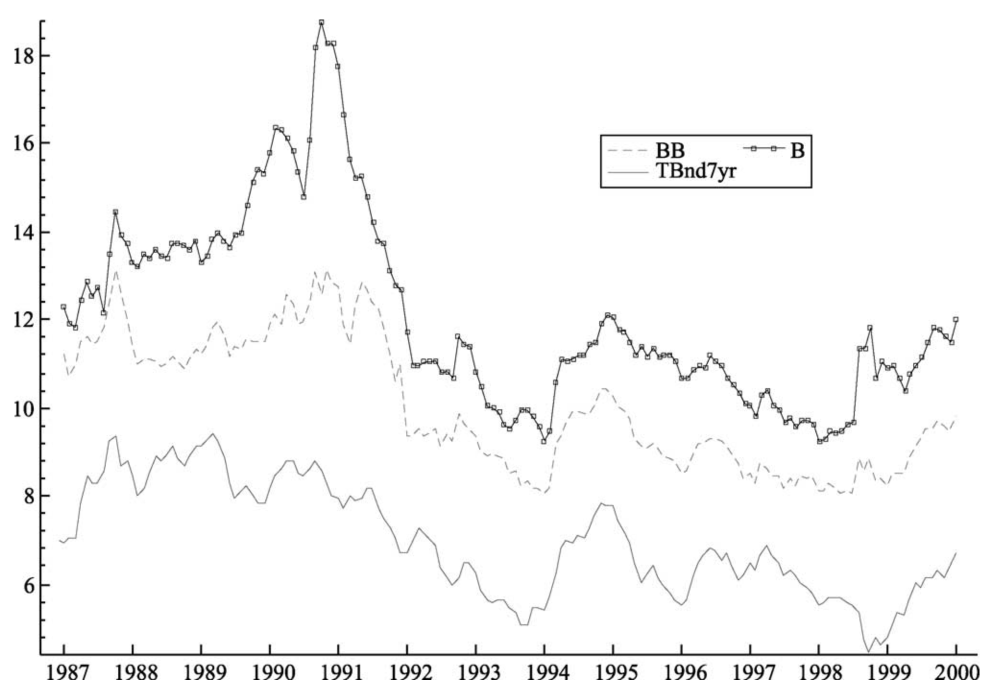

Fig. 1. Yields on 7-year Treasury, BB, and B bonds.

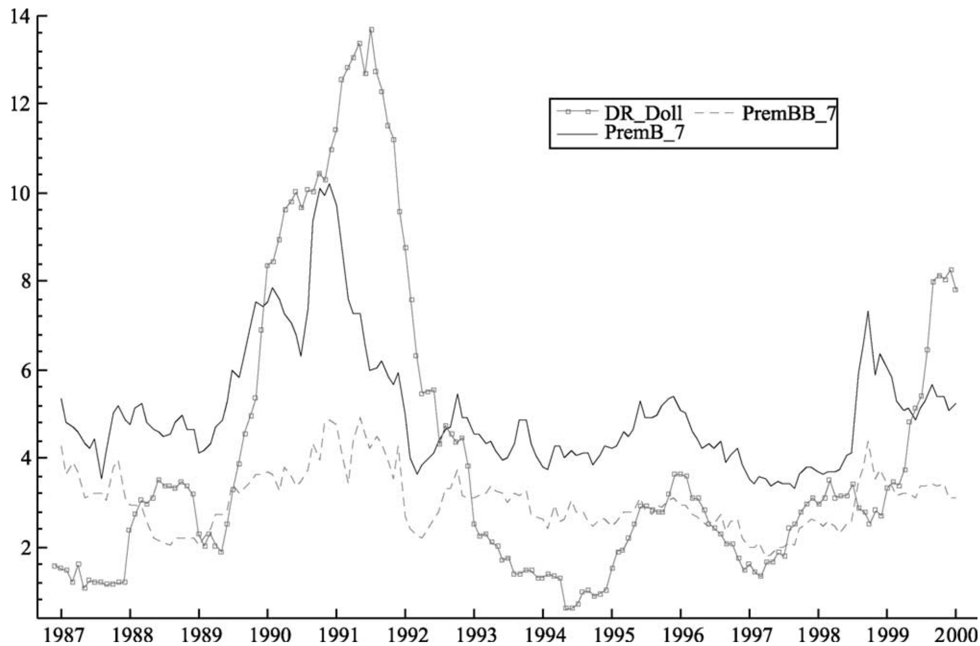

Fig. 2. Moody's default rates and yield spreads for BB and B bonds over T-Bonds.

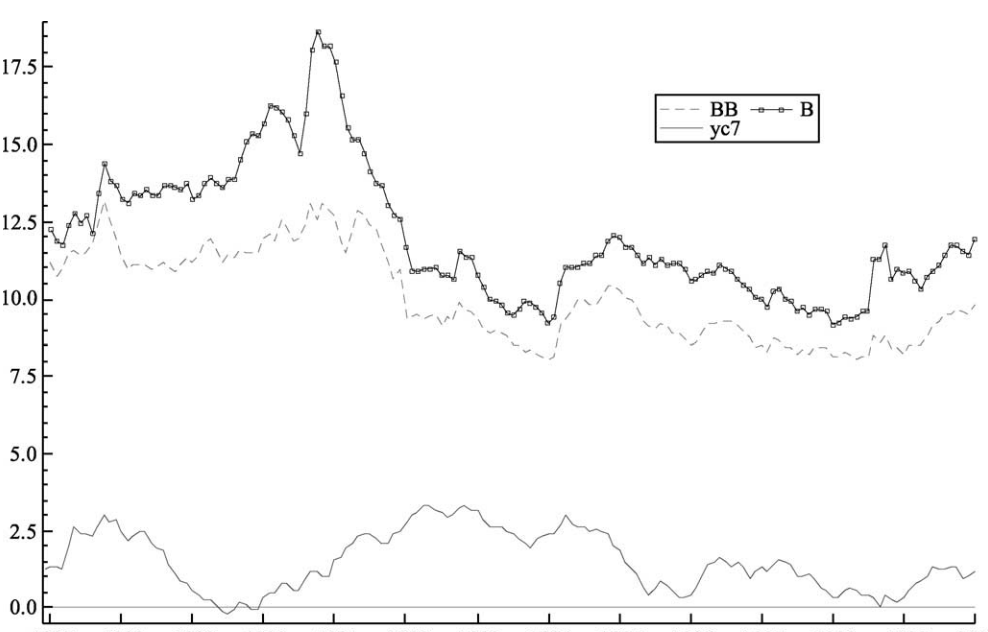

Fig. 3. Yields on BB, B, and the yield curve. (Spread of 7-year T-Bonds to 3-month T-bills).

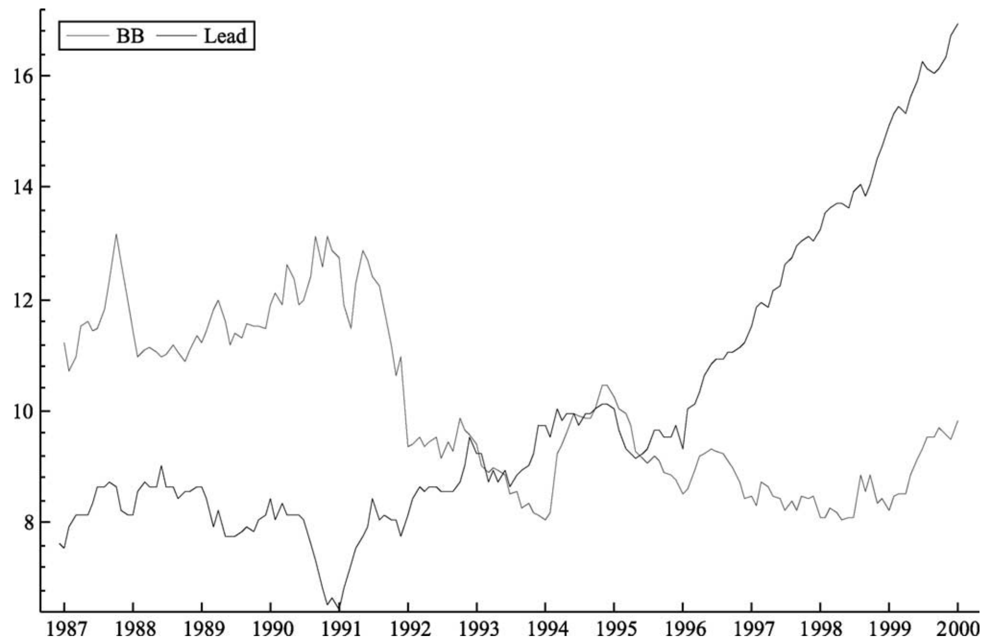

Fig. 4. Yields on BB bonds and the leading economic indicator.

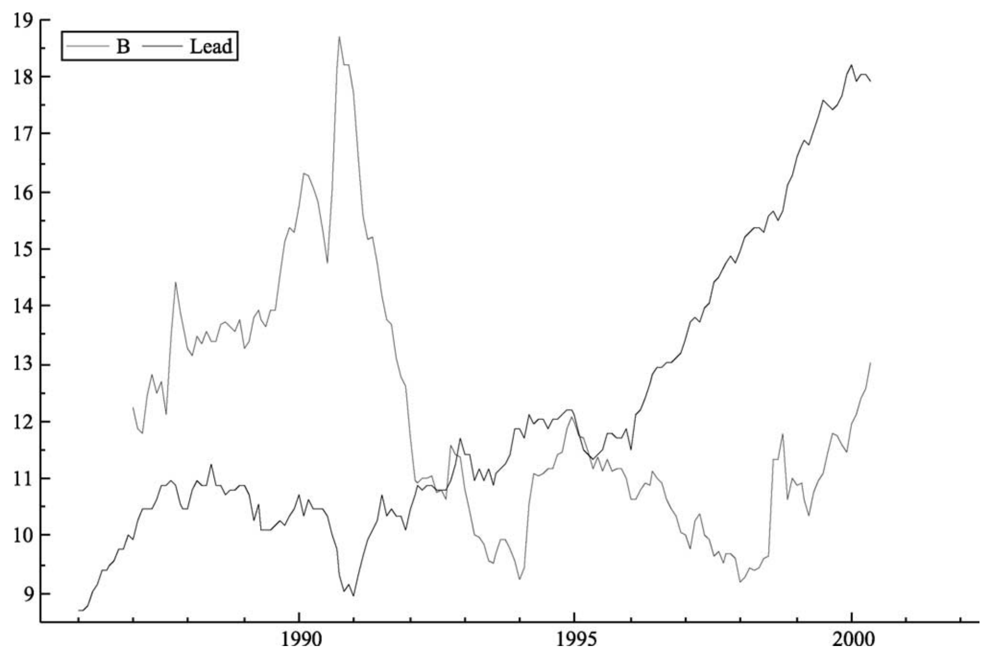

Fig. 5. Yields on B bonds and the leading economic indicator.

risk series and macroeconomic concerns. They do lead the default measure, because of the latter's construction.

BB and B returns and the yield curve of 7-year Treasuries to 3-month T-Bills are shown in Fig. 3. It is difficult to infer the relationship here because the yield curve is a function of the two assets and influence of monetary policy. When the curve flattens or inverts, it may suggest an economic slowdown, thus, an increase in the noninvestment yields.

We considered other measures like the yield curve, unemployment, the industrial production index, and the Conference Board's measure of the Leading Economic Indicators. The latter seems to capture the importance of future expectations and macroeconomic business cycle impacts on high-yield derivatives. The Conference Board's Leading Economic Indicator series is plotted in Figs. 4 and 5 with the BB and B yields, respectively. We observe the inverse relationship between trend(s) in the yields and index over the full sample. Also, when the leading indicator slows or declines, we see that yields increase.

We examine the relationship between noninvestment yield movements and equity markets. Previous research has supported the theory by observing correlations between equity prices and investment and nonvalue for the high-yield category on a monthly basis. To incorporate this into our model, we include the Russell 2000 Index and a measure of the relative pricing of equities (the log of S&P 500 price/earnings ratio) as independent variables in our analysis.

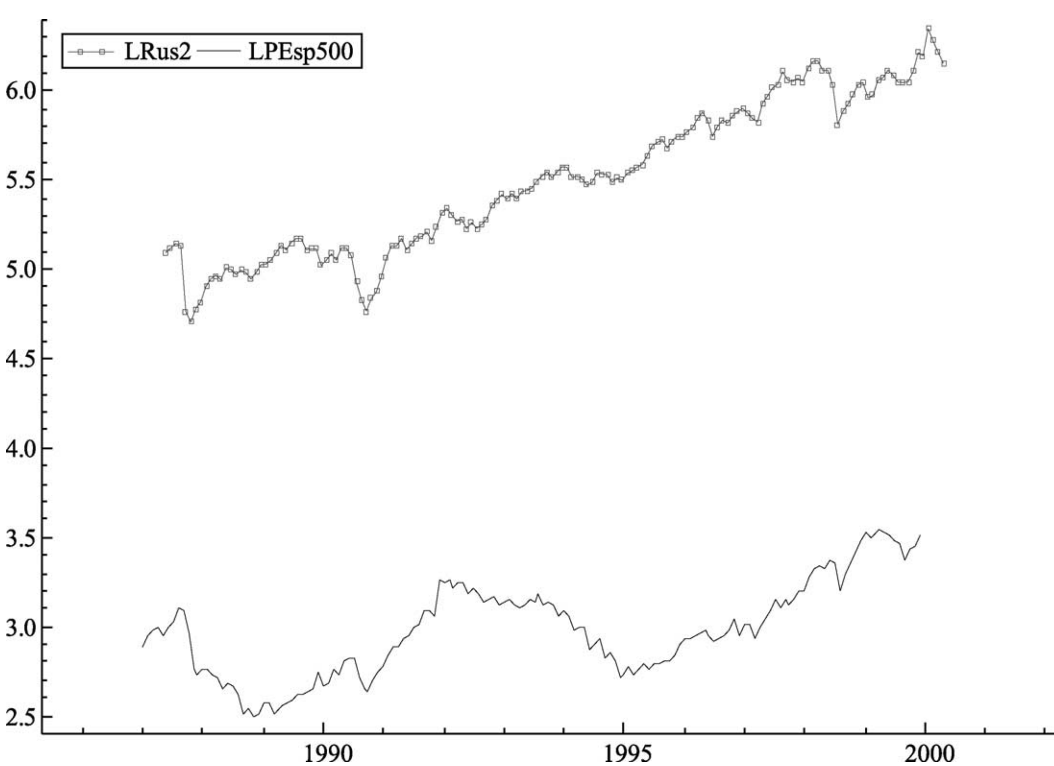

Fig. 6. Equity price measures. Log of the Russell 2000 Index and the S&P 500 price/earnings ratio.

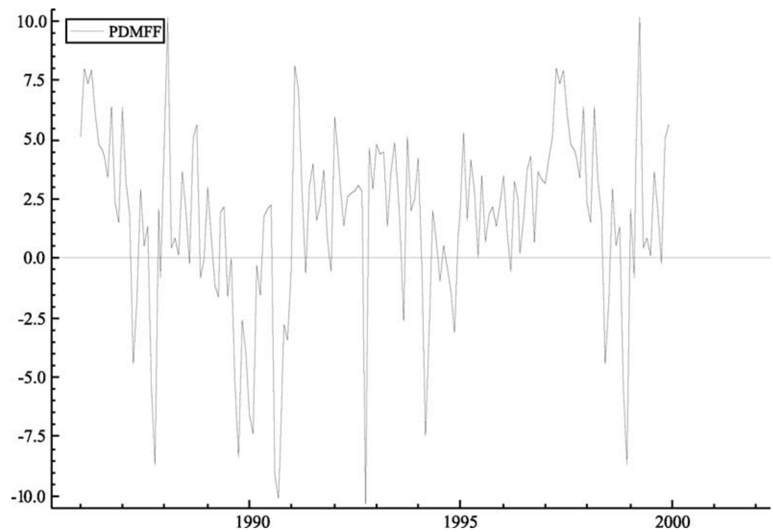

Fig. 7. Investment Company Institute. Net flows of funds into mutual funds for noninvestment grade assets.

The series are plotted in Fig. 6. These measures are only used to capture short-run movements, not the equilibrium correction relationship. We use a measure of the percentage change in the net inflows in the analysis. ICI provided mutual fund data for the current study. This measure is graphed in Fig. 7. Clearly, during times of uncertainty and optimism, the net flows move opposite to yields.

In this paper, we build an equilibrium model of the yield on noninvestment grade bonds in an effort to accurately price market-based credit derivatives. To do this, there is a need to better understand the effect of external shocks on the markets, and clearly, a number of one-time shocks have influenced the yield on risky debt. In our effort to build a stable model, we account for these historical shocks using dummy variables. If we understand the one-time effect that these shocks have on the system, we can better understand and project the magnitude of future shocks.

We have identified a number of external shocks to the market over the period. Dummy variables are included for the month(s) of the following events: the stock market crash (October 1987), the Drexel Burnham bankruptcy (September 1990), and the Iraq invasion of Kuwait (August 1990).

Table 1
ADF test for unit root in levels t statistics with lag selection based on AIC for sample July 1987–December 1999

Variable	Constant	Constant and trend
BB yields	− 1.98 (1)	− 2.18 (2)
B yields	− 1.82 (1)	− 2.08 (1)
Moody's default rate	− 2.63 (4)	− 2.70 (4)
Yields on 7-year T-Bonds	− 1.88 (1)	− 2.86 (1)
Leading Economic Indicator	1.62 (2)	− .68 (2)

Table 2
ADF test for unit root in first differences t statistics with lag selection based on AIC for sample July 1987–December 1999

Variable	Constant	Constant and trend
BB yields	– 7.93 * * (1)	– 11.84 * * (0)
B yields	– 7.30 * * (2)	– 8.61 * * (0)
Moody's default rate	– 2.96 * (3)	– 2.94 (3)
Yields on 7-year T-Bonds	– 8.05 * * (1)	– 6.09 * * (4)
Leading Economic Indicator	– 6.58 * * (1)	– 6.30 * * (4)

* Statistical significance at 5%.

* * Statistical significance at 1%.

In the summer and fall of 1998, there were several events contributing to the volatility in the high-yield markets. The Russian financial crisis and default precipitated the Asian financial crisis. The derivatives hedging firm Long-Term Capital Management (LTCM) collapsed. The Federal Reserve felt it necessary to respond to these earlier events and the potential impact of the collapse on financial markets. We find that individual dummies are appropriate to capture the impacts of these events and responses (August, September, October, and November 1998). The international financial crises led to "flights to quality" both internationally and domestically in mature markets like the U.S. This increased the spreads on high-yield instruments. The U.S. Federal Reserve encouraged a propping up and takeover of LTCM and lowered short-run interest rates at FOMC meetings in September and October 1998 to provide liquidity to markets and prevent further defaults.

The first step in analyzing the data and avoiding a potential spurious regression problem (Granger & Newbold, 1974; Phillips, 1986) is to determine the stationarity or order of integration of the variables. Tables 1 and 2 contain the results from the ADF tests in levels and first differences including specifications with only a constant and a constant and trend. The specifications for the ADF tests use a maximum of six lags in levels and five lags in differences. The t statistic is reported from the model where the lag length is selected by the Akaike information criterion. We cannot reject the null hypothesis of a unit root process for all the series in levels. Except for the default rate series, we clearly can reject the null hypothesis of a unit root for the series in differences. Further examination of the default rate tests suggests that the difference specification is stationary. The constant and trend models do not reject the null of a unit root, but the ADF t statistic is close to the 5% critical value. Also, the estimated coefficient on the lagged difference term is about 0.7 using three lags of the dependent variable in the ADF regression. Thus, we are reasonably confident that it is different from unity. Hence, we conclude that the five series are $I(1)$ processes.

4. Testing for long-run equilibrium correction relationships

Most financial and macroeconomic series are nonstationary. The traditional approach in modeling yields has been to model the data generating process in differences. While this is

Table 3
Tests of BB VAR system reduction—lag length selection [*F* test with *P* value (July 1987–December 1999)]

Lags	1	2	3	4	5	6
1	na					
2	3.19** [.00]	na				
3	2.49** [.00]	1.73* [.04]	na			
4	2.38** [.00]	1.90* [.03]	2.01* [.01]	na		
5	2.05** [.00]	1.61** [.01]	1.52* [.04]	1.03 [.42]	na	
6	1.84** [.00]	1.46* [.02]	1.35 [.07]	1.02 [.44]	1.01 [.45]	na

The BB VAR is a four equation system with the BB yield, Moody's trailing-12-month dollar-denominated default rate, yields on 7-year T-Bonds, and the difference in yields between 7-year T-Bonds and 3-month T-Bills. The system also includes constant seasonal dummy variables (d.v.), Drexel d.v., Kuwait Invasion d.v., 1987 market crash d.v., August 1998–December 1999 d.v., log of the S&P 500 price/earnings percent change noninvestment grade mutual fund flows. *F* tests and the associated *P* values are reported for the number of restrictions ($4 \times 4 \times$ no. of lags) and adjusted for the number of degrees of freedom.

* Statistical significance at 5%.

** Statistical significance at 1%.

common practice, it results in a potential loss of information from the long-run interaction or equilibrium relationship between variables. So instead of directly moving to a model utilizing differences, as in the second generation of yield spread models, we analyze the variables of interest to determine if there is a cointegrating vector. The implication of a cointegrating vector is that while the variables may be individually nonstationary a linear combination of variables is stationary (see Enders, 1995). Hence, a cointegrating vector indicates a long-run relationship between the variables.

We present the cointegration tests for long-run relationships between the simple yield spread model testing for an equilibrium correction model adjusting for default risk and macroeconomic conditions. Barnhill et al. (2000) found a model incorporating default risk into the traditional yield spread framework. This examines a slightly more complex relationship of the default adjusted yield-premium models by incorporating macroeconomic factors like by the Conference Board Leading Economic Indicator series. We considered other macroeconomic measures like variations of the yield curve, unemployment, and industrial production. However, the best results in terms of model stability and identification came from the leading indicator series.[2]

The multivariate methodology developed by Johansen (1988, 1991) is used to test for cointegration between the noninvestment grade yields and other factors. The first step in the Johansen methodology is to determine the appropriate lag structure to use in the VARs. Two VAR systems are used; the difference is the noninvestment yield choice in the model, either the BB or B. The VARs include the BB and B bond yields, T-Bond yields, Moody's default rates, and the leading economic indicator. In addition, the other possible explanatory variables not considered in the cointegrating vector enter the VAR system unrestricted.

To determine the appropriate lag structure, the log-likelihood, Schwartz criterion, Hannan–Quinn, and the *F* statistic for model comparison were utilized. Tables 3 and 4 present the results from the *F* tests and associated *P* values for restricting the number of lags for the BB VAR and B

[2] Test results are available from the authors upon request.

Table 4
Tests of single B VAR system reduction—lag length selection [F test with P value (July 1987–December 1999)]

Lags	1	2	3	4	5	6
1	na					
2	3.35 * * [.00]	na				
3	2.77 * * [.00]	2.09 * [.01]	na			
4	2.41 * * [.00]	1.87 * * [.00]	1.61 [.06]	na		
5	2.27 * * [.00]	1.83 * * [.00]	1.65 * [.02]	1.67 * [.05]	na	
6	2.00 * * [.00]	1.6 * * [.00]	1.41 * [.04]	1.30 [.13]	.94 [.53]	na

The single B VAR is a four-equation system with the single B yield, Moody's trailing-12-month dollar-denominated default rate, yields on 7-year T-Bonds, and the Conference Board's Leading Economic Indicator. The system also includes constant seasonal dummy variables (d.v.), Drexel d.v., Kuwait Invasion d.v., 1987 market crash d.v., August 1998 d.v., October 1998 d.v., November 1998 d.v., log of the S&P 500 price/earnings percent change noninvestment grade mutual fund flows. F tests are reported for the number of restrictions ($4 \times 4 \times$ no. of lags) and adjusted for the number of degrees of freedom.

* Statistical significance at 5%.

* * Statistical significance at 1%.

VAR systems, respectively. The maintained model begins with six lags. We reduce the model down to five lags and test for a loss in explanatory power. The process is repeated down to a single lag. In the BB VAR system, a model with four lags explains, as well as models, with five and six lags. When the B VAR system is reduced to four lags, it does not represent a restriction on the fit from six lags, but does for the five-lag model. The P value in the latter case is .05. Systems with fewer than four lags do impose significant zero restrictions on the dynamics. The test statistics suggested that a lag structure of four and five periods were appropriate for the BB and B yields VAR systems, respectively. The results from the information criterion like the Schwarz, Hannan–Quinn, and Akaike support these conclusions.

Below, we interpret the cointegration test results for the two systems with their respective lag lengths, interpret the cointegrating vector(s), and test for weak exogeneity. The results from Johansen cointegration tests on the BB VAR system are presented in Table 5. The initial null hypothesis of $r = 0$ is that there is no cointegrating vector. The Lambda or trace statistic that there are no cointegrating vectors is 68.45; the associated P value is less than 1%. All the trace eigenvalue statistics strongly reject the null hypothesis that there is more than one cointegrating vector. Thus, we conclude that there is a single cointegrating vector in the BB VAR system.

Table 6 contains the results from the B VAR system. Once again, the Lambda or trace statistic of 110.08 is significant at less than 1%. However, the null hypothesis that there is at most one cointegrating vector is rejected; the Lambda or trace statistic is 32.58 and appears significant at 2%. There is (marginal) evidence of a second cointegrating vector, but we were unable to identify a second stable cointegrating vector. Fig. 8 presents a plot of recursive estimates for the first and second eigenvalues. The second recursive eigenvalue appears to decline after the first half of the 1990s and is close to zero from 1997 on. The evidence suggests that the B VAR system contains a single long-run or equilibrium relationship.

The results in Tables 5 and 6, along with the correlation analysis above, demonstrate the danger of viewing a constant and instantaneous relationship in yields on very risky debt to

Table 5
Cointegration analysis of BB yields, Moody's trailing-12-month dollar-denominated default rate, yields on 7-year T-Bonds, and the Leading Economic Indicator

Eigenvalue	LogLik for	Rank	H_0: rank $=p$	Lambda	P value
	12.4	0			
0.27	36.2	1	$p==0$	68.45	.00
0.07	41.9	2	$p<=1$	20.93	.37
0.05	46.4	3	$p<=2$	9.58	.32
0.003	46.6	4	$p<=3$	.56	.46

Standardized eigenvalues, β values, and standard errors

BB	Default rate	Treasury yield	Leading indicator
1.00	− 0.10325**	− 0.79028**	0.16136**
–	0.0175	0.0818	0.0545

Standardized α coefficients and standard errors

	BB	Default rate	Treasury yield	Leading indicator
	− 0.3852**	0.1173	0.0003	0.0055
	0.0610	0.1106	0.0579	0.0567
Weak Exog	0.00	0.29	0.99	0.95
Joint Weak Exog ChiSq(3)			0.76	

The VAR system includes four lags of each variable. The system also includes constant seasonal dummy variables (d.v.), Drexel d.v., Kuwait Invasion d.v., 1987 market crash d.v., August 1998–December 1999 d.v., log of the S&P 500 price/earnings percent change noninvestment grade mutual fund flows. P values are reported for the weak exogeneity tests.

** Statistical significance at 1%.

changes in the risk-free security.[3] Conventional yield premiums for investment grade bonds are thought to be fairly constant. The yield on these assets moves 1:1 with T-Bond yields. However, in the noninvestment grade case, the likelihood for default is larger and may play a role in equilibrium relationship. Default rates are imperfect measures about the safety of these assets, because they are ex-post measures. Macroeconomic variables like the leading economic indicators, the yield curve, and industrial production can provide information about future states of the world and the future revenue potential for firms issuing this kind of debt.

We next identify the long-run or equilibrium relation in the two VAR systems. In both cases, we interpret them to be modifications of the conventional yield premium model. The yield premium model for noninvestment grade assets is augmented to incorporate default concerns and projections about the (macro)economy. Our hypotheses are that the noninvestment grade yield relationship jointly incorporates the three factors: the T-Bond premium, default factors, and leading procyclical variables. Individually, we expect the value for the T-

[3] Cointegrating vectors between investment grade indexes yields and Treasury yields were found for all investment grade indexes, which implies the legitimacy of a yield spread model as applied to investment grade indexes.

Table 6
Cointegration analysis of single B yields, Moody's trailing-12-month dollar-denominated default rate, yields on 7-year T-Bonds, and the Conference Board's Leading Economic Indicator

Eigenvalue	LogLik for	Rank	H_0: rank = p	Lambda	P value
	23.96	0			
0.401	62.71	1	$p==0$	110.08	.00**
0.146	74.60	2	$p<=1$	32.58	.02*
0.055	78.86	3	$p<=2$	8.81	.39
0.002	79.00	4	$p<=3$	.29	.59

Standardized eigenvalues, β values, and standard errors

B	Default rate	Treasury yield	Leading indicator
1.00	− 0.25076 **	− 0.6303 **	0.16601 *
–	0.030777	0.1223	0.08136

Standardized α coefficients and standard errors

	B	Default rate	Treasury yield	Leading indicator
	− 0.26619	0.13753	0.0042	0.0245
	0.0418	0.0668	0.0359	0.0343
Weak Exog	0.00**	0.04 *	0.89	0.44
Joint Weak Exog ChiSq(3)			0.20	

The VAR system includes five lags of each variable. The following variables are entered unrestricted: constant seasonal dummy variables (d.v.), Drexel d.v., Kuwait Invasion d.v., 1987 market crash d.v., August 1998 d.v., October 1998 d.v., November 1998 d.v., log of the S&P 500 price/earnings percent change noninvestment grade mutual fund flows. P values are reported for the weak exogeneity tests.

* Statistical significance at 5%.

** Statistical significance at 1%.

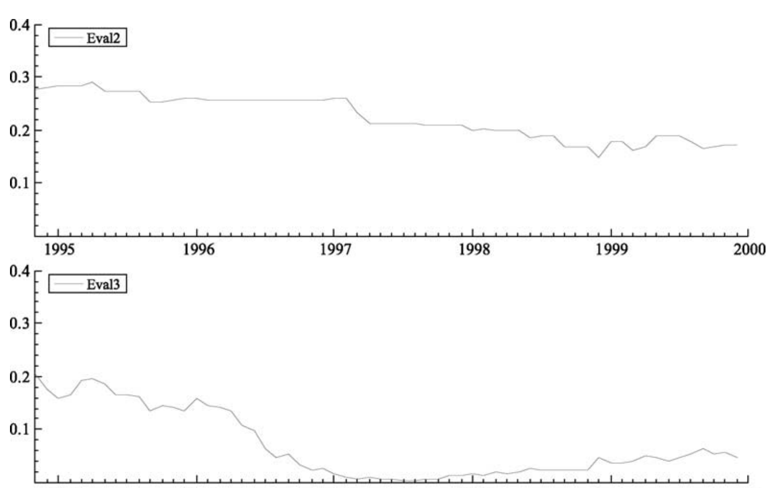

Fig. 8. Recursive stability test for cointegrating eigenvalue(s) in single B system.

Bond coefficient to be positive and less than unity. The relationship between the default rate and to the different yield indexes is as expected. When the bond credit quality decreases, signified by bond rating, the default rate has a greater effect on yield. If leading procyclical variables suggest a positive outlook for the economy, this will have a negative impact on yields as investors expect to earn capital gains on the noninvestment grade assets. Higher expected cash flows for firms will enable them to service their debts easier.

The cointegrating vector for the BB yields is given by the standardized eigenvalues in Table 5. Below is the implied relationship.

$$\text{BB Index Yield} = 0.79\text{T-Bond Yield} + 0.103\ \text{Moody's Default Rate} - 0.16\ \text{Lead} \tag{1}$$

Standard errors are reported below the eigenvalues in the table. The LM test for the significance of the three variables is a chi-square(3); the statistic is 32.8, which is significant at 1%. Individually, the signs and magnitudes of the coefficients for the three variable are as expected. The speed of adjustment or alpha coefficient for the BB yield equation is -0.38 and significant from zero, suggesting that the relationship is stable. The median lag for returning BB yields back to their equilibrium value is slightly more than a month.

The cointegrating vector for the B yields is given by the standardized eigenvalues in Table 6. The implied long-run or equilibrium relationship is (Eq. (2)):

$$\text{B Index Yield} = 0.63\text{T-Bond Yield} + 0.25\ \text{Moody's Default Rate} - 0.17\ \text{Lead} \tag{2}$$

The LM test for the significance of the three variables is 22.2, which is significant at 1%. Once again, the coefficients for the three variables are as expected. The speed of adjustment coefficient for the BB yield equation is $-.26$ and significant from zero, suggesting that the equilibrium correction relationship is stable. The response to disequilibrium appears faster in this market than for the BB yields. The median lag is about 2 months. In addition, with the lower grade bond, we see that the tie to the T-Bonds is lower and the sensitivity to default rates is nearly double that of the BB yield model. The leading economic indicator appears to have the same effect on both yields.

Next, we test to see if the cointegrating vector enters any of the four equations in the VAR system. This is a test for weak exogeneity and allows us to reduce or condition the number of equations to be modeled and estimated.

The standardized alpha coefficients are reported at the bottom of each table along with their respective standard errors. These statistics represent the speed of adjustment to disequilibrium comparable to a mean-reversion rate. In the BB VAR system, only the coefficient associated with the BB equation is significant. The joint test that the coefficients are insignificant for the default rate, the Treasury yields, and the Leading Economic Indicator has a *P* value of .76. This implies that we can treat these three variables as weakly exogenous and reduce or condition the system to a single equation in the BB yields. The results for the B VAR system are similar. Individually, the Treasury yields and Leading Economic Indicator coefficients are not significant. The test for whether default rates are not significant has a *P* value of .04, thus, there may be marginal evidence in favor of rejecting weak exogeneity for this variable. When we test for the three variables, the chi-square(3) has a P value of .20. We decided to treat the three factors in the modified yield premium relationship for single B's as weakly exogenous.

5. ECMs for noninvestment yields: empirical findings

The results in Section 4 suggest that there is a single cointegrating vector or an "equilibrium correction" explanation of the yield premium adjusted for the risk and macroeconomic factors. In addition, we found that this relationship was weakly exogenous for all factors in the relationship except the noninvestment grade yield. In this section, we develop the associated conditional single-equation ECM (for further discussion of ECMs, see Enders, 1995; Hendry, 1995). ECMs merge the information from the short-run dynamics of the high-yield indexes with the long-run relationship found in the cointegration analysis. The approach follows the general-to-specific methodology. We begin with an unrestricted autoregressive distributed lag (ADL) model, which includes the estimated "disequilibrium" or error correction mechanism and reduces down to a parsimonious and constant representation.

5.1. An ECM for BB yields

The BB VAR analysis in Table 3 suggested a four-period lag in levels was the appropriate structure. Hence, we convert this to a model in first differences with a maximum of three lags and include the lagged error correction term from the cointegrating vector (Eq. (1)). The specification of the general ADL is:

$$\begin{aligned}\Delta\text{BB}_t = {} & a_0 + \sum_{i=1}^{3} \pi_{1i}\Delta\text{BB}_{t-i} + \sum_{i=0}^{3} \pi_{2i}\Delta\text{Default}_{t-i} \\ & + \sum_{i=0}^{3} \pi_{3i}\Delta\text{T-Bond}_{t-i} + \sum_{i=0}^{3} \pi_{4i}\Delta\text{Lead}_{t-i} \sum_{j=0}^{1} \pi_{5j}\Delta\text{Rus}_{t-j} \\ & + \sum_{i=0}^{1} \pi_{6i}\Delta\text{S\&P}P/E_{t-j} \sum_{i=0}^{1} \pi_{7i}\Delta\text{\%MMFFlows}_{t-j} + a_1\text{January}_t \\ & + a_2\text{Drexel}_t + a_3\text{Iraq}_t + a_4\text{Mar97}_t + a_5\text{Aug98}_t + a_6\text{Sep98}_t + a_7\text{Oct98}_t \\ & + a_8\text{Nov98}_t + a_9\text{Dec98}_t + \alpha\text{ECM}_{t-1} + \varepsilon_t\end{aligned}$$

where $\text{ECM}_{t-1} = \text{BB}_{t-1} - (-0.10325\ \text{Default}_{t-1} - 0.79028\ \text{T-Bond}_{t-1} + 0.16136\ \text{Lead}_{t-1})$

This model is fit over the sample August 1987 through December 1999; there are 38 estimated coefficients and 149 observations. The regression R^2 is .66 and the standard error for the change in the yield is 22.8 basis points. There is evidence of an ARCH(1) process, which leads to rejecting normality because of excess kurtosis.[4]

[4] More detailed residual diagnostics available upon request.

Since the unrestricted model is overparameterized by definition, we begin the reduction process by examining the explanatory power of different lag lengths and sets of variables from the model always comparing the fit against the unrestricted model and previous reductions. Three decision criteria were used to determine the final specific. First, all variables that were statistically significant at the 95% confidence level were included. Second, F tests were performed on the alternative models to determine the significance of the loss of information from removing a variable or all variables at a given lag length. For example, the S&P price/earnings ratio while important in the initial VAR specification did not provide significant explanatory power in the final ECM model. Finally, we conducted residual diagnostic checks and recursive stability analysis for model constancy. The final model includes only 12 estimated coefficients and is given below.

$$\begin{aligned}\Delta \mathrm{BB}_t = {} & a_0 + \pi_{11}\Delta \mathrm{BB}_{t-i} + \sum_{i=0}^{1}\pi_{2i}\Delta \mathrm{Default}_{t-i} + (\pi_{30}+\pi_{31}+\pi_{32})\Delta \text{T-Bond}_{t-i} \\ & + \sum_{j=0}^{1}\pi_{5j}\Delta \mathrm{Rus}_{t-j} + \sum_{i=0}^{1}\pi_{7i}\Delta \%\mathrm{MMFFlows}_{t-j} + a_7 \mathrm{Sep98}_t + a_8 \mathrm{Oct98}_t \\ & + \alpha \mathrm{ECM}_{t-1} + \varepsilon_t\end{aligned}$$

Table 7 contains the results for the final model. Note the standard error for the change in the yield only increases to 22.9 basis points from 22.8 basis points in going from the unrestricted model to the final model. There are 26 restrictions on the coefficient estimates from the unrestricted ADL model. The F test for the null hypothesis that the final model explains, as well as unrestricted ADL model is 1.05 with a P value of .41. Thus, we cannot reject the null hypothesis that the final ECM has the same explanatory power as the general model.

There is no evidence of autocorrelation. However, the problem of an ARCH(1) process remains as does the rejection of normality due to excess kurtosis. The null hypothesis for the heteroscedasticity on the squares of the explanatory variables cannot be rejected with a P value of .4.

The speed of adjustment coefficient from the ECM term, -0.1247, is negative, significant, and consistent with theory. Thus, the deviation from the "equilibrium" long-run yield is important in helping to explain the short-run dynamics. Treasury rates influence both the long-run and short-run movements. We found that the coefficient on the current and lagged two periods of Treasury yields can be combined and a have positive impact on the change in BB yields. (This is effectively the change in the yield over the past quarter.)

The previous month's change in the own BB yield, -0.193, has a negative and significant effect. We interpret this as a form of volatility or overreaction to market information. So there is a partial offsetting of month-to-month changes.

Dynamic default risk measures clearly influence the short-run and long-run behavior of BB yields. An increase in the Moody's default measure has effects contemporaneously and with a 1-month lag. The coefficients are equivalent to 9 and 12 basis points, respectively. Conversely, the change in the Russell 2000 Index has negative effects in the current month and with a 1-month lag, -0.659 and -0.662, respectively. This equity index or market serves as a substitute for investors in high-yield funds.

Table 7
Final ADL model for noninvestment grade BB yields [estimated coefficients and standard errors (sample August 1987–December 1999)]

Variable	0 Lag	1 Lag
Long-run solution		
ECM (Lag 1)		– 0.1291 * * (0.042)
Interest rate risk		
ΔT-Bonds sum of 0–2 lags	0.307 * * (0.042)	
ΔBB bonds		– 0.191 * (0.075)
Default rate risk		
ΔMoody default rate	0.094 * (0.045)	0.122 * * (0.043)
ΔRussell 2000 Stock Index (ln)	– 0.659 (0.397)	– 0.662 (0.379)
Liquidity risk		
% New mutual fund flows	– 0.035 * * (0.005)	– 0.025 * * (0.005)
Pulse D.V. Aug 98	0.923 * * (0.259)	
Pulse D.V. Oct 98	0.771 * * (0.242)	
Constant	2.58 * * (0.848)	

R^2=.57, Standard error = .229, Durbin–Watson = 1.97, AR(1–4) $F(4,127) = .65$ [.62]
ARCH(3) $F(3,125) = 4.4$ [.01], Normality $\chi^2(2) = 10.8$ [.00], Hetero. Xi^2 $F(26,104) = 1.06$ [.40]

* Statistical significance at 5%.
* * Statistical significance at 1%.

Mutual fund flows have statistically significant and negative effects on changes in BB yields. The impact is not only for the current month, but also with a lag. This second effect suggests that mutual funds do not immediately invest the proceeds into the market, but instead invest (or divest) proceeds over a period.

External shocks play a small role in the BB ECM model. We found significant effects from the Russian and Southeast Asian financial crisis and LTCM collapse in the fall of 1998. In August, the beginning of the crisis, there was nearly a 100-basis-point increase in the jump of BB yields. As is evident by the rise in spreads, the crises and the surrounding uncertainty created flights to quality internationally and domestically. Following efforts by the Fed and other major central banks to contain the crisis (see International Monetary Fund, 1998), the spreads on bonds in the mature markets began to return to the previous levels. These included two cuts in short-term interest rates, implicit promises to provide liquidity to financial markets, and the engineering of a takeover/bailout of LTCM. However, our model finds a further increase in the change of BB yields of slightly more than 75 basis points in October 1998.

Figs. 9 and 10 show the recursive analysis results for the model and the estimated coefficients, respectively. Model and parameter constancy can be evaluated using recursive estimation techniques. Suppose the original model has T observations. The technique begins by estimating the model over first $s < T$ observations in the sample and then fit the model using $s+1$, $s+2$, ..., up to T observations. The process is repeated by adding one more observation until there are $s = T - 1$ observations. At this point, there are a number of tests for evaluating parameter and model constancy. They are often best presented in graphical form, because of the large number of statistics.

There are two types of recursive Chow tests. The first is the one-step Chow test. This looks at the sequence of one-period-ahead predictions from the recursive estimation for period s to T. A familiar statistical presentation is the one-step ahead residuals plus the standard error bound used to search for outliers. The one-step residuals are given by $\hat{e}_t = y_t - x_t \hat{\beta}_t$ and plotted with the current estimate of $\pm 2\hat{\sigma}_t$ on either side of zero. When $\hat{e}_t$ is outside the band, it can be interpreted as an outlier. The tests are $F(1, t-k-1)$ under the null hypothesis of parameter constancy. The statistic is calculated as:

$$\frac{(\mathrm{RSS}_t - \mathrm{RSS}_{t-1})(t-k-1)}{\mathrm{RSS}_{t-1}} \approx F(1, t-k-1) \text{ where } t = s, s+1, \ldots, T$$

The test assumes that the dependent variable, y_t, is normally distributed. In our case, this is the change in the BB yields appears to be stationary. This series is plagued by excess kurtosis as mentioned before and suggests that there will be several large outliers. Fig. 6 presents the plot of the one-step Chow tests, and there is only one significant event in late 1991.

The textbook approach to model constancy assumes that modeler knows the date of a possible structural break in the sample. They fit the model over the full sample and for the two “halves” of the sample. The full sample implicitly imposes the same model structure throughout and can be considered as a restricted model. This is evaluated against the unrestricted model comprised of the two “halves” using an F test. Recursive estimation conducts the Chow tests over the full sample and lets the data do the talking. The Break-Point Chow test is calculated as:

$$\frac{(\mathrm{RSS}_T - \mathrm{RSS}_{t-1})(t-k-1)}{\mathrm{RSS}_{t-1}/(T-s+1)} \approx F(T-s+1, t-k-1) \text{ where } t = s, s+1, \ldots, T$$

The results are presented graphically normalizing test statistics over the critical values at each observation. If the plot is above unity at an observation, this indicates a rejection of the hull hypothesis of no structural break at that point. The Ndn Chow test or Break-Point Chow test is graphed in the bottom half of Fig. 6 and does not suggest a structural break at any observation. We conclude that model-wise, the final ECM is stable.

Similarly, a graph of the estimated coefficients plus or minus twice the standard error is a revealing plot in that one can examine whether the estimate at some previous time t lies outside the confidence interval at later dates. This is a good test for examining individual coefficients. Fig. 7 presents these tests for each coefficient individually. The recursive coefficient estimates do not appear to significantly trend or jump. Thus, on a model and coefficient basis, we appear to have found a reasonably well-fitting and robust ECM, which is consistent with the theory.

5.2. An ECM for B yields

The B VAR analysis in Table 4 suggested a five-period lag in levels was the appropriate structure. Hence, we convert this to a model in first differences with a maximum of four lags and include the lagged error correction term from the cointegrating vector (Eq. (1)). The specification of the general ADL is:

$$\begin{aligned}\Delta \mathrm{B}_t &= a_0 + \sum_{i=1}^{4} \pi_{1i} \Delta \mathrm{B}_{t-i} + \sum_{i=0}^{4} \pi_{2i} \Delta \mathrm{Default}_{t-i} + \sum_{i=0}^{4} \pi_{3i} \Delta \text{T-Bond}_{t-i} \\ &\quad + \sum_{i=0}^{4} \pi_{4i} \Delta \mathrm{Lead}_{t-i} \sum_{j=0}^{2} \pi_{5j} \Delta \mathrm{Rus}_{t-j} + \sum_{i=0}^{2} \pi_{6i} \Delta \mathrm{S\&P} P/E_{t-j} \\ &\quad \times \sum_{i=0}^{2} \pi_{7i} \Delta \%\mathrm{MMFFlows}_{t-j} + a_1 \mathrm{January}_t + a_2 \mathrm{July}_t + a_3 \mathrm{Drexel}_t + a_4 \mathrm{Iraq}_t \\ &\quad + a_5 \mathrm{Sep90} + a_6 \mathrm{Mar97}_t + a_7 \mathrm{Aug98}_t + a_8 \mathrm{Sep98}_t + a_9 \mathrm{Oct98}_t + a_{10} \mathrm{Nov98}_t \\ &\quad + a_{11} \mathrm{Dec98}_t + \alpha \mathrm{ECM}_{t-1} + \varepsilon_t\end{aligned}$$

where $\mathrm{ECM}_{t-1} = \mathrm{B}_{t-1} - (-0.25076\ \mathrm{Default}_{t-1} - 0.6303\ \text{T-Bond}_{t-1} + 0.16601\ \mathrm{Lead}_{t-1})$

This model is fit over the sample October 1987 through December 1999; there are 42 estimated coefficients and 147 observations. The regression R^2 is .87 and the standard error for the change in the yield is 17.9 basis points. The general fit of the model appears better than the BB ECM model. Again, the unrestricted model is overparameterized by definition, so we begin the reduction process by examining the explanatory power of different lag lengths and sets of variables from the model always comparing the fit against the unrestricted model and previous reductions. The final model includes only 13 estimated coefficients and is given below.

$$\begin{aligned}\Delta \mathrm{B}_t &= a_0 + \pi_{11} \left(\sum_{i=1}^{4} \Delta \mathrm{B}_{t-i} \right) + \pi_{20} \Delta \mathrm{Default}_t + \pi_{30} \Delta \text{T-Bond}_t \\ &\quad + \pi_{70} \left(\sum_{j=0}^{2} \Delta \%\mathrm{MMFFlows}_{t-j} \right) + a_1 \mathrm{January}_t + a_4 \mathrm{Iraq}_t + a_5 \mathrm{Sep90}_t + a_6 \mathrm{Mar97}_t \\ &\quad + a_7 \mathrm{Aug98}_t + a_9 \mathrm{Oct98}_t + a_{10} \mathrm{Nov98}_t + \alpha \mathrm{ECM}_{t-1} + \varepsilon_t\end{aligned}$$

Table 8 contains the results for the final model. Note the standard error for the change in the yield increases to 19.2 basis points from 17.9 basis points in going from the unrestricted model to the final model in going from the unrestricted model to the final model. There are 25 restrictions on the coefficient estimates from the unrestricted ADL model. The F test for the null hypothesis that the final model explains, as well as the unrestricted ADL model, is 1.55 with a P value of .69. Thus, we cannot reject the null hypothesis that the final ECM has the same explanatory power as the general model.

Table 8
Final ADL model for noninvestment grade B yields [estimated coefficients and standard errors (sample August 1987–December 1999)]

Variable	0 Lag	1 Lag	2 Lags	3 Lags
Long-run solution				
ECM (Lag 1)		– 0.047 * * (0.023)		
Interest rate risk				
ΔT-Bonds	0.419 * * (0.071)		0.228 * * (0.071)	
ΔBB bonds sum of lags 1, 3, and 4			0.586 * * (0.075)	
Default rate risk				
ΔMoody default rate	0.180 * * (0.039)			– 0.086 * * (0.037)
Liquidity risk				
% New mutual fund flows	– 0.060 * * (0.005)	– 0.038 * * (0.006)	– 0.027 * * (0.005)	
January effect	– 0.207 * * (0.061)			
Iraq invasion Aug 90	0.658 * * (0.207)			
Pulse D.V. Sep 90	1.442 * * (0.203)			
Pulse D.V. Mar 97	0.456 * * (0.197)			
Pulse D.V. Aug 98	2.051 * * (0.199)			
Pulse D.V. Oct 98	0.830 * * (0.201)			
Pulse D.V. Nov. 98	– 1.851 * * (0.230)			
Constant	1.781 * * (0.571)			

R^2=.83, Standard error = .192, Durbin–Watson = 1.76, AR(1–6) F(6,122) = .90 [.49]
ARCH(3) F(3,122) = .29 [.83], Normality $\chi^2(2)$ = 8.02 [.02], Het. Xi^2 F(31,96) = 1.65 [.03]

* * Statistical significance at 1%.

The R^2 for the model is .83. There does not appear to be any autocorrelation of the residuals; the AR(6) test is 0.90 with a P value of .49. In addition, we do not observe an ARCH process found in the BB final ECM model. The lack of volatility or (conditional) heteroscedasticity in the model is a bit surprising. The distribution of residuals does not reject the Jarque–Bera normality test with a P value of .71. We do find that the specification is sensitive to the test for heteroscedasticity in the squared explanatory variables; the P value is .03.

The speed of the adjustment coefficient on the ECM term, – 0.047, is about half that of the BB model. Thus, returns on riskier assets have a faster reversion to their "equilibrium" values. "Excess" returns do not appear to be persistent. The current change and lags back 4 months in yields on T-Bonds have a positive effect of about 58 basis points on the change in B yields. T-Bonds affect noninvestment grade yields in both the level and changes in the level. Unlike the BB final ECM, we did not find an effect from previous changes in B yields.

The Moody's default rate measure enters the long-run equilibrium relation and the ECM model. An increase in the current change of the default rate has a positive impact on the change in B yields. The effect is about 18 basis points, but then they fall back by 8 basis points 3 months later.

Liquidity risk arises from mutual fund flows, calendar effects, and external shocks in the final ECM for B yields. New mutual fund flows put downward pressure on the change in B yields contemporaneously; unlike the BB model where there are lagged effects as well. This may be due to institutional effects, which constrain fund managers from investing in more risky derivatives.

There does appear to be a January effect in the final ECM for B yields. The impact is negative and at 5%. This variable is related to mutual fund flows into the noninvestment grade derivatives market (Maxwell, 1998).

The B index is more susceptible to external shocks than the BB final ECM models. These events influence the underlying yield on Treasury securities and have an additional effect of increasing the spread between Treasuries. This is often referred to as a ‘‘flight to quality’’ in the case of negative shocks and or times of uncertainty.

We find that the Iraqi invasion of Kuwait led to an increase in the required yield on B-rated bonds by 66 basis points in August of 1990, and a further 144 basis points in September of 1990 as concerns rose about higher oil prices and the negative impacts on economic growth. Oil prices were not the only factor; there already was pessimism about an economic slowdown according to reports in Business Week (9/24/90) during this time. Unemployment had risen from 5.2% in June to 5.6% in August. Private employment growth declined to it slowest pace in 7 years. The index of consumer sentiment produced by the University of Michigan’s Survey Research Center plunged from 77.3 to 62.9 in August. This decline was twice the size of the drop experienced in the aftermath of the stock market crash in October 1987.

In March 1997, there was a shock in the single B market causing yields to jump nearly 46 basis points. This appears to have been the result of a ‘‘surprise’’ in the credit markets. At the Federal Open Market Committee meeting on March 25, the federal funds rate was increased from 5.25% to 5.5%. This was the first increase in 2 years during which rates had been either stable or declining. Chairman Greenspan had hinted at his concerns in the Humphrey–Hawkins speeches before the Congress on February 26th and March 20th. Aggregate demand was very strong, and unemployment was at 5.3%; the economy was far above estimates of its full employment or nonaccelerating inflation rate of unemployment level (NAIRU). Productivity growth was not expected to offset these potential imbalances. The bond market initially did not respond to these statements and hints. Thus, Greenspan and the Fed felt that there was a rising risk of inflation. The increase in short-term rates was interpreted as a preemptive strike on inflationary pressures and there was speculation that only a single increase might be necessary according to Business Week (4/7/97). The economy was in the fifth year of expansion so there was a consensus view that it would be slowing down shortly.

External shocks had a greater impact in the B ECM model than in the BB ECM model. We found significant effects from the Russian and Asian financial crises and LTCM collapse in the fall of 1998. In August, the beginning of the crisis, there was a 200-basis-point increase in B yields—twice the effect of the change in BB yields. In October, yields increased approximately another 83 basis points. The market began to recover in November as investors felt more confident. We find a decline of nearly 180 basis points in that month.

Figs. 11 and 12 show the recursive analysis results for the model and the estimated coefficients, respectively. There are only three rejections in the one-step Chow test for the

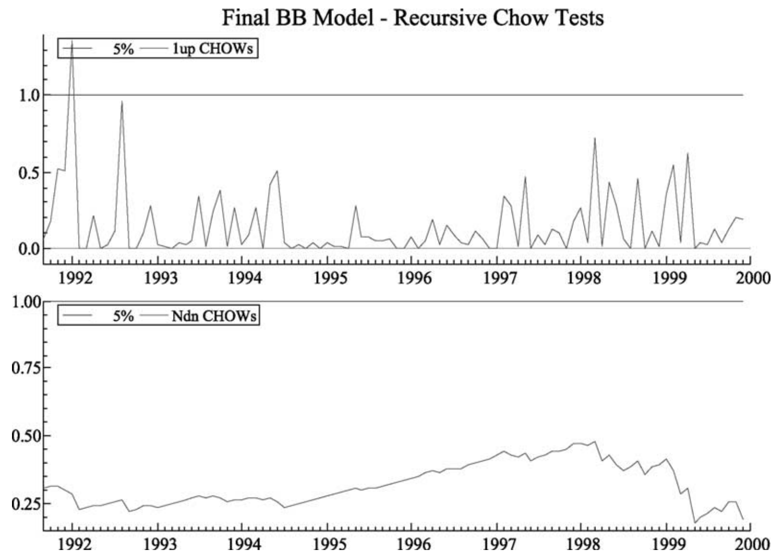

Fig. 9. Final BB Model-Recursive Chow Tests.

Spring of 1997 and 1998 and January 1999. The Break-Point Chow tests are close to rejections at 5% for these observations. Nevertheless, we feel that the final B ECM model reasonably explains the short-run dynamics in a parsimonious and constant manner.

6. Forecast evaluation of models

Given the test statistics, the stability of the models, and the high R^2, both models do a good job of modeling the ex-post factors that influence the yield spread. However, for the model to be useful in understanding any pricing trends in the market, it must accurately forecast movements in credit spreads. We examine the ability of the model to forecast yield premiums in this section.

We test the forecast performance of the BB and B models. The forecast evaluation period is from January 1998 through December 1999. There are two kinds of forecasts to compare for the BB and B models. Unconditional dynamic forecasts are made using the actual values for the exogenous variables in one test. In the other test, conditional dynamic forecasts are developed using AR(p) models to predict the exogenous variables.

The process begins by fitting the model(s) for the period July 1987 through December 1997. Forecasts are generated out 6 months (to June 1988 in the first case.) Then, one observation is added and the model(s) are refitted through January 1998. Once again, forecasts are made for 6 months ahead. The process is repeated until November 1999 when only a 1-month-ahead forecast can be made. Thus, we have 24 one-month-ahead forecasts, 23 two-month-ahead forecasts, 22 three-month-ahead forecasts, and 19 six-month-ahead forecasts for evaluation purposes.

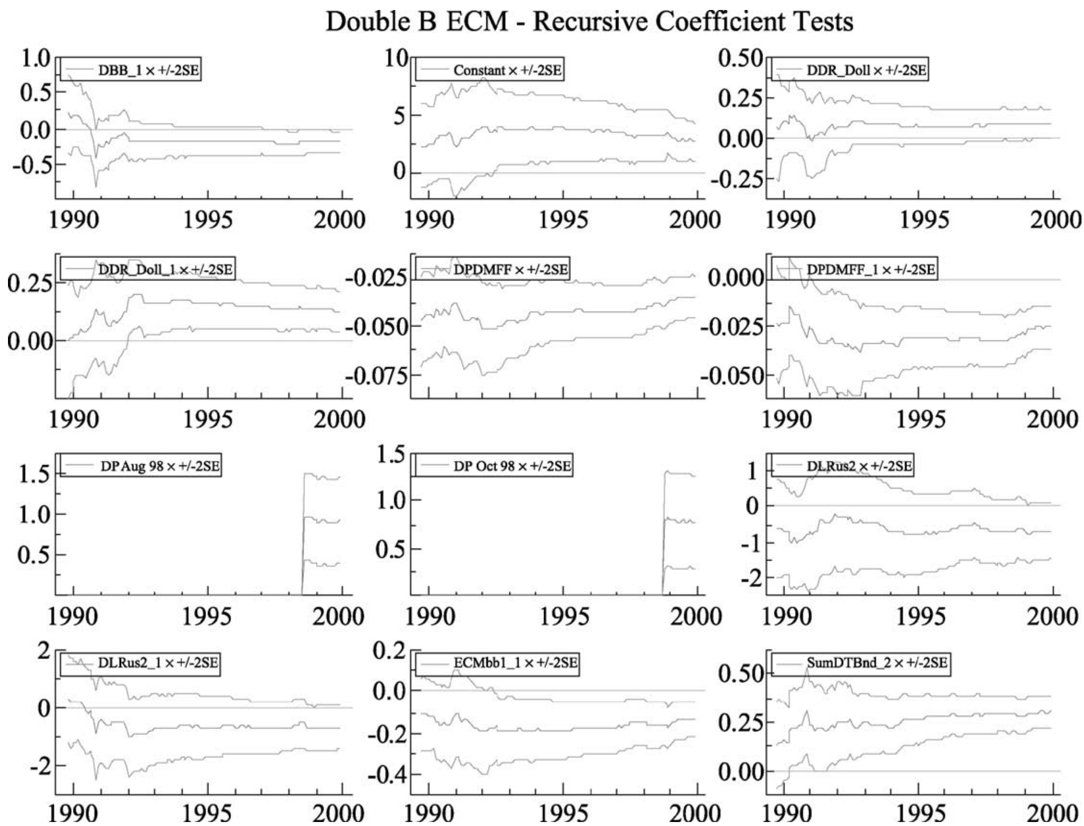

Fig. 10. Double B ECM-Recursive coefficient tests.

We tested if the cointegrating vector differed using the sample through December 1997 against the December 1999. The null hypothesis that they were the same for BB and B cointegrating relations could not be rejected, and the cointegrating relation is stable over time.

Conditional ECMs were estimated for BB and B yields based on the weak exogeneity tests, which revealed that system estimation was unnecessary. However, the weak exogeneity property is not sufficient for forecasting purposes (Engle, Hendry, & Richard, 1983; Ericsson, 1992, 1994). Strong exogeneity is required to perform conditional dynamic or multiperiod ahead forecasts. This can be tested for by using Granger causality tests or block exogeneity tests. We set up a four-variable VAR system for both the BB or B yields. The other three series in the VAR are the default rates, the 7-year T-Bond yields, and the leading economic indicators. Then, we test if these variables enter each equation in the respective systems and whether they do jointly.

In Table 9, we report the results from these tests for the BB system. The second column reports the block exclusion test for the variables in the BB equation individually and jointly. All variables have explanatory power for the BB yields. The first row presents the block or

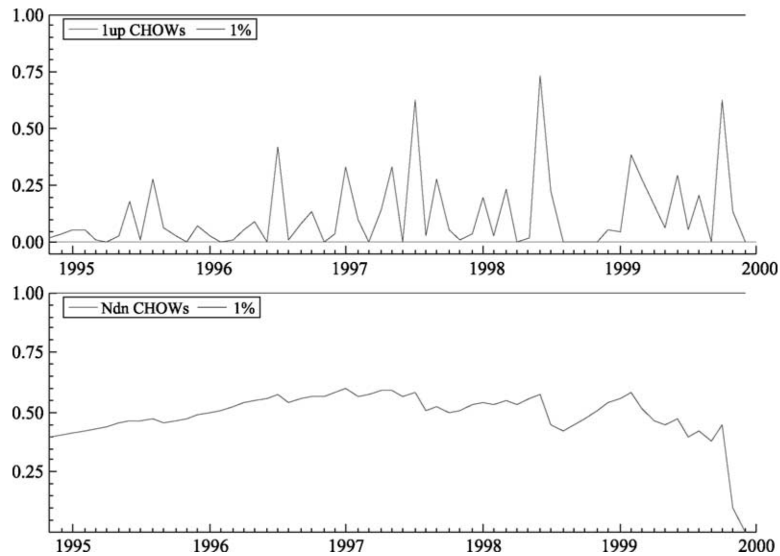

Fig. 11. Final B ECM Model-Recursive Chow Tests.

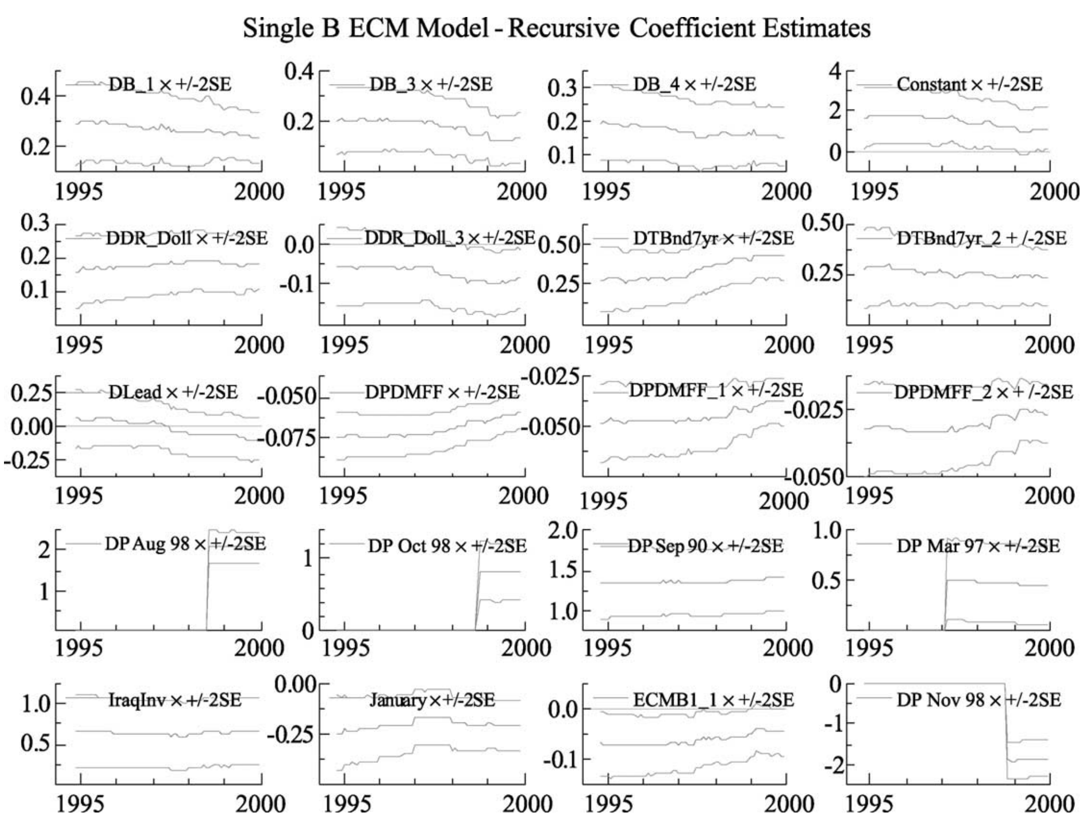

Fig. 12. Single B ECM Model-Recursive coefficient tests.

Table 9
VAR pairwise Granger causality or block exogeneity Wald tests [super exogeneity tests for conditional forecasting of BB yields (chi-square with 4 degrees of freedom and *P* values)]

Exclude	Equation			
	BB	PDMFF	TBnd7yr	Lead
BB		7.89 [.96]	8.37 [.08]	5.45 [.24]
PDMFF	10.8 [.03]		3.74 [.44]	5.11 [.28]
TBnd7yr	17.04 [.002]	6.77 [.15]		11.94 [.02]
Lead	8.02 [.09]	2.46 [.65]	14.55 [.006]	
All variables	48.14 [.00]	20.89 [.05]	28.21 [.01]	23.87 [.02]

The VAR system is in first differences with four lags of each variable and the sample is from July 1987 to December 1999.

Granger causality test for the BB yields in each of the other three equations. There is marginal evidence (*P* value .08) that BB yields provide explanatory power for the T-Bond equation. Table 10 reports similar test for the B yield system. Here, the evidence is mixed. It appears as though none of the variables helps to explain B yields. This is troubling, but it may be due to the omission of the cointegrating relation and the general difficulty in modeling this specialized and illiquid market. Surprisingly, B yields appear to Granger cause the leading economic indicator series; the *P* value is .06. This seems to be a statistical anomaly and cannot be supported by financial or macroeconomic theory. The results suggest that we can treat the variables as three variables as strong exogenous with respect to the noninvestment yields. Initially, we had anticipated that default rates might not be strongly exogenous with noninvestment yields. One explanation for why this may not be true is that the default rate is a 12-month average and is thus backward, not forward, looking.

Based on the strong exogeneity results, we decided to model the default rates, the 7-year T-Bond yields, the leading economic indicators, the net mutual fund flows, and Russell 2000 series using first difference autoregressive models with three lags. This removed serial correlation from the residuals. These models were then used to forecast the appearance of the respective variables in the ECM equation as simple changes and in the cointegrating or equilibrium correction relation.

Table 10
VAR pairwise Granger causality or block exogeneity Wald tests [super exogeneity tests for conditional forecasting of B yields (chi-square with 4 degrees of freedom and *P* values)]

Exclude	Equation			
	BB	PDMFF	TBnd7yr	Lead
BB		4.70 [.32]	6.44 [.17]	9.28 [.06]
PDMFF	2.97 [.56]		3.11 [.54]	5.89 [.21]
TBnd7yr	5.08 [.28]	4.40 [.35]		13.44 [.01]
Lead	3.99 [.41]	3.08 [.54]	6.90 [.14]	
All variables	13.97 [.30]	17.36 [.14]	22.53 [.03]	27.80 [.01]

The VAR system is in first differences with four lags of each variable and the sample is from July 1987 to December 1999.

Table 11 contains the results of the forecast error evaluation. Forecast errors are defined as the actual yield minus the predicted yield. The BB yield forecasts are presented in the top two parts of the table, and the B yield forecasts are presented in the bottom two parts of the table. The 1-month-ahead, 2-month-ahead, 3-month-ahead, and 6-month-ahead statistics are presented in the second through fifth column, respectively. The mean forecast error, mean absolute error (MAE), the root mean square error (RMSE), and the maximum and minimum forecast error are calculated.

The mean 1-month-ahead forecast error for the BB conditional predictions is 0.105, about 10 basis points. However, the error is unbiased, because the ratio of the mean error to the RMSE, effectively a t test is less than unity. This is true for all four sets of forecast errors and at all horizons. The MAE and the RMSE are measures of dispersion for forecast errors. As expected when the forecast horizon increases both measures increase. We find that the average forecast error is lower, only 3 basis points, for the B forecast. However, the B forecast

Table 11

Double B yield forecast error evaluation

	1 Month ahead	2 Months ahead	3 Months ahead	6 Months ahead
Unconditional forecasts				
Mean	0.105	0.180	0.247	0.390
MAPE	0.251	0.341	0.351	0.473
RMSE	0.333	0.436	0.507	0.597
Maximum	0.963	1.016	1.602	1.272
Minimum	− 0.316	− 0.465	− 0.504	− 0.466
Conditional forecasts				
Mean	0.112	0.206	0.323	0.596
MAPE	0.212	0.340	0.435	0.632
RMSE	0.305	0.438	0.531	0.853
Maximum	0.870	0.991	1.150	2.018
Minimum	− 0.273	− 0.417	− 0.359	− 0.439

Single B yield forecast error evaluation

	1 Months ahead	2 Months ahead	3 Months ahead	6 Months ahead
Unconditional forecasts				
Mean	0.032	0.084	0.130	0.303
MAPE	0.367	0.614	0.725	0.725
RMSE	0.634	0.874	1.058	0.957
Maximum	2.079	2.471	3.279	2.195
Minimum	− 1.863	− 2.054	− 1.875	− 1.085
Conditional forecasts				
Mean	0.041	0.116	0.225	0.580
MAPE	0.335	0.471	0.563	0.767
RMSE	0.518	0.644	0.794	1.001
Maximum	1.683	1.828	2.360	2.072
Minimum	− 1.238	− 0.842	− 0.924	− 0.785

error measures for the MAE and RMSE are larger than the similar measures for the BB. The largest underpredictions, positive errors, appear much bigger than the overpredictions. Nearly every one of these occurs in August 1998 or from September through November of the same year. The 6-month-ahead conditional forecasts for May 1999 are rather large as well. This must be due to forecasts of the exogenous variables, but it is not clear which of the variables is the culprit. The overpredictions are not clustered in any particular period. Overall, we find that the models do a good job of forecasting yields and should provide a useful tool in pricing credit derivative instruments.

7. Summary

In this paper, we build equilibrium models of the yield on noninvestment grade bonds. We do this to better understand how to price credit derivatives on the most volatile bond indexes. Our resulting model(s) provide insight into the underlying factors that drive credit spreads, and the models prove useful in forecasting yields. Both of the results are necessary to accurately price credit derivatives.

In the long run, there is equilibrium between the Treasury yields, default rates, a leading economic indicator and yield spreads. We also find that this long-run equilibrium is affected by dynamic factors, which leads noninvestment grade bonds to only slowly revert back towards the long-run equilibrium. The higher risk B index exhibits a faster reversion toward equilibrium but larger short-run dynamic changes in yield.

In addition to a long-run equilibrium, short-run dynamic factors also influence monthly yield spreads. The dynamics of the B and BB indexes are explained by changes in the Moody's default rate, changes in the Treasury yield, and changes in mutual fund flows. The strongest explanatory variable in each model is the change in mutual fund flow. Our results also indicate that the lower credit quality indexes are more sensitive to changes in mutual fund flow. A weakly significant January effect is found in B-rated bonds. A number of external events were found to have statistically and economically significant effects on yields. For both the B and BB index, the Russian and Asian financial crisis lead to a significant increase in the required premium for noninvestment grade bonds. For B-rated bonds, the Iraq invasion of Kuwait, and the Russian and Asian crises also lead to increased yield spreads over the equilibrium relation.

Furthermore, the estimated error-correction models are found to be useful in forecasting future changes in the yield spread. We find an average forecast error of 10 basis points and 4 basis points for the BB and B indexes. However, the dispersion of the errors is greater for the B index.

Finally, there is a danger in viewing the noninvestment grade market as being homogenous. While we find a number of common factors affecting B- and BB-rated bonds, the relative effect of these factors on the long-run equilibrium and the short-run model differ in degree and strength. We also find evidence that suggests a flight to quality from B- to BB-rated bonds during periods of pessimism and uncertainty in the macroeconomic outlook and turbulence in the financial markets.

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