MACROECONOMIC NEWS, TIME-VARYING RISK FACTORS, AND TIME-VARYING RISK PREMIA:

THE CASE OF THE US STOCK AND BOND MARKETS

Alexandre Vézina

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ABSTRACT

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The basic purpose of this paper is to investigate the sources of time-varying risk premia for both the U.S. stock and bond markets. In addition, we look at the sources of time-varying conditional variance and conditional covariance of these two markets. Although a large literature has emerged on the return and volatility of any of the two markets, few studies propose a model in which both markets are modeled together. Moreover, after all the research done, the reasons explaining the causes of the volatility of any of the two markets remain unclear. What we propose in this paper is a model that considers both markets' volatility simultaneously. Our model captures the change in the risk premium, if any, to each market's own volatility risk as well as to the covariance risk for specific events. More specifically, we investigate if macroeconomic news is a source of time-varying volatility as well as time-varying covariance, and whether these results in time-varying risk premia in either of the markets. We find that stocks, as opposed to bonds, mainly exhibit a change in the risk premium on variance risk. The results suggest that most of the change is due to the PPI announcements. Our models also indicate that there is a change in the bond risk premium on covariance risk on macroeconomic news announcement dates. Finally, linear regressions show that employment reports and PPI releases are a source of time-varying conditional variance for stock, notes and bond returns.

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« Dans un monde ou chacun triche, seul l'homme vrai fait figure de charlatan »

- Gide

« Les lâches meurent plusieurs fois avant leur mort ; Le brave ne goûte jamais la mort qu'une fois »

- Jules César

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Introduction

In finance, it is well known that volatility is used as a measure of risk. Of course, there are many kinds of risk in finance. Those risks can be divided into two broad classes: Macroeconomic risk (e.g., country specific risk and industry specific risk) and microeconomic risk (e.g., firm specific risk). Because the different macroeconomic and microeconomic characteristics vary through time, we should expect volatility to vary through time. These changing conditions are known to occur randomly. On the other hand, the disclosure of information to market participants can occur either randomly (e.g., merger announcements) or at pre-announced dates (e.g., employment report releases). Because risks vary through time, we wonder if risk premiums vary through time also.

Many researchers have modeled this time-varying volatility without making the difference between preannounced news releases and non-preannounced news releases. This is problematic, however. In a market with rational agents, the reaction of asset markets should depend only on the unanticipated component of the release. Since preannounced news releases are generally periodic and because investors can form better expectations than for non-preannounced news releases, the latter should generate, on average, higher volatility due to its larger unanticipated component. However, even a small unanticipated portion of a preannounced release could lead to large movement in stock and/or bond market returns. For example, a 0.1% difference below the anticipated unemployment rate number in period of high economic activity may adversely affect both the stock and bond markets due to higher inflation prospect.

Previous studies have examined the sensitivity to macroeconomic risks for individual assets classes. For example, Hardouvelis (1987) examines stock price indices while Ederington and Lee (1993) examine interest rate futures. Jones, Lamont, and Lumsdaine (1998) (JLL henceforth) look at bond markets. However, they leave many unanswered questions. They mention: "Since bonds but not stocks have high return variance on (macroeconomic) announcement days, we might expect that the conditional covariance of stock and bond returns falls on announcement days". We address that question in this study.

If the pricing of both assets (stock and bond) is sensitive to a particular risk, then we might expect the covariance of returns of these two assets to be the only risk factor to be rewarded. The reason is that there are no specific risks but instead a common risk. If both assets are equally sensitive, then the reward to risk should be the same for the two markets. On the other hand, if one particular asset exhibits specific risk over one particular (macroeconomic) risk, then we might expect the volatility of that particular asset to be the rewarded. In that case, we might expect the risk premium on variance risk to increase with the riskiness of the asset. Since we look at macroeconomic risks, we should find unusually high changes in the risk premium to covariance risk on macroeconomic release date if both markets are risk sensitive to the information contained in one particular macroeconomic release to compensate for the common risk. However, if only one market is risk sensitive to the information contained in one particular macroeconomic release, then we should find unusually high changes in its risk premium to variance risk on the release date to compensate for the specific risk exposure.

Recently, academicians have used relatively new types of models - the AutoRegressive Conditional Heteroskedastic model and its Generalized version - to study the time-varying return, time-varying volatility, and time-varying risk premium properties of different types of securities (see Bollerslev et al. (1992) for a survey of past literature on ARCH and GARCH models). Among other things, these models show that volatility in financial markets is correlated over time. Researchers are still debating why this is so. One possible explanation (see Lamoureux et al. 1990) is that the ARCH effect reported for daily returns is the result of a mixture of distributions, in which the rate of daily information arrival is the stochastic mixing variable. ARCH would in fact capture the time series properties of this mixing variable. In any case, ARCH and GARCH models seem to guide us one step closer to the ultimate goal of modeling financial securities' volatility with reasonable confidence levels.

We use a bivariate GARCH-M framework similar to the one used by Doukas and Switzer (2000) and Bekaert and Harvey (1995) to study the time-varying risk premium of two different security markets. This bivariate GARCH model is a variant of the original ARCH and GARCH models developed by Engle (1982) and Bollerslev (1986). The model we use is also a special form of the multivariate GARCH model first introduced by Bollerslev (1990) in that it does not impose a constant conditional correlation constraint as opposed to Bollerslev (1990). The reason for using constant conditional correlation is that it is computationally easier in that it reduces the number of matrix inversions. However, Longin and Solnik (1995) show that it is not appropriate to do so when modeling equity returns. Like the standard univariate ARCH and GARCH models, the

Multivariate GARCH model permits us to study time-varying return, time-varying volatility, and time-varying risk premium by having one advantage over the standard univariate ARCH and GARCH models. It allows the dependent variables, i.e., the returns, conditional variances or conditional covariance of returns, to be a function of the conditional covariance of two return series.

Our approach in this paper is to look at the effect of some preannounced macroeconomic news releases in order to explain some of the daily differences in risk premia. We investigate the impact, if any, of three of the most important macroeconomic news releases on the US stock and bond markets' risk premia. These variables are the employment report, the PPI, and industrial production. Our model estimates the impact of macroeconomic news releases on each market's risk premium to its own volatility risk, which depends on security-specific information. In addition, we examine, for the first time to our knowledge, the impact of news on risk premium to covariance risk, which should depend only on global information.

The paper is organized as follow. We first provide a brief review of the relevant literature. Next, we provide a discussion of the data and present preliminary statistics and analysis. In part 3, we describe the methodology used to model time-varying risk premium. More specifically, we present the different classes of bivariate GARCH-M models. The results of the estimation follow in part 4. We analyse conditional variance and conditional covariance of stock and bond returns in part 5. We conclude in part 6 and present some suggestions for future work.

1. Literature Review

Other studies that use the multivariate GARCH framework to examine the relation between conditional market volatility and expected returns concentrate on international stock markets (Doukas and Switzer (2000), Bekaert and Harvey (1995), and Chan, Karolyi, and Stulz (1992)) or exchange rate markets (Baillie and Bollerslev, 1990). We use the multivariate GARCH framework to study the US stock and US bond markets' risk premiums.

Macroeconomic variables, especially their unexpected components, were used extensively in past studies to explain stock and bond returns. We discuss some of these articles to emphasis the impact that some macroeconomic variables have on stocks and bonds. However, while research on (changing) volatility accrued during the last two or three decades, it is only recently that researchers seriously considered macroeconomic variables as possible explanatory variables in there models. Some researchers find that some macroeconomic variables are more important than others to explain volatility. For example, it appears from previous literature that the employment report and PPI news releases have a significant impact on the volatility of interest rate securities (Jones et al., 1998; McQueen and Roley, 1993; Ederington et al., 1993) as well as on large stocks' volatility (Connolly and Strivers, 1999) and option volatility - implied volatility (Ederington et al., 1996; Donders et al., 1996) on announcement days. Of course, the level of explanatory significance of macroeconomic variables may depend on the security that we study.

Most of the following studies do not discuss risk premia on macroeconomic risks but only discuss interest rate changes and stock price index responses to macroeconomic releases. They also discuss stock and bond volatility on macroeconomic news release dates.

Hardouvelis (1987) examines the impact of unanticipated changes of monetary and nonmonetary variables stock price indexes (the S&P 500, the Amex Major Market index, the Value Line index, and the NYSE Financial index) as well as on interest rate securities (3 month T-Bills and 20-year T-Bonds) over two sample periods: October 11, 1979 - October 5, 1982, and October 6, 1982 - August 16, 1984. The sample split is motivated by the Federal Reserve switch from non-borrowed reserves to borrowed reserves targeting in October 1982.

For the pre-October 1982 period, monetary announcements are shown to significantly impact stock prices (M1 and the federal discount rate have a negative sign, whereas the free reserves have a positive coefficient) as well as on interest rates (M1 and the federal discount rate have a positive sign, whereas the free reserves have a negative coefficient). The NYSE Financial index shows the strongest reaction to the monetary announcements.

Concerning the non-monetary variables, personal income and the trade deficit have a significantly positive effect on the stock indices (except for the S&P 500), whereas the unemployment rate and the trade deficit are significantly negative for T-Bills. Finally, the PPI and personal income are significantly positive and negative respectively for T-Bonds.

For the post-October 1982 period, Hardouvelis reports that monetary announcements have a weaker effect. Only M1 is significant for both stocks (negative coefficient) and interest rates (positive coefficient). Further, from the non-monetary announcements, only the unemployment rate is statistically significant for the stock indices (positive coefficient) and the T-Bill (negative coefficient), whereas the CPI (positive), the PPI (positive), the unemployment rate (negative), and the durable goods (positive) are significant for the T-Bond. Finally, the author reports that the structural response of the return series to the announcements change only for the three-month T-Bill rate after October 1982. The other series exhibit similar responses to the announcements in both sub-periods.

Hardouvelis (1988) studies the exchange rate, Federal funds rate, T-Bill rate, and T-Bond rate (and exchange rates) reactions to 15 unanticipated components of macroeconomic releases. Similar to Hardouvelis (1987), he uses a sample period from October 1979 through August 1984.

Hardouvelis first regresses the change in interest rates on the unanticipated component of the economic series announcements (the independent variables). Few significant results for the Federal funds rate are shown. However, he finds that monetary variables strongly influence the T-Bill and T-Bond rates. Unanticipated changes in M1 have a significantly positive effect on the T-Bill as well as on the T-Bond rates for the complete period. Also, unanticipated changes in the unemployment rate and in retail sales affect (significantly negative and positive respectively) both the T-Bill as well as the T-Bond rates. The author concludes that an unanticipated increase in the unemployment rate (retail sales) signals a future (increase) decrease in the aggregate demand which causes a decrease (an increase) in the T-Bill and T-Bond rates.

Further, it is shown that the free reserves (negative sign), the discount rate (positive sign), and the surcharge rate (positive sign) variables are significant in the T-Bill rate equation only. The free reserve reaction is due to the expected liquidity effect. On the other hand, Hardouvelis argues that the positive sign of the discount rate and surcharge rate is due to the market expectation of future tightening by the Fed, which increases the expected future real interest rate due to an expected liquidity effect.

Finally, inflation news has a strong positive effect on the T-Bond market (CPI and PPI are significantly positive). The personal income (negative sign) is also found to be significant in the T-Bond market. This is because an increase of the personal income is the result of an increase in the aggregate supply. This increase of the aggregate supply is deflationary and this causes the long-term interest rate to fall.

A more recent study that looks at the relationship between macro variable announcements on asset markets is Ederington and Lee (1993). This study uses intraday data to assess the impact of nineteen monthly scheduled macroeconomic news announcements on interest rate (and foreign exchange) futures markets' volatility for the period from 1988 through 1991. They find that these announcements are responsible for most of the observed intraday and day-of-the week volatility. In fact, once the impact of these announcements is removed, volatility is flat across the trading day and across the trading week. Also, like Harvey and Huang (1991), Ederington and Lee report that Thursdays and Fridays exhibit relatively higher interest rate volatility than other days of the week. They hypothesize that it is due to the employment report being released on Fridays and the PPI usually being released on Thursday or Friday.

They also conclude that employment, PPI, CPI and durable goods orders are the monthly macroeconomic variables with the greatest impact on interest rates. They find that most of the price adjustment occurs within one minute of the release. However, even if they report that return volatility is much higher between 8h30 and 8h35 than during any other time in the day, they also report that volatility continues to be higher than normal for another fifteen minutes, and slightly higher for several hours. The explanation they provide is that the release of those macroeconomic variables could affect interest rates because either they signal a likely change in the demand for credit or because the Federal Reserve is believed to consider these variables when setting monetary policy.

In a subsequent paper, Ederington and Lee (1995) examine the price adjustment of T-Bond, Eurodollar, and Deutschemark futures markets to scheduled macroeconomic news releases. Like their previous paper, they use 18 macroeconomic announcements. However, they also provide some results for the pooled major announcements. For the T-Bond market, the major announcements are the employment report, PPI, and CPI. Their sample consists of 10-second interval returns (as opposed to 5-minute intervals for Ederington and Lee, 1993) and tick-by-tick data for the period from November 7, 1988 through October 30, 1992. Ederington and Lee use a 12-minute window, from two minutes before the news release to 10 minutes after.

Their major findings are that these markets adjust very quickly to new information. Since we focus on T-Bonds, the next conclusions apply to this type of security only. First, markets adjust very quickly. When they consider the 18 announcements as a whole, volatility increases in the next 10 seconds following the news announcements, and reaches a peak in the 20 to 30 seconds interval. For both samples, the 18 announcements and the major announcements, most of the information adjustment is done within 40 seconds. Note that the adjustment is made with many small price changes rather than one large change. Finally, for the larger sample (18 announcements) only, they report a significantly negative reaction that starts 90 seconds after the release and lasts for 30 seconds.

They also report higher than normal volatility for the period preceding the announcement. However, they mention that the returns are not correlated with returns following the announcements. Finally, average abnormal returns (AARs) and cumulative abnormal returns (CARs) are small and insignificant for the period prior to the announcements. Thus, they conclude that it is unlikely that there is information leakage.

In a more recent paper, Ederington and Lee (1996) study the impact of information release – scheduled and unscheduled announcements – on implied volatility from the T-Bond, Eurodollar, and Deutschemark option markets. Only the results applying to the interest rate option market will be reported herein. The period covered is from November 11, 1988 through September 30, 1992.

They use 12 macroeconomic variables as the scheduled announcement news. From those 12 macroeconomic variables, the employment report, the PPI, and the CPI are the only statistically significant variables. The variance of returns (not ISD) on days when the employment report is released is 4.7 times the variance on days with no scheduled announcements, whereas it is 3.5 and 2.5 times when the PPI and CPI are released respectively.

Further, they report that the implied standard deviation (ISD) from the interest rate options markets increases (an average of 0.505%) in the pre-release period as the uncertainty is high, but drops back (an average of 0.781%) to normal once the announcement is made, and this source of uncertainty is resolved. Once again the employment report has a relatively strong effect. The ISD declines, on average, by 4.4% on the day the employment report is released. Also, in 80% of the times, releases of the employment report are followed by a decline in ISD.

The authors report that the greater the usual day t volatility of a particular announcement, the greater the decline in the ISD following the announcement. Once again, the employment report has a greater impact on the interest rate ISD than on any other variables. In addition, they find that, in general, on days with no scheduled announcements the rise is greater the shorter the option's time-to-expiration.

On the other hand, they find that the release of unscheduled announcements results in unexpectedly high volatility (high ISD) that remains in the post-release period. The reason might be that market participants anticipate other unscheduled news, consistent with the volatility clustering phenomena.

Finally, similarly to Ederington and Lee (1995), they show that the ISD pattern of falling on Fridays and rising on Mondays can be explained by the fact that scheduled announcements are generally released on Fridays. That is, from their sample, employment reports are issued on Friday in 44 of the 45 Fridays (and the ISD declines on average by 4.40%), whereas PPI are usually released on Thursdays or Fridays. On the other hand, Monday is the day with the lowest number of releases.

Jain (1988) studies the impact of money supply announcement surprises as well as of CPI, PPI, industrial production, and unemployment rate announcement surprises on hourly stock returns (S&P 500) and hourly trading volume (NYSE volume). He finds that the S&P 500 index adjusts to unanticipated change announcements in the money supply and CPI within one hour. Those announcements have significant negative effects on stock prices. On the other hand, he finds no reactions of the S&P 500 return index to the unemployment rate, the PPI, and the industrial production unanticipated components.

For that reason we might expect to find no significant reaction of the risk premium to variance risk on macroeconomic release dates. Another possibility could be that we find significantly negative reactions on announcement days if volatility increases. However, we must keep in mind that we use a different time period as well as a different framework. Furthermore, we are not dealing with anticipated or unanticipated components but with announcement dates only. Finally, Jain also finds that these macroeconomic variable announcements have no consequences for trading volumes.

Bollerslev et al. (2000) examine, using intraday data, return volatility of US Treasury bond futures contracts. They split the volatility process in three distinct components. The time-of-the-day patterns (intraday calendar effects), macroeconomic announcements (public information effects), and the well-documented interday volatility persistence (ARCH effects). They employ a MA(1) - FIGARCH model to estimate the daily volatility. They use this estimate in a Flexible Fourier form (FFF) regression to estimate the calendar, announcement, and day-of-the-week effects.

First, they find a time-of-the-day pattern in that the volatility is higher at 8h30 and 10h00. These two time periods correspond to the regularly scheduled macroeconomic announcements in the US. Second, they report a U pattern in the intraday volatility, which results in a (U-shaped) daily pattern in the autocorrelation of the absolute 5-minute returns. Third, they find that macroeconomic news announcements are the most important source of intra and interday volatility among the three components. More specifically, they find that the Humphrey-Hawkins testimony, the employment report, the PPI, the employment cost, retail sales, and the NAPM survey have the greatest impact. Finally, they report that the fixed income market exhibits long-memory volatility dependencies.

Connolly and Slivers (2000) study the volatility-clustering phenomenon. One explanation of the ARCH behaviour is the public-information hypothesis. More specifically, the ARCH behaviour reflects autocorrelated news-volatility that is associated with cyclical public-information releases. Another explanation for volatility clustering is the signal ambiguity hypothesis. This hypothesis suggests that ARCH reflects the presence of imperfect information with ambiguous signals. This explanation suggests a stronger ARCH effect following ambiguous market-information signals. In contrast to other studies, they examine firm-level stock returns of the 30 large firms that comprise the DJIA. They attribute volatility clustering in firm-level returns to two factors, namely common-factor (market level) and idiosyncratic-factors (firm-level).

They use an asymmetric GARCH(1,1) model similar to Glosten et al. (1993), which implies higher conditional volatility following negative return shocks, as compared to lagged positive return shocks of the same magnitude. Their major findings are that inter-temporal market-to-firm volatility flow:

- Decreases following macroeconomic news announcements (PPI and employment announcement days)
- Does not change during the high-news months when firms typically announce quarterly earnings
- Increases substantially following:
    A) Market periods with relatively high trading volume (they assume that periods with high trading volume reflect periods of high signal ambiguity and of diverse beliefs across traders),

B) High cross-sectional return dispersion periods,

C) High futures' open interest periods.

According to Connolly and Slivers, these findings suggest that volatility clustering is associated with signal ambiguity and diverse beliefs across traders, and not the autocorrelation in scheduled news releases.

Jones et al. (1998) first argue that public information that has no anticipated announcement days arrive in clusters, and that this information is generally significantly positively autocorrelated at daily frequencies. This would cause autocorrelated volatility. Thus, they decide to focus on information releases that are not autocorrelated, i.e. information for which the release dates are preannounced to investigate autocorrelation in volatility. They use two macroeconomic variables, namely the employment and producer price index (PPI) data. Their paper studies the daily Treasury bond price reaction to U.S. macroeconomic news releases. Thus, they test whether shocks to bond volatility on macroeconomic announcement days are as persistent as shocks on nonannouncement days.

The basic point of their work is to investigate whether these non-autocorrelated announcements give rise to autocorrelated volatility. More specifically, they try to find out if effects on volatility persist over time or if it is immediately incorporated into bond prices, consistent with the efficiency theory. Further, they address the question "is the investor rewarded for these macroeconomic risks?" In other words, if these macroeconomic news results in higher volatility, can investors expect higher returns from treasury bonds?

In order to investigate the impact of public information releases, they use a GARCH (1,1) model similar to the one of Bollerslev (1986). Then, where other authors have used ARCH in mean developed by Engle et al. (1987) to test whether time-varying risk premiums are a function of the estimated conditional volatility, Jones et al. test whether announcement days, which usually offer high bond market volatility, exhibit high expected returns.

Their major findings are the following. First, PPI and employment announcements have large contemporaneous effects on bond market volatility but this effect dissipates on the following day. For example, daily absolute excess returns, which is a proxy for volatility, are 0.375%, 0.558%, and 0.776% respectively for the 5-, 10-, and 30-year bonds on announcement days. On the other hand, the same measures are 0.254%, 0.388%, 0.543% for the nonannouncement days. Second, they find that bonds earn significantly higher excess returns on announcement days. The Sharpe measures on the announcement days are 0.166%, 0.145%, and 0.137%, respectively, for the 5-, 10-, and 30-year bonds, compared to 0.011%, 0.009%, and 0.008% for the nonannouncement days.

Both finding are supported by the fact that, using OLS to control for day of the week, they find that absolute excess returns as well as excess returns on days preceding and following the announcements for the 5-, 10-, and 30-year bonds are lower than on announcement days. The difference also increases with the bond's maturity in both cases.

Next, they use a GARCH(1,1) model in which a dummy variable is included to indicates the announcement day. This procedure permits one to measure the announcement-day effect on both conditional mean returns and conditional volatilities. The results confirm the previous findings. There is a significant risk premium on the announcement days for the three maturity bonds. Furthermore, volatility experiences a statistically significant increase on the announcement day.

Finally, Jones et al. check whether announcement-day volatility shocks are as persistent as nonannouncement-day volatility shocks. They use a model in which the conditional variance is a regime-switching GARCH process where the regime shifts occur at the announcement dates. They find that announcement-day volatility shocks exhibit no persistence at all, and that volatility on the days following the announcements is not higher than average.

Few papers examine linkages across different asset classes. Flemming et al. (1998) examine the nature of volatility linkages between stock futures, T-Bond futures, and T-Bill futures. Two sources of volatility linkages between the three markets are possible. First, common information, which is information that simultaneously affects multiple markets (e.g., Ederington and Lee, 1995). The second source of volatility linkage between markets is called information spillover. Information spillover can be caused by cross-market hedging. This happens when a shock (or information) alters expectations about one market (stocks or bonds). Because investors may rebalance their portfolios, demand for that market may change. This results in a cash transfer from one market to another. The cash transfer depend on the correlation of returns between the markets. Thus, demand for both markets is influenced by information that initially affects only one market. The information spillover generates trading and volatility in both markets. This is the second way that information creates volatility linkages between markets.

First, they consider daily information flow proportional to the variance of daily returns. Consistent with previous findings that volatility follows an autoregressive structure, they develop a stochastic volatility model that allows log volatility (information flow) to follows an AR (1) process. Further, instead of using multivariate GARCH models to measure the linkages, they use GMM. This model helps in determining how information creates cross-market linkages and in estimating the contemporaneous correlation between the information flows in the different markets. The correlation between the variance-covariance matrices of two markets measures the strength of the informational linkages between the two markets. In other words, if the variance-covariance matrices of the two markets are highly correlated, then this is an indication that the information linkage between the two markets is high, as any information will move both markets with similar amplitude for different reasons. On the other hand, return correlations indicate the effectiveness of cross-market hedging which should influence the degree of information spillover. However, as FKO mention, "this implicitly assumes that the best forecast of volatility is simply its unconditional mean", which is not necessarily true.

They find strong volatility linkages between the three markets but it is not a complete one. Whereas the cross-market correlations of returns for S&P 500 - T-Bond, S&P 500 - T-Bills, and T-Bond - T-Bills are 0.35, 0.13, and 0.66, the correlation between the log information flows (volatility) is 69% for the stock and Bond markets, 67% for the stock and Bill pairing, and 64% for the Bonds and money markets. The later results are consistent with large information spillover, and thus with strong volatility linkages across the three markets.

Finally, using Kalman filter estimates to test for structural stability, they find that the volatility linkage is stronger for the post 1987 stock market crash period. Also, they report that their model explains much of the skewness and excess kurtosis in the return series.

One explanation for the presence of ARCH is that daily returns follow a mixture of distributions, where the rate of daily information arrival is the stochastic mixing variable. The aim of Lamoureux and Lastrapes (1990) is to show that the ARCH effect of daily returns reflects the serial correlation of this mixing variable. They argue that the variance of daily price increments is positively related to the rate of daily information arrival. They use daily trading volume as a proxy for the mixing variable, the rate of daily information arrival.

In their paper, they use a GARCH(1,1) model to examine the variance of daily returns of 20 individual stocks. Their unrestricted model includes individual stock volume whereas the restricted version does not include volume. They report strong evidence that daily stock returns can be characterized by the GARCH model (the ARCH and GARCH terms are statistically significant) when the volume is not included in the variance equation. However, when including volume, it is found to have significant explanatory power regarding the variance of daily returns since the coefficient on volume is significantly positive for each of the 20 companies. Further, volume explains much of the non-normality of the unconditional distributions. Finally, the ARCH effects disappear when volume is included in the conditional variance equation for 16 of the 20 common stocks.

Lamoureux and Lastrapes conclude that ARCH is the result of the daily time dependence in the rate of information arrival to the market for actively traded individual stocks. Using stock volume, they provide evidence that the ARCH process observed in daily stock return series reflects information clustering. For this reason, we will also include the NYSE volume as an independent variable to explain conditional variances and covariances of stock and bond returns.

2. Data and Preliminary Results and analysis

Our Study

The first objective of this paper is to check whether there is a change in the risk premium to covariance risk as well as to variance risk on macroeconomic new release dates. This is important for different reasons, whether it is for investing purposes, hedging purposes, or for pricing purposes. It is even more important when the two markets consist of the US equity market and the US Treasury bond market, two of the largest security markets in the world. Finally, we explore whether macroeconomic news releases are a source of time-varying volatility for both the stock and bond markets. More specifically, we study the reactions of the conditional variances and conditional covariances of stock and bond returns on macroeconomic announcement days.

This paper is different than the one of Jones et al. (1998) in that not only do we check volatility and risk premium to volatility risk on macroeconomic announcement days for bonds, but we also do so for stocks and for bonds and stocks. We use a multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) in mean framework in which the expected returns in any security are regressed on their own return variance as well as on their return covariance with another security. The coefficients indicate the risk premia to variance risk and to covariance risk. This model accommodates for interaction effects within the conditional mean and conditional variance and covariance of two (or more) series. Thus, it provides a suitable framework to study the transmission mechanism of mean and volatility shocks across different securities. Furthermore, we include indicator variables that represent variance and covariance on specific macroeconomic news release dates. In this way, we are able to study if the risk premia change on those announcement days. Finally, we provide a check for time-varying conditional volatility as well as for time-varying conditional covariance.

Data

We use daily returns on the S&P 500 index, and on the five-, ten-, and thirty-year Treasury bonds. We obtain the S&P 500 index from Bloomberg. We use the 5-, 10-, and 30-Year Treasury constant maturity interest rate series from the Federal Reserve Bank of Saint-Louis. We calculate the excess return on the S&P 500 and on holding Treasury bonds using the secondary market three-month T-Bills rate also obtained from the Federal Reserve Bank of Saint-Louis.

The daily continuously compounded excess return on the S&P 500 is simply the difference between the logarithm of daily S&P 500 return and that of three-month T-Bills rate, or:

= ln(1 + S&P 500) -ln(1 + T-Bill)

We calculate daily continuously compounded excess returns on bonds in the same way as in Jones et al. (1998) and Ibbotson and Associates (1994). Total returns equal capital appreciation plus the excess income that accrues over the holding period. The holding period is assumed to be one business day, which means that the holding period may vary from 1 to four days due to weekends and holidays.

The return from buying and selling a bond is calculated as follow: We compute the end-of-period (one business day after having bought the bond) price on this bond using the end-of-period yield as the discount rate, and the current yield as the coupon rate. Then, we subtract the beginning-of-period price, which we assume to trade at par (coupon rate equal to the yield). For example, for calculating the daily continuously compounded excess return from 01/10/79 to 02/10/79 on the 30-year Treasury bond, we proceed as follow:

Date	3-mo T-Bill yield	30-yr yield
01/10/79	10.15%	9.32%
02/10/79	10.37%	9.28%

Total excess return = excess income + capital gain/loss

= (9.32%- 10.15%) * (N/365) + (P(9.28%,9.32%) - 100) / 100,

However, to compute the continuously compounded excess return, we proceed as follow:

= ln(1+((9.32%*(N/365)) + ((P(9.28%,9.32%) - 100) / 100))) – ln(1+10.15%*(N/365)))

Where P(x, y) is the price of a hypothetical 30-year bond with a coupon of y trading at a yield of x, and N is the number of days in the holding period. In this example, we are buying the bond on 01/10/79 and then selling it one day later on 02/10/79.

Like Doukas and Switzer (2000) and Bekaert and Harvey (1995), our model includes weights for each type of security. The US stock market capitalization is, by far, more important than the capitalization of government bonds. Market capitalization data for the U.S. were obtained from Morgan Stanley Capital International (MSCI), whereas outstanding amount for Treasury Bills, Treasury notes, and Treasury bonds were obtained from Wefa Group. Thus, those indices are used to compute weights. Because we have monthly series, we dynamically interpolate the market capitalization observations within the month using the index returns to approximate the real daily numbers. Extending the interpolations from the month end to the beginning of the month matches closely the actual beginning of the month weights reported by MSCI. As for the outstanding amount of each maturity debt, we also interpolated the monthly observations to get daily numbers. However, because of monthly offerings, interpolating using respective rates of each series result in imprecise numbers relative to actual end of the month figures. Thus, we use a linear interpolation to get closer numbers. Finally, we use NYSE daily share volumes from the NYSE.

The PPI and employment announcement dates are obtained from the U.S. Bureau of Labor Statistics. The industrial production release dates are obtained from the Federal Reserve Board.

As in Jones et al. (1998), we use a sample that starts on October 1979. The reasons are various. First, Jones el al. like others (e.g., Hardouvelis, 1988 and Jain, 1988) find evidence of a structural break in interest rate data in October 1979. More specifically, Jones et al. report that the effect of announcement days on Treasury securities' volatility for the period before October 1979 is minute. Also, they do not reject the hypothesis that release dates have no effect on the volatility of bonds prior to October 1979. One of the reasons explaining this shift is the change in the U.S. Monetary Regime. In fact, the US Federal Reserve shifted its focus in October 1979 from targeting interest rates to targeting monetary aggregates. The literature suggests that this change represents a shift in monetary policy. Note that the Federal Reserve shifted its focus once again in October 1982. Other reasons explaining the non-response of bonds' volatility to PPI and employment report releases are the changes in data quality (Krueger, 1996), learning by financial markets, and changes in macroeconomic structure.

Preliminary Results

Our sample period covers 249 months (5197 trading days) of data. Two employment reports were released on a Saturday (March 5, 1983 and November 1, 1986) whereas the PPI was released once on a Saturday (February 15, 1986) and once on a Sunday (February 12, 1989). Finally, one industrial production statistic was released on a Saturday (December 14, 1985). We classify those releases as if they were announced on the next trading day. Table 1, in the appendix, shows the distribution of the macroeconomic release dates throughout the weekdays for each announcement. As we can see for the three macroeconomic variables, the release dates often fall on Fridays. For the 747 announcements, 501 (67%) happen on Fridays. This is more obvious for the employment report (238/249) whereas the Industrial Production release dates are more evenly distributed. Note how Monday is an unpopular day for each of the three announcements.

It is also important to mention that only 15 days include both announcements - the employment report and the PPI - on the same day since October 1979. Furthermore, 14 of these 15 event dates occurred between January 1980 and September 1981. The only other case where the employment report and PPI were released in the same day happened on January 9, 1987. The PPI and the industrial production numbers were released 52 times during the same day. Finally, the employment report and the industrial production were never released together on the same day since October 1979. Thus, for the complete sample, there are 680 of the 5197 days (13.1%) with at least one announcement, and 4517 of the 5197 days (86.9%) with no announcement.

Table 2-A, in the appendix, gives summary statistics for the four financial series for the period from October 1, 1979 through July 5, 2000. The S&P 500's daily continuously compounded excess return is the largest with 0.022 % per trading day, whereas it ranges from 0.008% to 0.015% for the debt. The (daily) Sharpe measures range from 0.02 (30-year bonds) to 0.023 (5-year bonds). Also, magnitude of the daily excess returns for the S&P 500 is relatively large with returns as high as 8.69% (on October 21, 1987) and as low as –22.96% (on October 19, 1987). These extreme values might be an indication of negative skewness. However, notice that both of these extreme values occurred during the period surrounding the 1987 crash. On the other hand, the range of extreme values concerning daily excess returns for debt increases with maturity. The extreme values for the 30-year bonds are –3.94% (on February 19, 1980) and 7.25% (on October 20, 1987). Note that none of these dates are an announcement date. As suggested, the S&P 500 shows negative skewness (-2.31), while the debt securities show positive skewness that decreases with maturity. Finally, the S&P 500 series is much more fat-tailed (kurtosis of 51.48) than the debt series. The kurtosis measure decreases with debt maturity. It is 6.77 for the 5-year notes.

Since the Jarque Bera statistic is significantly different from zero for the three series, we reject the assumption of normality, that is, for the three debt series and for the S&P 500 series. Note that the Jarque Bera follows a Chi-square distribution with 2 degrees of freedom. At the 5% level, the critical value is 5.99.

We also present in table 2-A the compounded excess return on announcement days and non-announcement days for each security over the complete sample period. Those are the returns that investors would have earned over the complete period by investing in any of the four securities on each announcement day (non-announcement day) only. These returns do not include transaction costs.

Even if days with at least one announcement only account for 13% of the sample, they account for a large proportion of the returns earned during the total period. The S&P 500 earned 68.4% on days with at least one announcement versus 43.0% on days with no announcements. Also, most of the 30-year bond excess returns are earned during days with at least one announcement (69.3%) compared to days with no announcements (9.9%).

The autocorrelation coefficients are shown in table 2-B for the S&P 500, as well as for the 5-, 10-, and 30-year bonds. The first-order autocorrelation coefficients are positive and significant for the 5-, 10-, and 30-year bond excess returns (0.10, 0.08, and 0.05 respectively). The first-order autocorrelation coefficients are also positive and significant for the S&P 500, the 5-, 10-, and 30-year bonds' absolute excess return (0.19, 0.18, 0.15, and 0.06, respectively) as well as for the squared excess returns (0.12, 0.16, 0.12, 0.04, respectively). Note that the second-order autocorrelation coefficients are often the highest for the absolute and squared excess returns. Because absolute values are usually considered proxies for standard deviations, the four return series exhibit autocorrelated volatility. This may justify the use of ARCH/GARCH models to explain the conditional variances of returns. We formally test for ARCH/GARCH effects using a test from Engle (1982). To compute the test statistic, we regress asset returns on a constant and save the residuals. Then, we square the residuals and compute an autoregression of lag length n. Finally, the test statistic is calculated as $T*R^2$ where T is the sample size and R^2 comes from the autoregression. This statistic follows a χ^2 distribution with n degrees of freedom. Similarly to Connolly (1989), we estimate an autoregression of lag length 1, 2, 4, and 10. Table 3 reports the results. There is strong evidence of ARCH/GARCH effects in each of the security return series since we reject the null hypothesis at the 1% level for each lag length.

We also present (table 2-C) the cross-correlation of any of the 5-, 10-, or 30-year bond returns (at time T) and the S&P 500 returns (at time T – L, where L is the number of the lag). Note that if there are significant cross-correlations for the negative (positive) lags, then that indicates current values of a particular bond return series are correlated with future (past) values of stock returns, i.e., the bond returns (stock returns) are leading the S&P 500 returns (bond returns) by L periods.

Even if the daily excess return correlations for the bonds and stocks are the highest at time 0, i.e., the bonds and stocks' daily excess returns are contemporaneously correlated, the numbers are still very low to conclude that both markets are integrated. Note also that negative lags for the excess return series suggest that bond returns lead stock returns. However, the coefficients are either non-significant or very low. Concerning the absolute daily excess return series' correlations, the highest coefficients also occur at lag (0), followed by lag (–1), which suggests that all three bond series' (the 5-, 10-, and 30-year bonds) volatility are leading stocks' volatility to a certain extent (the coefficients are 0.085, 0.109, and 0.117 for the 5-, 10-, and 30-year bonds, respectively). Note that most of the lags are significant for all three pairs of absolute excess return series. Finally, we see that the squared excess returns series are relatively highly correlated (0.302, 0.382, and 0.502 for the 5-, 10-, and 30-year bonds, respectively) at lag (-1) compared to other lags. Once again, this suggests, to a certain extent, that bond volatilities are leading stock volatility by one day.

Tables 3, 4, and 5, in the appendix, present the means and standard deviations of the four daily excess return series on the pre-, post-, and announcement days for the employment report, PPI, and industrial production releases, respectively. We also show the covariance between the S&P 500 and any of the 5-, 10-, and 30-year bonds. Finally, we compute the Sharpe measure, which is a risk premium statistic. We do not pool the macroeconomic announcements together as in JLL (1998). The reason is that there are significant differences between the results for the three announcements.

First, most of the return series are non-normal. This is not surprising as we anticipate that each security exhibits different properties (unusual mean and volatility) on the three days surrounding macroeconomic announcements.

Next, for all three announcements over the three days (pre-, post-, and announcement days), stock volatility is higher than bond volatilities. Also, the standard deviation of bond returns as well as the covariance of stock returns and any of the bond returns increase with bond maturity for all three announcements over the three days.

Pre-Announcement days

Tables 4, 5, and 6 show that pre-announcement days of employment report and PPI (but not industrial production) releases are characterized by significantly lower than average stock and bond volatilities. Covariance of stock returns and bond returns appear slightly lower than average on employment report pre-announcement days, slightly higher than average on industrial production pre-announcement days, and reasonably higher than average on PPI pre-announcement days.

Also, the S&P 500 risk premium is negative on employment and PPI pre-announcement days but higher than average on industrial production pre-announcement days (4.9%). Bond risk premia are higher than average on industrial production (15.9%, 16.3%, and 17% for the 5-, 10-, and 30-year bonds respectively) and employment report (13%, 10.1%, and 4.1% for the 5-, 10-, and 30-year bonds respectively) pre-announcement days whereas they are negative on PPI pre-announcement days.

Announcement Days

From tables 4, 5, and 6, we note that the S&P 500 exhibits significantly higher than average volatility on employment report and PPI announcement dates (1.097 and 1.168 respectively versus 1.037 for the complete sample period). On the other hand, the stock index experiences significantly higher risk premia on release dates of any of the macroeconomic variables (Sharpe measure ranges from 5.4% to 6.2%) compared to the complete period (Sharpe measure of 2.2%).

The 5-, 10-, and 30-year bonds experience significantly higher volatility on employment and PPI release dates (at the 1% level). Thus, our results seem consistent with previous studies that find that the employment and PPI releases have more impact than industrial production releases on both bond and stock volatility. Similar to stocks, the risk premia of bonds are unusually high on any of the three macroeconomic announcement days. In fact, bonds risk premia rise considerably more than the S&P 500 risk premium on the employment, PPI, and industrial production release dates. Note that PPI announcements are associated with the highest risk premia of all announcements. The Sharpe measures range from 15.4% to 17% on PPI announcement dates compared to about 2% for the whole sample period for all three fixed income securities. Overall, we can say that macroeconomic risks are compensated with higher risk premia.

Stock return and bond return covariances experience significant increases on announcement days relative to pre-announcement days for the employment report and PPI releases. Compared to average, the covariances of stock index returns and the 5-, 10-, and 30-year bond returns double on employment report release dates, increase by half on PPI announcement dates, while they slightly decrease on industrial production announcement days. To the extent that conditional covariances behave similarly to these unconditional series, these results are not consistent with JLL (1998)'s conjecture. Formal examination of the conditional covariances follows in section 5.

Post-Announcement days

If we find persistent volatility following the macroeconomic news announcements, i.e., the announcement and post-announcement volatilities are similar, than we may conclude that macroeconomic news announcement shocks do not vanish and the market is unable to fully price the new information as uncertainty remains. On the other hand, if macroeconomic announcements do not cause permanent shocks to stocks and/or bonds, we should observe falling volatility on post-announcement dates. In this case, we may conclude that market quickly adjusts to public information. However, this does not necessarily suggest that the market is efficient as lower volatility does not necessarily suggest more accurate pricing.

We find that stock volatility reverts to normal on employment report post release days, as the volatility is no longer significantly different from volatility on average days. On the other hand, stock volatility soars on PPI and industrial production post-announcement days. Bond volatilities decrease on employment report and PPI post-announcement days, but are still significantly higher than average. On the other hand, similar to stocks, bonds volatilities increase on industrial production post-announcement days (from the announcement days). It seems reasonable to say that those announcements cause a shock – and autocorrelated volatility - to most of the securities, at least temporarily. The shock seems higher for stocks on PPI and industrial production release periods.

As we see from the three tables, the covariances of stock and bond returns decrease on all three macroeconomic post-announcement days. Not surprisingly, the highest decrease happens on PPI post-announcement days as stock volatility increases while bond volatilities decrease. On the macroeconomic news post-announcement days, the covariances fall to the point that they are lower than usual.

Finally, stock and bond risk premia experience a significant drop on each macroeconomic post-announcement day compared to the announcement days. In fact, stock risk premia are negative and lower than bond risk premia on the three macroeconomic post-announcement days. Bond risk premia are also negative on employment report post-announcement days and close to average on PPI and industrial production post-announcement days.

Using the F test, we show in tables 4, 5, and 6 whether or not announcement days (as well as pre- and post-announcement days) excess return variances are significantly different from variances of excess returns for the complete sample period. However, due to the nonnormality of most of the return series, we now will present more robust tests for similar return series. To perform these tests, we use log returns, $\ln(P_t/P_{t-1})$, as opposed to log excess returns, $\ln(P_t/P_{t-1}) - \ln(R_{Tbills,t})$.

Nonparametric Tests

We first present the Mann-Whitney U-test (see Sheskin, 1997), which is a median equality test for two subgroups. To perform this test, we rank the series from the smallest value (rank 1) to largest, and compare the sum of the ranks from subgroup 1 to the sum of the ranks from subgroup 2. If the groups have the same median, the values should be similar. The null hypothesis is that the two distributions are the same. The Mann-Whitney U statistic is computed as follow:

$$U = N_1(N_2) + \frac{N_1(N_1+1)}{2} - \sum R_1$$

Where ΣR_1 is the observed sum of ranks for sample 1, and $\{N_1N_2 + N_1(N_1+1)/2\}$ is the maximum possible value of ΣR_1.

We also present the Brown-Forsythe (modified Levene) test (Brown and Forsythe, 1974), which is useful for testing the null hypothesis of the equality of variances between subgroups. The test statistic is computed as follow:

Let $\tilde{e}_1$ and $\tilde{e}_2$ denote the median of the residuals in each group. Define

$$d_{i1} = |e_{i1} - \tilde{e}_1| \text{ and } d_{i2} = |e_{i2} - \tilde{e}_2|$$

$$t^* = \frac{\bar{d}_1 - \bar{d}_2}{s\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$$

and the statistic with

$$\bar{d}_j = \sum d_{ij} \text{ for } j = 1,2 \text{ and } s^2 = \frac{\sum\sum(d_{ij} - \bar{d}_j)^2}{(n-2)}$$

Because these tests assume that the subsamples are independent, we delete all announcement days from the complete sample period. We report the test statistics in tables 7 and 8 respectively for each security on each announcement days and on each pre- and post-announcement day.

As we see, the median of the 5-, 10-, and 30-year bond returns are significantly higher on PPI (1% level) and industrial production (10% level or less) announcement days than on nonannouncement days. This is somewhat surprising for returns on industrial production release days as excess returns on those days in table 6 are lower than excess returns on employment report announcement days in table 5. The median of the 5-, 10-, and 30-year bond returns on industrial production pre-announcement days are also significantly higher than on nonannouncement days at the 1% level. On the other hand, there is only weak evidence that median stock returns on any of the macroeconomic news release days is significantly higher than on nonannouncement days. However, we must keep in mind that the Mann-Whitney U-test is a conservative test as it is less likely to find a difference between the two subsamples if a real difference exists.

Concerning the variance equality tests, we see from table 8 that the Brown-Forsythe tests yield similar results to the F tests, at least when we compare the employment report and industrial production announcement days to the nonannouncement days. More specifically, stock return variance as well as the 5-, 10-, and 30-year bond return variances are significantly higher (at the 5% level or less) on employment report announcement and pre-announcement days than on nonannouncement days. The variances of returns on industrial production release days are not significantly different from those on nonannouncement days for all of the securities. Only on industrial production post-announcement days do we find that the variances of stocks, 10-, and 30-year bond returns are significantly higher than other days. Finally, the 5-, 10-, and 30-year bond return variances are statistically significantly higher (at 1% level) on PPI announcement days than on nonannouncement days whereas stock return variances are not. However, all four securities experience higher variances on PPI post-announcement days than on nonannouncement days.

Weekend Effect or Macroeconomic News Releases Effect?

One possible explanation for the declining stock and bond risk premia on macroeconomic post-announcement days might be that market participants overreact on announcement days and adjust the following day. Another explanation might be that the negative returns are due to the "Weekend Effect", or that the weekend effect is due to the tendency of important macroeconomic news to be released on Fridays. The rationale is that many of the news releases occur on Fridays, whereas the next trading is usually Monday.

In table 1, we report the release date distribution across days of the week. In table 9-A (see appendix), we report the mean daily excess returns for each security on the pooled macroeconomic news release dates classified by day of the week. In tables 9-B and 9-C, we report the test statistics (and their p-values) for mean tests (T-tests) and of median tests (Wilcoxon/Mann-Whitney tests), respectively. More specifically, we test whether or not excess returns on each day of the week (when there is at least one announcement) are significantly different from excess returns on nonannouncement days.

Since a large portion of the releases are made on Fridays one might ask: Are the abnormally high stock and bond returns on macroeconomic news release dates due to the releases themselves or because the announcements are confounded by other phenomena causing weekend effects? On the other hand, one could argue that the weekend effect is due to the large portion of important macroeconomic variables to be released on Fridays. In other words, if we find that announcements made on Fridays yield relatively higher returns than releases made on other days of the week, then it is possible that one effect causes the other. However, even in that case, it is possible that both effects are unrelated. On the other hand, if we find no evidence that returns are higher for macroeconomic news announcements made on Fridays, then we cannot conclude that macroeconomic news releases cause the weekend effect nor can we conclude that the higher returns on macroeconomic news release days are due to the weekend effect.

As we see from table 9-A, returns do not appear to be higher for announcements made on Fridays compared to announcements made on the other days of the week. Table 9-B suggests that the S&P 500 index returns are significantly higher than nonannouncement days when announcements are made on Mondays, Wednesdays and Thursdays. On the other hand, Tuesdays, Thursdays, and Fridays seem to be favourable announcement days for bonds as the mean excess returns are significantly different from nonannouncement days. However, the median tests (see table 9-C) do not indicate that bond excess returns are higher for announcements made on Fridays compared to nonannouncement days. Thus, it appears that macroeconomic announcements are not associated with unusual returns on weekends.

3. Modeling Time-Varying Risk Premia

As opposed to Engle et al. (1987) and others that use ARCH-in-means to test whether risk premiums of securities change over time, we use a multivariate GARCH-in-mean model similar to the one used by Chan et al. (1992). This type of model allows the conditionally expected returns of one type of security to be a function of its own return variance as well as its covariance with another security's returns, which is not the case for ARCH-in-mean models. It is an excellent tool to capture time-varying risk premium or time-varying volatility. The model suggests that if both markets do not share the same risk sensitivity, then each market will be compensated differently, i.e., expected returns of each market will be determined by its return variance times the price of variance. The price of variance depends on the weighted relative risk aversion of market participants in each market. If both markets share the same risk sensitivity, then both markets will be compensated equally according to their return covariance times the price of covariance.

Similarly to Bekaert and Harvey (1995), our models have three sources of time-variation in expected returns: variation in the prices of risk (coefficients), variations in the conditional risk measures (variances and covariance), and variations in the weights. Note that the weights for the S&P500/30-year bonds bivariate GARCH model vary from a minimum of 54.2% (December 1987) to a maximum of 94.2% (June 2000) in favour of the S&P 500. For the S&P500/5-year notes and S&P500/10-year notes bivariate GARCH models, the weights vary from a minimum of 71.3% (October 1990) to a maximum of 92.5% (June 2000) in favour of the S&P 500.

Our model also allows for time-varying correlations. We use the structure proposed by Engle and Kroner (1995), i.e. the BEKK parameterization, of the multivariate GARCH process. This ensures a positive semi-definite H_t (Variance-Covariance) matrix, which is necessary for the estimated variance to be greater than or equal to zero. This is the case because the BEKK parameterization makes use of quadratic forms in a way that no restrictions are required to ensure a positive semi-definite H_t matrix. The H_t matrix evolution is written as:

$\varepsilon_t \sim N(0, H_t)$,

$$H_t = \begin{bmatrix} h_{Stocks,t} & h_{Stocks-Bonds,t} \\ h_{Stocks-Bonds,t} & h_{Bonds,t} \end{bmatrix}$$

$$= C'C + A'H_{t-K}A + B'\varepsilon_t\varepsilon_t'B,$$

Where H_t is the 2X2 variance-covariance matrix, A and B are matrices of coefficients, and C is an upper triangular matrix of coefficients. ε_t is the vector of residuals with conditional mean 0 and conditional variance-covariance H_t. H_t is a linear function of its own K past values as well as of values of squared shocks.

Because this methodology implies no restriction of constant correlation between the S&P 500 and bonds, it allows us to check whether the correlations across securities are constant over time. Having no restriction of constant correlation implies that increased comovements in the stock index and bond series may be due to changes in both the covariance structure of returns as well as the correlation structure.

We are dealing with five bivariate GARCH models. Four of these are unrestricted models while the fifth is the restricted case. Each model includes the S&P 500 excess returns series as a dependent variable of one equation and any of the three bond excess return series – i.e., the five-, ten-, or 30-year Treasury bonds - as a dependent variable of the second equation. Similar to Bekaert and Harvey (1995) and Doukas and Switzer (2000), we add, in the unrestricted cases, indicator variables that allow us to check the effects of specific events on the risk premiums. We use macroeconomic news release dates as indicator variables. This framework tells us if there is a significant change in the risk premium to variance and covariance risk on macroeconomic release dates. The macroeconomic variables we analyse are the employment report, the PPI, and the industrial production releases.

Our first model includes two indicator variables that represent the two macroeconomic news releases that have the highest impact on both stock and bond returns as well as on stock and bond returns variances as recognised by the literature and confirmed by our preliminary analysis. These two variables are the PPI releases and the employment report releases.

Model 1:

$$R_{Stocks,t} = \alpha_{10} - (\beta_1 + \beta_{11}*Emp_t + \beta_{12}*PPI_t)w_{Stocks,t}h_{Stocks,t} - (\delta_1 + \delta_{11}*Emp_t + \delta_{12}*PPI_t)*(1\text{-}w_{Stocks,t})h_{Stocks\text{-}Bonds,t} + \varepsilon_{Stocks,t} \quad (1)$$

$$R_{Bonds,t} = \alpha_{20} - (\beta_2 + \beta_{21}*Emp_t + \beta_{22}*PPI_t)w_{Bonds,t}h_{Bonds,t} - (\delta_2 + \delta_{21}*Emp_t + \delta_{22}*PPI_t)*(1\text{-}w_{Bonds,t})h_{Stocks\text{-}Bonds,t} + \varepsilon_{Bonds,\,t} \quad (2)$$

Our second model includes an additional indicator variable that represents the industrial production releases.

Model 2:

$$R_{Stocks,t} = \alpha_{10} - (\beta_1 + \beta_{11}*Emp_t + \beta_{12}*PPI_t + \beta_{13}*Ind_t)w_{Stocks,t}h_{Stocks,t} - (\delta_1 + \delta_{11}*Emp_t + \delta_{12}*PPI_t + \delta_{13}*Ind_t)*(1\text{-}w_{Stocks,t})h_{Stocks\text{-}Bonds,t} + \varepsilon_{Stocks,\,t} \quad (3)$$

$$R_{Bonds,t} = \alpha_{20} - (\beta_2 + \beta_{21}*Emp_t + \beta_{22}*PPI_t + \beta_{23}*Ind_t)w_{Bonds,t}h_{Bonds,t} - (\delta_2 + \delta_{21}*Emp_t + \delta_{22}*PPI_t + \delta_{23}*Ind_t)*(1\text{-}w_{Bonds,t})h_{Stocks\text{-}Bonds,t} + \varepsilon_{Bonds,\,t} \quad (4)$$

In these first two models, Emp, PPI, and Ind are indicator variables that are set to 1 on the employment report, PPI, and Industrial Production release dates respectively, and equal 0 otherwise.

In model 3, we pool the employment report and PPI releases into a unique dummy, Dum.

Model 3:

$$R_{Stocks,t} = \alpha_{10} - (\beta_1 + \beta_{11}*Dum_t)w_{Stocks,t}h_{Stocks,t} - (\delta_1 + \delta_{11}*Dum_t)(1\text{-}w_{Stocks,t})h_{Stocks\text{-}Bonds,t} + \varepsilon_{Stocks,t} \quad (5)$$

$$R_{Bonds,t} = \alpha_{20} - (\beta_2 + \beta_{21}*Dum_t)w_{Bonds,t}h_{Bonds,t} - (\delta_2 + \delta_{21}*Dum_t)(1\text{-}w_{Bonds,t})h_{Stocks\text{-}Bonds,t} + \varepsilon_{Bonds,\,t} \quad (6)$$

In model 4, we now combine the three macroeconomic releases together to form a unique dummy, Dum.

Model 4:

$$R_{Stocks,t} = \alpha_{10} - (\beta_1 + \beta_{11}*Dum_t)w_{Stocks,t}h_{Stocks,t} - (\delta_{10} + \delta_{11}*Dum_t)(1\text{-}w_{Stocks,t})h_{Stocks\text{-}Bonds,t} + \varepsilon_{Stocks,t} \quad (7)$$

$$R_{Bonds,t} = \alpha_{20} - (\beta_2 + \beta_{21}*Dum_t)w_{Bonds,t}h_{Bonds,t} - (\delta_2 + \delta_{21}*Dum_t)(1\text{-}w_{Bonds,t})h_{Stocks\text{-}Bonds,t} + \varepsilon_{Bonds,\,t} \quad (8)$$

In (5) and (6), Dum is an indicator variable that is set to 1 on either the employment report release dates or on the PPI release dates. In (7) and (8), Dum is an indicator variable that is set to 1 on either the employment report release dates, on the PPI release dates, or on the industrial production release dates.

Finally, the restricted model 5 does not include any indicator variable.

Model 5:

$$R_{Stocks,t} = \alpha_{10} - (\beta_1)w_{Stocks,t}h_{Stocks,t} - (\delta_1)(1-w_{Stocks,t})h_{Stocks\text{-}Bonds,t} + \varepsilon_{Stocks,t} \quad (9)$$

$$R_{Bonds,t} = \alpha_{20} - (\beta_2)w_{Bonds,t}h_{Bonds,t} - (\delta_2)(1-w_{Bonds,t})h_{Stocks\text{-}Bonds,t} + \varepsilon_{Bonds,t} \quad (10)$$

4. The Multivariate GARCH results

Parameter estimates are obtained by maximizing the log-likelihood function. Conditional log-likelihood functions are computed as

$$L_t(\theta) = -\log 2\Pi - \tfrac{1}{2}\log|H_t| - \tfrac{1}{2}\, e_t'(\theta)H_{t-1}(\theta)e_t(\theta)$$

Where θ is the vector of all parameters β_{ij} for i = S&P 500, 5-, 10-, 30-year bond and j = 1 or 2 whether it is variance or covariance respectively. To maximize this log-likelihood function, we use the simplex and Berndt, Hall, Hall, and Hausman (1974) algorithms. The BHHH algorithm provides the final parameter estimates, associated standard errors, and p-values.

To test the null hypothesis that the estimated coefficients are equal to 0, we use the likelihood ratio test. For large sample sizes,

$$-2[L(\beta_R) - L(\beta_{UR})] \sim \chi^2_m$$

Where m is the number of restrictions. If the statistic is greater than the critical value, we reject the null hypothesis that the restriction applies, i.e., we conclude that the indicator variable coefficient estimate is significantly different from 0. In most situations involving linear models, especially those with large sample sizes, the more traditional F tests and the likelihood ratio tests should generate very similar results. However, the likelihood is more appealing when large samples are used in part because it requires no assumption of normality. Remember that we rejected previously the null hypothesis of normality for our four return series.

If the pricing of both assets (stock and bond) is sensitive to a particular risk, then we might expect the covariance of returns of these two assets to be the only risk factor to be rewarded. The reason is that there are no specific risks but instead a common risk. If both assets are equally risk sensitive, then the reward to risk should be the same for the two markets. On the other hand, if one particular asset exhibits specific risk over one particular (macroeconomic) risk, then we might expect the volatility of that particular asset to be the rewarded. In that case, we might expect the risk premium on variance risk to increase with the riskiness of the asset. Since we look at macroeconomic risks, we should find unusually high changes in the risk premium to covariance risk on macroeconomic release date if both markets are risk sensitive to the information contained in one particular macroeconomic release to compensate for the common risk. However, if only one market is risk sensitive to the information contained in one particular macroeconomic release, then we should find unusually high changes in its risk premium to variance risk on the release date to compensate for the specific risk exposure.

Statistically significant β_{ik} where k = 1, 2, or 3 indicate that security i's returns are significantly influenced by security i's own return volatility on macroeconomic variable k's announcement date. In other words, statistically significant β_{ik} indicate that security i's risk premium to variance risk is significantly different from 0 on macroeconomic variable k's announcement date. Statistically significant δ_{ik} where k = 1, 2, or 3 indicates that security i's returns are influenced by security i's returns covariance with security j's returns on announcement k's date. Thus, statistically significant δ_{ik} indicate that security i's risk premium to covariance risk is significantly different from 0 on macroeconomic variable k's announcement date. Many possibilities could explain that. It could be due to higher returns, lower covariance risk, a positive change in the covariance risk that is lower than a positive change in the security returns, or a negative change in the covariance risk that is higher than a negative change in the security returns. Finally, to a certain extent, we can say that employment report, PPI, and Industrial production release dates will be considered as a source of temporary increase (decrease) in integration if the estimated coefficients δ_{1k} is found to be significantly positive (negative).

The estimated coefficients, their t-statistics and p-values, as well as the likelihood ratio statistics of the multivariate GARCH models are reported in table 10 (see appendix).

Non-Pooled Macroeconomic Variables Models

Let us first analyse the results for models 1 and 2, i.e., the non-pooled macroeconomic variable models. We find that the likelihood ratio statistics are greater than the critical value at 1% for S&P500/5-year notes models. This indicates that employment report and

PPI releases create a regime shift. Furthermore, from model 2, we can reject the null hypothesis that the restrictions apply for the S&P500/10-year notes model at the 5% level. Finally, from model 1, it seems appropriate to reject the null hypothesis for the S&P500/30-year bond models.

As general conclusions, we find for models 1 and 2 that a stock-specific component of risk is rewarded on PPI release days. The β_{12} coefficient is significantly positive and varies from 0.16% to 0.23%. We also find for model 2 that stocks risk premium to covariance risk is significantly negative on PPI announcement days. δ_{12} ranges from –2% to –3.2%. Thus, stocks are compensated for a specific and common component of risk on PPI announcement days. Note that neither stock risk premium to variance risk (β_1) or stock risk premium to covariance risk (δ_1) are significantly different from 0 on regular trading days. On the other hand, bonds risk premium to covariance risk (δ_{22}) is significantly positive on PPI announcement days in both models. In fact, on PPI announcement days, a change of 1% in covariance results in a change of about 0.60% to 0.67% to any of the bond returns. Note that bonds risk premium to covariance risk is usually significantly negative (δ_2 is about –0.21%). This suggests that on regular trading days, excess returns decrease (increase) for a positive (negative) change in covariance.

Finally, most of the remaining significant relations involve the S&P 500/5-year notes. We see that δ_{21} is significantly positive in the two bivariate GARCH models involving the S&P 500/5-year note returns which implies that there is significantly positive shift in the 5-year notes risk premium to covariance risk on employment report announcement days.

On employment report release days, a one-percent change in covariance seems to produce a change of about 0.40% to 0.45% to the 5-year note returns. Finally, industrial production releases appear to have an impact on 5-year notes risk premium to volatility risk since the β_{23} is significantly positive in model 2-A. Note that on regular trading days, there seem to be a significantly positive premium to 5-year notes specific component of risk as β_2 is significantly positive.

Pooled Macroeconomic Variables Models

Finally, we pool the employment report and PPI announcements together. The results are reported for model 3. We also pool the employment report, PPI and industrial production announcement together and report the results for model 4. First, except for model 4-C, the likelihood ratio statistics indicate that we can reject the null hypothesis that the restrictions apply at the 5% level or less. This means that the macroeconomic releases are a source of temporary regime shifts for the period starting from October 1979 through July 2000.

Furthermore, there is a significantly positive change in the stocks' risk premium to volatility risk on announcement days. This suggests that stocks exhibit a specific component of risk to macroeconomic variable releases that market participants reward with higher returns.

Also, for both models (models 3 and 4), it seems that the risk premium on covariance risk for bonds increases on macroeconomic release days as δ_{21} is usually significantly positive. This is even truer for models that include the S&P 500 and the 10-year notes. Note that there is a significant relationship between bonds excess returns and bonds returns covariance with stocks returns on regular trading days.

While some macroeconomic variables are more important than others, the release time is also important. In fact, the employment report, which is generally considered to be the most important macroeconomic variable in the literature as well as among the financial community, is normally the first government release concerning economic activity in a given month. It is usually followed by the PPI, which is released before industrial production (and CPI). Thus, we might hypothesis that earlier releases can be used to predict the later releases, and from that, later releases are less important. This might explain why we find that industrial production releases do not offer significant changes in the risk premiums, the reason being that these macroeconomic announcements do not offer much more new information concerning the health of the economy. However, it does not explain why the PPI releases offer more evidence of a change in the risk premium to variance and covariance risks than employment report releases.

5. Modeling Conditional Variance and Conditional Covariance

Our next step is to model the conditional variance and conditional covariance of models 1 and 2. More specifically, we investigate if macroeconomic news announcements are sources of time-varying conditional variance and/or conditional covariance. We use the employment report, PPI, and industrial production releases as indicator variables. We also include the lag of the dependent variable (conditional variance or conditional covariance of any of the S&P 500, 5-, 10-, and 30-year bond returns) as an independent variable since we previously found the presence of ARCH/GARCH effects in each of the security return series. Note that we use the log of the conditional variance and conditional covariance. Since some of the covariances are negative and because we cannot compute the natural logarithm of a negative number, we added 11 to every covariance. The lowest covariance was –10.4. Finally, we include the NYSE volume as an independent variable to explain the conditional variances and conditional covariances. We set October 1, 1979 as our base period (i.e., the NYSE volume is set to 1 on October 1, 1979) and compute following trading day volume as a fraction of this basis.

We include the NYSE volume as an independent variable since previous studies found that volume explains the GARCH effect (Lamoureux and Lastrapes, 1990). On the other hand, remember that we previously found that the stock market exhibits unusually high volatility on macroeconomic news release days. Since market volume is usually positively correlated with the stock market's volatility (Karpoff, 1987, Crouch, 1970, Smirlock et al. 1988), we might expect NYSE volume to be relatively high on those days. One explanation for this "phenomena" is the one of Jain (1988). He notes that new information (may) causes investors to rebalance their portfolios, which (may) translate into unusually high volume (and return) to particular assets. For that reason, we might expect to find a particularly strong relationship between the NYSE volume and the conditional variances and/or conditional covariances on macroeconomic news release dates. However, this may negatively bias the significance level of our indicator variables in regressions that study the stock return conditional variance.

We use the conditional variances and conditional covariances of models 1A, 1B, and 1C (in which the employment report and PPI releases are used as indicator variables) as well as of models 2A, 2B, and 2C (in which the employment report, PPI, and the industrial production releases are used as indicator variables). Plots of these conditional variances and conditional covariances are shown in the appendix as figures 1 to 6. The conditional variance of the 5-year note returns is the least volatile series of the four securities, while the conditional variance of the S&P 500 returns is the most volatile series. This is true for both models. Moreover, conditional covariance of stock and 5-year note returns and conditional variance of 5-year note returns are of the same magnitude in both models (models 1A and 2A). A similar conclusion can be reached for conditional covariance of stock and 10-year note returns and conditional variance of 10-year note returns. Also, the period surrounding the end of 1991 and the end of 1997 seems relatively quiet in each series. Finally, from the six graphs, there is no specific trend.

Because each multivariate GARCH model produces two conditional variance series and one conditional covariance series, we have 18 linear regressions. We present the results in table 11 (appendix). We show the estimated coefficients as well as their t-statistics and p-values for each regression. We also present the R^2 bar, the F statistic and the p-value for each regression.

Remember that we found (see section 2 – preliminary analysis) that employment report and PPI releases have more impact on bond and stock return volatilities than industrial production releases. We also found that covariances of stock returns and any of the 5-, 10-, or 30-year bonds returns double on employment report release dates.

The results confirm our previous findings. First, we see that we can reject the null hypothesis that all coefficient estimates are not significantly different from zero as the F statistics are higher than the critical value at the 1% significant level. Also, the adjusted R^2 are higher than 0.75 in 13 of the 18 estimated equations. Moreover, the constant is significantly negative in each conditional variance equation whereas it is significantly positive in each conditional covariance equation. Second, not surprisingly, the first lag value of the conditional variance and conditional covariance are highly significantly positive.

We also see from table 11 that the employment report is a good explanatory variable for stock and bond conditional variance. The estimated coefficients are significantly positive at the 5% significant level or less and range from 0.013 (see table 8F – 30y bonds) to 0.106 (see table 8B – 10y notes). However, the results are mixed for conditional covariances. In fact, employment report releases only explain conditional covariance of stock and 10-year note returns as well as of stock and 30-year bond returns when only two indicator variables are included, i.e., the employment report and PPI releases. Estimated coefficients of indicator variables that represent PPI releases are significantly positive in most of the stock and bond conditional variance equations at the 10% level or less. However, this macroeconomic variable does not create time-varying conditional covariance between stock and bonds returns on announcement days. Finally, from models 11D, 11E, and 11F, we see that industrial production releases are not a significant source of time-varying conditional volatility nor they are a source of time-varying conditional covariance. The NYSE volume is significantly positive at the 1% level and explains conditional variance of stock and 30-year bond returns as well as covariance of stock and any of the 5-, 10-, and 30-year bonds returns. Note that the estimated coefficients are fairly low, however.

Thus, in summary, employment report and PPI releases do seem to be sources of time-varying conditional volatility for both stock and bonds returns, whereas industrial production releases are not found to be a source of unusually high volatility. On the other hand, except in model 11B, none of the employment report, PPI, or industrial production releases generate significant changes in conditional covariance of stock and any of the 5-, 10-, and 30-year bond returns on announcement days. This result does not support the JLL (1998) conjecture.

6. Conclusion

The first and second moments of daily returns of both stocks and bonds have been the subject of numerous studies. In this paper, we study the effect of macroeconomic news releases on stock and bond risk premium to variance and covariance risks. We use the employment report, the PPI, and the industrial production announcements as indicator variables.

From our preliminary results we see that bonds, like stocks, earn higher returns when exposed to macroeconomic risks. However, from the multivariate GARCH analysis, we conclude that stocks, as opposed to bonds, exhibit a change in the risk premium to variance risk on macroeconomic announcement days. From the non-pooled announcement models, we see that most of this effect is due to PPI announcements. This finding suggests that both assets (stocks and bonds) do not share the same level of macroeconomic risk. In fact, stocks have a specific component of risk and are more sensitive to macroeconomic news announcements.

On the other hand, macroeconomic news announcements create a significantly positive change to bonds risk premium to covariance risks. In other words, on macroeconomic news announcement days, bonds are rewarded for the common component of macroeconomic risk they share with stocks. This is in opposition to regular trading days where bonds earn a significantly negative risk premium to covariance risk.

As anticipated, industrial production releases do not affect significantly any of the models we estimated. More surprisingly, however, is the fact that employment report releases do not seem to have a significant impact on any of the security risk premia.

However, employment report and PPI releases do seem to be sources of time-varying conditional volatility for both stock and bonds returns, whereas industrial production releases are not found to be a source of unusually high volatility. On the other hand, none of the employment report, PPI, or industrial production releases seem to generate significant changes in the conditional covariance of stock and any of the 5-, 10-, and 30-

year bond returns on their announcement days. This is in contrast to what JLL (1998) conjectured.

Of course, we must be careful in interpreting our results. We should not forget that we study large indices and that specific industry and/or group of stocks (small vs large stocks, defensive vs aggressive, etc.) may exhibit different patterns. Of course, the news that we study represent only a small fraction of all public and private information and explain only a small fraction of the changes in asset risk premium to volatility and covariance risks.

Further studies could make use of intraday data instead of daily data. This would help to see if changes in risk premia occur quickly or gradually over the release days. Another possibility would be to examine whether there are significant changes in the risk premium to variance and/or covariance risks on days before or after macroeconomic news releases. Also, by using the expected and released statistics instead of the release dates, one could check if stock and/or bond volatility is higher following large unexpected component announcements. It could then be interesting to check whether changes in the risk premia vary with the level of uncertainty (unexpected component) of the releases. Finally, including more than two assets in the multivariate GARCH framework could result in a more complete framework and could lead to different and new results.

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Appendices

Table 1: Macroeconomic release dates distribution over the weekdays

	Monday	Tuesday	Wednesday	Thursday	Friday	Total
Employment Report	2	0	2	7	238	249
PPI	3	18	18	44	166	249
Industrial Production	21	52	51	28	97	249
Total	26	70	71	79	501	747

Table 2 A: Basic statistics for the period from October 1, 1979 through July 5, 2000

	S&P 500			5-yr			10-yr			30-yr		
	XR	XRSQ	XRABS	XR	XRSQ	XRABS	XR	XRSQ	XRABS	XR	XRSQ	XRABS
Mean excess return	0.022	1.075	0.699	0.008	0.133	0.247	0.011	0.297	0.386	0.015	0.579	0.553
Standard deviation	1.037	7.842	0.766	0.365	0.395	0.269	0.545	0.772	0.385	0.761	1.384	0.522
Covariance				0.095			0.160			0.242		
Sharpe Measure	0.022			0.023			0.020			0.020		
Minimum	-22.957			-2.484			-3.671			-3.943		
Maximum	8.693			3.014			4.692			7.252		
Skewness	-2.323			0.233			0.167			0.140		
Kurtosis	51.481			6.768			4.741			3.712		
Jarque Bera	576587			9965			4891			3000		
Normality Test	0.071	0.445	0.181	0.079	0.368	0.179	0.061	0.350	0.158	0.051	0.338	0.145
Number of observation	5197	5197	5197	5197	5197	5197	5197	5197	5197	5197	5197	5197
Compounded excess return on announcement and non-announcement days												
Returns on announ. days	0.684			0.328			0.473			0.693		
Returns on non-announ. days	0.430			0.121			0.114			0.099		

Note: For tables 2B and 2C,
* Significantly higher (or lower) from variance on average trading days at 10%
** Significantly higher (or lower) from variance on average trading days at 5%
*** Significantly higher (or lower) from variance on average trading days at 1%

Table 2 B: Autocorrelation

	S&P 500			5-yr			10-yr			30-yr		
	XR	XRSQ	XRABS	XR	XRSQ	XRABS	XR	XRSQ	XRABS	XR	XRSQ	XRABS
ρ1	0.017	0.115**	0.190***	0.104**	0.160***	0.183***	0.077**	0.124**	0.150***	0.048*	0.041*	0.063*
ρ2	-0.023	0.145***	0.167***	0.034*	0.157***	0.207***	0.030*	0.174***	0.194***	0.032*	0.098**	0.108**
ρ3	-0.046*	0.073*	0.158***	-0.009	0.104**	0.172***	-0.011	0.114**	0.163***	-0.003	0.069*	0.114**
ρ4	-0.020	0.018	0.135***	-0.023	0.145***	0.206***	-0.033*	0.133***	0.186***	-0.023	0.097**	0.133***
ρ5	0.018	0.135***	0.186***	0.025	0.136***	0.197***	0.022	0.130***	0.175***	-0.001	0.071*	0.123**
ρ6	-0.005	0.030*	0.136***	0.026*	0.109**	0.161***	0.007	0.124**	0.169***	-0.001	0.084**	0.124**
ρ7	-0.026*	0.009	0.098**	0.043*	0.148***	0.179***	0.033*	0.142***	0.149***	0.024	0.095**	0.110**
ρ8	0.006	0.055*	0.138***	0.023	0.139***	0.173***	0.000	0.114**	0.152***	0.017	0.081**	0.101**

Table 2 C: Cross-correlation

	S&P 500			5-yr			10-yr			30-yr		
Lag	XR	XRSQ	XRABS	XR	XRSQ	XRABS	XR	XRSQ	XRABS	XR	XRSQ	XRABS
8				0.012	0.003	0.014	0.005	0.005	0.025*	0.000	0.005	0.029*
7				0.022	0.007	0.017	0.013	0.012	0.030*	0.016	0.018	0.037*
6				0.013	0.019	0.044*	0.013	0.021	0.058*	0.007	0.007	0.041*
5				0.014	0.015	0.057*	0.009	0.021	0.070*	0.009	0.024	0.074*
4				-0.028*	0.048*	0.061*	-0.030*	0.062*	0.078**	-0.031*	0.081**	0.085**
3				0.021	0.024	0.031*	0.011	0.033*	0.042*	0.001	0.027*	0.032*
2				0.032*	0.018	0.043*	0.023	0.025*	0.057*	0.020	0.036*	0.068*
1				0.072*	0.041*	0.045*	0.067*	0.052*	0.047*	0.055*	0.069*	0.050*
0				0.251*	0.064*	0.193***	0.283***	0.066*	0.217***	0.306***	0.072*	0.222***
-1				-0.007	0.302***	0.085**	-0.004	0.382***	0.109**	-0.006	0.502***	0.117**
-2				-0.032*	0.023	0.045*	-0.018	0.029*	0.062*	-0.004	0.030*	0.059*
-3				-0.031*	0.042*	0.029*	-0.040*	0.079**	0.048*	-0.033*	0.087**	0.061*
-4				-0.020	0.009	0.041*	-0.025*	0.015	0.055*	-0.029*	0.024	0.072*
-5				-0.016	0.029*	0.049*	-0.013	0.034*	0.070*	-0.014	0.046*	0.088**
-6				0.024	0.003	0.031*	0.019	0.011	0.045*	0.022	0.011	0.048*
-7				-0.009	-0.000	0.021	-0.002	0.006	0.031*	-0.008	0.010	0.037*
-8				-0.015	0.005	0.025*	-0.021	0.011	0.046*	-0.020	0.006	0.047*

Table 3: Test results for ARCH errors

	Lag Length			
	1	2	4	10
S&P 500	68.08	158.39	169.32	262.46
5-year note	132.75	224.38	301.03	471.58
10-year note	79.68	212.52	284.69	402.56
30-year bond	8.58	56.26	112.84	206.25
χ^2 (0.01)	6.63	9.21	13.28	23.21

Note: The number of degrees of freedom in each test equals the lag length value. The critical χ^2 values are listed below each column.

Table 4: Employment Report Announcements

	S&P 500	5-year note	10-year note	30-year bond
Pre-announcement days				
Daily mean return (in%)	-0.023	0.041	0.050	0.028
Standard Deviation	0.840[c]	0.314[c]	0.492[c]	0.682[c]
Covariance		0.091	0.143	0.213
Sharpe	-0.028	0.130	0.101	0.041
Announcement days				
Daily mean return (in%)	0.068	0.049	0.061	0.069
Standard Deviation	1.097[a]	0.529[c]	0.766[c]	1.034[c]
Covariance		0.196	0.313	0.483
Sharpe	0.062	0.092	0.080	0.067
Post-announcement days				
Daily mean return (in%)	-0.099	-0.016	-0.022	-0.025
Standard Deviation	1.022	0.417[c]	0.612[c]	0.857[c]
Covariance		0.162	0.245	0.342
Sharpe	-0.097	-0.039	-0.036	-0.030

[a] Significantly higher (or lower) from variance on average trading days at 10%
[b] Significantly higher (or lower) from variance on average trading days at 5%
[c] Significantly higher (or lower) from variance on average trading days at 1%

Table 5: PPI Announcements

	S&P 500	5-year note	10-year note	30-year bond
Pre-announcement days				
Daily mean return (in%)	-0.084	-0.008	-0.004	0.000
Standard Deviation	0.969[a]	0.300[c]	0.492[c]	0.682[c]
Covariance		0.127	0.212	0.328
Sharpe	-0.086	-0.028	-0.008	0.000
Announcement days				
Daily mean return (in%)	0.063	0.070	0.099	0.146
Standard Deviation	1.168[c]	0.415[c]	0.644[c]	0.869[c]
Covariance		0.153	0.253	0.337
Sharpe	0.054	0.170	0.154	0.168
Post-announcement days				
Daily mean return (in%)	-0.061	0.006	0.021	0.017
Standard Deviation	1.805[c]	0.404[c]	0.572	0.808[a]
Covariance		0.012	0.049	0.169
Sharpe	-0.034	0.015	0.036	0.021

[a] Significantly higher (or lower) from variance on average trading days at 10%
[b] Significantly higher (or lower) from variance on average trading days at 5%
[c] Significantly higher (or lower) from variance on average trading days at 1%

Table 6: Industrial Production Announcements

	S&P 500	5-year note	10-year note	30-year bond
Pre-announcement days				
Daily mean return (in%)	0.050	0.056	0.085	0.126
Standard Deviation	1.012	0.352	0.520	0.745
Covariance		0.099	0.167	0.255
Sharpe	0.049	0.159	0.163	0.170
Announcement days				
Daily mean return (in%)	0.057	0.037	0.056	0.057
Standard Deviation	1.052	0.360	0.525	0.727
Covariance		0.067	0.128	0.212
Sharpe	0.054	0.102	0.106	0.078
Post-announcement days				
Daily mean return (in%)	-0.065	0.000	0.014	0.011
Standard Deviation	1.760[c]	0.406[c]	0.621[c]	0.849[c]
Covariance		0.032	0.086	0.210
Sharpe	-0.037	0.000	0.022	0.012

[a] Significantly higher (or lower) from variance on average trading days at 10%
[b] Significantly higher (or lower) from variance on average trading days at 5%
[c] Significantly higher (or lower) from variance on average trading days at 1%

Table 7: Median equality test for the S&P 500, 5-. 10-, and 30-year bonds returns: pre-, post-, and announcement days vs nonannouncement days

Wilcoxon/Mann-Whitney tie-adj. (one-tailed test)				
Employment Report	**S&P 500**	**5-year note**	**10-year note**	**30-year bond**
Pre-Announcement	1,07	1,49*	1,24	0,49
Announcement	0,65	0,87	1,05	1,06
Post-Announcement	1,00	1,05	0,58	0,55
PPI	**S&P 500**	**5-year note**	**10-year note**	**30-year bond**
Pre-Announcement	1,69**	0,62	0,03	0,05
Announcement	1,25	2,37***	2,42***	2,99***
Post-Announcement	1,93**	1,51*	1,44*	0,65
Industrial Production	**S&P 500**	**5-year note**	**10-year note**	**30-year bond**
Pre-Announcement	1,03	2,55***	2,85***	2,63***
Announcement	1,40*	1,70**	1,96**	1,58*
Post-Announcement	0,23	0,30	0,80	0,32

*** Significantly higher (or lower) from variance on nonannouncement days at 1%
** Significantly higher (or lower) from variance on nonannouncement days at 5%
* Significantly higher (or lower) from variance on nonannouncement days at 10%

Table 8: Variance equality test for the S&P 500, 5-. 10-, and 30-year bonds returns: Pre-, Post-, and announcement days vs nonannouncement days

Brown-Forsythe (one-tailed test)				
Employment Report	**S&P 500**	**5-year note**	**10-year note**	**30-year bond**
Pre-Announcement	3,08**	3,93**	2,85**	2,09*
Announcement	2,61**	79,78***	68,20***	65,27***
Post-Announcement	0,73	2,17*	1,72*	1,01
PPI	**S&P 500**	**5-year note**	**10-year note**	**30-year bond**
Pre-Announcement	0,07	1,16	0,68	0,43
Announcement	1,50	14,63***	19,24***	17,35***
Post-Announcement	4,64**	1,96*	1,57*	3,93**
Industrial Production	**S&P 500**	**5-year note**	**10-year note**	**30-year bond**
Pre-Announcement	0,11	0,65	0,35	0,74
Announcement	0,26	1,44	0,03	0,11
Post-Announcement	3,38**	1,23	1,76*	3,36**

*** Significantly higher (or lower) from variance on nonannouncement days at 1%
** Significantly higher (or lower) from variance on nonannouncement days at 5%
* Significantly higher (or lower) from variance on nonannouncement days at 10%

Table 9 A: Mean daily excess return of the S&P 500, 5-. 10-, and 30-year bonds on announcement days classified by days of the week

	S&P 500	5-year bond	10-year bond	30-year bond
Monday	0,186	(0,001)	0,033	0,111
Tuesday	0,075	0,091	0,145	0,213
Wednesday	0,200	0,009	0,029	0,022
Thursday	0,189	0,063	0,108	0,168
Friday	0,040	0,039	0,043	0,053

Table 9 B: Mean test for the S&P 500, 5-. 10-, and 30-year bonds returns

	S&P 500	5-year bond	10-year bond	30-year bond
Monday	1.733	0.072	0.591	1.455
	(0.083)	(0.942)	(0.554)	(0.146)
Tuesday	1.083	3.971	4.242	4.453
	(0.279)	(0.000)	(0.000)	(0.000)
Wednesday	3.029	0.342	0.848	0.430
	(0.003)	(0.737)	(0.397)	(0.667)
Thursday	3.044	2.966	3.417	3.787
	(0.002)	(0.003)	(0.001)	(0.000)
Friday	1.246	3.422	2.682	2.415
	(0.213)	(0.001)	(0.007)	(0.016)

Note: The mean test performed is a T-test. It tests if S&P500, 5-, 10-, and 30-year bond returns on announcement days, classified by weekdays, are significantly different from average returns. We present the test statistics and p-values (in parenthesis).

Table 9 C: Median test for the S&P 500, 5-. 10-, and 30-year bonds returns

	S&P 500	5-year bond	10-year bond	30-year bond
Monday	1.561	0.254	0.834	1.178
	(0.119)	(0.799)	(0.404)	(0.239)
Tuesday	0.452	2.518	2.843	2.672
	(0.651)	(0.012)	(0.005)	(0.008)
Wednesday	2.151	0.486	1.057	0.897
	(0.032)	(0.627)	(0.291)	(0.370)
Thursday	1.904	2.134	2.241	2.843
	(0.057)	(0.033)	(0.025)	(0.005)
Friday	1.387	1.258	0.971	1.015
	(0.165)	(0.209)	(0.332)	(0.310)

Note: The median test performed is the Wilcoxon/Mann-Whitney test. It tests if the median S&P500, 5-, 10-, and 30-year bond returns on announcement days, classified by weekdays, are significantly different from average returns. We present the test statistics and p-values (in parenthesis).

Table 10: Multivariate GARCH-M model results

Model 1: Two dummies, i.e., one for the employment report release and one for the PPI release

	α_{10}	β_1	δ_1	β_{11}	δ_{11}	β_{12}	δ_{12}	α_{20}	β_2	δ_2	β_{21}	δ_{21}	β_{22}	δ_{22}	[redacted]	**Max log-lik. Ratio**
A - S&P500/5y note	0,025	0,044	-0,739	0,055	1,494	0,228	-2,276	0,005	0,607	-0,220	0,132	0,432	0,600	0,602		
	1,090	1,511	-1,216	0,590	0,626	3,020	-1,159	0,736	2,076	-4,800	0,162	1,755	0,624	2,201	1585,039	1247,44
B - S&P500/10y note	0,027	-0,015	0,508	0,032	0,417	0,101	-0,066	0,017	0,124	-0,132	0,077	0,139	1,607	-0,020		
	0,896	-0,527	1,345	0,366	0,345	1,388	-0,056	0,801	0,436	-2,882	0,152	0,728	3,093	-0,092	-1136,651	-986,76
C - S&P500/30y bond	-0,007	0,052	0,049	0,054	0,334	0,094	0,061	-0,017	0,081	0,070	0,244	0,024	0,237	0,676		
	-0,212	1,292	0,163	0,595	0,247	1,168	0,069	-0,659	0,379	1,285	0,396	0,104	0,492	2,864	-2835,844	19,04

The T-statistics are below the coefficient estimates

Model 2: Three dummies, i.e., one for the employment report release, one for the PPI release and one for the Industrial Production release.

	α_{10}	β_1	δ_1	β_{11}	δ_{11}	β_{12}	δ_{12}	β_{13}	δ_{13}
A - S&P500/5y note	0,025	0,043	-0,870	0,051	1,786	0,190	-2,140	0,085	1,632
	1,096	1,445	-1,433	0,545	0,747	2,334	-1,064	1,097	0,671
B - S&P500/10y note	0,021	0,040	-0,355	0,056	0,690	0,222	-2,017	0,121	0,264
	0,870	1,342	-0,931	0,563	0,439	2,726	-1,695	1,525	0,176
C - S&P500/30y bond	-0,067	0,101	0,610	0,237	-2,893	0,164	-3,186	0,005	1,005
	-1,237	2,054	1,167	2,198	-1,496	2,061	-3,033	0,058	0,649

The T-statistics are below the coefficient estimates

Table 10: Multivariate GARCH-M results (cont'd)

Model 2: Three dummies, i.e., one for the employment report release, one for the PPI release and one for the Industrial Production release.

α_{20}	β_2	δ_2	β_{21}	δ_{21}	β_{22}	δ_{22}	β_{23}	δ_{23}		Max log-lik. Ratio
0,005	0,541	-0,211	0,252	0,404	0,367	0,671	1,761	-0,378		
0,770	1,828	-4,544	0,307	1,646	0,359	2,269	1,662	-1,436	1588,471	1254,30
0,012	0,315	-0,201	0,196	0,245	-0,083	0,658	0,919	-0,203		
1,032	1,440	-4,278	0,319	0,964	-0,124	2,457	1,238	-0,802	-630,923	24,70
0,106	-0,404	-0,384	0,230	-0,005	0,685	0,651	-0,066	0,044		
3,298	-1,677	-5,281	0,289	-0,017	1,228	2,246	-0,105	0,136	-2914,389	-138,05

The T-statistics are below the coefficient estimates

Model 3: One dummy that is equal to 1 when the employment report and/or the PPI are released.

	α_{10}	β_1	δ_1	β_{11}	δ_{11}	α_{20}	β_2	δ_2	β_{21}	δ_{21}		Max log-likelihood Ratio
A - S&P500 and 5-year note	0,021	0,001	0,265	0,256	-0,600	0,012	0,113	-0,144	1,236	0,271		
	0,715	0,027	0,417	3,946	-0,324	1,096	0,324	-3,002	1,992	1,378	1054,113	185,587
B - S&P500 and 10-year note	0,021	0,042	-0,323	0,167	-0,565	0,011	0,382	-0,209	-0,030	0,509		
	0,875	1,434	-0,865	2,727	-0,580	0,937	1,776	-4,535	-0,065	2,800	-635,390	15,763
C - S&P500 and 30-year bond	-0,015	0,058	0,357	0,135	-0,488	0,034	0,117	-0,149	0,152	0,378		
	-0,631	1,817	1,295	2,140	-0,770	2,076	0,810	-3,207	0,407	2,566	-2523,320	644,087

The T-statistics are below the coefficient estimates

Table 10: Multivariate GARCH-M results (cont'd)

Model 4: One dummy that is equal to 1 when the employment report and/or the PPI and/or the Industrial Production is/are released.

	α_{10}	β_1	δ_1	β_{11}	δ_{11}	α_{20}	β_2	δ_2	β_{21}	δ_{21}		Max log-likelihood Ratio
A - S&P500 and 5-year note	0,024	0,043	-0,818	0,116	0,748	0,005	0,587	-0,214	0,627	0,308		
	1,045	1,456	-1,366	2,117	0,514	0,719	2,001	-4,673	1,067	1,868	1581,625	1240,610
B - S&P500 and 10-year note	0,020	0,040	-0,341	0,138	-0,212	0,012	0,355	-0,206	0,180	0,309		
	0,850	1,349	-0,904	2,501	-0,242	0,991	1,633	-4,406	0,431	1,900	-636,782	12,978
C - S&P500 and 30-year bond	-0,089	0,171	-0,267	0,118	0,176	0,007	0,239	-0,068	0,096	-0,020		
	-2,332	4,529	-0,813	2,223	0,313	0,260	1,586	-0,763	0,299	-0,144	-2859,802	-28,877

The T-statistics are below the coefficient estimates

Model 5: Restricted Models

	α_{10}	β_1	δ_1	α_{20}	β_2	δ_2	
A - S&P500/5y note	0,074	-0,077	0,105	-0,007	0,110	0,167	
	3,355	-3,167	0,145	-0,707	0,284	2,213	961,320
B - S&P500/10y note	0,020	0,055	-0,338	0,012	0,388	-0,175	
	0,882	1,991	-0,935	1,049	1,870	-4,058	-643,271
C - S&P500/30y bond	0,025	0,032	-0,303	-0,008	0,044	0,074	
	0,772	0,921	-0,980	-0,325	0,216	1,314	-2845,363

The T-statistics are below the coefficient estimates

Figure 1: Conditional variance and conditional covariance of Model 1A

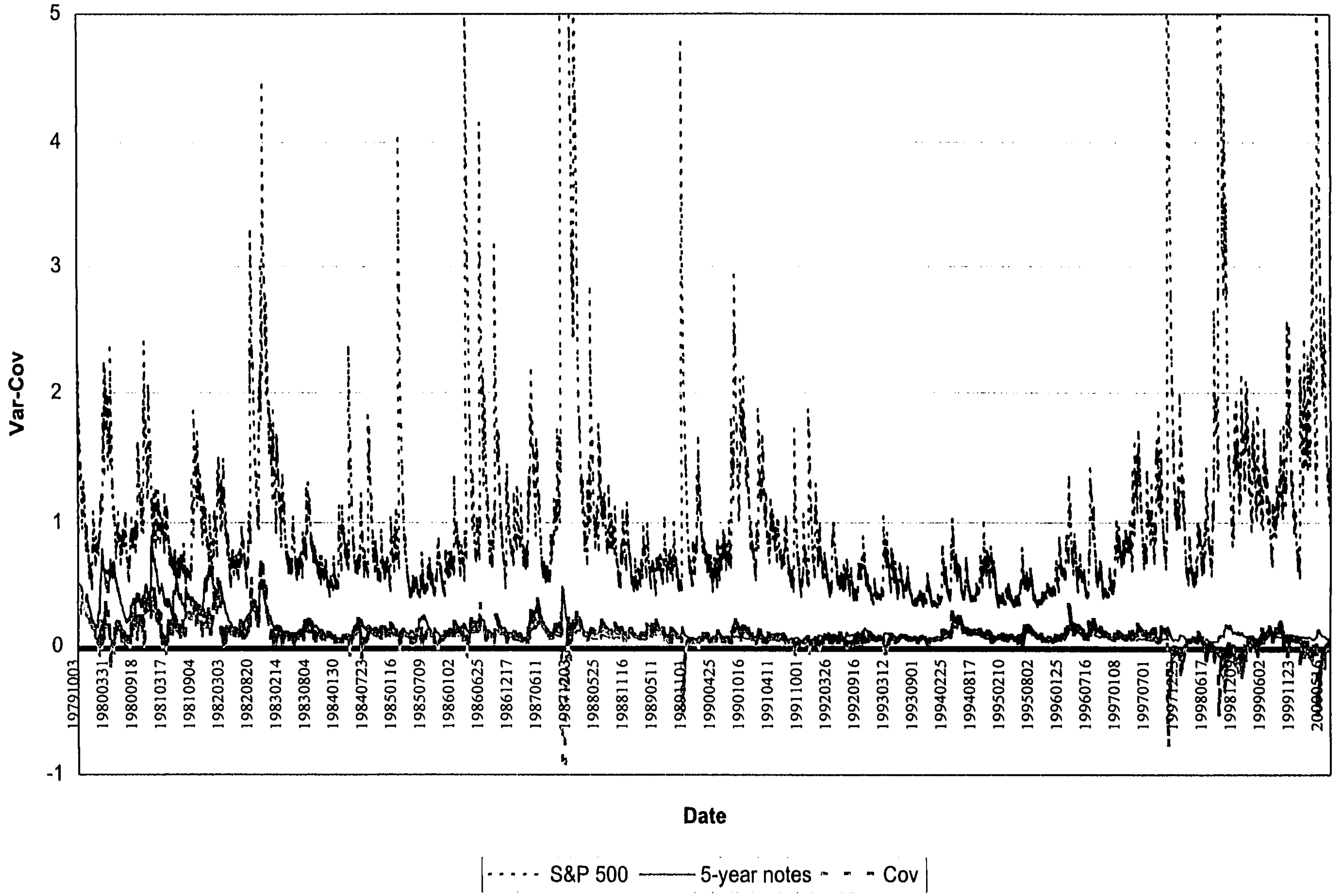

Figure 2: Conditional variance and conditional covariance of Model 1B

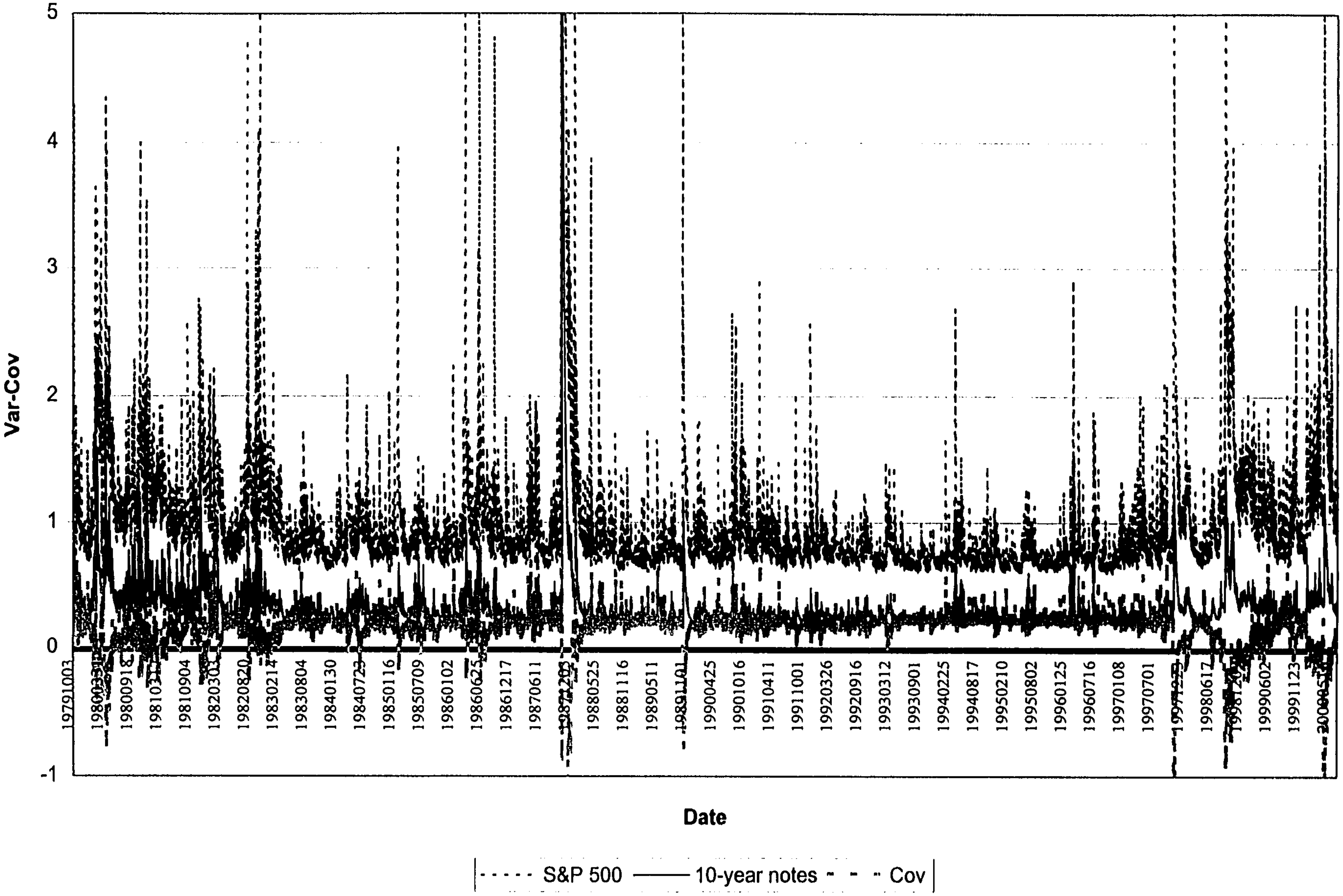

Figure 3: Conditional variance and conditional covariance of Model 1C

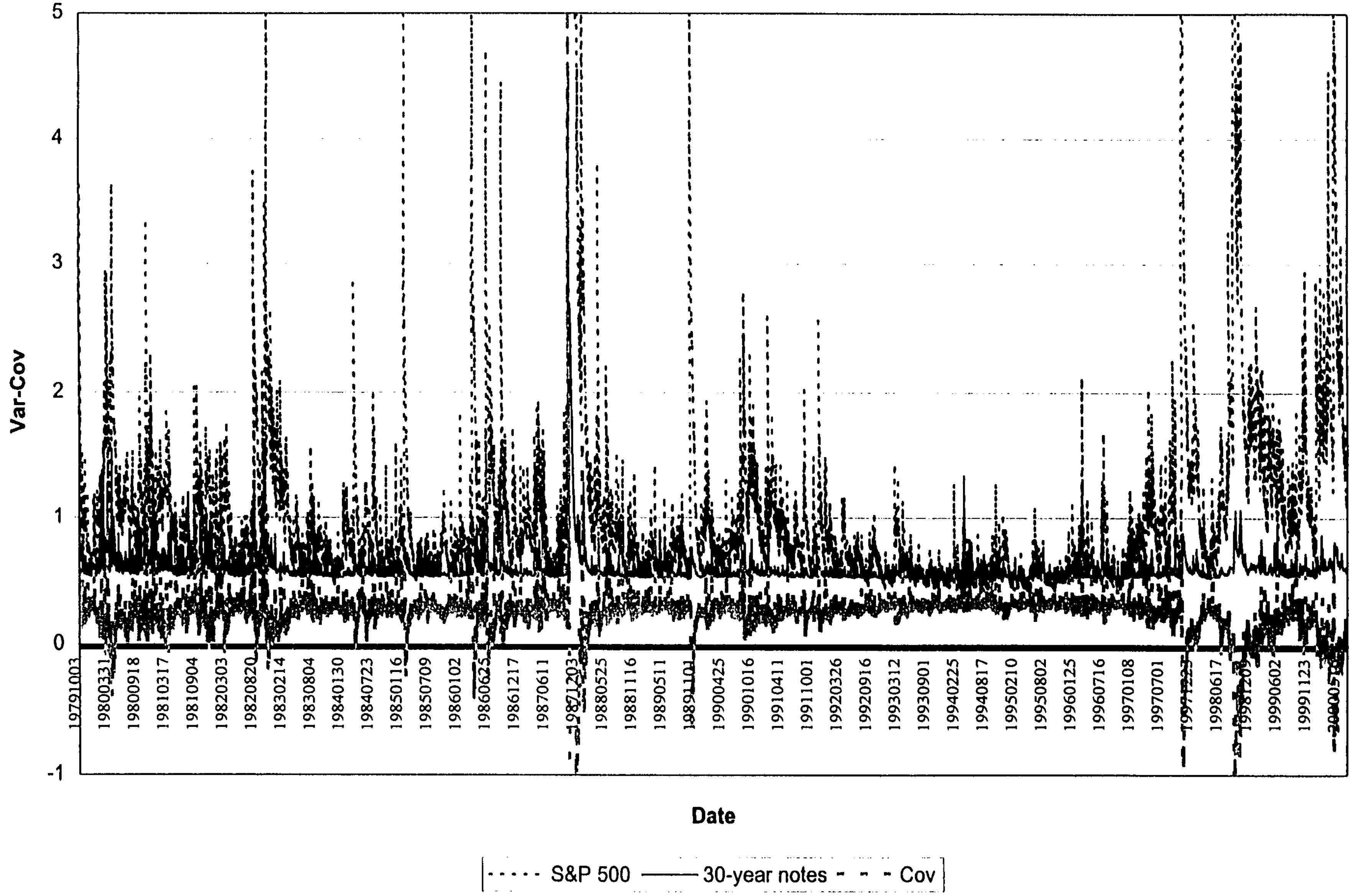

Figure 4: Conditional variance and conditional covariance of Model 2A

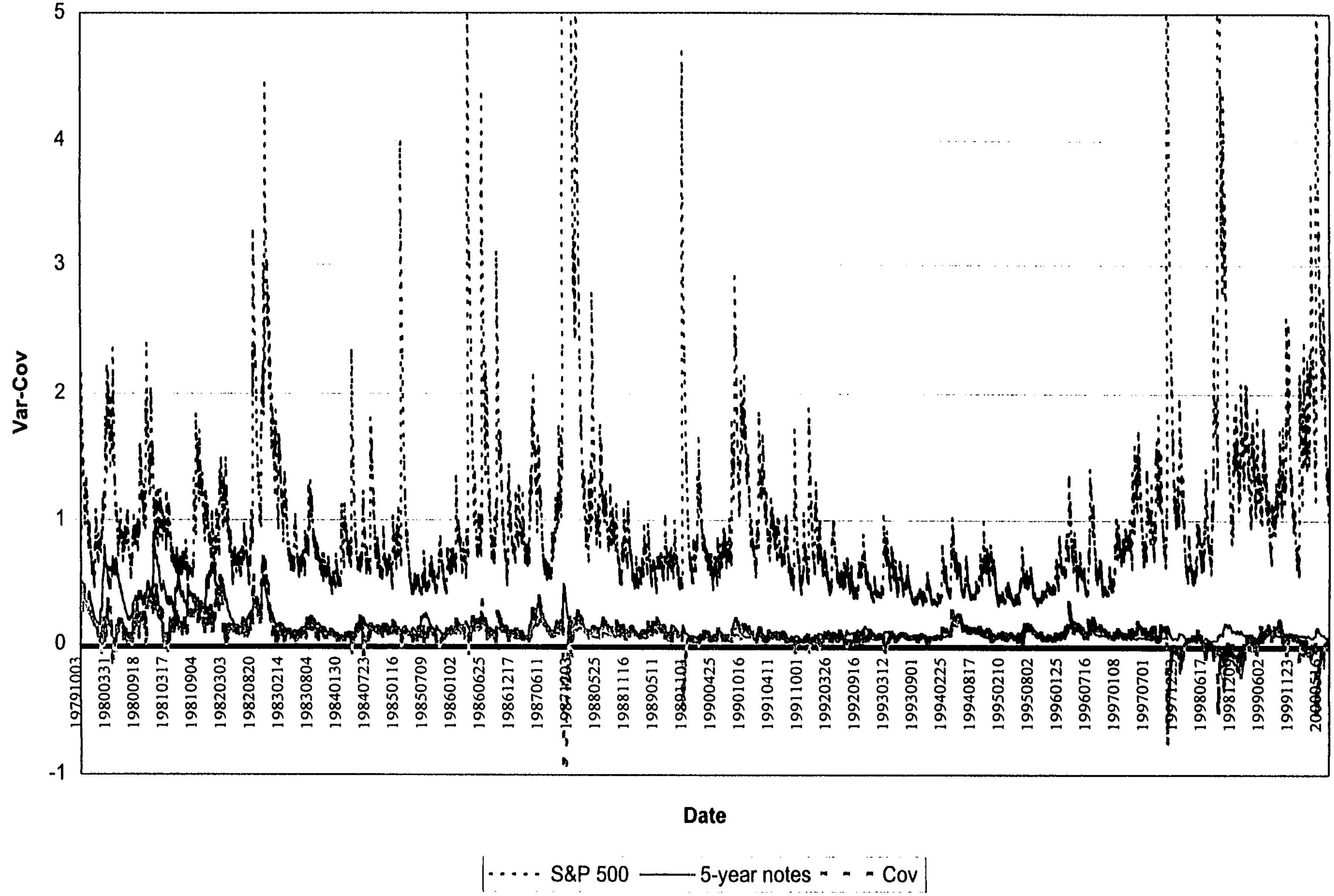

Figure 5: Conditional variance and conditional covariance of Model 2B

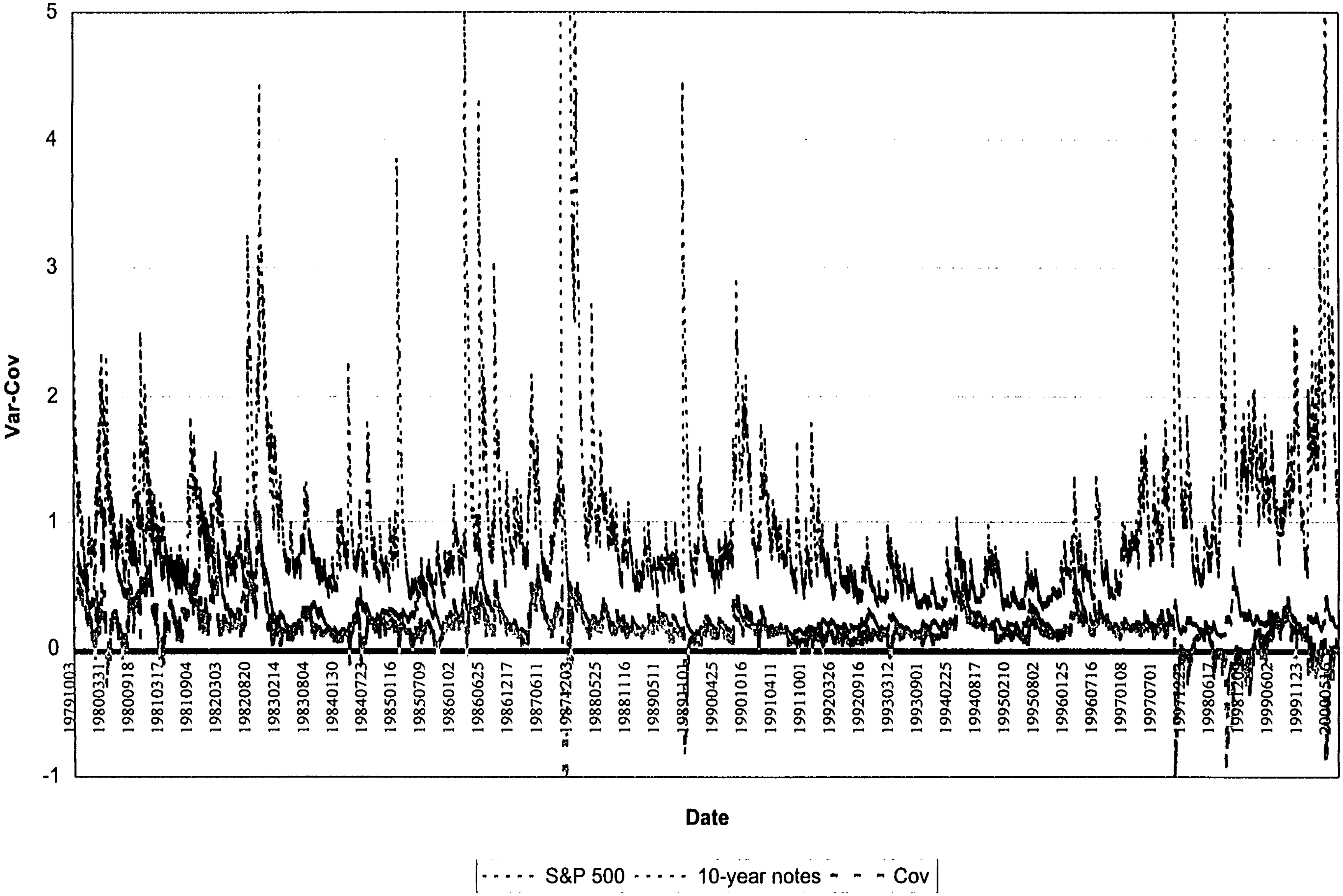

Figure 6: Conditional variance and conditional covariance of Model 2C

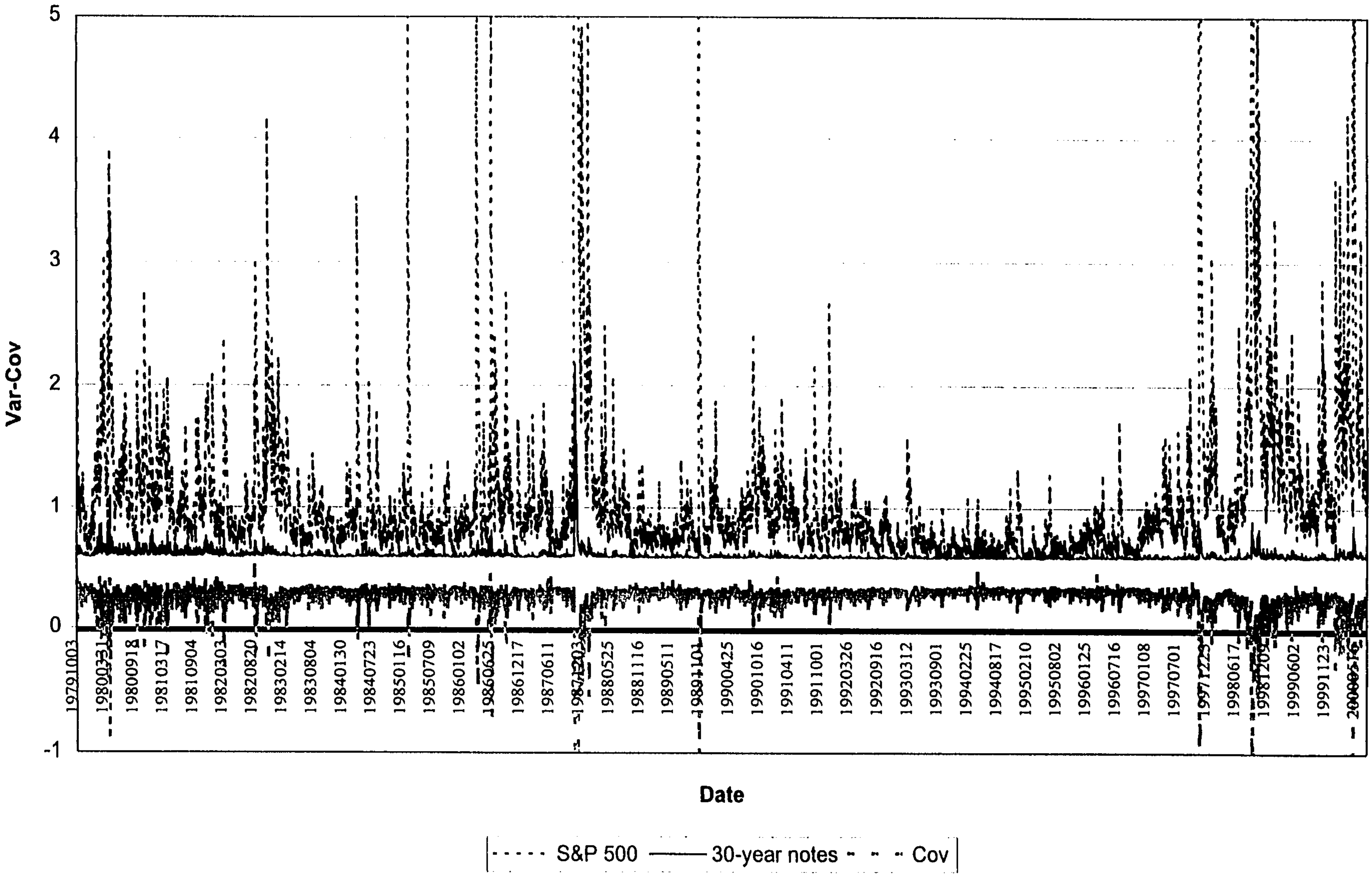

Table 11-A: Two indicator variables

	CONSTANT	X(t-1)	DEMP	DPPI	Volume	R Bar**2	F(4,5189)	p-value
Table 11A - Conditional variances and covariance of model 1A								
S&P 500 Variance	**-0,019**	**0,968**	**0,018**	**0,018**	**0,001**			
	-6,054	288,494	1,980	2,031	5,316	0,944	22039,256	0,000
	0,000	0,000	0,048	0,042	0,000			
5-year note Variance	**-0,016**	**0,995**	**0,054**	**0,012**	0,000			
	-4,453	621,800	12,325	2,738	0,739	0,989	116135,281	0,000
	0,000	0,000	0,000	0,006	0,460			
Covariance	**0,263**	**0,891**	0,000	0,000	**0,000**			
	17,527	143,355	0,625	0,431	-6,546	0,817	5810,427	0,000
	0,000	0,000	0,532	0,667	0,000			
Table 11B - Conditional variances and covariance of model 1B								
S&P 500 Variance	**-0,047**	**0,676**	**0,048**	0,025	**0,002**			
	-8,266	66,168	2,821	1,452	4,675	0,466	1135,735	0,000
	0,000	0,000	0,005	0,147	0,000			
10-year note Variance	**-0,333**	**0,746**	**0,106**	**0,044**	**0,001**			
	-26,605	81,115	6,981	2,902	3,452	0,562	1668,782	0,000
	0,000	0,000	0,000	0,004	0,001			
Covariance	**0,225**	**0,907**	**0,004**	**0,002**	**0,000**			
	15,997	155,607	3,888	1,880	-2,262	0,825	6134,141	0,000
	0,000	0,000	0,000	0,060	0,024			
Table 11C - Conditional variances and covariance of model 1C								
S&P 500 Variance	**-0,035**	**0,900**	**0,037**	0,021	**0,002**			
	-7,384	151,158	2,699	1,559	6,159	0,828	6253,991	0,000
	0,000	0,000	0,007	0,119	0,000			
30-year note Variance	**-0,234**	**0,592**	**0,051**	**0,018**	**0,001**			
	-35,167	53,168	6,915	2,473	3,982	0,360	732,110	0,000
	0,000	0,000	0,000	0,013	0,000			
Covariance	**0,316**	**0,870**	**0,003**	0,001	**0,000**			
	19,086	127,332	2,010	0,883	-2,605	0,759	4091,355	0,000
	0,000	0,000	0,044	0,377	0,009			

We first present the coefficient estimates, followed by their t-statistics and p-values in column 2 to 6. The R2 bar of each equation is shown in column seven. Column 8 and 9 show the F-statistic and p-value of each equation.

Table 11-B: Three indicator variables

	Constant	X(t-1)	DEMP	DPPI	DIND	Volume	R Bar**2	F(5,5188)	p-value
Table 11D - Conditional variances and covariance of model 2A									
S&P 500 Variance	-0,018	0,969	0,017	0,019	-0,001	0,001			
	-5,966	292,710	1,967	2,077	-0,102	5,290	0,946	18135,793	0,000
	0,000	0,000	0,049	0,038	0,919	0,000			
5-year note Variance	-0,016	0,995	0,055	0,011	0,006	0,000			
	-4,538	620,465	12,458	2,501	1,341	0,695	0,989	92527,049	0,000
	0,000	0,000	0,000	0,012	0,180	0,487			
Covariance	0,254	0,895	0,000	0,000	0,000	0,000			
	17,211	146,338	0,634	0,480	-0,361	-6,530	0,824	0,824	0,000
	0,000	0,000	0,526	0,631	0,718	0,000			
Table 11E - Conditional variances and covariance of model 2B									
S&P 500 Variance	-0,017	0,971	0,017	0,020	-0,001	0,001			
	-5,842	305,117	2,025	2,251	-0,134	5,203	0,950	19648,819	0,000
	0,000	0,000	0,043	0,024	0,894	0,000			
10-year note Variance	-0,015	0,992	0,048	0,015	0,001	0,000			
	-5,470	534,204	10,525	3,373	0,163	0,823	0,984	62984,517	0,000
	0,000	0,000	0,000	0,001	0,871	0,411			
Covariance	0,284	0,883	0,001	0,000	0,000	0,000			
	18,201	136,799	0,855	0,479	-0,217	-6,602	0,803	4238,603	0,000
	0,000	0,000	0,393	0,632	0,828	0,000			
Table 11F - Conditional variances and covariance of model 2C									
S&P 500 Variance	-0,022	0,913	0,021	0,020	0,004	0,002			
	-5,994	164,296	1,936	1,772	0,339	6,187	0,849	5847,092	0,000
	0,000	0,000	0,053	0,076	0,734	0,000			
30-year note Variance	-0,179	0,664	0,013	0,007	-0,001	0,000			
	-32,353	64,095	4,576	2,406	-0,445	3,637	0,446	836,690	0,000
	0,000	0,000	0,000	0,016	0,656	0,000			
Covariance	0,937	0,613	0,000	0,000	0,001	0,000			
	35,303	55,957	-0,012	-0,116	0,185	-3,153	0,379	636,092	0,000
	0,000	0,000	0,991	0,908	0,853	0,002			

We first present the coefficient estimates, followed by their t-statistics and p-values in column 2 to 6. The R2 bar of each equation is shown in column seven. Column 8 and 9 show the F-statistic and p-value of each equation.