Is Corporate Bond Market Performance Connected with Stock Market Performance?

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January 2008

Abstract

Stock markets and bond markets are known to interact. Specifically, the common stock market trend (i.e., business cycle also termed market/systematic risk) impacts common corporate bond market trend (i.e., credit cycle). First, we disentangle the common latent component from total stock returns (i.e., systematic/unobserved common stock market component). Second, we extract the common latent component from total bond returns (i.e., common unobserved systematic corporate bond component). Then, we estimate the dynamic relation between systematic total stock returns and systematic total bond returns over time (i.e., co- and anti-monotonicity risk). We characterize therefore the time-varying correlation risk (i.e., correlation risk structure) between stock performance and corporate bond performance. Results are instructive in a risk management prospect with regard to equity- and corporate bond-based portfolios…

Keywords: Corporate bonds, Flexible least squares, Kalman filter, Latent factor, Systematic risk, Total return.
JEL Codes: C32, C51, G1.
EFM Codes: 340, 450.

1 Introduction

During the last decade, financial research exhibited and highlighted four key features of corporate bonds. First, holding corporate bonds in a portfolio of assets is advocated by the related potential growth, the historical low risk as compared to stocks, and the related diversification benefits with the enlargement of efficient asset portfolio opportunities (Siegel, 2002). Second, there exists a strong trade-off between corporate bond markets and equity markets (e.g., fixed income arbitrage as reported by Duarte et al., 2005). Indeed, equity data and features have been widely used to assess some corporate bond determinants such as credit risk indicators for example (Carr and Wu, 2005; Collin-Dufresne et al., 2001; Cremers et al., 2005, 2006; Hull et al., 2003; Merton, 1974;[1] Vassalou and Xing, 2003; Zhang et al., 2005). Specifically, option data such as smiles features in equity options can reflect leverage patterns of companies (Hull, 2006). Moreover, equity volatility effects can explain a non-negligible fraction of corporate yield spreads (Campbell and Taksler, 2003). Third, corporate bond markets are prone to cyclicality (Allen and Saunders, 2003; Leippold, 2006; Pesaran et al., 2005). Namely, credit risk indicators (i.e., corporate bond determinants) exhibit a common dynamic component suggesting the existence of a credit cycle (Koopman et al., 2005). Finally, credit spreads (i.e., leading indicators of corporate bond markets) result from one systematic (i.e., market, business cycle) component and one independent idiosyncratic (i.e., specific) component (Cipollini and Missaglia, 2005; Gatfaoui, 2003; Koopman and Lucas, 2005; Xie et al., 2004). It reveals therefore necessary to consider the joint evolution of market and corporate bond determinants over time while valuing a portfolio composed of corporate bonds (i.e., credit risky assets) among others (Iscoe et al., 1999). Moreover, such a decomposition sheds light on the sector concentration risk in corporate bond-based portfolios (i.e., sectorial effects) among others. Indeed, corporate bond performance differs across economic sectors and evolves with business cycle over time (BIS study on credit risk concentration, 2006; McNeil and Wendin, 2005; Reilly and Wright, 2001).

In the lens of current academic and industry-based research, credit risk and market risk are clearly shown to interact, and to be connected (Gatfaoui, 2005, 2007; Gordy, 2000; Iscoe et al., 1999). The existence of such an interaction is extremely significant insofar as such a link impacts then strongly the

[1] Merton (1974) uses equity prices to estimate default probabilities.

valuation of risky assets (i.e., co-monotonicity risk of a portfolio), and consequently the performance of both credit portfolios and mixed portfolios (i.e., portfolios composed of both stock-specific assets and bond-specific assets). Namely, the extent to which the assets of a portfolio tend to move together over time (i.e., common dependence over time, or equivalently systematic risk) is highly important in a risk management prospect and under a portfolio optimization setting. We propose here to study the way the stock market (i.e., market risk) interacts with the corporate bond market (i.e., credit risk) while considering total return indices describing these two markets. Total return indices reveal to be indeed good performance indicators. Starting from these performance proxies, we study the potential interaction between stock market performance and corporate bond market performance (i.e., credit market performance). Under this setting, we question therefore the bridge prevailing between stock and corporate bond markets as well as the strength of such a link. Is there a strong and straightforward link between credit cycle (i.e., common component in corporate bonds) and business cycle[2] (i.e., systematic/market risk)? Basically, is corporate bond performance driven by stock market performance? To answer these questions, we need to split them into two distinct and more detailed questions. The first question focuses on how to exhibit the systematic factors describing both the U.S. stock market and the U.S. corporate bond market. The systematic stock market factor and the systematic corporate bond market factor represent the general trend peculiar to each market under consideration and give the global temperature of such markets. We extract the information content of available stock and bond market data to estimate such common latent factors, which are endogenous to our estimation process. The advantage of our methodology allows for bypassing the issue of selecting relevant explanatory systematic factors as well as related exhaustiveness concern about the optimal number of explanatory bond factors (Ammann et al., 2007; Blake et al., 1993; Burmeister and Wall, 1986; Fama and French, 1993). We do not seek for achieving a factor analysis but rather for extracting one unique systematic latent factor summarizing all potential systematic factors describing the general trend of stock market performance on one side, and the general trend of corporate bond market performance on the other side. The second question addresses the

[2] The state of the business cycle is commonly thought as a systematic risk factor since the systematic risk level is strongly correlated with macroeconomic fundamentals (Fama and French, 1989).

strength of the bridge existing between the stock market and the corporate bond market, or equivalently, the extent to which the systematic stock market factor and the systematic corporate bond market factor are linked. More specifically, it focuses on the dynamic correlation risk between U.S. corporate bond global performance and U.S. stock market global performance (i.e., correlation risk of the general trends in both markets). Rather than seeking for a causality link, we investigate a potential interaction between the stock market and the corporate bond market. Indeed, we employ an econometric method accounting for dynamic relationships between stock market performance's trend and corporate bond performance's trend under a linear framework. Our methodology has the advantage of assessing the dynamic correlation risk between the trends of both stock market and corporate bond market performances. Consequently, the added value of our study is twofold. First, it allows for estimating endogenously the general trends of U.S. stock market and U.S. corporate bond market performances over time, namely the systematic stock market factor and the systematic corporate bond factor. Second, our analysis allows for studying the link prevailing between the general trend of U.S. stock market performance and the general trend of U.S. corporate bond market performance over time, namely the dynamic correlation risk between stock market's global trend and corporate bond market's global trend.

Our paper is organized as follows. Section 2 introduces the U.S. index-based data set as well as related features (i.e., performance indicator) and statistical properties. Section 3 exhibits and describes briefly the common latent component peculiar to U.S. corporate bond performance as a function of respective sector and maturity (i.e., credit cycle indicator). The common latent component inherent to the U.S. stock market performance is also inferred and studied (i.e., business cycle indicator). Then, section 4 investigates the potential dynamic link prevailing between the common latent performance component of U.S. corporate bonds and the common latent performance component of U.S. stock market. Finally, section 5 draws some concluding remarks and proposes possible future extensions.

2 Data set

We introduce the data set under consideration as well as a set of key related features.

2.1 Market indices

All the data under consideration come from Dow Jones Corporation database and range from January 3, 1997 to August 14, 2006, namely 2435 observations per series. We therefore consider an homogeneous dataset whose information content we filter and exploit to handle our main quantitative risk study. Moreover, such a data sample allows for studying the general trend of both stock and corporate bond markets as well as testing the link prevailing between the stock market's trend and the corporate bond market's trend whatever the direction of the financial market. Indeed, the time period under consideration encompasses many disturbing financial and economic events such as the Asian crisis in 1997, the Russian default as well as LTCM hedge fund's collapse in 1998, massive Treasury bonds' buybacks and bonds' flight-to-quality issues in 2000, the dotcom bubble burst in 2000/2001, and the may 2005 credit crisis[3] among others.

First, we consider a set of daily Dow Jones indices. As indicators of the U.S. stock market, we consider five Dow Jones Average indices (see table 1). Those representative and diversified indices are price-weighted and account for the most liquid and most renowned float-adjusted market capitalizations for their financial and economic strength. Moreover, they are reviewed periodically along with firm-based events (e.g., stock splits, spin-offs, merger and acquisitions, IPOs). As indicators of the U.S. corporate bond market, we consider twenty corporate bond indices (see table 1) that describe the U.S. investment-grade bond market. Those equally-weighted and diversified indices account for the most liquid and most traded corporate bonds while exhibiting a high bond market representativeness. Specifically, the aggregate/composite Dow Jones corporate bond index (i.e., TOTAL_DJCORP) accounts for non-callable bonds (no optional feature) and encompasses 96 distinct issues from 96 different issuing firms or companies all maturities and sectors included. This composite index is divided into three sector indices (i.e., financial, industrial, utilities/telecom)[4] which encompass each one 32 issues all maturities included (e.g., TOTAL_DJCIND). Moreover, each sec-

[3] Two big firms, namely General Motor and Ford were downgraded from investment grade to speculative grade level (i.e., worsening of credit ratings).

[4] The financial sector relates to banks, insurance and financial services companies among others. The utilities/telecom sector relates to gas, electric, water, fixed-line and mobile phone companies among others. The industrial sector encompasses oil and gas, basic materials, industrials, consumer goods, health care, consumer services companies and technology industries in accordance with the industry classification benchmark (ICB).

Table 1: Dow Jones Indices

Index	Name	Number of issues
Dow Jones Industrial Average	DJI	30
Dow Jones Financial Services	FSV	30
Dow Jones Composite Average	DJC	65
Dow Jones Transportation Average	DJT	20
Dow Jones Utility Average	DJU	15
Dow Jones Corporate Bond (Total)	DJCORP	96
Dow Jones Corporate Financial (Total)	DJCFIN	32
Dow Jones Corporate Industrial (Total)	DJCIND	32
Dow Jones Corporate Utility (Total)	DJCUTL	32

tor index as well as the composite corporate bond index are also divided into four distinct maturity-based indices for investment horizon prospects, namely two, five, ten and thirty years (e.g., 5Y_DJCIND). Basically, each maturity-based index encompasses eight distinct issues at a sector level (e.g., 2Y_DJCFIN) and 24 distinct issues at an aggregate maturity level (e.g., 10Y_DJCORP).[5] Corporate bond indices are reviewed periodically in the lens of solvency and liquidity control criteria for corporate issues (e.g., default event, credit rating downgrade).

Second, we focus specifically on total return indices in order to investigate market performance in a portfolio risk management prospect. Indeed, total return is an accurate performance indicator since it accounts for both income (e.g., dividends, interest payments) and capital growth (e.g., price/value depreciation or appreciation). Therefore, we consider U.S. dollar-based total return Dow Jones indices.[6] For comparability prospects, we compute then the relative percentage changes of each total return series from day to day (i.e., 2434 observations per series ranging from January 6, 1997 to August 14, 2006). Such a ratio is a good indicator of the daily percentage total return over time and therefore a good performance measure for both the U.S. stock and U.S. investment-grade bond markets.

[5] Recall that each DJCORP type index is divided into three sector-based indices (i.e., financial, industrial and utility). For example, each index 10Y_DJCFIN, 10Y_DJCIND and 10Y_DJCUTL encompasses eight corporate bond issues. Therefore, 10Y_DJCORP encompasses all the issues embedded in 10Y_DJCFIN, 10Y_DJCIND and 10Y_DJCUTL respectively, namely 24 corporate bond issues.

[6] Total return series' plots are displayed in the appendix.

Finally, our data sample is mainly motivated by empirical results. For example, Peters (1994, 2003) advocates that investors analyze the information content of market data according to their investment horizon. Moreover, corporate bond performance depends on related economic sector as well as prevailing business cycle (Reilly and Wright, 2001). Consequently, portfolio risk management as well as target performance or performance forecast (e.g., target returns and risk management policy in order to add value and to generate portfolio return/growth) require to consider both sector concentration risk (BIS study on credit risk concentration, 2006) and co-monotonicity risk among others (Iscoe et al., 1999). Such an issue leads to question the link between stock market performance and corporate bond performance in the lens of business cycle.

2.2 Properties

We introduce some basic descriptive statistics to investigate the behavior of daily total return series expressed in percent (see table 2).

As a first striking feature, median total return values are very different from and above corresponding average total return values whatever the index under consideration (i.e., stock or bond market). Second, stock market total returns exhibit a standard deviation that is generally more than three times higher than the standard deviation of corporate bond total returns. These features support the historical facts according to which stocks are riskier and provide a better average return than corporate bonds among others (Siegel, 2002). Moreover, all daily total return series are left-skewed (i.e., downside performance risk) except for the two-year corporate bond industrial index 2Y_DJCIND, the two-year corporate bond financial index 2Y_DJCFIN and the financial services stock market index FSV. Seemingly, the two-year corporate bond and stock market financial sectors as well as the two-year corporate bond industrial sector seem to perform (i.e., positive gross performance over the considered time horizon in 55.8888 percent of observed cases on average). Namely, there exists more sufficiently good days (with positive and above-average gross performance) than bad or 'unexceptional' days (with negative or below-average total returns). By the way, excluding DJI, FSV, 30Y_DJCORP, 2Y_DJCFIN, 5Y_DJCFIN, 2Y_DJCIND and 30Y_DJCUTL, corporate bond total returns are more left-skewed than stock total returns apart from the limited upside pattern of corporate bonds

Table 2: Descriptive statistics for daily total return percentages

Index	Mean	Median	Std. dev.	Skewness	Excess Kurtosis
DJC	0.0389	0.0435	1.0500	-0.1694	3.8848
DJI	0.0357	0.0336	1.1285	-0.0808	3.8524
DJT	0.0417	0.0118	1.4786	-0.2135	5.8264
DJU	0.0482	0.0649	1.1855	-0.3096	7.0958
FSV	0.0434	0.0323	1.3503	0.2292	2.5337
2Y_DJCORP	0.0230	0.0203	0.1441	-0.2213	6.7779
5Y_DJCORP	0.0252	0.0296	0.2671	-0.1952	3.2588
10Y_DJCORP	0.0280	0.0327	0.3884	-0.2453	1.6403
30Y_DJCORP	0.0296	0.0430	0.5881	-0.1171	1.1057
TOTAL_DJCORP	0.0265	0.0308	0.3293	-0.1924	1.3332
2Y_DJCFIN	0.0236	0.0199	0.1465	0.1038	4.6498
5Y_DJCFIN	0.0262	0.0263	0.2591	-0.1079	2.5025
10Y_DJCFIN	0.0262	0.0269	0.3855	-0.3046	1.5766
30Y_DJCFIN	0.0351	0.0441	0.5904	-0.1814	1.4408
TOTAL_DJCFIN	0.0279	0.0299	0.3266	-0.2173	1.2753
2Y_DJCIND	0.0221	0.0207	0.1375	0.1031	2.9174
5Y_DJCIND	0.0259	0.0274	0.2553	-0.1704	2.1687
10Y_DJCIND	0.0287	0.0329	0.3921	-0.2686	1.8356
30Y_DJCIND	0.0315	0.0350	0.5992	-0.1829	1.2661
TOTAL_DJCIND	0.0271	0.0280	0.3252	-0.2331	1.2102
2Y_DJCUTL	0.0232	0.0189	0.2184	-2.7161	61.3048
5Y_DJCUTL	0.0238	0.0281	0.3715	-0.9040	20.4246
10Y_DJCUTL	0.0291	0.0326	0.4599	-0.2601	5.3779
30Y_DJCUTL	0.0220	0.0277	0.7106	-0.1688	10.4970
TOTAL_DJCUTL	0.0247	0.0324	0.3931	-0.4619	7.5234

Table 3: Correlation coefficients of daily total stock returns

Kendall (Spearman)	DJC	DJI	DJT	DJU	FSV
DJC	1	0.7958	0.6463	0.4253	0.5468
DJI	(0.9406)	1	0.5050	0.3146	0.5585
DJT	(0.8269)	(0.6832)	1	0.2349	0.4198
DJU	(0.5884)	(0.4450)	(0.3334)	1	0.2639
FSV	(0.7288)	(0.7400)	(0.5795)	(0.3768)	1

(see related mean and median values). Consequently, a U.S. corporate bond portfolio is clearly more difficult to diversify over time than a stock portfolio (Amato and Remolona, 2003; Carey, 2001; Gordy, 2000; Lucas et al., 2001). Finally, excess kurtosis statistics are positive for all total return series (i.e., fatter distribution tails than Gaussian ones). Therefore, daily total return percentage series exhibit non-normal probability distributions since they have asymmetric (i.e., left-skewed) and leptokurtic behaviors. As a conclusion, stock market and corporate bond total returns behave generally in the same way. In unreported results, we noticed also the common stationary feature of total returns in general (a one percent Phillips-Perron test).

The previous commonality leads to investigate further statistical links between stock market performance and corporate bond market performance. Before enquiring about a link between asset groups, we study the strength of the link prevailing inside each asset group (i.e., U.S. stocks and U.S. corporate bonds). Due to the asymmetric feature of total return series, we compute separately for the stock market total returns' group on one side, and the corporate bond market total returns' group on the other side, the corresponding Kendall and Spearman correlation coefficients, namely related non-parametric correlation coefficients (see tables 3 and 4). Computed correlation coefficients are generally significant at a one percent bilateral test level.

As regards stock market correlations (see table 3), they are all positive and exhibit a non-negligible positive link between stock market total returns to some extent.

As regards corporate bond market correlations (see table 4), they are all positive and exhibit a strong positive link between corporate bond market total returns since correlation values lie above 0.8000 level. In unreported

Table 4: Correlation coefficients of daily corporate bonds' total returns

Kendall (Spearman)	TOTAL_DJCORP	TOTAL_DJCFIN	TOTAL_DJCIND	TOTAL_DJCUTL
TOTAL_DJCORP	1	0.8693	0.8753	0.8490
TOTAL_DJCFIN	(0.9649)	1	0.8271	0.7416
TOTAL_DJCIND	(0.9680)	(0.9475)	1	0.7462
TOTAL_DJCUTL	(0.9562)	(0.8761)	(0.8822)	1

results, we find the same correlation level for the total returns of sector- and maturity-based indices (i.e., for the remaining 16 corporate bond indices).

Consequently, corporate bond performance indicators exhibit a significant positive common link across global corporate bond market, sectors and maturities. Analogously, stock market performance indicators exhibit also a significant positive common link across global stock market and sectors. The common underlying total return behavior being far more stronger for the U.S. corporate bond market. We can now investigate the strength of the link prevailing first between U.S. stock market performance indicators, and second, between U.S. corporate bond market performance indicators.

3 Common latent components

We resort to Kalman methodology to infer the unobserved common component in the total returns of both U.S. corporate bonds on one side and U.S. stocks on the other side. Namely, we investigate the dynamic common link prevailing between U.S. corporate bond performance determinants on one side, and U.S. stock market performance components on the other side.

3.1 Kalman filter

Kalman filter (Kalman, 1960; Simon, 2006) consists of a state-space model that allows for estimating/disentangling an unobserved variable from a set of empirical observations (i.e., observed variables). The observed variables are considered as disturbed observations of the common latent component (i.e., unobserved variable) over time. The disturbance is usually represented by a random noise also termed measurement error/noise. Moreover, Kalman methodology applies to both stationary and non-stationary estimation settings. Under our general stationary setting, we target specifically to extract the common latent component in both stock and corporate bond total returns as a function of sector and/or maturity. As regards stock market data, the common latent total return component represents the business cycle state. As regards corporate bond market data, the common latent total return component illustrates some credit cycle.

Assuming a first order Markov dynamic for the common latent component in total returns, we consider the following representation:

$$TR_t = \alpha \cdot L_t + \varepsilon_t \tag{1}$$

$$L_t = \alpha_L \cdot L_{t-1} + \eta_t \tag{2}$$

where $TR_t' = \left[\begin{array}{ccc} TR_t^1 & \cdots & TR_t^N \end{array} \right]$ represents the set of total returns under consideration, $\alpha' = \left[\begin{array}{ccc} \alpha_1 & \cdots & \alpha_N \end{array} \right]$ represents the sensitivity of total returns to their corresponding common latent component L_t (i.e., systematic component),[7] $\varepsilon_t' = \left[\begin{array}{ccc} \varepsilon_t^1 & \cdots & \varepsilon_t^N \end{array} \right]$ represents related measurement errors (i.e., unsystematic/idiosyncratic components), α_L is a state transition coefficient, η_t is a related dynamic error (i.e., market-specific disturbances), and time t ranges from 1 to T=2434.[8] Incidentally, relation (1) is first a linear measurement equation whereas relation (2) is a state/transition equation. Moreover, related measurement and dynamic equation errors are further assumed to be two independent Gaussian white noises. Specifically, we term H_t the covariance matrix and Q_t the variance parameter of errors ε_t and η_t respectively. Basically, H_t is termed measurement error covariance matrix and Q_t is the state variance. Second, we also assume that the initial value L_0 of the common latent component is independent of all equation errors and follows a

[7]We can expand the common latent component L_t so as to encompass the effect of investors' transactions. Indeed, Kumar and Lee (2006) exhibit the systematic correlation in retail trades and their significance in explaining stock return comovements. Those authors underline the impact of investor sentiment (i.e., systematic retail trading) on returns' formation and evolution (i.e., stock return comovements).

[8]Dimension N depends on the analysis level that is achieved. As regards U.S. stock market, N is 5 since we consider five U.S. stock indices. As regards U.S. corporate bond market, N is 4 at the aggregate level (i.e., four composite indices termed with TOTAL suffix). At a sector level, N is 5 whatever the industry under consideration (i.e., we consider five corporate bond indices for each sector). At a maturity level, N is finally 4 for each of the four possible maturities (i.e., 2-, 5-, 10- and 30-year horizons) since we consider three sectors and one aggregate corporate bond level.

Gaussian law with expectation ℓ_0 and variance P_0. For the sake of simplicity, we finally assume a stationary representation where all the parameters are time-invariant so that α, α_L, $Q_t = \sigma_L^2$ are constant parameters and $H_t = H$ is a $N \times N$ diagonal covariance matrix with elements $(\sigma_i^2,\ 1 \leq i \leq N)$.[9]

Consequently, employing Kalman filter requires to solve representation (1) and (2) while estimating $2N + 4$ parameters (i.e., α, α_L, σ_L^2, H, ℓ_0, P_0) over the studied time horizon apart from the common latent component itself. Given that TR_t follows a conditional multivariate Gaussian distribution, Kalman methodology yields the maximization of the log-likelihood function of the conditional probability distribution of TR_t.

3.2 Estimates

Kalman methodology allows for splitting total returns into two independent components, namely one common latent component (i.e., systematic component) and one idiosyncratic component (i.e., unsystematic component). Basically, the common latent component illustrates the co-monotonicity risk in total returns (i.e., the extent to which total returns tend to move together over time), or equivalently the general common trend in total returns. Differently, the idiosyncratic component refers to sector concentration risk (i.e., the extent to which a portfolio is undiversified) or investment horizon risk (i.e., time diversification) among others.

Our estimation process consists of two steps. The first step estimates the common latent component L^{Mkt} in stock market total returns while filtering all available stock market indices, namely DJI, FSV, DJC, DJT, and DJU. The second step estimates the common latent component in corporate bond total returns and yields nine distinct common latent factors. The first corporate bond-based latent factor L^{Bond} is estimated from all available composite/aggregate corporate bond indices (i.e., all maturities included), namely DJCORP_TOTAL, DJCFIN_TOTAL, DJCIND_TOTAL, and DJCUTL_TOTAL. Four other corporate bond-based latent factors (i.e., sector-based latent components L^{Corp}, L^{Fin}, L^{Ind}, and L^{Utl}) are estimated from all available corporate bond indices of a given sector (e.g., DJCFIN_2Y, DJCFIN_5Y, DJCFIN_10Y, DJCFIN_30Y, DJCFIN_TOTAL).[10] Finally,

[9] Incidentally, we also set the state variance parameter to be constant over time, namely $Var\,(L_t) = P_t = P$ whatever time t.

[10] Under this estimation scheme, the common latent factor dealing with all available DJCORP type indices illustrates the common latent component peculiar to the overall

the four remaining corporate bond-based latent factors (i.e., maturity-based latent components L^{2y}, L^{5y}, L^{10y}, and L^{30y}) are estimated from all available corporate bond indices for a given maturity (e.g., DJCORP_2Y, DJCFIN_2Y, DJCIND_2Y, and DJCUTL_2Y).

As regards U.S. stock market, L^{Mkt} is that part of total returns resulting from market-based effects (i.e., systematic risk factor, or equivalently business cycle). As regards U.S. corporate bond market, L is that part of total returns resulting from systematic effects at the investment grade level and in the lens of sector and maturity risk dimensions (i.e., credit cycle). We estimate any common latent component with a Broyden, Fletcher, Goldfarb and Shano optimization scheme and require a five digit accuracy level for corresponding relative gradients (see tables 5 and 6).

With regard to table 5, α_L coefficients are first significant at a five percent Student test level, and lie far below unity. Therefore, common latent factors in asset total returns exhibit a stable behavior over time. Second, corresponding state variance parameters σ_L^2 are generally significant except for the two-year L^{2y} and 30-year L^{30y} latent components. This issue comes probably from the high frequency pattern of our data sample (i.e., a daily basis scheme emphasizing disturbances in financial markets such as announcement effects or market anomalies in a more general way). Finally, initial values L_0 of common latent components as well as corresponding variance levels P_0 are all insignificant at a five percent Student test level.

With regard to table 6, average latent factor levels lie generally above corresponding median values. We also notice a negative skewness as well as a positive excess kurtosis whatever the common latent component under consideration. Consequently, the behavior of common components in asset total returns is far from being Gaussian (i.e., asymmetric and leptokurtic). Moreover, corporate latent factors seem to behave in a similar way to the stock market latent factor. Hence, we investigate this feature while computing the non-parametric correlation coefficients between stock market common latent factor and corporate latent factors (see table 7). We also focus on the following relative absolute noise measure (RANM) in previous table:

U.S. investment grade corporate bond market. Such an estimate represents the general dynamic trend underlying the total returns of U.S. investment grade corporate bonds.

Table 5: Kalman estimates

Estimates (t-statistics)	α_L	σ_L^2	P_0	L_0	N
L^{Mkt}	0.0547	0.7232	0.5999	0.5999	5
	(2.9741)	(5.8883)	(0.0617)	(0.0670)	
L^{Bond}	0.2550	0.5169	0.4497	0.4479	4
	(7.0020)	(2.2921)	(0.2206)	(0.0440)	
L^{Corp}	0.0338	0.8405	0.4000	0.4000	5
	(18.8424)	(23.4863)	(0.0103)	(0.0198)	
L^{Fin}	0.0780	0.6996	0.4999	0.4998	5
	(3.3251)	(21.5318)	(0.1212)	(0.2227)	
L^{Ind}	0.0458	0.9958	0.4000	0.3998	5
	(3.3597)	(3.3597)	(0.2185)	(0.0204)	
L^{Utl}	0.0455	0.7122	0.4799	0.4798	5
	(1.8920)	(22.0961)	(0.0067)	(0.0068)	
L^{2y}	0.1688	0.5785	0.3998	0.3998	4
	(5.0803)	(1.2523)	(1.2485)	(0.1563)	
L^{5y}	0.2651	0.5398	0.3998	0.3993	4
	(7.9548)	(11.6181)	(0.0317)	(0.2225)	
L^{10y}	0.1687	0.7000	0.2500	0.2495	4
	(5.4073)	(9.2113)	(0.1574)	(0.0215)	
L^{30y}	0.1520	0.5418	0.5002	0.4975	4
	(4.7731)	(1.2739)	(0.1587)	(0.1269)	

Table 6: Descriptive statistics of latent components in total returns

Latent factors	Mean	Median	Std. dev.	Skewness	Excess Kurtosis
L^{Mkt}	0.0738	0.0548	0.6820	-1.5598	23.7856
L^{Bond}	0.0641	0.0674	0.3864	-0.3568	3.0861
L^{Corp}	0.0848	0.0661	0.8146	-1.2430	25.1593
L^{Fin}	0.0765	0.0571	0.6561	-1.2925	21.3019
L^{Ind}	0.0976	0.0762	0.9470	-1.5218	24.2119
L^{Utl}	0.0745	0.0577	0.6778	-1.4419	32.0039
L^{2y}	0.0628	0.0602	0.4481	-0.3528	4.0824
L^{5y}	0.0676	0.0649	0.4055	-0.3499	3.2822
L^{10y}	0.0802	0.0752	0.5579	-0.3834	4.2412
L^{30y}	0.0615	0.0502	0.4353	-0.3877	4.9494

Table 7: Non parametric correlation coefficients and RANM for latent factors

Latent factors	Spearman	Kendall	RANM
L^{Mkt}	1.0000	1.0000	7.8548
L^{Bond}	0.4237	0.2892	4.2322
L^{Corp}	0.4603	0.3472	7.7611
L^{Fin}	0.6280	0.5030	7.5178
L^{Ind}	0.2574	0.1751	7.7738
L^{Utl}	0.1783	0.1208	7.4162
L^{2y}	0.3093	0.2074	5.2483
L^{5y}	0.3302	0.2243	4.5631
L^{10y}	0.3718	0.2556	5.2672
L^{30y}	0.5081	0.3622	6.0831

$$RANM = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{X_t - Median\,(X)}{Median\,(X)}\right| \tag{3}$$

where (X_t) is a given latent component time series with T observations and $Median\,(X)$ is the corresponding median value. Basically, the RANM is a relative risk measure, which is less sensitive to extreme values than classical moment statistics. The lower the RANM is, the more stable the corresponding latent component is. It allows then for classifying latent components from the less risky to the most risky in term of risk variation relative to a corresponding median value.

First, all correlation coefficients are significant at a one percent bilateral test level. Second, all non parametric correlation coefficients are positive exhibiting therefore a clear significant positive link between the common trend in corporate bond performance indicators and the general trend in stock market performance determinant. Moreover, in unreported results the correlation matrix between those ten latent components is also significant at a one percent bilateral test level and exhibits positive correlation coefficients. Specifically, Kendall correlation coefficients range from 0.1208 to 0.6259 whereas Spearman correlation coefficients range from 0.1783 to 0.8061 respectively. Finally, sector-based latent components exhibit the same level of relative risk (RANM) as the common latent market component, the other corporate latent components exhibiting a lower level of relative risk. Moreover, the RANM is a non-monotonous function of corporate bond maturity, the five-year systematic performance indicator being the less risky. Incidentally, the five-year systematic corporate bond performance L^{5y} exhibits the same relative risk level as the aggregate systematic corporate bond performance L^{Bond}.

4 Are credit cycle and market cycle linked?

Along with the trade-off between equity markets and corporate bond markets (Merton, 1974; Vassalou and Xing, 2003), we question the positive link prevailing between the common market performance trend and common corporate performance trend in the light of aggregate corporate level, sector and maturity dimensions. We focus specifically on the impact of general market performance (i.e., business cycle indicator) on corporate bond performance (i.e., credit cycle indicator). We target therefore to investigate a dynamic linear dependence between corporate bond market performance and stock market performance (i.e., co-monotonicity risk between stocks and corporate bonds). For this purpose, we resort to the flexible least squares (FLS) methodology to run regressions of common corporate bond performance components on common stock market performance component.

4.1 FLS regressions

The flexible least squares methodology (Kalaba and Tesfatsion, 1989, 1996) allows for estimating soundly time-varying linear regressions. Specifically, FLS method is robust to correlated observations, non-stationary data, data outliers and data specification errors among others. Moreover, this methodology can handle gradual economic and financial evolutions in approximately linear settings (i.e., approximately linear economic or financial relationships).

Investigating a dynamic linear relation between common market performance trend L_t^{Mkt} and common corporate performance trend L_t at the aggregate level or in the light of sector and maturity risk dimensions (e.g., L^{Bond}, L^{Corp}, L^{Fin}, L^{Ind}, L^{Utl}, L^{2y}, L^{5y}, L^{10y}, and L^{30y}), we consider the following regression at each time t ranging from 1 to $T = 2434$:

$$L_t = X_t \cdot \beta_t + e_t \tag{4}$$

where $\beta'_t = \begin{pmatrix} a_t & b_t \end{pmatrix}$ is a vector of regression coefficients, $X_t = \begin{pmatrix} 1 & L_t^{Mkt} \end{pmatrix}$ is a vector of explanatory variables, and e_t is a residual measurement error for step t. The trend coefficient a_t represents the general trend (i.e., average level) of systematic corporate bond performance over time whereas the slope coefficient b_t represents the dynamic (i.e., instantaneous) correlation risk between the general corporate performance trend and the general market performance trend. The residual measurement error represents that part of systematic corporate bond performance, which is unexplained by general systematic/stock market performance, namely the systematic corporate-specific performance. However, FLS framework states that measurement errors (e_t) (see equation 5) as well as specification errors (v_t) (see equation 6) have to be approximately zero.

$$e_t = L_t - X_t \cdot \beta_t \approx 0 \tag{5}$$

$$v_t = \beta_t - \beta_{t-1} \approx 0 \tag{6}$$

Basically, FLS methodology targets to minimize the following objective function $F(\beta)$ relative to $\beta = (\beta_t, 1 \leq t \leq T)$ along with a given incompatibility cost matrix C:

$$F(\beta) = \sum_{t=1}^{T} e_t^2 + \sum_{t=2}^{T} v'_t \cdot C \cdot v_t \tag{7}$$

where $C = \begin{pmatrix} c_1 & 0 \\ 0 & c_2 \end{pmatrix}$.[11] The objective function accounts for both the sum of squared measurement errors (i.e., indicator of equation errors), and the weighted sum of squared specification errors (i.e., indicator of coefficient variation), the related weights corresponding to the incompatibility cost coefficients in matrix C. Then, the impact of coefficient variation is lowered when incompatibility cost coefficients are low (i.e., volatile time-paths for regression coefficients) whereas this impact is increased when corresponding incompatibility cost coefficients are high (i.e., smooth or constant time-paths for regression coefficients).

[11] The optimal coefficient sequence $\hat{\beta} = \left(\hat{\beta}_t, 1 \leq t \leq T\right)$ is estimated conditional on observed latent components (L_t) and $\left(L_t^{Mkt}\right)$ in total asset returns.

Table 8: Incompatibility cost matrix parameters

Latent factors	c_1	c_2
L^{Bond}	50	1E-05
L^{Corp}	100	1E-06
L^{Fin}	10,000	1E-06
L^{Ind}	100	1E-06
L^{Utl}	100	1E-06
L^{2y}	10,000	1E-04
L^{5y}	100	1E-04
L^{10y}	1000	1E-04
L^{30y}	1000	1E-04

Finally, we usually assume that measurement and specification errors (e_t) and (v_t) are uncorrelated white noises (i.e., stationary uncorrelated residual errors with constant variances). Consequently, a convenient minimization scheme (see relation 7) is achieved when residual errors become white noises.

4.2 Econometric results

We run FLS regressions in order to infer to what extent common market performance trend (i.e., business cycle) drives common corporate bond performance (i.e., credit cycle) at the aggregate corporate level as well as in the light of industry and maturity patterns.

First, we get the incompatibility cost matrix parameters estimates as listed in table 8. The first coefficient c_1 is generally far more large than the second coefficient c_2, meaning that a_t time series (i.e., time-varying trend coefficient in the FLS regression) evolves generally in a stable or more regular way than its extremely volatile counterpart known as b_t time series (i.e., time-varying regression coefficient representing the sensitivity of corporate latent components to the stock market latent component).[12]

Second, we plot the more stable evolution of a_t estimates over time (see figures 1 and 2) for all available corporate latent components. The time-varying trend in corporate latent components is non-monotonous over time and exhibits frequent sign changes in general. Generally speaking (except

[12]Coefficient b_t illustrates the sensitivity of systematic corporate bond performance to systematic stock market performance over time.

for Total corporate bond sector, Utility, Financial and two-year corporate bond sectors), the trend in corporate bond performance (i.e., a_t time series) increases during key financial and economic events such as the Asian crisis, Russian default and dotcom bubble. As regards Financial and two-year corporate bond sectors, corresponding a_t time series exhibits a general decreasing trend over time.

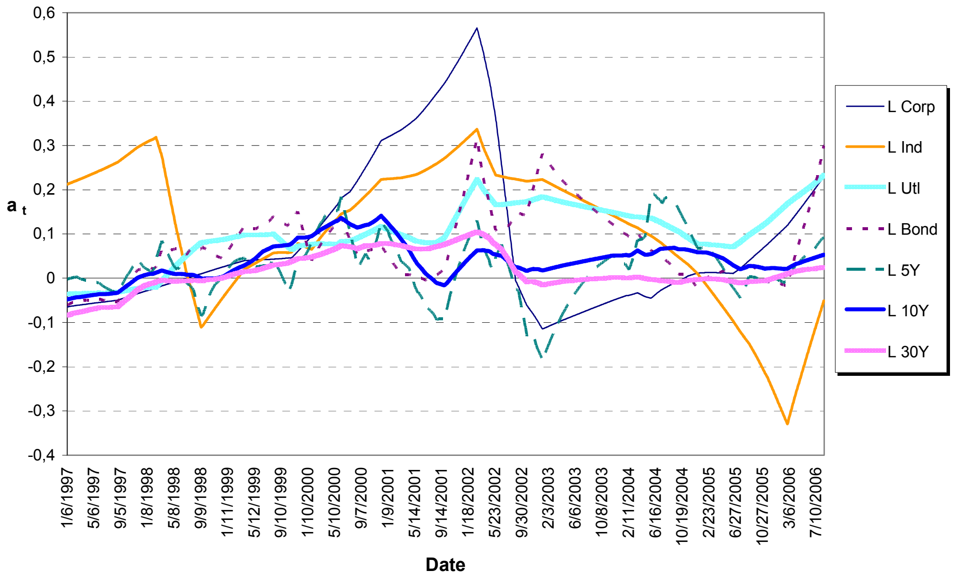

Figure 1: Regression coefficient a_t for corporate latent components.

Third, we display some informative descriptive statistics about the extremely volatile b_t time series as well as the number N_+ of observed positive values among a set of $T = 2434$ possible values (see table 9). Therefore, the link prevailing between the latent component in U.S. corporate bond total returns and the latent component in U.S. stock market total returns is extremely volatile and mitigated. On average, U.S. stock market performance drives U.S. corporate bond market performance (i.e., positive b_t coefficient) in 65.0735 percent of observed cases, the lowest ratio being 55.7518 percent for the Utility corporate bond sector and the highest proportion being 81.3887 percent for the Financial corporate bond sector. Specifically, U.S. corporate

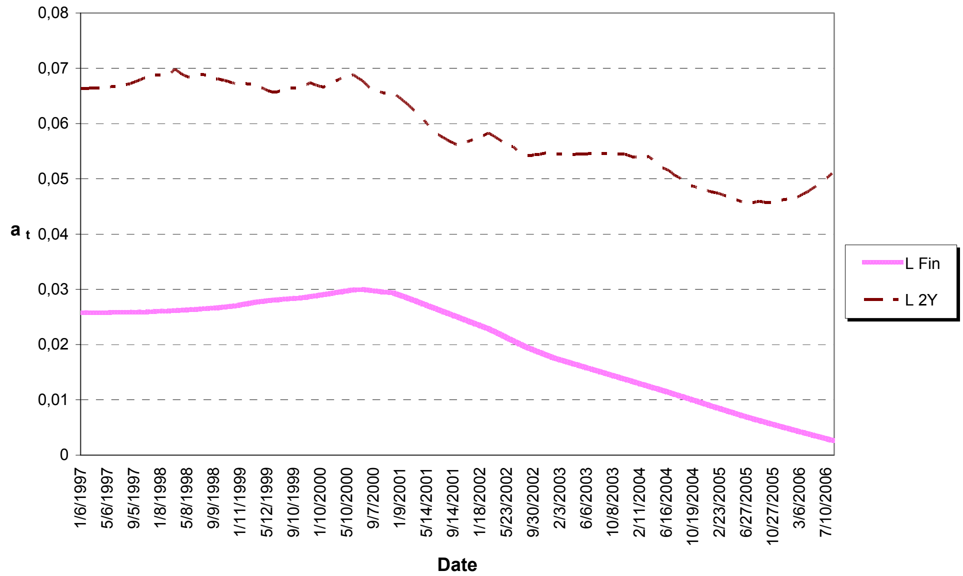

Figure 2: Regression coefficient a_t for corporate latent components.

bond market performance tends to magnify U.S. stock market performance (i.e., b_t coefficient above unity) in 32.7764 percent of observed cases on average, the lowest ratio being 26.0887 percent for the Total corporate bond sector (i.e., L^{Bond}) and the highest proportion being 50.5752 percent for the Financial corporate bond sector (see figure 3). Consequently, stock market performance tends to drive corporate bond market performance over our studied time horizon on an average basis. Excluding L^{Bond}, L^{10y} and L^{30y} latent factor cases, b_t median values lie above corresponding average values. Moreover, b_t time series are generally left-skewed (except for L^{Bond}, L^{Fin} and L^{Ind} latent factors) and exhibit a positive excess kurtosis.

In unreported results, we controlled for the soundness of our residuals (e_t) while checking successively for stationary and independency assumptions (i.e., appropriateness of classic and partial autocorrelations), and related white noise assumption (i.e., adequacy of Ljung-Box statistics). As a rough guide, we display in table 10 some related descriptive statistics.

Table 9: Descriptive statistics for b_t regression coefficients

Latent factors	Mean	Median	Std. dev.	Skewness	Excess Kurtosis	N_+
L^{Bond}	0.3485	0.2599	5.3220	0.1523	27.1993	1554
L^{Corp}	0.5103	0.6899	21.2327	-4.9673	259.5786	1699
L^{Fin}	0.9716	1.0056	11.7919	11.4982	345.3534	1981
L^{Ind}	0.1301	0.3016	27.4327	0.6871	208.0716	1432
L^{Utl}	0.0161	0.1443	14.8257	-5.2950	143.5135	1357
L^{2y}	0.1487	0.1648	4.1100	-0.5654	23.2422	1468
L^{5y}	0.1953	0.2178	3.6407	-1.0423	21.2114	1498
L^{10y}	0.4031	0.3370	5.0308	-0.6394	26.3664	1572
L^{30y}	0.4531	0.3872	3.2771	-0.9243	40.7619	1694

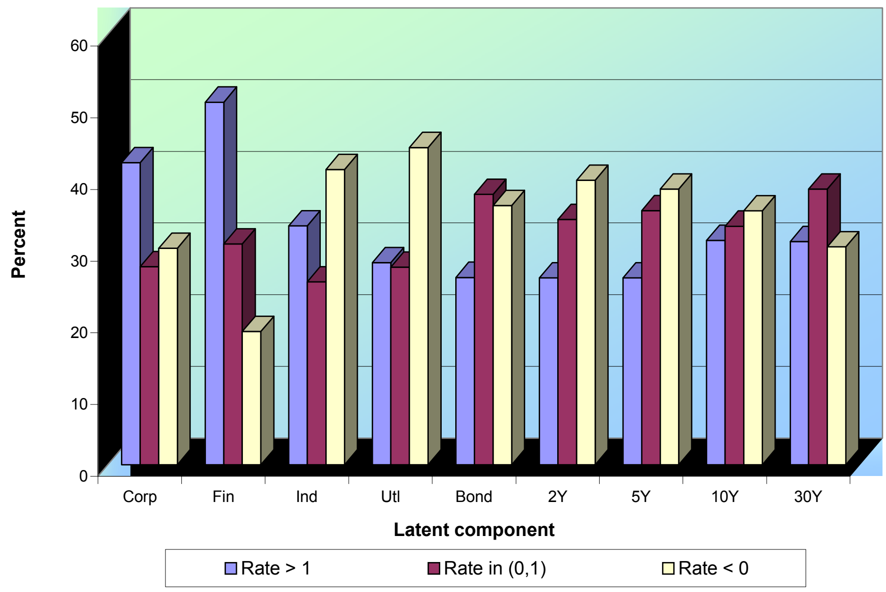

Figure 3: Percentage of values taken by b_t regression coefficient.

Table 10: Descriptive statistics for regression errors

Latent factors	Mean	Median	Std. dev.	Skewness	Excess Kurtosis
L^{Bond}	-4.0314E-12	-3.3427E-06	0.0146	246.3233	8.6547
L^{Corp}	-2.6432E-12	-4.4580E-07	0.0134	755.1069	-2.9004
L^{Fin}	1.4310E-12	-4.1666E-07	0.0054	488.2257	3.2944
L^{Ind}	-1.5589E-12	-1.1530E-06	0.0157	396.5067	-6.8359
L^{Utl}	-2.8228E-13	-7.7237E-07	0.0072	555.4439	13.2975
L^{2y}	4.1411E-12	-3.5422E-05	0.0513	94.1475	5.4030
L^{5y}	5.6501E-12	-7.9819E-06	0.0422	63.2563	1.5871
L^{10y}	-3.0597E-11	-1.6680E-05	0.0705	139.2004	5.3921
L^{30y}	-2.2914E-12	-1.8002E-05	0.0410	91.4251	-0.7365

Finally, we display in table 11 the corresponding RANM for (a_t) and (b_t) coefficients whereas the ANM (absolute noise measure) is listed for residuals (e_t). Indeed, ANM risk measure is preferable to RANM one given the nearly zero level of residuals and corresponding extremely small median values.[13] Specifically, the ANM is simply the average absolute difference of residuals from their corresponding median value as follows:

$$ANM = \frac{1}{T}\sum_{t=1}^{T} |X_t - Median\,(X)| \tag{8}$$

With regard to (a_t) coefficient, the riskier series is for L^{30y} latent factor and the less risky is for L^{2y} latent factor. The FLS regression trend is therefore the most volatile for L^{30y} case and the most stable for L^{2y} case. With regard to (b_t) coefficient, the riskier series is for L^{Utl} latent factor and the less risky is for L^{Fin} latent factor. Hence, the sensitivity of corporate bond performance to stock market performance is the most volatile for L^{Utl} case and the less volatile for L^{Fin} case. With regard to (e_t) coefficient, the riskier series is for L^{10y} latent factor and the less risky is for L^{Fin} latent factor. As a conclusion, there exists a dynamic link between corporate bond performance and stock market performance, which depends on industry and maturity among others. The structure of this link varies over time so that the co-monotonicity risk between U.S. stock market and corporate bond performance indicators exhibits

[13] Such patterns yield extremely high values for corresponding RANM.

Table 11: Absolute risk measures for FLS regression estimates

Latent factors	a_t	b_t	e_t
L^{Bond}	0.9851	8.6688	2.4845E-03
L^{Corp}	5.3180	6.9957	1.0986E-03
L^{Fin}	0.2914	2.4843	5.0281E-04
L^{Ind}	0.8815	22.4286	1.4893E-03
L^{Utl}	0.5088	29.3685	7.8459E-04
L^{2y}	0.1265	12.1362	1.2846E-02
L^{5y}	1.9637	8.4184	1.1127E-02
L^{10y}	0.8794	7.1179	1.6205E-02
L^{30y}	102.3261	4.0413	9.6974E-03

a time-varying structure. By the way, figure 3 illustrates the corresponding average co-monotonicity risk over the studied time horizon as a function of corporate bond industry and maturity among others. The co-monotonicity risk between stock market performance and corporate bond performance is obviously non-negligible.[14]

5 Conclusion

Analyzing daily U.S. stock and corporate bond total return indices (i.e., performance indicators), we shed light on the impact of stock market performance on corporate bond market performance. We realized a two-dimension study in the light of sectorial effects and maturity patterns. Sector dimension allows for investigating sector concentration risk whereas maturity dimension underlines the investment horizon risk in the light of business cycle conditions over time.

[14] In unreported results, we estimated the linear regressions for first order differences (i.e., daily changes $\Delta X_t = X_t - X_{t-1}$) of corporate bond latent factors ΔL_t on stock market latent factor ΔL_t^{Mkt} (with a constant term). All regressions exhibit significant Fisher statistics at a one percent test level although R-squares range from 0.0120 (for the two-year latent factor) to 0.1320 (for the financial latent factor) levels. All regression coefficients for ΔL_t^{Mkt} exhibit significant Student statistics at a five percent test level. Moreover, those coefficients are positive illustrating then a positive impact of stock market performance changes on corporate bond performance changes except for Utility corporate sector (i.e., negative coefficient). Finally, constant regression coefficients exhibit nearly zero values and are all insignificant at a five percent Student test level.

Our two-step analysis extracted first unobserved systematic total stock and bond returns while employing Kalman filtering methodology. We estimated the systematic stock market performance (i.e., common unobserved stock market performance trend) and the systematic corporate bond market performance (i.e., common unobserved corporate bond market performance trend) as a function of industry and maturity, and at an aggregate level as well. The systematic performance components of both stocks and corporate bonds exhibited similarities with regard to their respective behaviors over time (i.e., behavioral commonalities). Second, we investigated whether the risk/return trade-off of the U.S. stock market was driving the risk/return trade-off of the U.S. investment grade corporate bond market (i.e., investigating some strong dynamic link). Specifically, we characterized the dynamic linear link between systematic stock and corporate bond performances (i.e., time-varying correlation risk). The structure of this link revealed to be highly volatile. By the way, we disentangled times when this link was negative from times when this link was positive (or even times when the corporate bond market was magnifying stock market shocks). Over the studied time horizon, systematic U.S. stock market performance seemed to drive systematic U.S. corporate bond market performance (in more than fifty five percent of observed cases).

Our study can however be expanded to analyze speculative grade corporate bonds as well (i.e., riskier corporate issues). Moreover, Kalman filtering methodology could be used in a forecast prospect or for a scenario analysis purpose (i.e., stress testing) rather than as an estimation tool (e.g., forecasting the global systematic risk of an asset portfolio). This concern is significant for determining the degree of comovements between the corporate issues of a credit portfolio along with the sensitivity of credit risk determinants (e.g., total returns of corporate bonds) to systematic risk factors for example. Basically, the significance is supported by both the severity of credit portfolios' potential losses and corresponding correlation/contagion risk (e.g., systematic risk management in corporate bond portfolios).

Finally, our methodology is a preliminary investigation for establishing new adapted performance reporting and credit risk monitoring tools. Indeed, it could yield a useful methodology for sorting and discriminating between corporate bonds in credit portfolios. Therefore, our study could be the prelude to a useful selection and classification tool in a (credit) portfolio risk management prospect.

6 Appendix: Index plots

To get an initial view, we display underneath the plots describing the Dow Jones Total return indices under consideration. Plots are ordered according to sectors and maturities respectively.

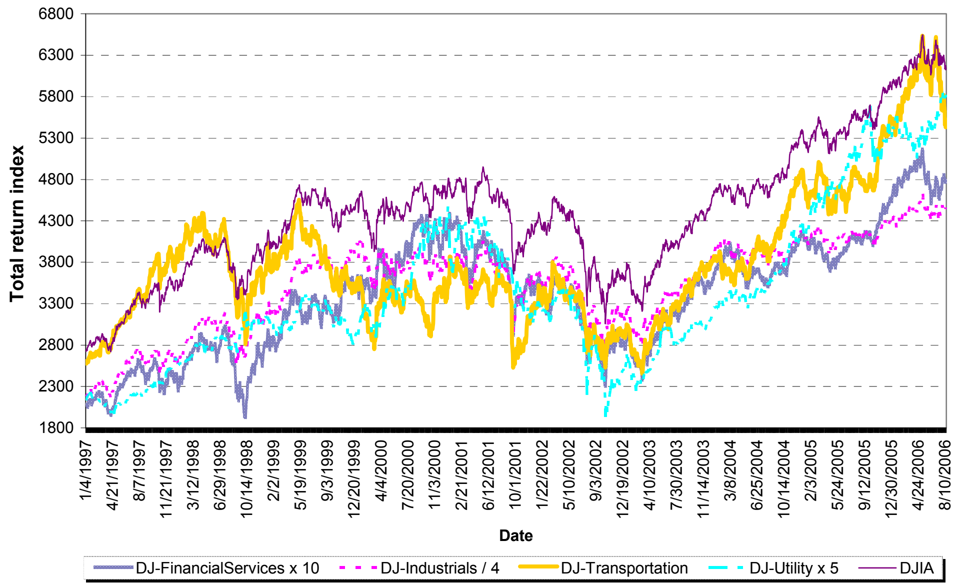

Figure 4: Dow Jones stock market indices.

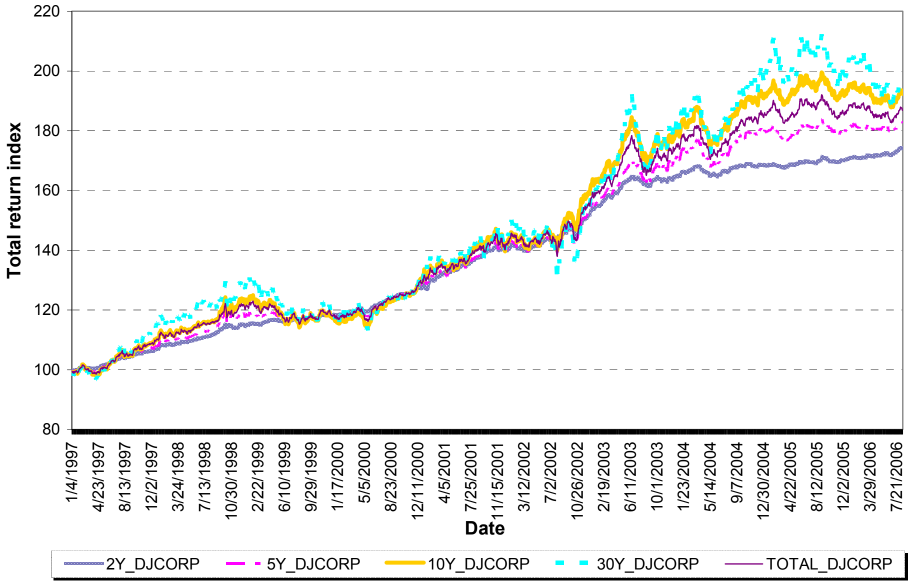

Figure 5: Dow Jones composite corporate bond index.

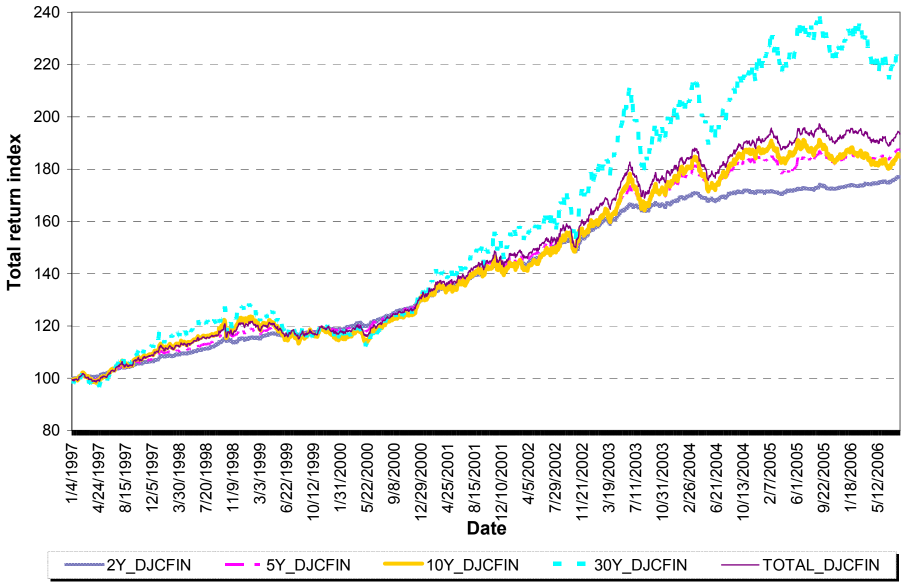

Figure 6: Dow Jones financial corporate bond index.

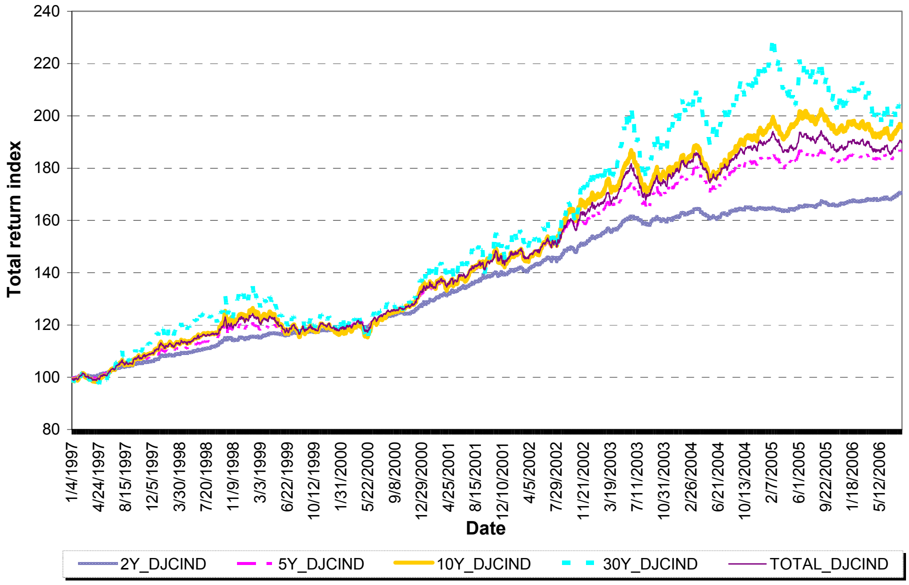

Figure 7: Dow Jones industrial corporate bond index.

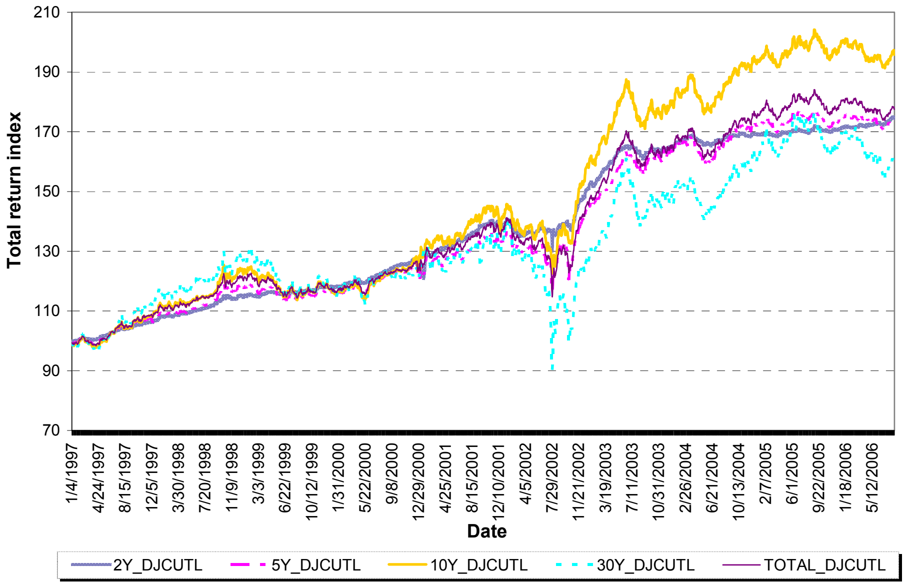

Figure 8: Dow Jones utility corporate bond index.

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