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Abstract: The authors study time-variation in the co-movements between daily stock and Treasury bond returns over 1986 to 2000. Their innovation is to examine whether variation in stock-bond return dynamics can be linked to non-return-based measures of stock market uncertainty, specifically the implied volatility (IV) from equity index options and detrended stock turnover (DTVR). The authors investigate two empirical questions suggested by recent literature on stock market uncertainty and cross-market hedging. First, from a forward-looking perspective, they find that the levels of IV and DTVR are both negatively associated with the future correlation between stock and bond returns. The probability of a negative correlation between daily stock and bond returns over the next month is several times greater following relatively high values of IV and DTVR. Second, from a contemporaneous perspective, the authors find that bond returns tend to be relatively high (low) during days when IV increases (decreases) and during days when stock turnover is unexpectedly high (low). Their findings suggest that stock market uncertainty has cross-market pricing influences that play an important role in understanding joint stock-bond price formation. Further, our results imply that stock-bond diversification benefits increase with stock market uncertainty.

JEL classification: G11, G12, G14

Key words: stock and bond market return linkages, stock implied volatility, stock turnover

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Stock implied volatility, stock turnover, and the stock-bond return relation

1 Introduction

It is well known that stock and bond returns exhibit a modest positive correlation over the long term (Campbell and Ammer, 1993). However, there is substantial time-variation in the relation between stock and bond returns over the short term, including sustained periods of negative correlation (Fleming, Kirby, and Ostdiek, 2002; Gulko, 2002; Li, 2002; and Hartmann, Straetmans, and Devries, 2001). Characterizing this time-variation has important implications for understanding the economics of joint stock-bond price formation and may have practical applications in asset allocation and risk management.

In this paper, we study time-variation in the relation between daily stock and Treasury bond returns over 1986 to 2000 with a special interest in periods with a negative stock-bond return correlation. We extend prior work by examining whether non-return-based measures of stock market uncertainty can be linked to variation in the stock-bond return relation. Our motivation follows from recent literature on stock market uncertainty (Veronesi, 1999 and 2001; and David and Veronesi, 2001 and 2002) and cross-market hedging (Fleming, Kirby, and Ostdiek, 1998; and Kodres and Pritsker, 2002).

Most prior literature on joint stock-bond pricing has taken a traditional, fundamental approach and examined monthly or annual return data. This approach is well represented by Campbell and Ammer (CA) (1993).[1] CA discuss several offsetting effects behind the correlation between stock and bond returns. First, variation in real interest rates may induce a positive correlation since the prices of both assets are negatively related to the discount rate. Second, variation in expected inflation may induce a negative correlation since increases in inflation are bad news for bonds and ambiguous news for stocks. Third, common movements in future expected returns may induce a positive correlation. The net effect in their monthly return sample over 1952 to 1987 is a small positive correlation between stock and bond returns ($\rho = 0.20$).[2]

[1] Related earlier work includes Shiller and Beltratti, 1992; Fama and French, 1989; Barsky, 1989; and Keim and Stambaugh, 1986.

[2] Recent examples of related work include Bekaert and Grenadier (BG) (2001), Scruggs and Glabadanidis (2001), and Mamaysky (2001). We discuss BG in Section 2.

Thus, in the fundamental approach of CA, the only factor that may induce a negative correlation between stock and bond returns is a differential response to inflation expectations. Yet, the 1986 to 2000 period displays both relatively low, stable inflation and sizable time-variation in the stock-bond return relation, including sustained periods of negative correlation. While Forbes and Rigobon (2002) show that heteroskedasticity can impact return correlations even if the underlying economic relation between the two return series has not changed, heteroskedasticity alone cannot explain why two series that normally have a positive correlation occasionally have periods of negative correlation. This suggests other pricing influences beyond the fundamentals considered in CA, such as the cross-market-hedging influences suggested in Fleming, Kirby, and Ostdiek (1998) (FKO) and Kodres and Pritsker (2002) (KP).

KP propose a rational expectations model of financial contagion. Their model is designed to describe price movements over modest periods of time, such as days or a week, during which macroeconomic conditions can be taken as given. With wealth effects and asset substitution effects, a shock in one asset market may generate cross-market asset rebalancing with pricing influences in the non-shocked asset markets. Thus, shocks in stock uncertainty may influence bond pricing. FKO (1998) also consider cross-market hedging. They estimate a model on daily returns that takes cross-market-hedging effects into account and find that information linkages in the stock and bond markets may be greater than previously thought. The issues in FKO (1998) and KP are better examined with high frequency returns, in contrast to the monthly and longer horizons examined in CA and other related studies.

Pricing influences associated with dynamic cross-market hedging seem likely to be related to stock market uncertainty in the sense of Veronesi (1999) and (2001), and David and Veronesi (2001) and (2002). These papers argue that economic-state uncertainty may be important in understanding price formation and return dynamics. In these papers, the economy features state-uncertainty in a two-state economy where the drift in future dividends shifts between unobservable states. During times of higher uncertainty about the state, Veronesi (1999) predicts that new information may receive relatively higher weighting, which may induce time-varying volatility and volatility clustering. Veronesi (2001) introduces the idea of "aversion to state-uncertainty". Regarding bonds and stock volatility, this paper states, "Intuitively, aversion to state-uncertainty generates a high equity premium and a high return volatility because it increases the sensitivity of the marginal utility of consumption to news. In addition, it also lowers the interest rate because it increases the demand for bonds from investors who are concerned about the long-run mean of their consumption." David and Veronesi (2001) test whether the volatility and covariance of stock and bond returns vary with uncertainty about future inflation and earnings. Their uncertainty measures are derived both from survey data (at the semi-annual and quarterly frequency) and from their model estimation (at the monthly horizon). They find that fundamental's uncertainty appears more important than the volatility of fundamentals in explaining volatility and covariances. David and Veronesi (2002) argue that the economic-uncertainty should be positively related to the implied volatility from options.

Chordia, Sarkar, and Subrahmanyam (2001) provide evidence consistent with a linkage between dynamic cross-market hedging and uncertainty. They examine both trading volume and bid-ask spreads in the stock and bond market over the June 1991 to December 1998 period and find that the correlation between stock and bond spreads and volume-changes increases dramatically during crises (relative to normal times). During periods of crises, they also find that there is a decrease in mutual fund flows to equity funds and an increase in fund flows to government bond funds. Their results are consistent with increased investor uncertainty leading to frequent and correlated portfolio reallocations during financial crises.

The notion of dynamic cross-market hedging with uncertainty is also frequently suggested in the popular press. For example, an article in the Wall Street Journal on November 4, 1997 (during the Asian financial crisis) speculates that the recent decoupling between the stock and bond markets may be due to the high stock volatility and uncertain economic times. Another Wall Street Journal article on October 17, 1989 states, "The sudden flight-to-quality that triggered Friday's explosive bond-market rally was reversed yesterday in a flight-from-quality rout. The setback, in which Treasury bond prices plummeted, reflected a rebound in the stock market and profit-taking."

In our empirical study, we examine daily stock and U.S. Treasury bond returns over 1986 to 2000. As indicated in Figure 1, Panel A, the stock-bond return correlation in this period is typically positive, but there are times of sustained negative correlation. Our empirical investigation focuses on two distinct, but related, questions that are suggested by recent literature on stock market uncertainty and cross-market hedging.

The first question has a forward-looking focus and asks whether variation in the relative *level* of stock market uncertainty is informative about the *future* stock-bond return relation. If periods with high stock uncertainty are also times with higher volatility in the relative attractiveness of stocks versus bonds, then higher stock market uncertainty suggests a higher probability of a negative stock-bond return correlation in the near future. Such behavior could explain occasional periods of a negative correlation between stock and bond returns, even when inflation is essentially constant.

Our second empirical question has a contemporaneous focus and asks whether a day's *change* in stock market uncertainty is associated with differences in the day's stock-bond return relation. This question directly evaluates a flight-to(from)-quality hypothesis with increased (decreased) stock uncertainty. Our examination of these two questions provides new evidence concerning the role of stock uncertainty and cross-market hedging in understanding joint stock-bond price formation.

Our empirical work uses two measures of stock market uncertainty suggested by the literature. First, we use the implied volatility from equity index options, specifically the Chicago Board Option Exchange's Volatility Index (VIX).[3] Existing literature suggests that the implied volatility may reflect both the level and the uncertainty of future expected stock volatility. Second, we use abnormal stock turnover.[4] Prior work has argued that turnover may contain information about the dispersion-in-beliefs across investors or may be associated with changes in the investment opportunity set. Our assertion that turnover may be informative about uncertainty assumes that dispersion-in-beliefs or changing investment opportunity sets describe an aspect of stock market uncertainty. By examining turnover, our study also takes up the challenge from Lo and Wang (2000) for more research to better understand "the time-series variation in volume and the relation between volume, prices, and other economic quantities."

Our empirical investigation uncovers several striking results. First, we find that the level of VIX and our detrended stock-turnover measure (DTVR) are both negatively associated with the future correlation between stock and bond returns. For example, when VIX_{t-1} is greater than 25% (about 19% of the days) then there is a 36.5% chance of observing a subsequent negative correlation between stock and bond returns over the next month (days t to $t+21$).[5] However, when VIX_{t-1} is less than 20% (about 54% of the days) then there is only a 6.1% chance of observing a subsequent negative correlation between stock and bond returns over the next month. We find qualitatively similar results with DTVR, across subperiods, and for a variety of different empirical frameworks.

[3] The CBOE's Volatility Index is also commonly referred to as a market "Fear Index".

[4] For brevity in our introduction, we postpone the detailed description of these two measures and the related literature review until Section II.

[5] All the representative results in our introduction use 10-year T-bond returns and subsequent 22-trading-day correlations (over days t to $t+21$). We choose 22 trading days because this horizon corresponds to the option maturity for VIX and because much prior literature has formed monthly statistics from daily observations.

Second, we find that bond returns tend to be relatively high (low) during periods when VIX increases (decreases) and during periods when unexpected stock turnover is high (low).[6] For example, unconditionally, average daily 10-year bond returns are 0.028%. However, average daily bond returns are +0.067% (-0.011%) when stock turnover is higher (lower) than expected. Further, for the days when the unexpected stock turnover exceeds its 95^{th} percentile, the average daily bond return is +0.115%, over four times the unconditional daily mean of bond returns.

Overall, our findings suggest that stock market uncertainty has cross-market pricing influences that play an important role in joint stock-bond price formation. Our findings also suggest that implied volatility and stock turnover may prove useful for financial applications that need to understand and predict stock and bond market co-movements. Finally, all of our empirical results suggest that the benefits of stock-bond diversification increase during periods of high stock market uncertainty.

This study is organized as follow. Section 2 further discusses our primary empirical questions and our measures of stock market uncertainty. Section 3 presents the data. Next, sections 4 and 5 examine stock-bond return dynamics jointly with VIX and stock turnover, respectively. Section 6 examines a regime-shifting approach and Section 7 concludes.

2 Empirical questions and measures of stock market uncertainty

2.1 Primary empirical questions

To provide perspective on our two primary empirical questions, consider a simple economy with three primary markets for financial assets: a stock market, a long-term bond market, and a money market. From a fundamental approach to asset valuation, stock and bond prices can be represented as:

$$P_{i,0} = \sum_{t=1,T} [\frac{E(CF_{i,t})}{(1 + (R_f + \phi_{i,t}))^t}] \tag{1}$$

where $P_{i,0}$ is the price of asset i at time 0, $E(CF_{i,t})$ is the expected cash flow of asset i at time t, R_f is the short-term, risk-free rate from the money market, $\phi_{B,t}$ ($\phi_{S,t}$) is the bond's (stock's) premium in the discount rate beyond the risk-free rate for expected cash flows in period t. The ϕ's are asset-specific and may reflect both risk differentials (in the sense of the classic single-period Capital Asset

[6] By unexpected turnover, we mean the residual from an autoregressive model of turnover.

Pricing Model of Sharpe and Lintner) and hedging influences (in the sense of intertemporal asset pricing in Merton (1973)). Daily changes in an asset's ϕ may be due to changes in perceived risk for the given asset, and/or pricing influences attributed to cross-market hedging effects (due to asset substitution effects and wealth effects). Changes in cross-market hedging may also be attributed to shocks in the investment opportunity set of non-traded assets, in the sense of Wang (1994). Thus, as in Kodres and Pritsker (2002), shocks in one market may generate pricing influences in another market, even if the news in the shocked market appears to have no direct relevance in the non-shocked market.

Here, we are interested in government bonds so the future nominal cash flows are known with certainty for the bonds. This means that bond return shocks are directly tied to shocks in ϕ_B and R_f. However, stock price shocks may be attributed to either changes in the stock market's expected future cash flows, changes in ϕ_S, or changes in R_f. Since R_f is common to both stocks and bonds, we are interested in co-movements between the remaining stochastic variables that impact daily stock and bond returns: the expected future cash flows of the stock market, the ϕ_S's, and the ϕ_B's.

From this simple perspective, periods of negative correlation between daily stock and bond returns must be associated with either: (1) a negative correlation between changes in ϕ_S and ϕ_B, (2) a positive correlation between changes in the stock's expected cash flows and changes in ϕ_B, or (3) a combined effect where changes in the stock's expected cash flows are both negatively correlated with changes in ϕ_S and positively correlated with changes in ϕ_B. Holding inflation expectations constant, such statistical associations seem more plausible during times of high uncertainty with more frequent revisions in cross-market hedging and rebalancing decisions.[7] From this perspective, we are interested in the following two empirical questions.

Empirical Question One (EQ1): Is variation in the relative level of stock market uncertainty associated with future variation in the stock-bond return relation?

The framework in the Veronesi papers suggest that news may have a greater influence on changing investor's priors with high economic-state uncertainty and that variation in uncertainty may influence stock return moments and interest rates. KP point out that shocks in one market may induce price change in another unshocked market through cross-market hedging. In our view, this intuition suggests that periods with high stock market uncertainty may also be times when investor's fre-

[7]See the related discussion of Veronesi (1999) and (2001), Fleming, Kirby, and Ostdiek (1998) and Kodres and Pritsker (2002) in our introduction.

quently revise their estimate of the relative attractiveness of stocks versus bonds. In this section's framework, this would mean that times with high stock uncertainty are likely to have: (1) a less positive or even negative correlation between changes in ϕ_S and ϕ_B, (2) a more positive relation between changes in stock expected cash flows and changes in ϕ_B, or (3) some combined effect. If so, then higher stock market uncertainty suggests a higher probability of a negative stock-bond return correlation in the near future. Here, the null hypothesis is that periods of negative stock-bond return correlation may exist in daily returns, but it is an *ex post* phenomenon and periods with negative correlation cannot be associated with lagged, non-return-based measures of stock market uncertainty.

Bekaert and Grenadier (BG) (2001) investigate stock and bond prices within the joint framework of an affine model of term structure, present-value pricing of equities, and consumption-based asset pricing. They study three different economies and find that the "Moody" investor economy provides the best fit of the actual unconditional correlation between stock and bond returns. In this economy, prices are determined by the three factors of dividend growth, inflation, and stochastic risk aversion. While BG examine annual return data and do not directly address time-varying correlations in daily data, their results for the "Moody" economy includes two features of interest for our EQ1. First, shocks to dividend growth are likely to be negatively correlated with risk aversion. This suggests that shocks to dividend growth may be associated with changing risk-premia and, possibly, portfolio rebalancing between stocks and bonds for some investors. Second, concerning bond pricing, they note that uncertainty may induce agents to save, thereby depressing interest rates. Both these features seem capable of contributing to the conditional statistical associations required to generate a negative stock-bond return correlation during times with high stock market uncertainty.

We stress that EQ1 does not test a simple flight-to-quality (FTQ) hypothesis that assumes abrupt, discrete shocks to the stock market with quick and complete responses in portfolio rebalancing and cross-market hedging. Under these assumptions, simple FTQ effects should essentially be within period (contemporaneous) and lagged measures of uncertainty seem unlikely to be informative about future stock-bond return dynamics. Thus, EQ1 considers a more complex world with the intuition that time-varying uncertainty may have cross-market pricing influences with forward-looking implications.

Empirical Question Two (EQ2): Is the day's change in stock market uncertainty associated with relative differences in the day's stock-bond return relation?

If: (1) increases in stock market uncertainty are associated with either decreases in the stock's expected future cash flows or increases in ϕ_S, and (2) these changing stock market conditions are also associated with cross-market pricing influences that tend to decrease ϕ_B, then increases (decreases) in stock market uncertainty may be associated with relatively high (low) bond returns. Tests of this sort may provide further evidence about the empirical relevance of cross-market hedging as proposed in FKO (1998) and Kodres and Pritsker (2002). Note, that in contrast to our EQ1, EQ2 focuses on changes in stock market uncertainty and has contemporaneous implications. Here, the null hypothesis is that changes in non-return-based measures of stock market uncertainty are not reliably related to the contemporaneous stock-bond return relation.

2.2 Stock market uncertainty and the implied volatility of equity index options

For our primary measure of perceived stock market risk or uncertainty, we use the implied volatility index (VIX) from the Chicago Board Option Exchange. It provides an objective, observable, and dynamic measure of stock market uncertainty. Recent studies find that the information in implied volatility provides the best volatility forecast and largely subsumes the volatility information from historical return shocks, including volatility measures from 5-minute intraday returns. (Blair, Poon, and Taylor, 2001; Christensen and Prabhala, 1998; and Fleming, 1998).

Under the standard Black-Scholes assumptions, implied volatility should only reflect expected stock market volatility. However, the Black-Scholes implied volatility of equity index options has been shown to be biased high. Coval and Shumway (2000) and Bakshi and Kapadia (2001) present evidence that option prices may also contain a component that reflects the risk of stochastic volatility. If options are valuable as hedges against unanticipated increases in volatility, then option prices may be higher than expected under a Black-Scholes world of known volatility. If so, option prices would typically yield a Black-Scholes implied volatility that is higher than realized volatility, which could explain the well-known bias.

David and Veronesi (2002) present an option-pricing model that incorporates economic-state uncertainty. Their model generates a positive association between investor's uncertainty about fundamentals and the implied volatility in traded options. Their arguments provide further motivation for our use of the implied volatility from equity index options. For the purposes of this article, we lump these possible interpretations of implied volatility together and refer to movements in implied volatility as movements in "stock market uncertainty".

2.3 Stock market uncertainty and stock turnover

We also evaluate stock turnover as a second measure of stock market uncertainty. Prior literature suggests several reasons for turnover. These include asymmetric information with disperse beliefs across investors, changes in investment opportunity sets outside the traded stock market, and changes in the investment opportunity set of traded stocks (or changing stock return distributions). For example, Wang (1994) presents a dynamic model of competitive trading volume where volume conveys important information about how assets are priced in the economy. One prediction from Wang is that "the greater the information asymmetry (and diversity in expectations), the larger the abnormal trading volume when public news arrives." In Chen, Hong, Stein (2001), periods with relatively heavy volume are likely to be periods with large differences of opinion across investors. Also, see Harris and Raviv (1993) and Shalen (1993) for further discussion that relates turnover to heterogeneous information and beliefs; Heaton and Lucas (1996) and Wang (1994) for discussion that relates turnover to changes in investment opportunity sets; and Lo and Wang (2000) for additional motives for trading volume.

Thus, episodes of relatively high stock turnover may reflect periods with more diverse beliefs across investors or times with large changes in the investment opportunity set. It seems plausible to describe such times as having more stock market uncertainty. Further, our intuition suggests that periods with high economic uncertainty in the sense of Veronesi are also likely to be periods with higher dispersion-in-beliefs across investors.[8] Thus, we examine the relative level of stock turnover (detrended turnover) as a second metric that may reflect variation in the relative level of stock market uncertainty.

3 Data Description and Statistics

3.1 Returns and implied volatility

We examine daily data over the 1986 to 2000 period in our analysis because the CBOE's VIX is first reported in 1986. This period is also attractive because inflation was modest over the entire sample. This suggests that changes in inflation expectations are unlikely to be the primary force behind the

[8] This conjecture does not follow from Veronesi, since his modeling framework assumes that investors have imperfect but symmetric information.

striking time-series variation that we document in the stock-bond return relation. In our subsequent empirical testing, we also evaluate the following subperiods: 1988 to 2000 (to avoid econometric concerns that our empirical results might be dominated by the October 1987 stock market crash),[9] 1/86 to 6/93 (the first-half subperiod), and 7/93 to 12/00 (the second-half subperiod).

The CBOE's VIX, described by Fleming, Ostdiek, and Whaley (1995), represents the implied volatility of an at-the-money option on the S&P 100 index with 22 trading days to expiration. It is constructed by taking a weighted average of the implied volatilities of eight options, calls and puts at the two strike prices closest to the money and the nearest two expirations (excluding options within one week of expiration). Each of the eight component implied volatilities is calculated using a binomial tree that accounts for early exercise and dividends.[10]

We believe that the daily return horizon is most appropriate for our study for the following reasons. First, the model in Kodres and Pritsker (2002) is meant to apply to short horizons, such as daily. Second, the use of daily data follows from the empirical work in Fleming, Kirby, and Ostdiek (1998). Finally, sizable changes in stock market uncertainty may occur over a trading day. For example, in our sample, VIX changes by 15% or more for 94 different days, by 10% or more for 303 different days, and by 5% or more for 1,113 days.[11]

For daily bond returns, we analyze both 10-year U.S. Treasury notes and 30-year U.S. Treasury bonds. We calculate implied returns from the constant maturity yield from the Federal Reserve. Hereafter, we do not distinguish between notes and bonds in our terminology and refer to both the 10-year note and the 30-year bond as "bonds". We choose longer-term securities over shorter-term securities because long-term bonds are closer maturity substitutes to stocks and because monetary policy operations are more likely to have a confounding influence on shorter-term securities.[12]

[9] In addition to the extreme stock return of -17% on October 19, 1987, the implied volatility of equity index options exceeded 100% for a few days around the crash.

[10] In calculating the VIX, each option price is calculated using the midpoint of the most recent bid/ask quote to avoid bid/ask bounce issues. The VIX construction uses four calls and four puts to minimize mis-measurement concerns and any put/call option clientele effects.

[11] By a change here, we mean $(VIX_t - VIX_{t-1})/VIX_{t-1}$, where VIX_t is the implied volatility level at the end-of-the-day.

[12] Studies that consider the impact of Federal Reserve policy and intervention on bond prices include Harvey and Huang (2001) (HH) and Urich and Wachtel (2001) (UW). HH examine the 1982 to 1988 period and find that Fed open market operations are associated with higher bond volatility but that the effect on bond prices is not reliably different for reserve-draining versus reserve-adding operations. UW find that the impact of policy changes on short-

Fleming (1997) characterizes the market for U.S. Treasury securities as "one of the world's largest and most liquid financial markets." Using 1994 data, he estimates that the average daily trading volume in the secondary market was \$125 billion. Fleming also compares the trading activity by maturity for the most recently issued securities. He estimates that 17% of the total trading is in the 10-year securities and only 3% of the total trading is in the 30-year securities. Accordingly, we choose to report numbers in our tables using the 10-year bond return series. Our results throughout are qualitatively similar using the 30-year bond return series.

For robustness, we also evaluate a return series from the Treasury bond futures contract that is traded on the Chicago Board of Trade. To construct these returns, we use the continuous futures price series from Datastream International. The correlation between the futures returns and our ten-year bond returns is 0.915 over 1986 through 2000. Our empirical results are qualitatively similar when using the futures returns in place of the ten-year bond returns.

For the aggregate stock market return, we use the value-weighted NYSE/AMEX/ NASDAQ return from the Center for Research in Security Prices (CRSP). When merging the stock and bond returns, we find that there are a few days when there is not an available yield for the bonds (on Federal holidays when the stock market was still open). After deleting these days, we have 3755 observations for each data series. All returns are in daily percentage terms.

Table 1, Panel A (Panel B), reports univariate statistics for the data series over the 1986 to 2000 period (the 1988 to 2000 period). Table 1, Panel C, report the simple correlations between the variables. We note that the unconditional correlation between the daily stock and bond returns is modest at around 0.22 to 0.25, which is quite close to the monthly return correlation reported in Campbell and Ammer (1993).

Figure 1, Panel A, reports the time-series of 22-trading-day correlations between stock and bond returns, formed from days t to $t + 21$. Here, the correlations are calculated assuming the expected daily returns for both stocks and bonds are zero, rather than the sample mean for each respective 22-day period. This figure illustrates the substantial time-series variation in the stock-bond return relation. Casual inspection of this series indicates a clustering of the periods with a negative correlation. The vast majority of the negative correlations occur from October through December 1987, from October 1989 through February 1993, and from October 1997 through December 2000. Next, Figure 1, Panel B, reports the time-series of the VIX. This figure displays the substantial

term interest rates have declined in the 1990's since the Fed started making announcements on policy targets.

time-series variation in VIX. Further, periods of high VIX and/or increases in VIX seem to be associated with the periods of negative correlation in Panel A.

3.2 Stock market turnover

We also collect daily trading volume and shares outstanding for U.S. firms from CRSP over 1986 to 2000. Using this data, we construct a daily turnover measure for each firm, where turnover is defined as shares traded divided by shares outstanding. Wang (1994) and Lo and Wang (2000) provide a theoretical justification for using turnover instead of other volume metrics. We then form size-based, decile portfolios by sorting firms on their market capitalization and calculate each decile-portfolio's turnover (defined as the equally-weighted average of the individual firm turnovers). We use the turnover of the largest size-based, decile portfolio in our subsequent empirical work because the large-firm portfolio both approximates the aggregate stock market (in a market capitalization sense) and avoids small-firm concerns (such that high non-synchronous trading or excessive idiosyncratic trading in small firms might cloud a market turnover statistic). For our purposes, large-firm turnover may also be more informative if large-firm trading is more attributed to portfolio re-balancing and less attributed to private information (as compared to small firm turnover). The time-series of our large-firm portfolio's turnover is presented in Figure 1, Panel C.

We then form a de-trended turnover measure in the spirit of Campbell, Grossman, and Wang (1993)(CGW) and Chen, Hong, and Stein (2001). Following closely from CGW, we form our detrended stock turnover at period $t-1$ as follows.

$$DTVR_{t-1} = \left[\frac{1}{5}\sum_{i=1}^{5}\ln(TVR_{t-i})\right] - \left[\frac{1}{245}\sum_{i=6}^{250}\ln(TVR_{t-i})\right] \tag{2}$$

where TVR_t is the average turnover of the firms that comprise our U.S. large-firm portfolio in day t. We use a five-day moving average in (2) to remove some of the noise from the turnover series and to avoid day-of-the-week effects. The time-series of DTVR_{t-1} is presented in Figure 2, Panel A. We assume that DTVR variation is informative about variation in the level of stock market uncertainty, as discussed in Section 2.3.

We also need to measure a day's unexpected turnover for our subsequent analysis. To construct a time-series of turnover shocks, we follow the procedure in Connolly and Stivers (2002) and we use their terminology. The time-series of turnover shocks is termed the relative turnover (RTO) and is estimated as follows. The RTO_t of our large-firm portfolio is the residual, u_t, obtained from estimating the following time-series regression model:

$$ln(TVR_t) = \gamma_0 + \sum_{k=1}^{10} \gamma_k ln(TVR_{t-k}) + u_t, \tag{3}$$

where TVR_t is the turnover for our large-firm portfolio, and the γ's are estimated coefficients. Thus, RTO_t is defined as the unexpected variation in turnover after controlling for the autoregressive properties of turnover. The R^2 for model (3) is 67.0% and the model effectively captures the time-trend in turnover. The estimated coefficients γ_1 through γ_{10} are positive and statistically significant for all of the first five lags and eight of the ten. The time-series of RTO_{t-1} is presented in Figure 2, Panel B.

3.3 Description of bond and stock return volatility

To provide some perspective before proceeding to our principal results, we first provide a brief comparison of the daily volatility in stock and 10-year T-bond returns. For the 1988 to 2000 period, the unconditional daily variance of the stock returns is about four times as large as the unconditional daily variance of the 10-year bond returns.[13]

We also estimate a time-series of conditional volatilities for the stock and bond return series for comparison. For this discussion, conditional volatility refers to the conditional standard deviation, estimated by a GARCH(1,1) model that includes the lagged VIX as an explanatory term in the variance equation.[14] We find that the time-variation in stock conditional volatility is much larger than the time-variation in bond conditional volatility. For our sample, the time-series standard deviation of the bond conditional volatility is only about one-sixth as large as the time-series standard deviation of the stock conditional volatility. Finally, we note that the correlation between the stock conditional volatility series and the bond conditional volatility series is a modest 0.176. When considering cross-market pricing influences, these relative differences suggests that variation

[13]We report on the 1988 to 2000 period for this comparison to avoid concerns that the October 1987 crash drives our numbers. See Schwert (1989) and Campbell, Lettau, Malkiel, and Xu (2001) for evidence on time-variation in stock market volatility.

[14]We include the VIX as an explanatory variable because prior studies have shown that implied volatility largely subsumes information from lagged return shocks in estimating stock conditional volatility. In our sample, the VIX is not a statistically significant explanatory variable for the bond conditional volatility.

in stock market uncertainty (as measured by stock volatility) is likely to be a first-order concern; while, by comparison, variation in bond market volatility is likely to be a second-order concern.

4 The stock-bond return relation and implied volatility

Figure 1, Panel A, demonstrates the sizable time-variation in the stock-bond return relation over our sample and Figure 1, Panel B, suggest an association between VIX and the stock-bond return behavior. In this section, we investigate how the stock-bond return relation varies with VIX. In the first subsection, we examine EQ1 from Section 2 using two different approaches. Then, in the next subsection, we examine EQ2 from Section 2 using a day's change-in-VIX as a change-in-uncertainty metric.

4.1 Empirical Question 1: With variation in VIX level

4.1.1 Variation in 22-trading-day stock-bond return correlations

First, in Table 2, we report on the distribution of forward-looking correlations (formed from daily returns over days t to $t + 21$) following a given VIX_{t-1} value. For this exercise, we calculate the correlations assuming that the expected daily stock and bond returns are zero (rather than the sample mean from each respective 22-day period). We believe that this choice is closer to reality and prevents extreme returns from implying large positive or negative expected returns over specific 22-day periods. We choose the 22-trading-day horizon because this horizon corresponds to the maturity of VIX and because much prior literature has formed monthly statistics from days within the month.

We find that these forward-looking correlations vary negatively and substantially with the VIX level. The unconditional probability that the 22-trading-day correlation between stock and bond returns is negative is 15.6%. However, for the days when VIX_{t-1} is greater than 25% then the probability of a subsequent negative correlation is 36.5%, which is six times greater than the 6.1% probability of a negative correlation when VIX_{t-1} is less than 20%. Here, these probabilities are calculated from the occurrence of each outcome in our sample.

For comparison to the Table 2 results, we calculate a bootstrapped-based distribution for the mean of the 22-trading-day correlations and find that the bootstrapped 1^{st} to 99^{th} percentile range for the mean correlation covers the interval from 0.3277 to 0.3541.[15] Thus, the mean of the 22-trading-day correlations for the different VIX conditions in Table 2 are all well outside this inner 98^{th} percentile range for the distribution of the mean correlation over our entire sample.

The results are qualitatively similar in one-half subperiods, although the contrast is substantially greater in the second-half subperiod. For the first-half subperiod, the unconditional probability of a 22-trading-day negative correlation is only 7.3%. In contrast, for the days when VIX_{t-1} is greater than 35%, then the probability of a subsequent negative correlation is tripled at 22.5%. For the second-half subperiod, the unconditional probability of a 22-trading-day negative correlation is 24.0%. However, for the days when VIX_{t-1} is greater than 30%, then the probability of a subsequent negative correlation is more than tripled at 80.3%. Further, for the second-half subperiod, the probability of a negative correlation is only 2.7% for the observations when VIX_{t-1} is less than 20%.

4.1.2 Perspective of conditional bond return distributions

Our perspective here is as follows. Consider the bond and stock return shocks as a bivariate distribution of random variables with a non-zero correlation. Denote the bond and stock return shocks as ϵ_t^B and ϵ_t^S, respectively. Then, we are interested in how the $E(\epsilon_t^B|\epsilon_t^S)$ relation might vary with the lagged VIX (and later our lagged DTVR).

We are interested in the $E(\epsilon_t^B|\epsilon_t^S)$ (rather than the $E(\epsilon_t^S|\epsilon_t^B)$) because our lagged conditioning variables are assumed to be related to stock market uncertainty (in the sense of the Veronesi papers) or stock market shocks (in the sense of Kodres and Pritsker (2002)). Thus, the focus of our study suggests that we consider the stock uncertainty or shock to have a first-order effect on the stock market and a second-order effect on the bond market. This intuition leads to our focus on the $E(\epsilon_t^B|\epsilon_t^S)$ relation since we are interested in the stock-to-bond return relation, as depicted in our test (6) below.[16]

If the bivariate distribution of ϵ_t^B and ϵ_t^S was well described by a stable bivariate normal dis-

[15] All of our bootstrapped-based distributions in this paper are based on 1000 draws with replacement from the respective sample.

[16] Of course, stock and bond returns shocks are both endogenous variables in the economy and both are jointly determined. Thus, we stress that our investigation here is not from the perspective of a structural economic model, but from the perspective of the conditional distribution of bond returns.

tribution, then the $E(\epsilon_t^B|\epsilon_t^S)$ would be just a constant times the observed ϵ_t^S where the constant equals the covariance between ϵ_t^B and ϵ_t^S divided by the variance of ϵ_t^S. However, with time-varying variances and correlations between ϵ_t^B and ϵ_t^S, the expected ϵ_t^B given ϵ_t^S is likely to vary. Note, however, that heteroskedasticity alone cannot generate a negative relation between two random variables that are positively correlated.

Since we are interested in the bond and stock return shocks, we first perform the following auxiliary regressions to orthogonalize the bond and stock returns from lagged information.

$$B_t = \alpha_0 + \alpha_1 \ln(VIX_{t-1}) + \alpha_2 DTVR_{t-1} + \alpha_3 Cr_{t-1} + \sum_{i=1,2} \varphi_i B_{t-i} + \sum_{i=1,2} \gamma_i S_{t-i} + \varepsilon_t^B \tag{4}$$

$$S_t = \beta_0 + \beta_1 \ln(VIX_{t-1}) + \beta_2 DTVR_{t-1} + \beta_3 Cr_{t-1} + \sum_{i=1,2} \psi_i B_{t-i} + \sum_{i=1,2} \phi_i S_{t-i} + \varepsilon_t^S \tag{5}$$

where B_t (S_t) is the daily 10-year bond (stock) return, VIX_{t-1} is the lagged CBOE's Volatility Index, DTVR_{t-1} is our lagged, detrended stock turnover from section 3.2, Cr_{t-1} is the 22-trading-day stock-bond return correlation over days $t-1$ to $t-22$, ε_t^B (ε_t^S) is the residual for the bond (stock) return, and the α_i's, φ_i's, γ_i's, β_i's, ψ_i's, and ϕ_i's are estimated coefficients.

We retain the residuals from (4) and (5) for use in estimating (6) below. In addition to controlling for lagged information, the auxiliary regressions also ensure that our interactive conditioning variables in (6) are orthogonal to both ϵ_t^B and ϵ_t^S. In practice, the estimation of (4) and (5) explain very little of the daily bond and stock returns. The adjusted R^2 of (4) is only 0.44%, and the adjusted R^2 of (5) is only 0.93%. The correlation between the raw bond (stock) return and the bond (stock) residual from the auxiliary regression is 0.996 (0.994).

Our primary interest in this subsection is whether the $E(\epsilon_t^B|\epsilon_t^S)$ varies with the lagged VIX, as depicted by the following regression:

$$\epsilon_t^B = (a_0 + a_1 \ln(VIX_{t-1}) + a_2 CV_{t-1})\epsilon_t^S + \nu_t \tag{6}$$

where ϵ_t^B and ϵ_t^S are the daily 10-year T-bond and stock return residuals from our auxiliary regressions (4) and (5), respectively; $ln(VIX_{t-1})$ is the natural log of the VIX in period $t-1$; ν_t is the residual, CV_{t-1} is an additional conditioning variable explained later, and the a_i's are estimated coefficients. We use the log transformation of VIX to reduce the skewness of the implied volatility series. Table 3 reports the results from estimating four variations of (6).

Table 3, Panel A, reports on a variation of (6) that restricts a_1 and a_2 to be zero. As expected, these results indicate an unconditional positive relation between ϵ_t^B and ϵ_t^S. The R^2's are modest at 4.8% for the entire sample and only 1.96% for the second-half subperiod.

Next, Table 3, Panel B, reports on a variation of (6) that restricts a_2 to be zero. We find that the stock-to-bond return relation varies negatively and very reliably with the lagged VIX. The variation in the stock-bond return relation appears substantial. For example, over the 1988 to 2000 period, the total implied coefficient on ϵ_t^S is 0.364 at the 5^{th} percentile of VIX_{t-1}. In contrast, at the 95th percentile of VIX_{t-1}, the total implied coefficient on ϵ_t^S is essentially zero at 0.009. Results in other periods are qualitatively similar. The results for the second-half subperiod in column 4 are especially dramatic. For this period, the total implied coefficient on ϵ_t^S is 0.490 (-0.044) at the VIX's 5^{th} (95^{th}) percentile. Also note the substantial increases in R^2 for the results in Panel B, as compared to the Panel A results. For the second-half subperiod, the R^2 increases from about 2% to over 15% when adding the lagged VIX information.

For comparison to these VIX-based variations in the total implied coefficient on ϵ_t^S, we calculate bootstrap-based distributions of the a_0 coefficient for the model variation in panel A (a_1 and a_2 restricted to zero) over all four sample periods. The inner 90^{th} percentile range for the bootstrap-based distribution of a_0 is 0.0771 to 0.1307, 0.0783 to 0.1215, 0.0955 to 0.208, and 0.0378 to 0.0878; for the entire sample, the 1/88 to 12/00, the 1/86 to 6/93, and the 7/93 to 12/00 periods, respectively. Thus, the implied total coefficients on ϵ_t^S at the VIX's 95^{th} and 5^{th} percentile in Table 3, Panel B, are all outside the respective inner 90^{th} percentile range except for the VIX-95^{th} percentile estimate for the first-half subperiod. This comparison further suggests that the VIX-based variations are substantial and statistically significant.

Table 3, Panel C, reports results on the case where CV_{t-1} is the correlation between the stock and bond returns from period $t-1$ to $t-22$. First, for all four periods in Table 3, the estimated a_1 is negative and highly statistically significant. Thus, the negative relation between lagged VIX and the $E(\epsilon_t^B|\epsilon_t^S)$ relation remains reliably evident, even when directly considering the information from recent stock-bond return correlations. Next, we find that there does tend to be information from the lagged rolling-correlation estimates. The estimated a_2 coefficient is positive and significant for the overall sample and for two of the three subperiods.

Finally, Figure 1, Panel A, indicates strong and persistent negative stock-bond correlations in late 1997 and the second half of 1998. These observations suggest that the Asian financial crisis of 1997 and the Russian financial crisis of 1998 may be particularly influential in our results. The variation of (6) in Table 3, Panel D, addresses this issue. For this case, CV_{t-1} equals one during the Asian crisis and/or the Russian crisis, and equals zero otherwise. We use the crises dates from Chordia, Sarkar, and Subrahmanyam (2001), (October 1, 1997 through December 31, 1997 for the Asian crisis and July 6, 1998 through December 31, 1998 for the Russian crisis).

We note that this variation of (6) is different because now an interactive conditioning variable uses *ex post* information, rather than only lagged information (as in Panel B and C). We find that the estimated a_2 on the CV_{t-1} variable is negative and highly statistically significant for both crises, both jointly and individually. However, the estimated a_1 on VIX_{t-1} also remains negative and highly statistically significant. The statistical significance of a_1 even increases in the Panel D case, as compared to the Panel B case. We also extend our crises variable to include the Persian Gulf war (August 1990 through February 1991) and find nearly the same result for the estimated a_1 coefficient. Thus, the lagged VIX relation remains strong even when directly controlling for these crisis period using *ex post* information.

We also run the tests in Table 3 in a GARCH system where the mean equation is given by equation (6) and with the following conditional variance equation.

$$h_t = \gamma_0 + \gamma_1 \nu_{t-1}^2 + \gamma_2 h_{t-1} + \gamma_3 VIX_{t-1}, \tag{7}$$

where h_t is the conditional variance, the γ_i's are estimated coefficients, and the other terms are as defined for (6). We estimate this GARCH system simultaneously by maximum likelihood using the conditional normal density. We estimate Bollerslev and Wooldridge (1992) standard errors that are robust to departures from conditional normality of the system residuals. The results are qualitatively and quantitatively similar to the OLS results in Table 3 and the γ_3 coefficient is statistically insignificant. We conclude that our results are robust to allowing for conditional heteroskedasticity in the bond returns.

4.2 Empirical Question 2: With the daily VIX change

It is known that stock returns are negatively and reliably associated with contemporaneous changes in VIX, see Fleming, Ostdiek, and Whaley (1995). However, the issue of whether bond returns are related to changes in VIX has not been explored. In Table 4, we report on this issue by sorting observations on their change-in-VIX and then calculating subsample statistics for the different change-in-VIX groupings. Panel A reports univariate statistics and Panel B reports bivariate statistics.

First, these results suggest that the correlation between stock and bond returns decrease during periods with substantial VIX increases. For the top five (25) percentile of VIX increases, the stock-bond return correlation is -0.055 (0.112), in contrast to the 0.223 unconditional correlation. Further, our results suggest that T-bond returns are large, relative to stocks, during periods of very large VIX increases. For example, for the largest five percentile of VIX increases, the average daily stock return is -1.891%, which is over two stock-return standard deviations from the unconditional stock mean. In contrast, for the largest five percentile of VIX increases, the average daily bond return is -0.044%, which is only about one-fifth of a bond-return standard deviation from the unconditional bond mean. Further, for the largest five percentile of VIX increases (as reported in column five of Table 4, Panel B), nearly half the daily observations have a negative stock return and a positive bond return. This contrasts to the 19.4% unconditional probability of observing both a negative stock return and a positive bond return. These findings seem consistent with the idea of cross-market hedging (or flight-to-quality) during periods when stock market uncertainty increases substantially.

5 The stock-bond return relation and stock turnover

In this section, we investigate how the stock-bond return relation varies with stock turnover. We perform the same battery of tests as in the preceding section, but here we use our stock turnover measures, rather than VIX. In addition to the notion that turnover is associated with diverse beliefs and uncertainty from Section 2.3, it also seems likely that high turnover would be associated with periods of substantial changes in cross-market hedges and portfolio rebalancings.

5.1 Empirical Question 1: With variation in detrended stock turnover

5.1.1 Variation in 22-trading-day stock-bond return correlations

First, in Table 5, we report on the distribution of forward-looking correlations (formed from daily returns over days t to $t+21$) following a given DTVR_{t-1} value. As before, we calculate the correlations assuming that the expected daily stock and bond returns are zero (rather than the sample mean from each respective 22-day period).

Our results indicate that these forward-looking correlations vary negatively and substantially with the DTVR_{t-1} level. When DTVR_{t-1} is greater than its 90^{th} percentile, then there is a 34.2% chance of observing a subsequent negative correlation between stock and bond returns. However, when DTVR_{t-1} is less than its 25^{th} percentile, then there is only a 11.7% chance of observing a subsequent negative correlation between stock and bond returns. Further, the mean of the 22-trading-day correlations for the different DTVR conditions in Table 5 are all outside the inner 98^{th} percentile range of the bootstrap-based distribution for the mean of the 22-trading-day correlations over our entire sample.

This qualitative comparison is also consistent in one-half subperiods, although the contrast is substantially greater in the second-half subperiod. For the first-half subperiod, the unconditional probability of a 22-trading-day negative correlation is only 7.3%. In contrast, for the days when DTVR_{t-1} is greater than its 90^{th} percentile, the probability of a subsequent negative correlation is doubled at 14.4%. For the second-half subperiod, the unconditional probability of a 22-trading-day negative correlation is 24.0%. For the days when DTVR_{t-1} is greater than its 90^{th} percentile, the probability of a subsequent negative correlation is more than doubled at 51.3%.

5.1.2 Perspective of conditional bond return distributions

Here, we estimate the following regression to further investigate variation in the stock-to-bond return relation associated with the lagged detrended stock turnover. Our perspective and the intuition behind this regression is the same as in Section 4.1.2. for the comparable VIX regression.

$$\epsilon_t^B = (a_0 + a_1 DTVR_{t-1} + a_2 CV_{t-1})\epsilon_t^S + \nu_t \tag{8}$$

where ϵ_t^B and ϵ_t^S are the daily 10-year T-bond and stock return residuals from our auxiliary regressions (4) and (5), respectively; $DTVR_{t-1}$ is our lagged detrended stock turnover as defined in section 3.2; ν_t is the residual, CV_t is an additional conditioning variable explained later, and the a_i's are estimated coefficients.

Table 6, Panel A, reports on the simple variation of (8) with no interactive conditioning variables. The results are described in Section 4.1.2. Next, Table 6, Panel B, reports results on the variation of (8) with only the DTVR information (restricts a_2 to be zero). We find that the stock-bond return relation varies negatively and very reliably with the lagged DTVR. At the 5th percentile of DTVR_{t-1}, the total implied coefficient on ϵ_t^S is substantial at a value of 0.220. In contrast, at the

95th percentile of the lagged DTVR, the total implied coefficient on ϵ_t^S is only 0.046. Subperiod results are similar.

We also compare the DTVR implied coefficients to our bootstrap-based distribution of the a_0 coefficient for the case where a_1 and a_2 are restricted to be zero. (See the bootstrap-based distributions of a_0 for each subperiod in Section 4.1.2.) The implied total coefficients on ϵ_t^S at the DTVR's 95^{th} and 5^{th} percentile are all outside the respective inner 90^{th} percentile range of the bootstrap-based distribution for a_0. This further suggests that the DTVR-based variations are substantial and statistically significant.

Table 6, Panel C, reports on the case where CV_{t-1} equals the correlation between the stock and bond returns from period $t-1$ to $t-22$. Our estimation indicates the following. First, for the overall sample, the estimated a_1 remains negative and highly statistically significant. For the subperiods, the estimated a_1 remains negative, but it is insignificant in two of the subperiods. There does tend to be information from the lagged rolling-correlation estimates. The estimated a_2 coefficient is positive and significant for all periods except 1/86 - 12/93.

Finally, Table 6, Panel D, reports on the case where CV_{t-1} equal one during the Asian crisis and/or the Russian crisis, and equals zero otherwise. (See the details in Section 4 when describing the comparable VIX model.) As for the VIX model, we find that the estimated a_2 on the CV_{t-1} variable is negative and highly statistically significant for both crises, both jointly and individually. However, the estimated a_1 on the lagged DTVR variable also remains negative and highly statistically significant. We also extend our crises variable to include the Persian Gulf war (August 1990 through February 1991) and find nearly the same result for the estimated a_1 coefficient. Thus, the lagged DTVR relation also remains strong even when directly controlling for these crises using ex post information.

As we did in Section 4.1.2, we also estimate the relation in (8) within a GARCH system where the mean equation is given by (8) and the conditional variance equation is given by (7), except that DTVR replaces the VIX term. The results are qualitatively and quantitatively similar to the OLS results in Table 6 and the DTVR term is not reliably related to the bond conditional volatility. We conclude that the DTVR results are also robust to allowing for conditional heteroskedasticity in the bond returns.

5.2 Empirical Question 2: With unexpected stock turnover

Finally, we examine how stock and bond returns vary with the contemporaneous unexpected turnover in the stock market. We use our RTO measure, as described in Section 3.2, to measure the turnover shock. Table 7 reports the results.

We find that the mean bond return increases nearly monotonically with the RTO. For example, for the under-5th (under-25th) percentile RTO days, the mean bond return is negative at -0.028% (-0.009%). In contrast, for the above-95th (above-75th) percentile RTO days, the mean bond return is positive at 0.115% (0.099%). The difference between the mean bond return of the under-5th and above-95th (under-25th and above-75th) percentile RTO days is statistically significant at a p-value of 1.3% ($< 1\%$). Further, the mean bond return for the above-95th percentile RTO days is over four times the unconditional mean of the bond return. These findings also suggest that cross-market pricing influences have an appreciable effect on bond returns.

In contrast, none of the differences in means for the stock returns is significantly different across the RTO subsamples. However, during periods of extremely high unexpected stock turnover, the average stock returns are low, relative to the average bond returns. For the above-95th percentile RTO days, the average stock return is below its unconditional average at 0.044% and the average bond return is much higher than its unconditional average at 0.113% (numbers are for the sample excluding the October 19, 1987 crash).

6 Regime-shifting analysis

6.1 Models of regime switching in the stock-bond return correlation

To this point, our empirical investigation has produced significant new evidence that links the stock-bond return relation to both the relative level and changes in VIX and stock turnover. Our findings provide strong support for a "Yes" answer to our empirical questions, EQ1 and EQ2, in Section 2. Further, we have shown that VIX and stock turnover continue to provide valuable information about the stock-bond return relation even when directly controlling for lagged, rolling correlations and major international financial crises.

In this section, we explore a regime-shifting approach to modeling these shifts in the stock-bond return relation. There is considerable evidence of regime switching in both stock and bond returns.[17] Our purpose in this section is three-fold: (1) to show that a simple regime-switching model also picks up statistically reliable time-variation in the stock-bond return relation, (2) to show that the probability of switching from one regime to another depends on the lagged VIX and our lagged DTVR in a manner consistent with our findings in Sections 4 and 5, and (3) to show that inflation behavior exhibits little variation across the regimes. Our regime-shifting analysis also has implications for asset allocation between stocks and bonds.

Since regime-switching models are well established in the literature, we provide only a quick sketch of the method. As Engel and Hamilton (1990) point out, even simple versions of these models are capable of capturing a wide variety of time-series dynamics. To provide a benchmark estimate of the dynamics of stock-bond return comovement, we first estimate a basic two-state regime-switching model given by

$$B_t = a_0^s + a_1 B_{t-1} + a_2^s S_t + \epsilon_t, \tag{9}$$

where B_t and S_t are the daily T-bond and stock returns, respectively; ϵ_t is the residual; and the a's are estimated coefficients. The superscript s indicates regime 0 or regime 1, where s can be regarded as an unobserved state variable that follows a two-state, first-order Markov process. The transition probability matrix can be written as follows:

$$\mathbf{X} = \begin{pmatrix} p & 1-p \\ 1-q & q \end{pmatrix} \tag{10}$$

where $p = Pr(s_t = 0|s_{t-1} = 0)$, and $q = Pr(s_t = 1|s_{t-1} = 1)$. We refer to this model subsequently as the constant transition probability regime-switching (CTP-RS) model. Our discussion in Section 4.1.2 explains why we estimate this model with the bond return as the dependent variable and the stock return as an explanatory variable, rather than vice versa. We choose to estimate this model with raw returns, rather than return shocks, for simplicity since it makes no difference in practice

[17] There is a relatively large literature applying variants of Hamilton's regime-switching model in financial economics, see Hamilton (1994) for an overview. Gray (1996) is a seminal application of regime-switching methods to short-term yields. Boudoukh, Richardson, Smith, and Whitelaw (1999) argue that bond returns display behavior consistent with regime switching. Kim and Nelson (2001) provide an excellent discussion of regime-switching models and their application to bond and stock returns. Ang and Bekaert (2002a, b) explore the use of regime-switching models in bond pricing. Also, see Whitelaw (2000) and the earlier-cited Veronesi papers for other important explorations of regime-switching in financial economics.

(due to the near-zero predictability in daily returns, again see our discussion and results in Section 4.1.2).

If the stock-bond return relation is persistently positive and then persistently negative, we expect a_2^0 and a_2^1 to have opposite signs and both p and q to be large. This is strongly contrasted by the case where the stock-bond return relation in a period is independent of the relation in the previous period. If this holds, we expect 1-p to be equal to q.

We also estimate a more sophisticated regime-switching model with time-varying transition probabilities in order to address the fundamental question: Does the probability of switching vary significantly with lagged VIX (or our lagged DTVR)? Specifically, instead of constraining the p and q to be constants, we follow Diebold et al. (1994), and specify time-varying transition probabilities as follows:

$$p(s_t = j | s_{t-1} = j; I_{t-1}) = \frac{e^{c_j + d_j ln(VIX_{t-1})}}{1 + e^{c_j + d_j ln(VIX_{t-1})}}, j = 0, 1. \tag{11}$$

We refer to this model subsequently as the time-varying transition probability regime-switching (TVTP-RS) model. This model specification encompasses our CTP-RS model. We can test directly for the superiority of this TVTP-RS model over our simpler CTP-RS model. This test is effectively a test of the null hypothesis that the probability of shifting from one regime to another has no relation to the lagged VIX (DTVR).

For our regime-shifting estimation, we elect not to model heteroskedasticity in the bond returns for parsimony and the following reasons. First, time-variation in bond return volatility is much smaller than time-variation in stock return volatility. Second, the correlation between time-varying stock volatility and time-varying bond volatility is modest. Finally, the lagged VIX is not reliably related to time-varying bond volatility.

6.2 Empirical results

In Table 8, we report the estimates of our CTP-RS model, applied to the 10-year Treasury bond returns over both the 1986 to 2000 period and the 1988 to 2000 period (to exclude the October 1987 crash period). The results are similar for both periods. To summarize, we find strong evidence of regime-shifting behavior with substantial contrast between the regimes. The estimated p and q probabilities are large and reliably estimated, and indicate the regimes are persistent.

In the first regime (denoted regime-zero in the table), we find that the a_2^0 coefficient on stock returns is large and statistically significant at a value of 0.304. The intercept term is negative but insignificant. In contrast, in the second regime (denoted regime-one in the table), we find that the a_2^1 coefficient on stock returns is negative and statistically significant at a value of -0.050. For regime-one, the intercept term is positive and statistically significant.

Figure 3 displays the regime-shifting behavior. In Figure 3, the upper series is the VIX and the lower series is the smoothed probability of being in regime-one for the 10-year T-bond returns. The close mapping between the periods with negative correlation in Figure 1, Panel A, and the regime-one periods in Figure 3 give us additional confidence in the regime-shifting estimation.

We also compare the stock and bond average returns, volatility, and correlations across the two regimes. Table 8, Panel B, reports results for the 10-year T-bonds, over both the 1986 to 2000 period and the 1988 to 2000 period. Recall that we categorize an observation as belonging to a particular regime if there is at least an 80% probability of the observation being in the particular regime. This comparison indicates the following. First, regime-zero comprises about two-thirds of the daily observations. In regime-zero, the correlation between the stock and bond returns is quite high at 0.52, average stock returns are high (relative to the bond returns), and stock volatility is modest. Second, regime-one comprises less than one-fourth of the observations. For regime-one, the correlation between the stock and bond returns is much lower than normal at about -0.20, average bond returns are high (relative to stock returns), and stock volatility is much higher than normal. Finally, bond volatility does not vary substantially across the regimes, which supports our choice to not model bond heteroskedasticity. These differences across regimes casually suggest a "more normal, lower uncertainty" regime versus a "more abnormal, higher uncertainty" regime.[18]

Next, in Table 9, we report our results for the TVTP-RS model, estimated over 1988 to 2000.[19] The regime behavior and the estimated a_i^j coefficients are similar to those for the CTP-RS model

[18]A few observations are not clearly classified in either regime. We also calculate the statistics for the different regimes for the first-half (1/86 - 6/93) and second half (7/93 - 12/00) periods. For the first half, the stock-bond correlation is 0.501 (-0.131) for regime-zero (regime-one), which encompasses 1347 (208) observations. For the second half, the stock-bond correlation is 0.551 (-0.239) for regime-zero (regime-one), which encompasses 1177 (621) observations.

[19]For the TVTP-RS model, we formally report results for the 1988 to 2000 period only. We made this choice due to econometric concerns related to the extreme VIX around the October 1987 crash. However, we also estimate the TVTP-RS model for the entire 1986-2000 period. The regime-shifting behavior is very similar to that depicted in Table 9 but the coefficients are less precisely estimated.

in Table 8. For the transition probabilities in the TVTP-RS model, we note that the estimated d_0 is significantly negative. This indicates that a high VIX_{t-1} will lower the probability of staying in regime zero. For regime-one, the estimated d_1 is positive (but statistically insignificant), which suggests that a high VIX_{t-1} may increase the probability of staying in regime one. Both the TVTP-RS model and the CTP-RS model confirm the presence of statistically-significant regime-shifting in the stock-bond return relation.

We perform a likelihood ratio test that compares our CTP-RS model to our TVTP-RS model. This test indicates that the estimated d_0 and d_1 are jointly statistically significant with a p-value < 0.001, and thus rejects the CTP-RS model in favor of the TVTP-RS model. This result also suggests that stock market uncertainty plays a functional role in explaining the dynamics of the stock-bond return relation.

Table 9, Panel B, reports basic descriptive statistics for the return observations in each regime for the TVTP-RS model. Figure 4 presents the relation between VIX movements and the regimes graphically. The comparison of return statistics across regimes is very similar to that for the CTP-RS model, but the regimes exhibit less persistent. The difference in correlations across regimes is even greater at 0.950 for our TVTP-RS model versus 0.767 for our CTP-RS model.

For both our CTP-RS and TVTP-RS model, the regime-one behavior can be smoothed and roughly categorized into three periods. The months from 10/87 to 12/87, 10/89 to 2/93, and 10/97 to 12/00 can be described as substantially regime-one months. The remainder of the months can be categorized as predominantly regime-zero. We use this approximate regime breakdown in our examination of inflation below.

Recall that Campbell and Ammer's (1993) fundamental approach suggests that only movements in inflation should induce a negative correlation between stock and bond returns. Thus, it would be interesting to see if inflation behavior varies across the regimes. For inflation, we evaluate monthly changes in the seasonally-adjusted Consumer Price Index. For the predominantly regime-zero months, the average inflation was 0.250% per month and the inflation volatility was 0.144% per month (proxied for by the average absolute change in the month-to-month inflation rate). For the predominantly regime-one months, the average inflation was 0.270% per month and the inflation volatility was 0.162% per month. These differences in the mean and volatility of inflation across the regimes seem modest and are not statistically significant. Thus, this comparison further suggests that inflation is not the primary factor behind our results.

Finally, we also investigate whether the lagged DTVR is useful in modeling the transition probabilities in the regime-shifting model. We estimate our TVTP-RS model, except that DTVR replaces the ln(VIX) term. The results and regime behavior are qualitatively similar to the results in Table 9 for the VIX model, except that the d_j coefficients on the DTVR terms are less precisely estimated. As for the VIX model, the estimated d_0 is negative and the estimated d_1 is positive. However, for the DTVR model, both the d_j coefficients are statistically insignificant. For brevity, we do not repeat the regime description for the DTVR model.

6.3 Duration of regimes and portfolio management

The transition probability estimates provide some additional insights into the implications of the regime-switching for portfolio management. We explore these issues briefly in this subsection. Since our testing rejects the CTP-RS model in favor of the TVTP-RS VIX model, we focus on the TVTP-RS model here.

In the TVTP-RS model, the estimated duration depends on the value of VIX.[20] Evaluating our TVTP-RS model at a VIX_{t-1} value of 15%, the expected duration of staying in regime zero is 53 days. When VIX_{t-1} is 30%, the expected duration of staying in regime zero falls to only 16 days. The expected durations for regime one are 13 days (when VIX_{t-1} is 15%) and 34 days (when VIX_{t-1} is 30%). The length of these durations and the variability of the durations with the lagged VIX may be of interest to portfolio managers who are trying to maximize performance metrics such as the Sharpe ratio. In this respect, our investigation may be extended and linked with research by Ang and Bekaert (2002c) into the consequences of regimes for asset allocation.

7 Conclusion

We study time-variation in the co-movements between stock and bond returns over the 1986 to 2000 period. As in other studies, we document substantial time-variation in the stock-bond return relation. Particularly intriguing are the periods of sustained negative correlation between daily stock and bond returns, which contrasts with the overall modest positive correlation. Since there is little difference in inflation behavior over our sample period, it seems unlikely that difference in inflation concerns are behind the time-variation in the stock-bond return relation. Further, while

[20] The expected duration of regime i is calculated as follows: $E(D) = \frac{1}{1-p_{ii}}, p_{ii} \equiv Pr(s_t = i | s_{t-1} = i)$.

heteroskedasticity can impact return correlations even if the underlying economic relation between the two return series has not changed (Forbes and Rigobon, 2001), heteroskedasticity alone cannot explain the periods of negative correlation. So, the question remains as to what is driving this substantial time-variation in the stock-bond return relation, especially the periods of sustained negative correlation.

Our goal in this study is to consider the role of stock market uncertainty. We assume that the time-series behavior of VIX and stock turnover may be informative about variation in stock uncertainty. We investigate two empirical questions suggested by recent literature on stock market uncertainty and cross-market hedging. First, from a forward-looking perspective, we find that the level of IV and DTVR are both negatively associated with the future correlation between stock and bond returns. The probability of a negative correlation between daily stock and bond returns over the next month is several times greater following relatively high values of IV and DTVR. Second, from a contemporaneous perspective, we find that bond returns tend to be relatively high (low) during days when IV increases (decreases) and during days when stock turnover is unexpectedly high (low).

Collectively, our forward-looking and contemporaneous results suggest that stock market uncertainty may generate important cross-market pricing influences, as suggested in Fleming, Kirby, and Ostdiek (1998) and Kodres and Pritzker (2002). Further, our findings suggest that times of high stock uncertainty are also times with much volatility in the relative attractiveness of stocks and bonds, which could explain periods of negative correlation between stock and bond returns even in stable inflationary times. Our findings also suggest that stock implied volatility and detrended stock turnover may be useful as state variables that are informative about economic uncertainty in the sense of Veronesi, 1999 and 2001; and David and Veronesi, 2002.

An interesting question is whether the time-variation in the stock-bond return relation is more of an international phenomenon or a country-specific phenomenon. In Appendix A, we take an initial look at this question by examining whether the stock-bond return correlation in the other G-7 countries varies across the regimes suggested by our U.S. results (see Section 6, Table 8, and Figure 3). We find that each country's stock-bond return correlations vary similarly and significantly across the U.S. regimes, except for Japan. For example, the U.K.'s stock-bond return correlation is 0.467 during the U.S.'s "primarily regime-zero months" versus only 0.078 during the U.S.'s "substantially regime-one months". These findings suggest a strong international flavor to our findings and further suggests a role for such international crises as the Asian crisis of 1997 and the Russian crisis of 1998.

Another interesting question is whether the behavior of mutual fund flows varies across our regimes from Section 6. Cross-market pricing influences associated with stock market uncertainty seem likely to also be reflected in fund flow behavior. As noted in our introduction, Chordia, Sarkar, and Subrahmanyam (CSS) (2001) examine the 1991 to 1998 period and find evidence that net equity-fund flows decreased and net government-bond-fund flows increased during the Asian crisis of 1997 and Russian crisis of 1998. These crises occur in our regime-one months and our regime-one encompasses nearly all of the periods with a negative stock-bond return correlation. In Appendix B, we also examine monthly fund flows from the Investment Company Institute but expand the analysis from 1986 to 2000. Consistent with CSS, we find evidence that stock (bond) fund redemptions are higher (lower) in our regime-one, as compared to our regime-zero.

From a practical perspective, our results may have direct financial applications. Specifically, the implied volatility from equity-index options and stock turnover may be useful for financial applications that need to understand and predict stock and bond market co-movements. For example, our findings imply that joint stock-bond return models should allow for the stock-bond return correlation to vary and suggest that our uncertainty variables that may be useful in modeling this variation. Further, our findings suggest increased diversification benefits for portfolios of stocks and bonds during periods of high stock market uncertainty. Such a timely diversification benefit is in contrast to cross-equity market diversification, where much of the literature (see, e.g., King and Wadhwani, 1990; and Lee and Kim, 1993) has argued that cross-market equity returns may be more positively linked during times of high stock market uncertainty. Future research to better pinpoint the theoretical and practical implications of our findings should prove interesting.

References

Ang, Andrew and Bekaert, Geert, 2002a, Regime switches in interest rates, *Journal of Business and Economic Statistics* 20, April 2002, 163-182.

Ang, Andrew and Bekaert, Geert, 2002b, Short rate nonlinearities and regime switches, *Journal Of Economic Dynamics And Control* 26, 1243-1274.

Ang, Andrew and Bekaert, Geert, 2002c, How do regimes affect asset allocation?, Graduate School of Business working paper, Columbia University.

Bakshi, Gurdip, and Nikunj Kapadia, 2001, Delta-hedged gains and the negative market volatility risk premium, *The Review of Financial Studies*, forthcoming.

Barsky, R., 1989, Why don't the prices of stocks and bonds move together?, *American Economic Review* 79, 1132-1145.

Bekaert, Geert, and Steven Grenadier, 2001, Stock and bond pricing in an affine economy, Working paper, Columbia University.

Blair, Bevan, Ser-Huang Poon, and Stephen Taylor, 2001, Forecasting S & P 100 volatility: The incremental information content of implied volatilities and high-frequency index returns, *Journal of Econometrics* 105, 5-26.

Bollerslev, Tim, and Jeffrey Wooldridge, 1992, Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances, *Econometric Reviews* 11, 143-172.

Boudoukh, Jacob, Matthew Richardson, Tom Smith, and Robert Whitelaw, 1999, Regime shifts and bond returns, Working paper, New York University.

Campbell, John, and John Ammer, 1993, What moves the stock and bond markets? A variance decomposition for long-term asset returns, *The Journal of Finance* 48, 3-37.

Campbell, John, Sanford Grossman, and Jiang Wang, 1993, Trading volume and serial correlation in stock returns, *The Quarterly Journal of Economics*, 905-939.

Campbell, John, M. Lettau, B. Malkiel, and Y. Xu, 2001, Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *The Journal of Finance* 56, 1-43.

Chen, Joseph, Harrison Hong, and Jeremy Stein, 2001, Forecasting crashes: Trading volume, past returns and conditional skewness in stock prices, *Journal of Financial Economics* 61, 345-381.

Chordia, Tarun, Asani Sarkar, and Avanidhar Subrahmanyam, 2001, Common determinants of bond and stock market liquidity: The impact of financial crises, monetary policy, and mutual fund flows, Working paper, Emory University, the Federal Reserve Bank of New York, and UCLA.

Christensen, B.J. and N.R. Prabhala, 1998, The relation between implied and realized volatility. *Journal of Financial Economics* 50, 125-150.

Connolly, Robert, and Chris Stivers, 2002, Momentum and reversals in equity-index returns during periods of abnormal turnover and return dispersion, *The Journal of Finance*, forthcoming.

Coval, Joshua, and Tyler Shumway, 2001, Expected option returns, *The Journal of Finance* 56, 983-1009.

David, Alexander, and Pietro Veronesi, 2002, Option prices with uncertain fundamentals: Theory and evidence on the dynamics of implied volatilities, Working paper, University of Chicago.

David, Alexander, and Pietro Veronesi, 2001, Inflation and earnings uncertainty and the volatility of asset prices: An empirical investigation, Working paper, University of Chicago.

Diebold, F.X., J.H. Lee, and G. C. Weinbach, 1994, Regime shifting with time-varying transitions probabilities, in C. Hargreaves, (ed.) *Time Series Analysis and Cointegration* (Oxford University Press).

Edelen, Roger and Jerold Warner, 2001, Aggregate price effects of institutional trading: A study of mutual fund flow and market returns, *Journal of Financial Economics* 59, 195 - 220.

Engel, Charles, and James Hamilton, 1990, Long swings in the dollar: Are they in the data and do markets know it?, *Journal of Financial Economics* 25, 23-49.

Fama, Eugene, and Kenneth French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23-49.

Fleming, Jeff, 1998, The quality of market volatility forecasts implied by S&P 100 index options, *Journal of Empirical Finance* 5, 317-345.

Fleming, Jeff, Chris Kirby, and Barbara Ostdiek, 1998, Information and volatility linkages in the stock, bond, and money markets, *Journal of Financial Economics* 49, 111-137.

Fleming, Jeff, Chris Kirby, and Barbara Ostdiek, 2002, The economic value of volatility timing using "realized" volatility, *Journal of Financial Economics* forthcoming.

Fleming, Jeff, Barbara Ostdiek, and Robert Whaley, 1995, Predicting stock market volatility: A new measure, *The Journal of Futures Markets* 15, 265-302.

Fleming, Michael, 1997, The round-the-clock market for U.S. Treasury securities, *Economic Policy Review* 9-32.

Forbes, Kristin, and Roberto Rigobon, 2001, No contagion, only interdependence: Measuring stock market co-movements, *The Journal of Finance*, forthcoming.

Gray, Stephen, 1996, Modeling the conditional distribution of interest rates as a regime-switching process, *Journal of Financial Economics* 42, 27-62.

Gulko, Les, 2002, Decoupling, *Journal of Portfolio Management* 28, 59-66.

Hamilton, James, 1994, *Time-series analysis* (Princeton University Press, Princeton, New Jersey).

Harris, Milton and Artur Raviv, 1993, Differences of opinion make a horse race, *The Review of Financial Studies* 6, 473-506.

Hartmann, P., S. Straetmans, and C. Devries, 2001, Asset Market Linkages in Crisis Periods, Working paper No. 71, European Central Bank.

Harvey, Campbell, and Roger Huang, 2002, The impact of the Federal Reserve Bank's open market operations, *Journal of Financial Markets* 6, 223-257.

Heaton, John and Deborah Lucas, 1996, Evaluating the effects of incomplete markets on risk sharing and asset pricing, *Journal of Political Economy* 104, 443-487.

Keim, Donald and Robert Stambaugh, 1986, Predicting returns in bond and stock markets, *Journal of Financial Economics* 17, 357-390.

Kim, Chang-Jin and Charles Nelson, 1999, State-space models with regime switching, Cambridge: MIT Press.

King, Mervyn, and Sushil Wadhwani, 1990, Transmission of volatility between stock markets, *The Review of Financial Studies* 3, 5-33.

Kodres, Laura, and Matthew Pritsker, 2002, A rational expectations model of financial contagion, *The Journal of Finance* 57, 769-799.

Lee, Sang and Kwang Kim, 1993, Does the October 1987 crash strengthen the co-movements among national stock markets?, *Review of Financial Economics* 3, 89-102.

Li, Lingfeng, 2002, Correlation of stock and bond returns, Working paper, Yale University.

Lo, Andrew and Jiang Wang, 2000, Trading volume: Definitions, data analysis, and implications of portfolio theory, *The Review of Financial Studies* 13, 257-300.

Mamaysky, Harry, 2001, On the joint pricing of stocks and bonds: Theory and evidence, Working paper, Yale School of Management.

Merton, Robert, 1973, An intertemporal capital asset pricing model, *Econometrica* 41, 867- 887.

Newey, Whitney, and Kenneth West, 1987, A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Schwert, G. William, 1989, Why does stock market volatility change over time?, *The Journal of Finance* 44, 1115-1153.

Scruggs, John, and Paskalis Glabadanidis, 2001, Risk premia and the dynamic covariance between stock and bond returns, *Journal of Financial and Quantitative Analysis*, forthcoming.

Shalen, Catherine, 1993, Volume, volatility, and the dispersion of beliefs, *The Review of Financial Studies* 6, 405-434.

Shiller, Robert, and Andrea Beltratti, 1992, Stock prices and bond yields: Can their comovements be explained in terms of present value models?, *Journal of Monetary Economics* 6, 405-434.

Urich, Thomas, and Paul Wachtel, 2001, Financial market responses to monetary policy changes in the 1990's, *Contemporary Economic Policy* 19, 254-267.

Veronesi, Pietro, 1999, Stock market overreaction to bad news in good times: A rational expectations equilibrium model, *The Review of Financial Studies* 12, 975-1007.

Veronesi, Pietro, 2001, Belief-dependent utilities, aversion to state-uncertainty and asset prices, Working paper, University of Chicago.

Wang, Jiang, 1994, A model of competitive stock trading volume, *Journal of Political Economy* 102, 127-168.

Warther, Vincent, 1995, Aggregate mutual fund flows and security returns, *Journal of Financial Economics* 39, 209 - 235.

Whitelaw, Robert, 2000, Stock market risk and returns: An equilibrium approach, *The Review of Financial Studies* 13, 521-547.

Table 1: Descriptive statistics

This table reports the descriptive statistics for the data used in this article. S, B10, and B30 refer to the stock, 10-year Treasury bond, and 30-year Treasury bond return series, respectively. The returns are in daily percentage units. VIX is the Chicago Board Option Exchange's Volatility Index in annualized, percentage, standard deviation units. TVR is the average turnover of the firms that comprise our large-firm NYSE/AMEX portfolio, in daily percentage units. Std. Dev. denotes standard deviation and ρ_i refers to the ith autocorrelation. Panel A reports the sample moments of the data from 1986 to 2000. Panel B reports the sample moments of the data from 1988 to 2000. Panel C reports the correlation matrix. The correlation coefficients for the 1986-2000 sample period is shown in brackets and on the upper triangle. The correlation coefficients for the 1988-2000 sample period is on the lower triangle.

Panel A: Sample Moments, 1986-2000					
	S	B10	B30	VIX	TVR
Mean	0.058	0.028	0.034	20.51	0.331
Median	0.090	0.021	0.021	19.38	0.311
Maximum	8.669	4.822	7.540	150.19	1.398
Minimum	-17.17	-2.73	-3.80	9.04	0.071
Std. Dev.	0.97	0.446	0.677	7.83	0.114
Skewness	-1.86	0.12	0.25	4.40	1.60
Excess Kurtosis	33.31	5.69	5.56	50.17	5.38
ρ_1	0.079	0.072	0.040	0.942	0.797
ρ_2	-0.041	0.009	0.023	0.892	0.734
ρ_3	-0.042	-0.019	-0.011	0.875	0.712
ρ_{10}	-0.017	0.032	0.038	0.720	0.687

Table 1: (continued)

Panel B: Sample Moments, 1988-2000

	S	B10	B30	VIX	TVR
Mean	0.061	0.028	0.035	19.84	0.329
Median	0.084	0.021	0.021	18.69	0.305
Maximum	4.828	1.926	3.082	49.36	1.393
Minimum	-6.592	-2.732	-3.805	9.04	0.071
Std. Dev.	0.892	0.414	0.633	6.29	0.329
Skewness	-0.461	-0.220	-0.132	0.88	1.52
Kurtosis	5.828	2.38	1.79	0.987	4.48
ρ_1	0.060	0.075	0.032	0.975	0.816
ρ_2	-0.022	-0.005	0.014	0.956	0.762
ρ_3	-0.037	-0.044	-0.028	0.942	0.744
ρ_{10}	0.001	0.034	0.040	0.884	0.735

Panel C: Correlation Matrix

	S	B10	B30	VIX	TVR
S	1.000	[0.223]	[0.250]	[-0.186]	[-0.019]
B10	0.218	1.000	[0.938]	[0.045]	[0.054]
B30	0.250	0.936	1.000	[0.039]	[0.046]
VIX	-0.133	-0.025	-0.030	1.000	[0.432]
TVR	0.015	0.034	0.025	0.467	1.000

Table 2: VIX level and the subsequent 22-trading-day stock-bond return correlation

This table reports on the relation between the VIX level and the subsequent 22-trading-day correlation between stock and bond returns. For this table, the VIX criterion refers to the VIX level in period $t-1$. The subsequent 22-trading-day correlation refers to the correlation between stock and bond returns over days t through $t+21$, following the respective VIX_{t-1}. In this table, the correlations are calculated assuming that the expected daily returns for both stocks and bonds are zero, rather than the respective sample means for each 22-trading-day period. VIX is in annualized standard deviation units. The overall sample spans from 1986 through 2000.

Summary statistics of 22-trading-day stock-bond return correlations

VIX Criterion	Observ.	Proportion of Correlations < 0	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.
All	n=3733	15.62 %	0.340	0.420	0.160	0.599
VIX $>$ 40%	n=65	53.85 %	0.062	-0.051	-0.191	0.376
VIX $>$ 35%	n=123	48.78 %	0.084	0.043	-0.194	0.375
VIX $>$ 30%	n=249	46.59 %	0.079	0.050	-0.231	0.422
VIX $>$ 25%	n=713	36.47 %	0.177	0.236	-0.181	0.556
VIX $<$ 20%	n=2008	6.08 %	0.415	0.454	0.269	0.616

Table 3: Lagged VIX and the relation between daily bond and stock returns

This table reports results from estimating the following regression:

$$\epsilon_t^B = (a_0 + a_1 \ln(VIX_{t-1}) + a_2 CV_{t-1})\epsilon_t^S + \nu_t$$

where ϵ_t^B and ϵ_t^S are the daily 10-year T-bond and stock return residuals from our auxiliary regressions (4) and (5), respectively; $ln(VIX_{t-1})$ is the natural log of the VIX in period $t-1$; ν_t is the residual, CV_{t-1} is the additional conditioning variable noted in Panels C and D, and the a_i's are estimated coefficients. The overall sample period is 1986 to 2000. The regression is estimated by OLS and T-statistics are in parentheses, calculated with autocorrelation and heteroskedastic consistent standard errors per the Newey and West (1987) method with five lags.

Panel A: Restrict a_1 & $a_2 = 0$

	1/86-12/00	1/88-12/00	1/86-6/93	7/93-12/00
a_0	0.101	0.099	0.142	0.062
	(5.04)	(5.85)	(3.39)	(3.08)
$R^2\%$	4.83	4.59	8.77	1.96

Panel B: Restrict $a_2 = 0$

	1/86-12/00	1/88-12/00	1/86-6/93	7/93-12/00
a_0	0.840	1.251	0.656	1.761
	(5.86)	(9.27)	(6.42)	(10.45)
a_1	-0.224	-0.362	-0.152	-0.525
	(-5.14)	(-8.58)	(-5.38)	(-9.98)
$R^2\%$	9.58	10.66	11.83	15.28
$a_0 + a_1 ln(VIX)$	0.178	0.193	0.209	0.180
(at the median VIX)				
$a_0 + a_1 ln(VIX)$	0.069	0.009	0.127	-0.044
(at VIX's 95th percentile)				
$a_0 + a_1 ln(VIX)$	0.289	0.364	0.263	0.490
(at VIX's 5th percentile)				

Table 3: (continued)

Panel C: CV_{t-1} = Lagged 22-day stock-bond return correlation

	1/86-12/00	1/88-12/00	1/86-6/93	7/93-12/00
a_0	0.539	0.624	0.596	1.078
	(5.64)	(4.52)	(4.46)	(5.39)
a_1	-0.147	-0.176	-0.141	-0.316
	(-5.12)	(-4.11)	(-4.09)	(-4.99)
a_2	0.244	0.264	0.059	0.217
	(5.13)	(8.97)	(0.59)	(4.74)
R^2 (%)	13.39	14.51	11.92	17.43

Panel D: CV_{t-1} = Asian-Russian Crisis Dummy[1]

	1/86-12/00 Asian & Russian crisis	1/86-12/00 Asian only	1/86-12/00 Russian only
a_0	0.790	0.840	0.793
	(7.60)	(6.17)	(7.03)
a_1	-0.201	-0.222	-0.205
	(-6.58)	(-5.39)	(-6.10)
a_2	-0.193	-0.184	-0.181
	(-6.44)	(-5.15)	(-4.92)
R^2 (%)	11.38	10.10	10.75

1. For the 'Asian crisis only' model, CV_{t-1} =1 over the October 1 to December 31, 1997 period, and zero otherwise. For the 'Russian crisis only' model, CV_{t-1} =1 over the July 6 to December 31, 1998 period, and zero otherwise. For the Asian & Russian crisis, CV_{t-1} =1 over both crisis periods.

Table 4: Daily VIX changes and the stock-bond return relation

This table reports on the association between daily VIX changes and the stock-bond return relation. The VIX-change criteria below refers to the percentile range for the daily change in VIX, from the most negative changes (0 to 5^{th} percentile) to the most positive (95 to 100^{th} percentile). In the table, μ refers to the mean, σ refers to the standard deviation, and ρ refers to the correlation for the stock and bond return observations in each respective VIX-change sub-sample. The correlations in this table are calculated assuming that the daily expected returns for both the stock and bonds are zero, rather than the sub-sample mean. $B10$ and S refer to the ten-year bond return and stock-market return, respectively. The rows below that are denoted with an * exclude the stock market crash of October 19, 1987 from the sub-sample. Panel A reports univariate return statistics and Panel B reports bivariate return statistics. In Panel B,$(S - B10)$ refers to the difference between the daily stock and 10-year bond returns. The overall sample spans from 1986 through 2000.

Panel A: Univariate return statistics, sorted by the daily VIX change

VIX-Change Criteria	Observ.	μ_{B10}	σ_{B10}	μ_S	σ_S
All	n=3754	0.028	0.446	0.059	0.969
0 to 5^{th} pctl	n=188	0.120	0.591	1.481	1.188
0 to 25^{th} pctl	n=936	0.114	0.457	0.724	0.871
25^{th} to 50^{th} pctl	n=937	0.063	0.382	0.212	0.508
50^{th} to 75^{th} pctl	n=936	0.013	0.421	0.002	0.573
75^{th} to 100^{th} pctl	n=936	-0.078	0.493	-0.703	1.166
$^*75^{th}$ to 100^{th} pctl	n=935	-0.079	0.493	-0.685	1.035
95^{th} to 100^{th} pctl	n=188	-0.044	0.658	-1.891	1.737
$^*95^{th}$ to 100^{th} pctl	n=187	-0.047	0.659	-1.810	1.330

Table 4: (continued)

Panel B: Bivariate return statistics, sorted by the daily VIX change

VIX-Change Criteria	Observ.	μ_{S-B10}	σ_{S-B10}	Proportion[1] $S<0, B10>0$	Proportion[2] $S>0, B10<0$	$\rho_{S,B10}$
All	n=3754	0.031	0.972	19.4%	18.6%	0.223
0 to 5^{th} pctl	n=188	1.362	1.282	2.7%	34.0%	0.206
0 to 25^{th} pctl	n=936	0.610	0.909	5.2%	30.0%	0.287
25^{th} to 50^{th} pctl	n=937	0.148	0.526	14.2%	21.5%	0.361
50^{th} to 75^{th} pctl	n=936	-0.011	0.579	24.0%	16.3%	0.352
75^{th} to 100^{th} pctl	n=936	-0.625	1.250	34.2%	6.8%	0.112
$^{*}75^{th}$ to 100^{th} pctl	n=935	-0.607	1.119	34.2%	6.8%	0.138
95^{th} to 100^{th} pctl	n=188	-1.848	1.950	49.5%	1.6%	-0.055
$^{*}95^{th}$ to 100^{th} pctl	n=187	-1.763	1.570	49.2%	1.6%	-0.030

1. For each respective sub-sample, this column reports the proportion of daily observations where the stock return was negative and the bond return was positive.

2. For each respective sub-sample, this column reports the proportion of daily observations where the stock return was positive and the bond return was negative.

Table 5: Stock turnover and the subsequent 22-trading-day stock-bond return correlation

This table reports on the relation between stock turnover and the subsequent 22-trading-day correlation between stock and bond returns. For this table, the DTVR criterion refers to the percentile range of our detrended turnover measure. $DTVR_{t-1} = \left[\frac{1}{5}(\sum_{i=1}^{5} \ln(TVR_{t-i})\right] - \left[\frac{1}{245}(\sum_{i=6}^{250} \ln(TVR_{t-i})\right]$ where TVR_t is the average turnover of the firms that comprise our U.S. large-firm portfolio in day t. The subsequent 22-trading-day correlation refers to the correlation between stock and bond returns over periods t through $t+21$, following the respective DTVR_{t-1}. In this table, the correlations are calculated assuming that the expected daily returns for both stocks and bonds are zero, rather than the respective sample means for each 22-trading-day period. The overall sample spans from 1986 through 2000.

Summary statistics of 22-trading-day stock-bond return correlations

DTVR Criterion	Observ.	Proportion of Correlations < 0	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.
All	n=3734	15.61 %	0.341	0.420	0.160	0.599
95^{th} to 100^{th} pctl	n=187	42.78 %	0.074	0.054	-0.185	0.324
90^{th} to 100^{th} pctl	n=374	34.22 %	0.170	0.184	-0.121	0.471
75^{th} to 100^{th} pctl	n=933	21.22 %	0.304	0.374	0.071	0.578
0^{th} to 25^{th} pctl	n=933	11.68 %	0.374	0.452	0.230	0.617

Table 6: Detrended stock turnover and the relation between daily bond and stock returns

This table reports results from estimating the following regression:

$$\epsilon_t^B = (a_0 + a_1 DTVR_{t-1} + a_2 CV_{t-1})\epsilon_t^S + \nu_t$$

where ϵ_t^B and ϵ_t^S are the daily 10-year T-bond and stock return residuals from our auxiliary regressions (4) and (5), respectively; $DTVR_{t-1}$ is our lagged detrended stock turnover, as defined in Table 5; ν_t is the residual, CV_{t-1} is the additional conditioning variable noted in Panels C and D, and the a_i's are estimated coefficients. The overall sample period is 1986 to 2000. The regression is estimated by OLS and T-statistics are in parentheses, calculated with autocorrelation and heteroskedastic consistent standard errors per the Newey and West (1987) method with five lags.

Panel A: Restrict a_1 & $a_2 = 0$

	1/86-12/00	1/88-12/00	1/86-6/93	7/93-12/00
a_0	0.101	0.099	0.142	0.062
	(5.04)	(5.85)	(3.39)	(3.08)
$R^2\%$	4.83	4.59	8.77	1.96

Panel B: Restrict $a_2 = 0$

	1/86-12/00	1/88-12/00	1/86-6/93	7/93-12/00
a_0	0.137	0.122	0.175	0.100
	(8.92)	(7.89)	(6.97)	(4.55)
a_1	-0.352	-0.351	-0.345	-0.353
	(-7.29)	(-4.21)	(-5.08)	(-3.12)
$R^2\%$	7.58	6.32	12.45	3.47
$a_0 + a_1 DTVR$	0.128	0.112	0.181	0.079
(at the median DTVR)				
$a_0 + a_1 DTVR$	0.046	0.031	0.091	0.004
(at DTVR's 95th percentile)				
$a_0 + a_1 DTVR$	0.220	0.207	0.263	0.169
(at DTVR's 5th percentile)				

Table 6: (continued)

Panel C: CV_{t-1} = Lagged 22-day stock-bond return correlation

	1/86-12/00	1/88-12/00	1/86-6/93	7/93-12/00
a_0	0.071	0.059	0.139	0.055
	(5.32)	(4.41)	(4.11)	(3.16)
a_1	-0.234	-0.091	-0.321	-0.041
	(-3.49)	(-1.28)	(-4.04)	(-0.44)
a_2	0.274	0.324	0.091	0.376
	(5.08)	(10.85)	(0.86)	(9.85)
R^2 (%)	12.75	13.59	12.70	15.01

Panel D: CV_{t-1} = Asian-Russian Crisis Dummy[1]

	1/86-12/00 Asian & Russian crisis	1/86-12/00 Asian only	1/86-12/00 Russian only
a_0	0.165	0.146	0.155
	(9.92)	(9.42)	(9.40)
a_1	-0.347	-0.363	-0.336
	(-6.39)	(-7.44)	(-6.33)
a_2	-0.234	-0.224	-0.222
	(-8.03)	(-7.34)	(-6.35)
R^2 (%)	10.29	8.35	9.39

1. For the 'Asian crisis only' model, CV_{t-1} =1 over the October 1 to December 31, 1997 period, and zero otherwise. For the 'Russian crisis only' model, CV_{t-1} =1 over the July 6 to December 31, 1998 period, and zero otherwise. For the Asian & Russian crisis, CV_{t-1} =1 over both crisis periods.

Table 7: Stock turnover shocks and the stock-bond return relation

This table reports on the association between stock turnover shocks and the stock-bond return relation. The relative turnover (RTO) criteria below refers to the percentile range of our stock turnover shock, as detailed in Section 3.2. In the table, μ refers to the mean, σ refers to the standard deviation, and ρ refers to the correlation for the stock and bond return observations in each respective RTO sub-sample. $B10$ and S refer to the ten-year bond return and stock-market return, respectively. The rows below that are denoted with an * exclude the stock market crash of October 19, 1987 from the sub-sample. The overall sample spans from 1986 through 2000.

Summary statistics for the stock and bond returns, sorted by RTO_t

RTO Criteria	Observ.	μ_{B10}	σ_{B10}	μ_S	σ_S	$\rho_{B10,S}$
All	n=3755	0.028	0.446	0.058	0.968	0.223
0 to 5^{th} pctl	n=188	-0.026	0.384	0.046	0.582	0.275
0 to 25^{th} pctl	n=939	-0.009	0.378	0.023	0.604	0.209
25^{th} to 50^{th} pctl	n=939	-0.013	0.423	0.050	0.714	0.292
50^{th} to 75^{th} pctl	n=939	0.034	0.439	0.048	0.967	0.216
75^{th} to 100^{th} pctl	n=938	0.099	0.522	0.113	1.393	0.209
*75^{th} to 100^{th} pctl	n=937	0.099	0.522	0.131	1.274	0.240
95^{th} to 100^{th} pctl	n=188	0.115	0.677	-0.048	2.061	0.157
*95^{th} to 100^{th} pctl	n=187	0.113	0.678	0.044	1.639	0.232

Table 8: The relation between daily bond and stock returns in a regime-shifting model

This table reports on the following regime-shifting model:

$$B_t = a_0^s + a_1 B_{t-1} + a_2^s S_t + \epsilon_t$$

where B_t and S_t are the daily 10-year T-bond and stock returns, respectively; ϵ_t is the residual; and the a's are estimated coefficients. The superscript s indicates regime 0 or regime 1. p and q are transition probabilities where $p = Pr(s_t = 0|s_{t-1} = 0)$, and $q = Pr(s_t = 1|s_{t-1} = 1)$. The sample period is 1986 to 2000. T-statistics are in parentheses for the estimated coefficients and standard errors are in brackets for the estimated probabilities. Panel A reports the coefficient estimates and Panel B reports the sample moments for each regime, where an observation is classified as belonging to a particular regime if the probability is greater than 80%.

Panel A: Coefficient estimates

	1/86-12/00		1/88-12/00	
a_0^0	-0.0088	(-1.07)	-0.0060	(-0.70)
a_0^1	0.0544	(4.07)	0.0523	(3.97)
a_1	0.0575	(3.88)	0.0621	(3.90)
a_2^0	0.3044	(22.7)	0.3035	(19.7)
a_2^1	-0.050	(-5.17)	-0.062	(-5.40)
p	0.9941	[0.0026]	0.9931	[0.0034]
q	0.9860	[0.0059]	0.9847	[0.0074]

Panel B: Sample moments for each regime

		Stock Returns		T-Bond Returns		
Regime	Observ.	Mean	St.Dev.	Mean	St. Dev.	Correlation(B_t, S_t)
1986-2000						
All observations	n=3754	0.0589	0.969	0.0281	0.446	0.222
Regime-zero	n=2527	0.0799	0.741	0.0175	0.459	0.520
Regime-one	n=828	0.0128	1.521	0.0602	0.432	-0.203
1988-2000						
All observations	n=3254	0.0613	0.892	0.0282	0.414	0.218
Regime-zero	n=2143	0.0709	0.710	0.0166	0.429	0.517
Regime-one	n=771	0.0347	1.301	0.0548	0.385	-0.250

Table 9: The extended regime-shifting model for stock and bond returns with lagged VIX

This table reports the results for the following regime-switching model.

$$B_t = a_0^s + a_1 B_{t-1} + a_2^s S_t + \epsilon_t,$$

where the regime variable s_t has time-varying transition probabilities:

$$p(s_t = j | s_{t-1} = j; I_{t-1}) = \frac{e^{c_j + d_j ln(VIX_{t-1})}}{1 + e^{c_j + d_j ln(VIX_{t-1})}}, j = 0, 1.$$

where I_{t-1} is the information set at $t-1$, the c_j's and d_j's are estimated coefficients, and the other terms are as defined in Table 8. The sample period is 1988 to 2000. T-statistics are in parentheses. Panel A reports the coefficient estimates and Panel B reports the sample moments for each regime, where an observation is classified as belonging to a particular regime if the probability is greater than 80%.

Panel A: Coefficient estimates

a_0^0	-0.0156	(-1.51)
a_0^1	0.0558	(4.26)
a_1	0.0577	(3.63)
a_2^0	0.3430	(14.7)
a_2^1	-0.0609	(-4.99)
c_0	8.9163	(2.93)
d_0	-1.8327	(-1.86)
c_1	-1.6240	(-0.55)
d_1	1.5090	(1.59)

Panel B: Sample moments for each regime

		Stock Returns		T-Bond Returns		
Regime	Observ.	Mean	St.Dev.	Mean	St. Dev.	Correlation(B_t, S_t)
Regime-zero	n=1741	0.0607	0.695	-0.0142	0.447	0.617
Regime-one	n=671	0.0015	1.39	0.0407	0.393	-0.333

Figure 1

This figure displays the time-series of 22-trading-day correlations between stock and 10-year Treasury bond returns over days *t* to *t+21* (Panel A), the CBOE's Volatility Index (VIX) at day *t* (Panel B), and the average turnover of the firms in our large-firm portfolio over days *t-1* through *t-5* (Panel C). The sample spans 1986 to 2000.

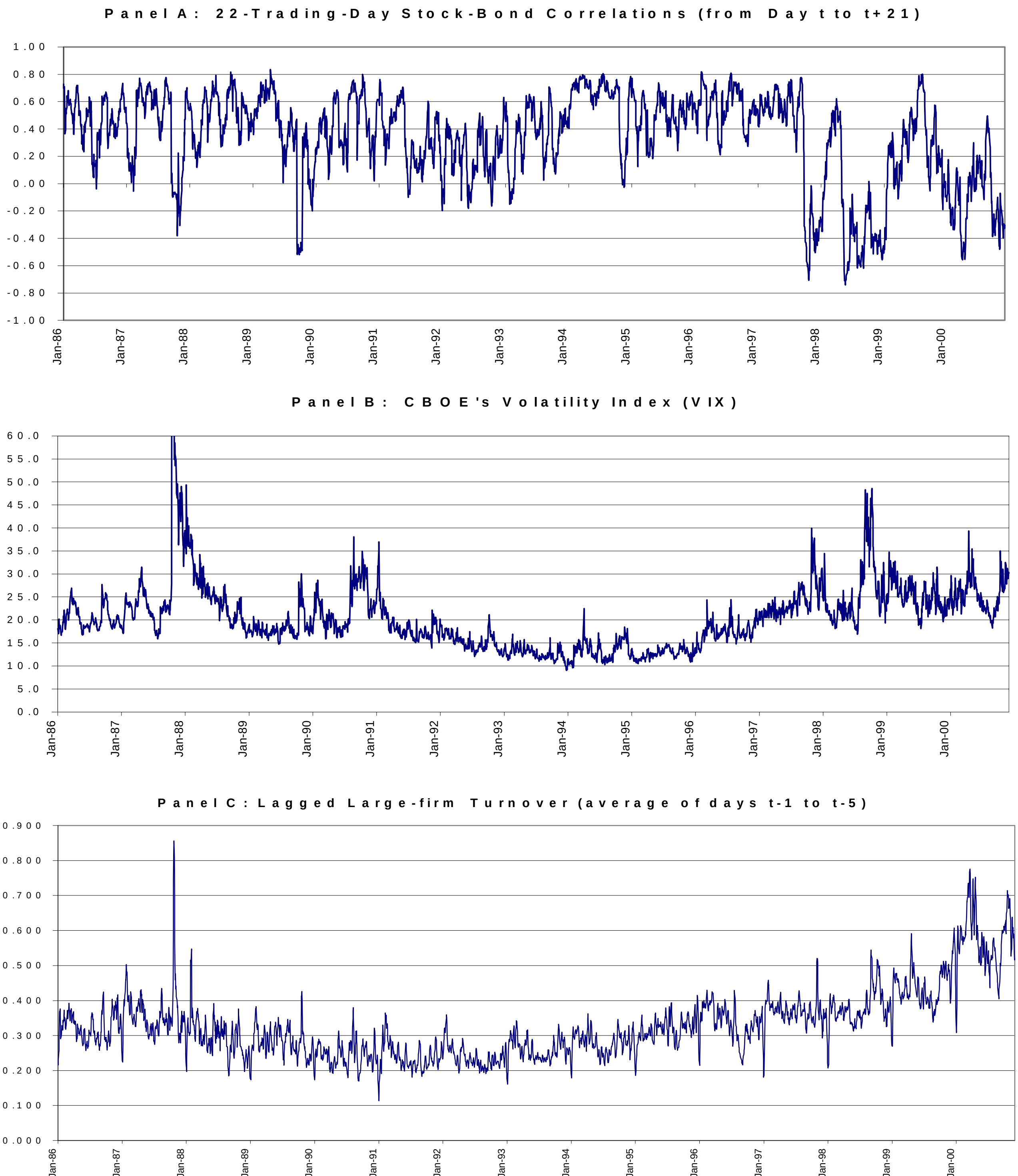
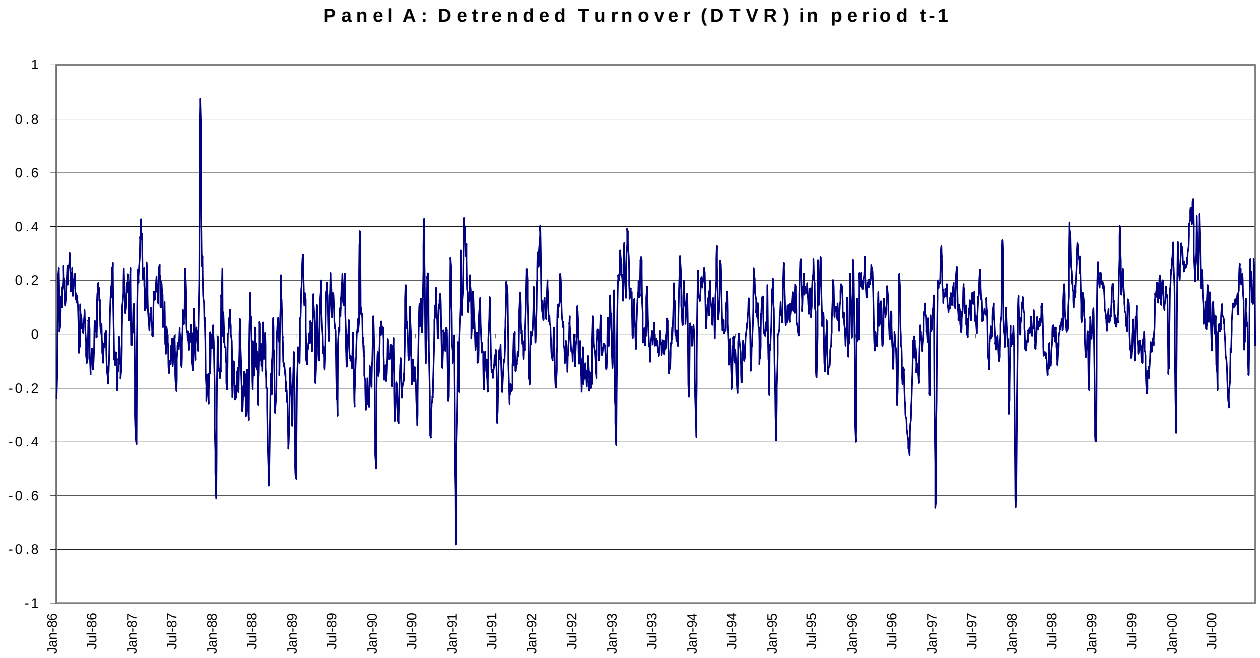


Figure 2

This figure displays our lagged, detrended turnover ($DTVR_{t-1}$), (Panel A), and our relative turnover (RTO_t) (Panel B). Both measures are formed from the daily turnover of firms in the largest size-based, decile-portfolio of NYSE/AMEX stocks. See Section 3.2 for details. The sample spans from 1986 to 2000.



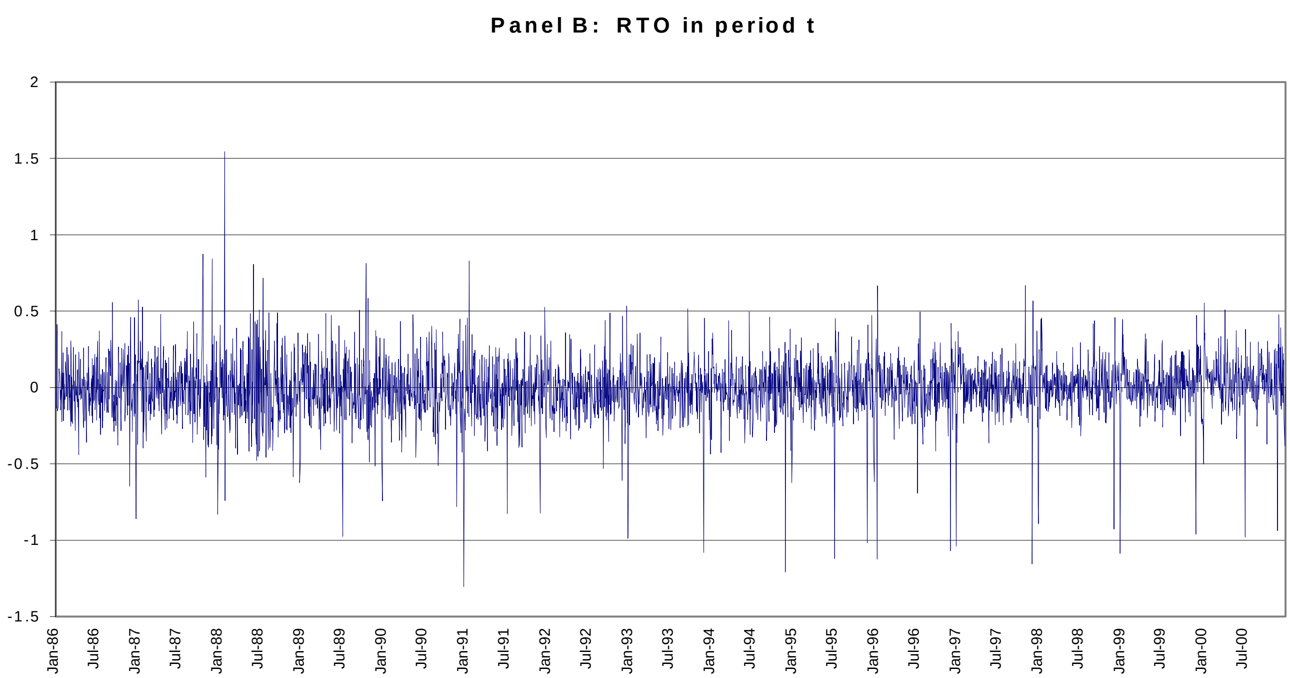


Figure 3

This figure displays the CBOE's Volatility Index (upper series) and the smooth probability of being in regime-one (lower series) from the basic regime-shifting model in Table 8 for the 10-year Treasury bond returns. The sample period is 1986 to 2000.

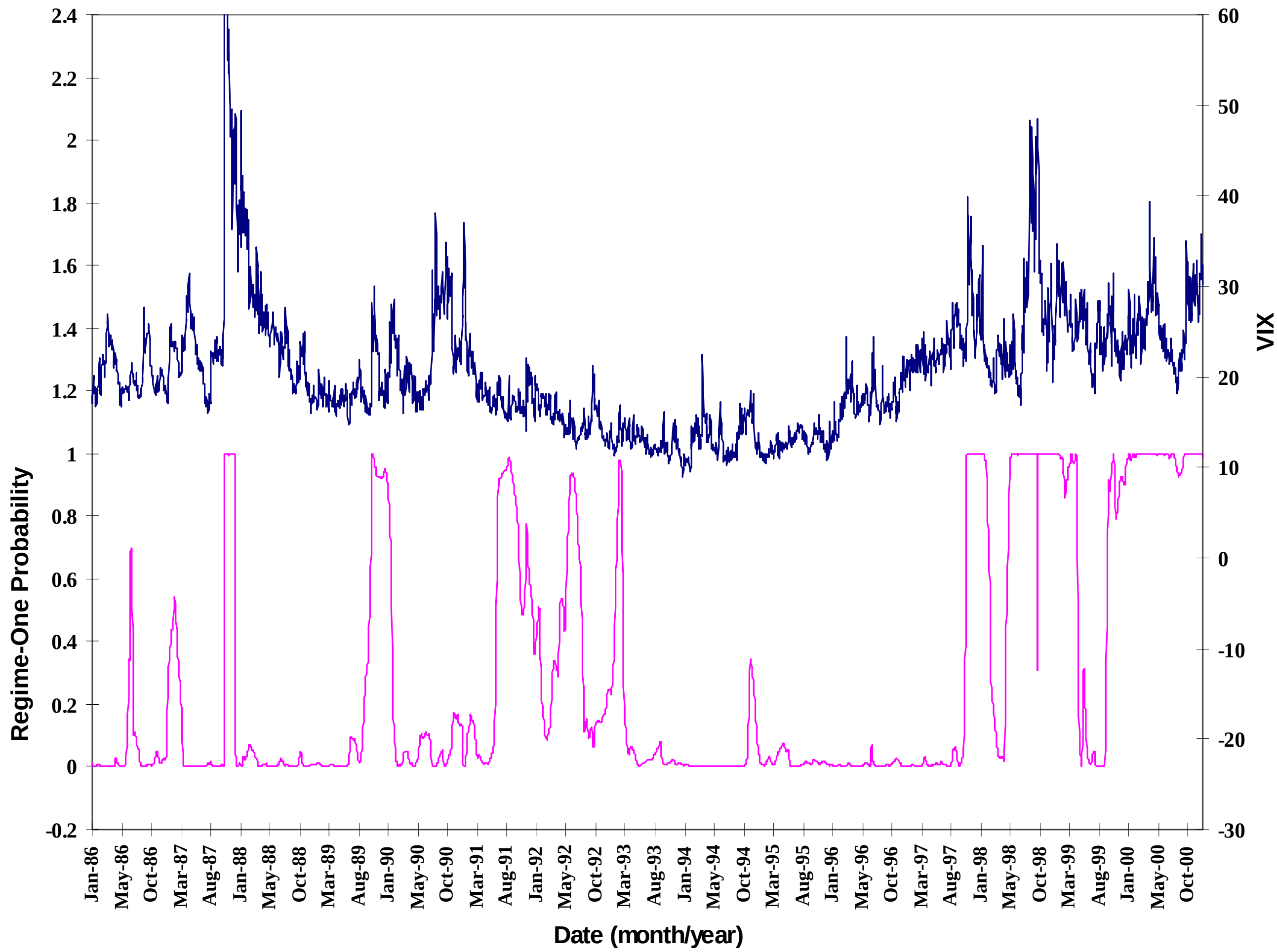
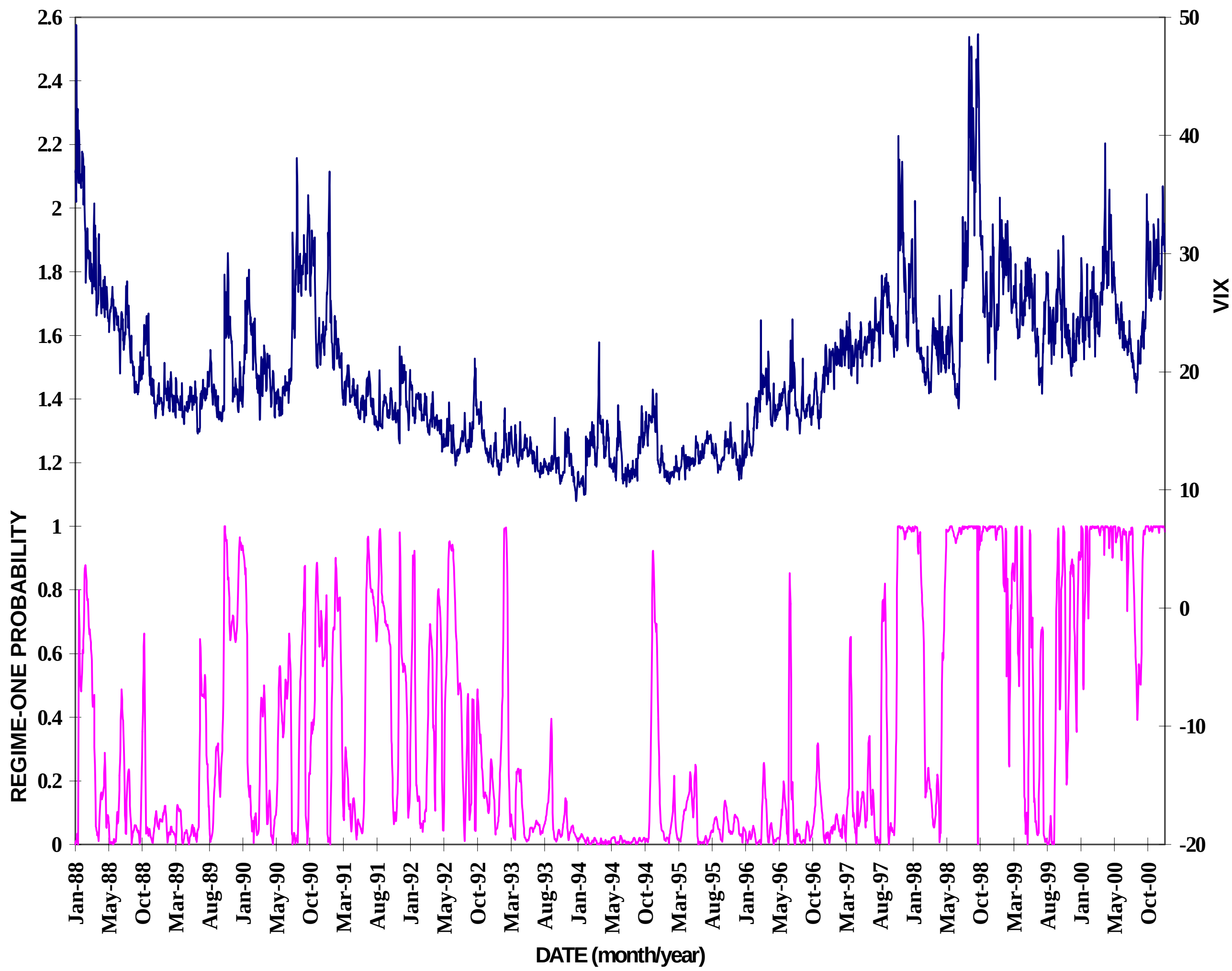


Figure 4

This figure displays the CBOE's Volatility Index (upper series) and the smooth probability of being in regime-one (lower series) from the extended regime-shifting model in Table 9 for the 10-year Treasury bond returns. The sample period is 1988 to 2000.



Appendix A

As we noted in our conclusions, it is an interesting, unresolved question whether the time-variation in the stock-bond return correlation is a general phenomenon or a country-specific finding. In this appendix, we examine whether the stock-bond return correlation in the other G-7 countries (Canada, France, Germany, Italy, Japan, and the U.K.) varies across the regimes suggested by our U.S. results (see Section 6, Table 8, and Figure 3).

The daily international stock and bond data used to calculate return correlations are all from DataStream International. The individual data items (with the DataStream code in parentheses) are listed below by country. The sample periods vary somewhat among these countries owing to different data availability. The day of the first sample observation is indicated in the rightmost column. Bond returns for these countries are calculated using the same methods as were used to calculated bond returns for the U.S.

Country	Asset	Data Description	Start Date
Canada	Stock	Toronto SE 35 - Price Index (TTSEI35)	8/19/88
	Bond	Canada Benchmark Bond 10 Yr. (CNBRYLD)	
France	Stock	France CAC 40 - Price Index (FRCAC40)	7/9/87
	Bond	France Benchmark Bond 10 Yr. (FRBRYLD)	
Germany	Stock	DAX 30 DataStream Calculated - Price Index (DAXINDZ)	1/1/86
	Bond	Germany Benchmark Bond 10 Yr. (BDBRYLD)	
Italy	Stock	Milan COMIT 30 DataStream Calculated - Price Index (MIBCI3Z)	3/6/91
	Bond	Italy Benchmark Bond 10 Yr. (ITBRYLD)	
Japan	Stock	Nikkei 225 Stock Average - Price Index (JAPDOWA)	1/1/86
	Bond	Japan Benchmark Bond 10 Yr (JPBRYLD)	
U.K.	Stock	FTSE 100 - Price Index (FTSE100)	5/15/86
	Bond	UK Benchmark Bond 10 Yr. (UKMBRYD)	

Means and standard deviations for the bond and stock return series for each country are reported in the following table. Here, separate statistics are reported for the "primarily regime-zero" months and the "primarily regime-one" months, where the classification is as suggested in Figure 3 and are the same that we use in our inflation comparison across regimes in Section 6. The "primarily regime-one" months are from 10/87 to 12/87, 10/89 to 2/93, and 10/97 to 12/00. The remainder of the months are classified as "primarily regime-zero". This table reflects two patterns. First, stock return volatility substantially exceeds bond return volatility for each country. Second, while the standard deviation of bond returns is stable across the two regimes, stock return volatility rises considerably from regime-zero to regime-one. That is, foreign country stocks become riskier in regime-one, but foreign bond risk is essentially unchanged. This pattern is similar to that observed in the U.S. data.

Mean and Standard Deviation of Bond Returns

Regime	Country:	Canada	France	Germany	Italy	Japan	U.K.
Regime 0	Mean	0.0343	0.0291	0.0180	0.0657	0.0208	0.0220
	Std. Dev.	0.4885	0.3953	0.3457	0.5946	0.4520	0.4575
Regime 1	Mean	0.0320	0.0290	0.0241	0.0316	0.0214	0.0412
	Std. Dev.	0.4325	0.4505	0.3397	0.3922	0.3992	0.4503

Mean and Standard Deviation of Stock Returns

Regime	Country:	Canada	France	Germany	Italy	Japan	U.K.
Regime 0	Mean	0.0617	0.0657	0.0619	0.0719	0.0648	0.0676
	Std. Dev.	0.6732	1.0127	1.0802	1.3545	1.0759	0.7417
Regime 1	Mean	0.0220	0.0297	0.0116	0.0599	-0.0523	0.0109
	Std. Dev.	1.0128	1.4398	1.5410	1.5433	1.6551	1.1885

With this data, we also compute stock-bond return correlations using daily data for each country for each regime (we include the full sample correlation for comparison). The results are reported in the following table.

Stock-Bond Return Correlations for Other G-7 Countries

Country: Regime	Canada	France	Germany	Italy	Japan	U.K.
Full	0.181	0.290	0.227	0.292	0.026	0.232
Regime 0	0.378	0.444	0.361	0.453	-0.013	0.467
Regime 1	0.048	0.202	0.123	0.128	0.061	0.078
Difference	0.330*	0.242*	0.238*	0.325*	-0.074	0.389*

* indicates statistically significant at a p-value of less than 1%

Rather than relying on normal distribution theory to test for differences in correlation, we apply bootstrap methods to each sample and construct the distribution of differences in estimated correlations across the bootstrap replications. We then base our inferences about significant differences in correlation across different regimes on the bootstrap-based distribution of differences. Underlying deviations from normality should have no significant impact on the inferences using this method. The specific steps are as follows. First, we resample the data from each regime and construct 1000 estimates of the stock-bond return correlation. Second, we construct densities of the differences in correlations (sample size = 1000) and test whether the mean of the difference is zero using the empirical distribution.

Except for Japan, the differences in the correlations are statistically significant at the one per cent level (or better) in every case. The size of the differences for Canada and the U.K. approach the magnitudes in the U.S. data. This leads us to conclude that our findings for the U.S. are mirrored in other countries, and these results suggest a role for such international crises as the Asian crisis of 1997 and the Russian crisis of 1998. Note the negative stock-bond correlations around these crises in our Figure 1, Panel A.

Appendix B

In this appendix, we examine aggregate mutual fund flows over the 1986 to 2000 period. Specifically, we are interested in whether the fund flow behavior varies across our regimes from Section 6. We use the same monthly regime categorization as reported in Appendix A and Section 6 for the inflation comparison. All the monthly mutual fund flow data is from the Investment Company Institute. The monthly return data that we use is from the Ibbotson 2001 Yearbook.

Our investigation here focuses on redemption rates for stock and bond funds. This choice reflects our belief that redemptions require active choices by investors whereas a significant portion of the new flows to bond and stock funds reflect allocation choices that are less responsive to current market conditions. We calculate the redemption rate as the aggregate stock (bond) fund redemptions for a given month normalized by the total assets of stock (bond) funds for that month.

We concentrate primarily on the ratio of the redemption rate for stock funds to the redemption rate for bond funds. We find this ratio averages .814 during regime-zero and 1.063 during regime-one. Using a bootstrap, this difference is statistically significant at better than the 1% level. Changes in both stock and bond redemption rates contribute to this difference. The stock redemption rate increases from 1.4% (regime-zero) to 1.6% (regime-one) and the bond redemption rate decreases from 1.8% (regime-zero) to 1.5% (regime-one). Bootstrap computations show that these changes are statistically significant at better than the 1% level.

Following earlier work in the aggregate mutual fund flow literature (Warther (1995) and Edelen and Warner (2001)), we also repeat this analysis controlling for a number of potential determinants of relative redemption dynamics. Specifically, we regress the relative redemption rate (stocks divided by bonds) on lagged values of the relative redemption rate series, relative cumulative returns over the previous six months and the six months before that, and a sequence of monthly dummy variables to capture strong seasonal variation in the relative redemption rate series. We also included a dummy variable for regime-one to capture variation in this ratio after controlling for other influences. The coefficient on this dummy variable is positive, meaning stock (bond) fund redemptions are relatively larger (lower) in regime-one than in regime-zero, and the estimate (.058) is significant at the 1% level (t-statistic = 2.86). The R^2 for the regression is 74%.