Commonality in the Time-variation of Stock-Bond and Stock-Stock Return Comovements[1]

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Abstract

We jointly investigate time-variation in stock-bond return comovements within country and stock-stock return comovements across countries by analyzing asset returns from the U.S. and Europe over 1992 to 2002. We examine how daily return comovements vary with stock uncertainty, as measured by the implied volatility (IV) from equity index options. Our findings suggest a striking commonality in the time-variation of stock-bond and stock-stock return comovements. In our sample, stock-bond return comovements tend to be substantially positive (modestly negative) following low (high) IV days and on days with small (large) changes in IV. Cross-country stock return comovements tend to be stronger (weaker) following high (low) IV days and on days with large (small) changes in IV. Our findings support recent research that suggests price formation can be materially influenced by time-varying uncertainty with associated cross-market asset revaluations. Our work also bears on understanding time-varying diversification benefits.

JEL: G12, G15, D80

1 Introduction

Understanding the comovement of financial asset returns remains a fundamental question in financial economics. This issue has important theoretical implications for understanding price formation and it has important practical applications in asset allocation and risk management. The recent surge in comovement research attests to the importance and interest in the area. Recent work has focused on both stock-stock comovement (see, e.g., Barberis, Shleifer, and Wurgler (2003), Forbes and Rigobon (2002), Kodres and Pritsker (2002), Ang and Bekaert(2002a), Ang and Chen (2002), and Ribeiro and Veronesi (2002)) and stock-bond comovement (see, e.g., Fleming, Kirby, and Ostdiek (1998), (2001), and (2003), Scruggs and Glabadanis (2003), Hartmann, Straetmans, and Devries (2001), Connolly, Stivers, and Sun (2003), Gulko (2002), and Li (2002)).

In this study, we investigate and attempt to tie together time-variation in stock-bond return comovements within country and stock-stock return comovements across countries by analyzing asset returns from the U.S. and Europe. We conduct a comprehensive investigation of how return dynamics vary with a measure of stock market uncertainty, the implied volatility from equity index options. Our work is motivated by existing theory and empirical work that suggests price formation can be materially influenced by time-varying uncertainty with associated cross-market asset revaluations.[1] We contribute by providing new evidence about the empirical importance of these ideas and by further characterizing how diversification benefits vary with stock uncertainty.

We jointly examine the U.S. and European markets over 1992 to 2002 for several reasons. First, these markets are sizable, internationally important, and considered to be substantially integrated. Second, both a European and a U.S. stock implied volatility index are available from 1992.[2] Third, European stock and bond markets provide an interesting additional setting in which to study return comovements. As the 1990's progressed, inflation rates tended to fall and stabilize among the European countries with the transition to the Euro. This provides a contrast in inflation behavior over

[1]Since this is an empirical paper and we desire a succinct introduction, we postpone a formal discussion of related theoretical literature until Section 2. Section 2 also further discusses this paper's use and interpretation of the implied volatility from equity index options.

[2]For the U.S., we use the Chicago Board Options Exchange's Volatility Index (VIX), which is derived from options on the S&P 100 equity index. For Europe, we use the German VDAX, which is derived from options on the DAX equity index.

time and suggests that explanations of stock-bond comovements that rely on changing inflation are unlikely over the second half of our sample.

In this paper, our primary contribution is to document a striking commonality in the time-variation of stock-bond and stock-stock return comovements. To support this primary contribution, we first contribute by re-examining time-variation in stock-bond return comovements in the spirit of Connolly, Stivers, and Sun (2003). We extend their work by evaluating more countries over a more recent period, by analyzing the stock-bond relation across stock portfolios of different systematic risk, and by evaluating the potential economic value of the findings. Second, we also contribute by investigating how cross-country stock return comovements vary with the implied volatility from equity index options. Third, we build on these results with a regime-shifting analysis that further characterizes and ties together the different comovement variations.

To begin with, we document two strong stock-bond comovement patterns over our 1992 to 2002 sample period. First, we find that the stock-bond correlations tend to be negative following high levels of stock implied volatility (IV) and tend to be positive following low IV.[3] For example, in U.K returns, the probability of a negative stock-bond monthly correlation following the lowest VIX quintile of observations is only 2.0%. However, the probability of a negative stock-bond monthly correlation following the highest VIX decile of observations is 87.3%. Further, the stock-bond correlations following high IV periods tend to be more negative for portfolios of high market-beta stocks. These results are consistent with related findings in Connolly, Stivers, and Sun (2003) and suggest that times of high stock uncertainty are also times with higher volatility in the relative attractiveness of stocks versus bonds, which indicates that cross-asset pricing influences are important in the sense of Kodres and Pritsker (2002). Further, we also find that the stock-bond correlations are negative or near zero for days with either sizable increases or decreases in IV and that the stock-bond correlations are sizably positive for days with little change in IV.[4] In other words, there is a "frown shape" in the variation in return correlations as a function of the daily IV change. For example, for the U.S., the stock-bond correlation for the days with the most extreme 20% of decreases (increases) in VIX

[3]The correlations are monthly correlations, calculated from rolling 22-trading-day windows under the assumption that the mean daily returns are zero.

[4]Here, the correlations are for quintile subsets of return observations, with observations sorted by the VIX or VDAX daily change. In calculating the correlation, we set the mean return equal to the overall sample mean, rather than the subset mean.

is -0.110 (-0.109). On the other hand, the correlation is 0.219 on the days when the VIX-change is within its inner 60^{th} percentile. These contemporaneous findings support the notion of flight-to-quality (flight-from-quality) pricing influences with increased (decreased) stock uncertainty.

Next, we find that cross-country stock correlations tend to be more positive following high values of IV and tend to be less positive following low values of IV. For example, for daily U.S. and German stock returns, the median monthly correlation is 0.410 following the low VDAX quintile of observations. However, the median monthly correlation following the highest VDAX decile is 0.758. Further, we find that the cross-country stock correlations are appreciably stronger for days with either sizable increases or decreases in stock IV. In other words, there is a pronounced "smile shape" in the variation of stock return correlations as a function of the daily IV change. For example, for the German:U.K. case, the cross-country stock correlation for the days with the most extreme 20% of decreases (increases) in VDAX is 0.793 (0.784). On the other hand, the correlation is 0.472 for the days when the VDAX-change is within its inner 60^{th} percentile. Our cross-country stock findings suggests that VIX and VDAX are informative about the uncertainty and volatility of a global common factor rather than a country-specific factor (in the sense of King and Wadwhani (1990)). Further, the stronger stock linkages following high IV and during large IV changes seems consistent with the notion of flight-to-quality (flight-from-quality) pricing influences with increased (decreased) stock uncertainty.[5]

Finally, we conduct a two-state, regime-shifting analysis which indicates that the different co-movement patterns move substantially together over time, both across countries and across assets. We estimate separate regime-shifting models for each country's stock-bond return relation and for the different cross-country stock return relations. Our specification allows the transition probabilities to vary with the lagged IV. In one regime, the comovements between stocks and bonds are sizably

[5]We also evaluate one-half subperiods in isolation. This seems particularly important because of the distinct change in the stock IV behavior in mid-1997 (roughly corresponding to the onset of the Asian financial crisis, see Figure 1). In our second-half subperiod, we find that the correlations vary with lagged IV in a similar manner to that observed in the overall sample. For our first-half subperiod, the cross-country stock correlations vary with the lagged IV in a similar manner; however, the stock-bond correlations vary little with lagged IV. Overall, our subperiod analysis reinforces the empirical relevance of our findings and seems intuitive given that the second-half period is much more crises-laden; with, for example, the Asian financial crisis of 1997, the Russian default crisis of 1998, and the September 2001 terrorism crisis.

positive, the comovements between cross-country stock returns are weaker, and IV tends to be low. An increase in IV dramatically decreases the probability of staying in the first regime. In the other regime, the comovements between stocks and bonds are modestly negative, the comovements between cross-country stock returns are much stronger, and IV tends to be high. The probability of staying in the second regime tends to increase with IV, but the effect is marginal. Our regime-shifting results further suggest that the comovement patterns reflect an international economic phenomenon, rather than country specific ones.

The variations in the correlation patterns appear well in excess of variations predicted by a simple heteroskedasticity argument in the sense of Forbes and Rigobon (2002). Further, traditional long-term, present-value models of asset prices do not seem well suited to explain the comovement patterns. Rather, our findings support theory that suggests price formation may be materially influenced by time-varying stock uncertainty with associated cross-market asset revaluations. Our findings also suggest that stock IV is a useful state variable that is informative about the uncertainty or risk of an international stock common risk-factor. Finally, our findings suggest practical implications for asset allocation and risk management by further characterizing how stock-bond and cross-country stock diversification benefits vary with stock uncertainty.

In the next section, we discuss additional literature that provides more background and motivation for our study. Section 3 describes the data. We present the forward-looking comovement patterns in Section 4 and the contemporaneous comovement patterns in Section 5. Section 6 reports on our regime-shifting analysis and Section 7 concludes.

2 Related literature and background discussion

2.1 Uncertainty and the stock market's implied volatility

In this paper, we use the implied volatility (IV) from equity-index options as a proxy for stock market uncertainty. We appeal to a broad interpretation of IV, where IV may convey information about several aspects of uncertainty.

First, under the assumptions of the Black-Scholes option pricing model that are used to derive the IV, IV simply reflects the expected volatility over the life of the option.[6] Consistent with this

[6] Our discussion here follows from similar arguments in Connolly, Stivers, and Sun (2003).

interpretation, recent literature has found that the information in IV can be used to provide the best estimate of conditional volatility. Note that this does not mean that the standard IV is the best volatility forecast, because of the well-known upward bias in index IV. Rather, in time-series models of volatility, IV (as an explanatory variable) largely subsumes the information from historical return shocks (see, e.g., Blair, Poon, and Taylor (2001), Christensen and Prabhala (1998), Fleming (1998) and Mayhew and Stivers (2003)).

Second, IV may be influenced by the uncertainty about the subsequent expected volatility. As noted above, there is a well-known upward bias in IV when compared to the realized volatility. Work such as Coval and Shumway (2001) and Bakshi and Kapadia (2003) suggest that option prices may contain a premium attributed to stochastic volatility. The intuition is that if options are useful as hedges against changing volatility, then option prices may be higher than predicted from the standard Black-Scholes framework. If so, IV would tend to be biased high and time-variation in IV would also reflect time-variation in the uncertainty about future volatility.

Third, a higher IV may be associated with higher economic-state uncertainty in the sense of David and Veronesi (2002). They present an option-pricing model that features a positive relation between IV and investor uncertainty about fundamentals. Relatedly, we note that the CBOE's VIX is also commonly referred to as a market "Fear Index" by market participants.

2.2 Return comovement literature

What factors and pricing influences might be important for understanding the daily comovements that we investigate? Here, we discuss related comovement literature that bears on this question. The literature below also provides motivation and intuition for our study.

One perspective for considering stock-bond correlations is the traditional fundamentals approach, exemplified by Campbell and Ammer (1993). They document a small positive correlation of about 0.20 in monthly returns over 1952 to 1987 and identify economic factors that contribute to explaining the correlation. First, variation in real interest rates promotes a positive correlation since the prices of both assets are negatively related to the discount rate. Second, variation in expected inflation promotes a negative correlation since increases in inflation are bad news for bonds and ambiguous news for stocks. Third, common movements in future expected returns promotes a positive correlation. Their study and other related ones (see, e.g., Shiller and Beltratti (1992), Fama and French (1989), and Keim and Stambaugh (1986)) are interested in how expected returns vary with economic conditions and business cycles; and, accordingly, have examined monthly or lower frequency data over long periods. In this fundamental approach, only changes in inflation expectations promote a negative correlation between stock and bond returns. However, for the U.S. since the late 1980s, there has been both relatively low, stable inflation and sizable time-variation in stock-bond return correlations, including sustained periods of negative correlation. This suggests other pricing influences beyond the fundamentals considered in this branch of the literature.

Other comovement literature has focused on pricing influences related to revaluations across asset classes with time-varying equity risk. In Fleming, Kirby, and Ostdiek (1998), they study multi-market volatility linkages and argue that cross-asset hedging may be an important factor for understanding the linkages between daily stock and bond market volatility. Relatedly, in the rational expectations model of Kodres and Pritsker (2002), a shock in one asset market may generate cross-market rebalancing with pricing influences in the non-shocked asset markets. Thus, presumably, uncertainty shocks or crises in one stock market may also influence bond valuation and cross-country stock valuation.

In our view, the popular term "flight-to-quality" is another way to express the idea of dynamic cross-asset revaluations with time-varying stock uncertainty. Here, international financial and political crises of modest duration may increase stock uncertainty and lead to frequent cross-market asset revaluations, which could induce temporary negative stock-bond return correlations.[7] Daily return data seems better suited for examining these issues with the added benefit that one may safely ignore time-variation in expected returns when studying daily return dynamics (see, e.g., Fleming, Kirby, and Ostdiek (1998) and Connolly, Stivers, and Sun (2003)).

Results in Chordia, Sarkar, and Subrahmanyam (2001) also suggest a link between time-varying uncertainty and dynamic cross-asset rebalancing. 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 correlations between stock and bond spreads and volume-changes increase dramatically during crises (relative to normal times). During periods of crises, they also find that there is a decrease (increase) in mutual fund flows to equity funds (government bond funds). Their results are consistent

[7] By modest duration, we mean a few days up to several months; in contrast to long-term business cycle influences that may span many months or years.

with increased investor uncertainty leading to frequent and correlated portfolio reallocations during financial crises. Along similar lines, Longstaff (2002) shows that the flight-to-liquidity premium in Treasury bonds increases with multiple indicators of investor interest in a safe haven.

Relatedly, our empirical analysis is also motivated by the recent literature on economic-state uncertainty (Veronesi, 1999 and 2001; David and Veronesi, 2001 and 2002, and Ribeiro and Veronesi, 2002). These papers develop the connections between economic-state uncertainty, price formation, and return dynamics. The economy in these papers features state-uncertainty in a two-state economy where the drift in future dividends shifts between unobservable states. For example, Ribeiro and Veronesi (2002) propose a rational expectations model where higher economic-state uncertainty promotes higher stock return correlations across markets. Consistent with our use of implied volatility, David and Veronesi (2002) argue that economic uncertainty should be positively related to the implied volatility from options.

Finally, Ang and Bekaert (2002a) provide additional motivation for the regime-shifting aspect of our work. They explore international asset allocation in a regime-switching framework. Studying monthly returns from the U.S., U.K., and Germany over 1970 to 1997, they find significant time-variation in the correlations of equity-index returns across countries. Accounting for these correlation differences can have economic value, particularly for long-horizon investors.[8]

[8]There are other approaches to understanding the comovement of asset returns. Barberis, Shleifer, and Wurgler (2002) note that in addition to the traditional fundamentals approach to return comovement, there are at least two other interesting models of investor behavior that may help to explain asset return comovement. 'Category-based' comovement happens when investors regard otherwise different securities as belonging to the same class and trade securities in this class in a correlated manner. 'Habitat-based' comovement occurs when investors limit their trading to a subset of securities and trades these securities in a similar manner. They present evidence favoring the two nontraditional models over the fundamentals approach. For our results, this intuition may be useful in understanding how changes in stock uncertainty may change the relative attractiveness of asset classes with a corresponding influence on both stock-bond and cross-country stock return comovements. King and Wadhwani (1990) consider cross-country stock comovements in a model that features a signal extraction problem. As the signal-to-noise ratio rises in a market, cross-market return correlations rise.

3 Data Description

3.1 Raw Data

Our empirical work relies on total return indices for the U.S. and European countries computed by DataStream International. Based on closing prices, DataStream computes a value-weighted total return index on the equity market for each country. Similarly, they provide a total return index for 10-year maturity benchmark government bonds. For each of our countries, we use these total return indices to compute daily returns over the January 1, 1992 to December 31, 2002 period.[9]

In our tables and discussion, we focus on results for the U.S., Germany, and the U.K. for brevity and for the following reasons. First, stock implied volatility (IV) indices are only available for the U.S. and Germany. Second, Germany has the largest economy in Europe, has the largest bond market, and has among the largest stock markets. Third, the U.K. has the largest stock market in Europe and enables us to evaluate a third country in terms of the IV series from the U.S. and Germany. Additionally, the U.K. has not adopted the Euro and remains more distinct from Germany, as compared to European countries that have adopted the Euro. We also examine stock and government bond returns for Belgium, Denmark, France, Italy, the Netherlands, Spain, and Switzerland. We summarize the results for these other countries in Section 7.

Table 1, Panel A, presents basic descriptive statistics for the daily U.S., German, and U.K. returns. Note that the stock return variance is about 6.2, 13.1, and 5.5 times the bond return variance for the U.S., Germany, and the U.K., respectively. Also, as reported in Table 4, we note that stock volatility varies much more with the IV indices than does bond volatility. For example, for the U.S., the variance of stock (bond) returns following the top quintile of VIX observations is 11.9 (1.8) times the variance of stock (bond) returns following the bottom quintile of VIX observations. These comparisons of the volatility in daily stock and bond returns seem to support this paper's notion that stock market volatility (or uncertainty) is a first-order primary concern, while bond volatility and variation in bond volatility is a second-order concern.

[9] For comparison, the U.S. daily stock returns from the DataStream index and CRSP value-weighted index return are correlated at 0.995, with practically the same daily standard deviation. Further, our daily bond returns from Datastream and daily bond returns calculated from the yield of the 10-year constant maturity series from the Federal Reserve are correlated at 0.982, with practically the same daily standard deviation.

Parts of our cross-country stock analysis require intraday data. From DataStream, we gather the 2:00 p.m. Greenwich Mean Time (GMT) values of the German and U.K. stock indices, and calculate 2:00-to-2:00 GMT returns. This timing corresponds to 9 AM, U.S. Eastern time, which is only 30 minutes different from the opening of trade on the New York Stock Exchange. Accordingly, we gather opening prices of the S&P500 index and form open-to-open returns on this index. Due to data availability this sample begins on July 16, 1992. We use these returns to analyze "nearly synchronous" stock comovements across European and U.S. markets. Portions of our analysis use vector autoregressions to remove any time-series predictability due to this slight timing mismatch.

For the cross-country stock return analysis, we report comovements using stock returns denominated in the home currency of each respective country. We make this choice because these comovements represent movements in the value of the stock only, relative to each respective country, and are not confounded by exchange rate movements. In results not reported in the tables, we also repeat the comovement analysis using stock returns in a common currency. Specifically, we examine U.S.:U.K. (U.S.:German) stock comovements with the U.K. (German) returns converted to dollar returns, and we examine the U.K.:German return comovements with German returns converted to sterling returns. The comovement patterns with "common currency" stock returns are nearly identical to those reported in Tables 3 and 6. This is not surprising since the stock returns denominated in the home currency and the stock returns denominated in the foreign currency are highly correlated with a correlation coefficient of about 0.90 for all three cases in our sample.

For the IV of the U.S. and German stock markets, we rely on the VIX and VDAX volatility indices. The U.S. VIX is produced by the Chicago Board Options Exchange (CBOE). The VIX measures the IV of an at-the-money option on the S&P 100 index with 30 calendar days until expiration. The CBOE constructs this VIX as a weighted average of the IV extracted from eight options, controlling for dividend payments and the possibility of early exercise; see Fleming, Ostdiek, and Whaley (1995) for more background. The VDAX index is based on implied volatilities recovered from German stock index (DAX) options. The underlying DAX index consists of the 30 largest German companies and covers approximately 70% of the overall German market capitalization. The VDAX is constructed using the same principles as the U.S. VIX but with a longer 45 day maturity. Summary statistics for the VIX and VDAX series are provided in Table 1, Panel B.

As one would expect, the VIX and VDAX tend to move together and have a simple correlation of 0.83 over our sample period. Figure 1 exhibits the time-series of VIX and VDAX, and depicts substantial variability in each series. We explore the dynamics of VIX and VDAX with standard VAR methods. For both the VAR in log levels and in log first-differences, VIX Granger-causes VDAX. This finding is robust across subperiods and different lag length choices for the VAR. The evidence suggests that either U.S. stock uncertainty leads the German stock uncertainty, or that the U.S. VIX incorporate uncertainty information more quickly. We further discuss IV behavior in subperiod analysis in Section 4.1.2.

3.2 Measuring rolling correlations over time

Much of our work has a forward-looking or predictive focus. In Section 4, we relate the value of VIX or VDAX (at t-1) to the correlation of stock and bond returns (within country) or stock-to-stock returns (across countries) over the next 22 trading days (days t to t+21). This choice: (1) corresponds to the VIX maturity horizon, (2) follows from many prior studies that estimate monthly statistics from daily observation within the month, and (3) allows us to capture short-term comovement variations such as flight-to and flight-from-quality during crises.

We calculate the correlations assuming the daily mean returns for both the stock and bond returns are zero for each 22-trading-day period. We make this choice because expected daily returns are essentially zero and this method prevents extreme return realizations from implying large positive or negative expected returns over specific 22-trading-day periods.[10] Specifically, for a given IV at the end of period t-1, we estimate 22-trading-day correlations as follows:

$$\rho(r_1, r_2|IV_{t-1}) = \frac{\sum_{i=0}^{21} r_{1,t+i} r_{2,t+i}}{\sqrt{\sum_{i=0}^{21} r_{1,t+i}^2}\sqrt{\sum_{i=0}^{21} r_{2,t+i}^2}} \quad (1)$$

Summary statistics for the time-series of rolling 22-trading-day correlations are presented in Table 1, Panel C (stock-bond correlations) and Panel D (cross-country stock correlations).

4 Comovement variation and the level of stock implied volatility

In this section, we report how return comovements vary with the lagged level of stock implied volatility (IV). Thus, this aspect of our empirical investigation has a forward-looking perspective. We

[10] This approach follows from Fleming, Kirby, and Ostdiek (2001).

first report on stock-bond correlations (Section 4.1) and then cross-country stock correlations (Section 4.2). In Section 4.3, we evaluate the correlation differences and argue that the variations appear statistically different. Next, in Section 4.4, we argue that heteroskedasticity, by itself, seems unable to explain the time-varying comovements. Finally, in Section 4.5, we comment on the economic value implied by our findings from the perspective of recent literature.

4.1 Variations in stock and bond return correlations

4.1.1. Overall sample. First, Table 2 reports on the distribution of 22-trading-day stock-bond correlations (formed from days t to $t+21$) following days when IV_{t-1} falls within the stated percentile range of the IV distribution. Section 3.2 details how we calculate the 22-trading-day correlations.

We find that the stock-bond correlations vary negatively and substantially with the lagged IV. For example, for the U.K., the unconditional probability of a negative 22-trading-day correlation is 33.1%. However, when VIX_{t-1} is at its 80^{th} (90^{th}) percentile or greater, then the subsequent correlations are negative 72.9% (87.3%) of the time. In contrast, when VIX_{t-1} is below its 20^{th} percentile, the subsequent correlations are negative only 2.0% of the time. The mean (median) correlations vary from 0.539 (0.556) for the low-quintile VIX to -0.372 (-0.411) for the high-decile VIX. Results for the U.S. and Germany are similar. Both VIX and VDAX are associated with similar patterns but the VIX variations are typically somewhat stronger, even for the European countries. Figure 2, Panels A and C, exhibit these correlation results graphically for the U.S. and Germany, respectively. Our results here reinforce and extend findings in Connolly, Stivers, and Sun (2003).

4.1.2. Subperiod results. Our sample period has a distinct change in IV behavior commencing in the summer of 1997, which roughly corresponds to the onset of the 1997 Asian financial crisis. Accordingly, we also analyze one-half subperiods. From 1/92 to 6/97, the average VIX level is 15.0%, the standard deviation of daily VIX changes is 0.87%, and the daily U.S. stock-bond return correlation is 0.456. In contrast, from 7/97 to 12/02, the average VIX level is 27.1%, the standard deviation of daily VIX changes is 1.92%, and the daily U.S. stock-bond return correlation is -0.204.

To further contrast the two one-half subperiods, we examine the days with the top 1% of VIX increases. Of the 28 largest VIX-increase days, 25 occur in the second-half. Six are in the fall of 1998 around the Russian foreign debt crisis, two are in the fall of 1997 with the Asian financial crisis, and two are in September 2001 following the 9/11 crisis. These comparisons suggest that pricing influences related to flight-to-quality are much more likely in the second half of our sample.

Accordingly, we are interested in whether the correlation variations with IV are also evident when separately evaluating the one-half subperiods. For the second-half, we report on this investigation in Appendix A. To summarize, for the second-half, we find that the variation in correlations with VIX and VDAX are qualitatively similar and statistically significant. For example, for the U.S. over this second-half subperiod, the median stock-bond correlation is -0.019 following the lowest quintile of VIX observations and -0.473 following the largest decile of VIX observations. In contrast, we find little variation in stock-bond correlations with IV over our first-half subperiod.

The subperiod results suggest the following. First, the comovement patterns do not simply reflect a gross difference between two distinctly different half-periods because IV variations are informative both in the overall sample and separately in the second-half. Second, high IV with high IV variability seems necessary to observe the comovement patterns that suggest flight-to-quality pricing effects. We discuss subperiods further in Section 4.2.2 and our regime-shifting analysis in Section 6.

4.1.3. Stock portfolios with different systematic risk. We also examine whether the stock-bond comovement patterns are different for stock portfolios with higher systematic risk, measured by a stock's market-beta. If the correlation patterns are related to flight-to-quality pricing influences as the perceived uncertainty changes, then the patterns may be stronger for stocks with higher systematic risk. We divide the individual stocks that comprise the S&P 100 (FTSE-100) into three beta-sorted groupings to form U.S. (U.K.) portfolios with different systematic risk.[11]

We then repeat the IV sorting that is performed in Table 2 with each beta-sorted portfolio used in place of the stock index return. We find that the negative stock-bond correlations following the higher VIX observations tend to be more negative for the high-beta portfolios. For the U.S. (U.K.) following the largest quintile of VIX observations, the median correlation is -0.310 (-0.333) when using the high-beta stock portfolio and -0.112 (-0.102) when using the low-beta stock portfolio. These results further suggest a flight-to-quality pricing influence.

4.2 Variations in cross-country stock return correlations

4.2.1. Overall sample. Next, we evaluate whether the IV level is related to the subsequent correlation between cross-country stock market returns. As discussed in Section 2, if stock IV is

[11] We do not similarly examine the German DAX because it only includes 30 firms.

informative about the stock risk or uncertainty at an international level (as suggested by our findings in Section 4.1), then it seems likely that the correlations across equity markets would increase with the IV level. Alternately, if time-variation in IV largely reflects changes in country-specific stock risk, then the cross-country correlations would be likely to decrease with high IV.

In Table 3, we report on the distribution of 22-trading-day cross-country stock correlations (formed from days t to $t + 21$) following days when IV_{t-1} is within a stated percentile range of the IV distribution. We find that these correlations vary positively and substantially with the VIX and VDAX level for all three pairwise stock combinations. For example, for the German:U.K. case, the mean (median) correlation between the two stock returns across the entire sample is 0.590 (0.626). However, the mean (median) correlation varies from 0.430 (0.480) following the low-quintile VIX observations to 0.800 (0.824) following the high-decile VIX observations. Results for the German:U.S. and U.K.:U.S. cases are similar. Figure 2, Panels B and D, graphically exhibit how the cross-country stock correlations vary with lagged IV for the U.S.:German and German:U.K. case, respectively.

To further evaluate return patterns associated with the lagged IV, we calculate the corresponding means, volatilities, and Sharpe ratios of each return series for subsamples sorted on the VIX/VDAX value at $t - 1$. The results for the means and volatilities are presented in Table 4. We make three primary observations. First, the means display little reliable variation across the VIX/VDAX groupings. While this seems at odds with a fundamental risk-return tradeoff, the results are not surprising since measuring expected returns over modest sample periods is notoriously unreliable. Second, Sharpe ratios also seem to convey relatively little information because they rely on the imprecise mean returns. Third, the return volatilities vary as expected with the VIX/VDAX. For the U.S. and U.K., the stock volatility increases monotonically and substantially with VIX. For Germany, the stock volatility increases monotonically and substantially with VDAX. In contrast, the volatilities of the bond returns increase only modestly with IV.

4.2.2. Subperiod results. We are also interested in whether the cross-country stock comovement patterns are evident across subperiods (see Section 4.1.2). We report second-half results in Appendix B. We find that the stock correlation patterns are also evident in our second-half subperiod, but the patterns are somewhat more modest as compared to the overall sample.

For the first-half subperiod, we find that the cross-country stock correlations also vary with lagged IV for the U.S.:German and U.S.:U.K. cases. For example, for the U.S.:German case, the median 22-trading-day correlation following the low (high) VIX-quintile is 0.437 (0.652). We find little variation in the German:U.K. stock correlations in our first-half period. We further consider subperiod variation in the regime-shifting investigation of Section 6.

4.3 Evaluating differences in the correlations

Next, we evaluate whether the differences in the correlations across the different IV subsets are statistically significant. We rely on bootstrap methods that make draws with replacement over 1000 cycles to generate a bootstrapped distribution and then use the distribution to evaluate whether the comovement variations are reliably different.[12] Underlying deviations from normality should have no significant impact on the inferences using this method.[13]

For example, we examine whether the average of the 22-trading-day correlations following days when IV is in its top quintile is statistically different than the average of the 22-trading-day correlations over the entire sample. For each cycle, we randomly draw correlations with replacement from the set of actual 22-trading-day correlations following the high IV-quintile days. We make draws until we have a set of correlations where the number of correlations equals the number of correlations in the original subset. Then, we calculate the average of the drawn 22-trading-day correlations. Likewise, we perform the same exercise but with the entire set of actual 22-trading-day correlations and calculate the average of these drawn 22-trading-day correlations. Finally, we take the difference between the average correlation following the high IV days and the average correlation for the entire sample and retain the difference. We then repeat this cycle 1000 times to generate a distribution of the differences in the average correlations between the two groupings.[14]

For the stock-bond cases in Table 2, this bootstrap method indicates that the average stock-bond correlations following the extreme IV observations are statistically significantly different than

[12]Bootstrap methods are well developed in statistics and econometrics. See Horowitz (2002) for an introduction to bootstrap methods. We gratefully acknowledge Roberto Rigobon's suggestion in this regard.

[13]Note that, for this subsection, we do not try to evaluate whether the comovement patterns are different than that suggested by heteroskedasticity arguments (in the sense of Forbes and Rigobon (2002)). Rather we comment on heteroskedasticity effects in Section 4.4.

[14]The 1000 cycles also provides a distribution of the average 22-trading-day correlations for each IV_{t-1} subset, which can be used to calculate standard errors for the subset average correlation. The standard errors for the average correlations are modest (ranging from 0.007 to 0.019) and are only slightly higher (within a few percent) than standard errors calculated assuming normality.

the average correlation for the entire sample at a 1% p-value for all three countries (here, extreme means the low quintile, high quintile, and high decile of the IV distribution). For example, for the U.K. stock-bond correlations, when bootstrapping the difference between the average correlation for the high VIX-quintile subset to the average correlation for the overall sample, we find that the inner 98^{th} percentile of this difference's distribution is -0.462 to -0.384. For the cross-country stock cases in Table 3, this bootstrap method also indicates that the average stock correlations following the extreme IV observations are statistically significantly different than the average correlation over the entire sample at a 1% p-value for all three pairwise combinations (again, extreme means the low quintile, high quintile, and high decile of the IV distribution). See Appendix D for additional supporting evidence of these comovement patterns.[15]

4.4 The correlation variations and heteroskedasticity

Forbes and Rigobon (2002) note that heteroskedasticity alone can generate variation in measured return correlations, even if the economic relation between two return series has not changed. Accordingly, in this subsection, we evaluate the correlation variation in our data with heteroskedasticity effects in mind. First, we consider our findings from the perspective of the simple numerical example in Forbes and Rigobon (see pp. 2230-2231 of their article). Their example assumes the economic relation between two return series is constant, which means (in their context) that $E(r_{y,t}|r_{x,t})$ is a fixed proportion of the given $r_{x,t}$. When market x has a shock with accompanying higher return volatility, then the measured correlation between the two series should increase. In Appendix C, we present examples with our data that address the following: Given the observed heteroskedasticity in our data and the assumptions in this Forbes-Rigobon example, what variation in correlations would you expect to see due only to the differing heteroskedasticity across the return series? We find that,from the perspective of the Forbes-Rigobon example, the observed heteroskedasticity is unable to explain the observed variation in correlations. Further, heteroskedasticity is not capable of explaining cases where correlations go from positive to negative, as observed for the stock-bond relations.

Next, we also evaluate comovements in a GARCH system that directly models the heteroskedas-

[15] We also perform a second bootstrap evaluation with correlations from non-overlapping 22-trading-day periods (for all the cases in Tables 2 and 3). The inferences are consistent with our inferences using the correlation series from overlapping 22-trading-day periods.

ticity in the dependent variable. Additionally, since the estimated return relations in the following model capture a somewhat different notion of comovement (as compared to the rolling 22-trading-day correlations), this investigation supplements our results in Tables 2 and 3.[16] For the stock-bond return relations within country, we estimate the following GARCH system.

$$B^r_{x,t} = (\beta_0 + \beta_1 ln(IV_{t-1}))S^r_{x,t} + \epsilon_t \tag{2}$$

$$h_t = \frac{\gamma_0 + \gamma_1 \epsilon^2_{t-1}}{1 - \gamma_2 L} + \gamma_3 IV^2_{t-1} \tag{3}$$

where $B^r_{x,t}$ ($S^r_{x,t}$) is the bond-return residual (stock-return-residual) for country x and superscript r indicates the residual retained from the VAR model given by (4) and (5) below, $\ln(IV_{t-1})$ is the natural log of the lagged implied volatility (either VIX or VDAX), h_t is the conditional variance of the residual ϵ_t from (2), IV^2_{t-1} is the lagged implied variance from either the VIX or VDAX series, L is the lag operator, and the βs and γs are estimated coefficients.[17] We use the log of IV in (2) to more normalize the IV series. The coefficient of interest is β_1. The GARCH system is estimated with a conditional normal density. For inference, we calculate standard errors that are robust to departures from conditional normality, see Bollerslev and Wooldridge (1992).

For (2), we use the return-residuals retained after estimating the following VAR system:

$$B_{x,t} = \alpha_0 + \sum_{i=1,4} \varphi_i B_{x,t-i} + \sum_{i=1,4} \gamma_i S_{x,t-i} + B^r_{x,t} \tag{4}$$

$$S_{x,t} = \alpha_1 + \sum_{i=1,4} \psi_i B_{x,t-i} + \sum_{i=1,4} \phi_i S_{x,t-i} + S^r_{x,t} \tag{5}$$

where $B_{x,t}$ ($S_{x,t}$) is the daily 10-year bond (stock) return from country x, $B^r_{x,t}$ ($S^r_{x,t}$) is the residual from the bond (stock) return equation, and the αs, φs, γs, ψs, and ϕs are estimated coefficients. We choose the number of lags based on the Akaike information criterion, final prediction error, and the sequential modified likelihood ratio test statistic. The criteria suggest one to four lags, depending upon the specific bivariate system. For uniformity, we estimate all the VAR systems with four lags.

[16]It is important to note that these specifications are not intended to represent econometric structural models of the dependent variable. Rather, these specifications are meant to further characterize contemporaneous comovements and document statistical association, rather than economic causality.

[17]Note that the specification for the conditional variance follows from Blair, Poon, and Taylor (2001) and ensures that only the most recent observation of IV feeds into the conditional variance equation.

We estimate the VAR to control for time-series predictability in the returns due to market microstructure effects, such as non-synchronous trading, and due to possible time-variation in expected returns. Thus, the model in (2) and (3) is intended to examine the comovement between the unexpected component of daily returns. In practice, the VAR explains very little of the daily returns. The R-squareds ranges from 0.21% (for U.K. bond returns) to 1.32% (for U.K. stock returns). The correlation of the raw return variables with the corresponding VAR residual is greater than 0.994 for all six return series. This result also suggests that non-synchronous trading does not have a material influence on the index returns and correlations reported in our earlier results.

For the cross-country stock return relations, we estimate the following GARCH system.

$$S^r_{y,t} = (\beta_0 + \beta_1 ln(IV_{t-1}))S^r_{x,t} + \epsilon_t \tag{6}$$

$$h_t = \frac{\gamma_0 + \gamma_1\epsilon^2_{t-1}}{1 - \gamma_2 L} + \gamma_3 IV^2_{t-1} \tag{7}$$

where $S^r_{y,t}$ ($S^r_{x,t}$) is the stock-return residual for country y (country x) and the superscript r indicates the residual retained from the VAR model given by (8) and (9) below, and the other terms and model estimation details are the same as for (2) and (3).

For (6), we use the return-residuals retained after estimating the following VAR system:

$$S_{y,t} = \alpha_0 + \sum_{i=1,4} \varphi_i S_{y,t-i} + \sum_{i=1,4} \gamma_i S_{x,t-i} + S^r_{y,t} \tag{8}$$

$$S_{x,t} = \alpha_1 + \sum_{i=1,4} \psi_i S_{x,t-i} + \sum_{i=1,4} \phi_i S_{y,t-i} + S^r_{x,t} \tag{9}$$

where $S_{y,t}$ ($S_{x,t}$) is the return from country x (country y), $S^r_{y,t}$ ($S^r_{x,t}$) is the residual from the stock return equation for country x (country y), and the αs, φs, γs, ψs, and ϕs are estimated coefficients. See our discussion following (4) and (5) for model estimation details and the reasoning behind the VAR. Also, the VAR also controls for the time-series predictability due to the slight lead-lag relation between the stock-return pairs (see Section 3.1). In practice, the VAR explains little of the daily returns. The R-squareds for the VAR range from 0.96% (for U.K. stock returns) to 4.09% (for U.S. stock returns in the German:U.S. case, the relatively high R-squared for this case is likely due to the slight non-synchronicity in the two return series). The correlations of the raw stock returns with the corresponding VAR residuals are greater than 0.979 for all cases.

Table 5 presents the results from estimating the model in equations (2) and (3) for the stock-bond relations and equations (6) and (7) for the cross-country stock-stock relations. First, for the stock-bond case in Panel A, the estimated β_1 is sizably negative for all countries. This indicates that the comovements decrease with increasing stock IV. For the U.K., for example, the implied relation between the bond and stock return-residuals is 0.361 at the 5^{th} percentile of VIX_{t-1} and -0.080 at the 95^{th} percentile of VIX_{t-1}.

Next, for the cross-country stock cases, we find that the estimated β_1 is sizably positive for all cases (see Table 5, Panel B). This indicates that the stock comovements increase with increasing stock IV. For example, for the German return-residual as a function of the U.K. return-residual, the implied relation between the two stock return-residuals is 0.384 at the 5^{th} percentile value of VIX_{t-1} and 1.004 at the 95^{th} percentile value of VIX_{t-1}. For the reverse case (the U.K. return-residual as a function of the German return-residual), the implied relation between the two stock return-residuals is 0.363 at the 5^{th} percentile value of VIX_{t-1} and 0.652 at the 95^{th} percentile value of VIX_{t-1}. Note that the comovement variations are qualitatively similar in all cases when reversing the order of the return pairs (x:y) in equation (6), which is inconsistent with the comovement variations being driven by heteroskedasticity in a single shocked stock market. Thus, the Table 5 results reinforce the comovement results depicted in Tables 2 and 3.[18]

We also estimate the models given by equations (2) through (9), for one-half subperiods for each case reported in Table 5. For our second-half period, the estimated β_1s depict the same Table 5 relations for all cases and the β_1s are statistically significant for all cases except the U.S.:German stock case. However, for our first-half period, the same patterns are only reliably evident in a few cases (the U.S. stock-bond case, the U.S.:U.K. stock case, and the U.S.:German stock case). Thus, these subperiod results are consistent with our findings in Sections 4.1.2 and 4.2.2.

[18]For the conditional variance equations in the Table 5 models (equations (3) and (7)), we find standard GARCH behavior. All of the estimated γ_1 and γ_2 coefficients are positive and significant with an average γ_1 of 0.060 and an average γ_2 of 0.855. For the lagged implied-variance term, we find that the estimated γ_3 coefficients are positive and statistically significant for all six of the stock cases in Panel B (with a minimum t-statistic of 3.86) and for two of the three stock-bond cases in Panel A (the estimated γ_3 is positive but insignificant for the U.K. stock-bond case).

4.5 Economic value of the comovement patterns

Recent research suggests that volatility timing in daily returns has economic value in dynamic asset allocation and portfolio management settings (see, e.g., Fleming, Kirby, and Ostdiek (2001) and (2003), and Busse (1999)). Here, we evaluate the economic value of the forward-looking comovement patterns in Tables 2 and 3 from the perspective of Fleming, Kirby, and Ostdiek (2001) (FKO hereafter). In their analysis, FKO form one-day ahead estimates of the variance-covariance matrix for an investment opportunity set that includes stock-index futures, government bond futures, gold futures, and cash equivalents. They use a simple rolling estimator formed from lagged returns to form the forecasted variance-covariance, where an exponential decay function determines the weights on lagged returns. Using mean-variance analysis and assuming that daily mean returns are constant (because expected daily returns are essentially zero and exhibit little predictability), they find that volatility timing in a dynamic strategy adds appreciable economic value over a static portfolio.

In FKO's framework, our findings should have economic value if they lead to a better estimate of the one-step ahead covariance matrix. As compared to the economic value suggested in FKO's sample, it seems likely that a similar investigation over our sample period, especially with the incorporation of IV information, would imply even greater economic value. This is because the forward-looking comovement patterns are particularly strong in the crisis-laden second half of our sample (7/97 through 12/02) and FKO's sample only covers the 1983 to 1997 period.

To further investigate this issue, we use FKO's method (approximately) to forecast a conditional covariance for the asset return pairs covered in our Tables 2 and 3. We use return lags from t-1 to t-50 to form a conditional covariance estimates for time t, with the weights on each lag determined by the exponential decay function from FKO. We then estimate the subsequent realized covariance using return observations t through t+49 (to form the realized covariance, we use the mirror image of the same exponential decaying weights that were used to form the lagged rolling estimator). Then, we regress the realized covariance against this conditional covariance (formed from lagged returns) and retain the residual. Finally, we regress this retained residual from the regression against $\log(\mathrm{IV}_{t-1})$ to evaluate whether IV contains incremental information for the realized covariance (beyond the information from the lagged rolling estimator). For all pairwise return combinations in Tables 2 and 3, we find that IV_{t-1} is reliably related to the retained residual from the covariance-forecast regression at a 0.1% p-value. For example, for the U.K. stock-bond case, the estimated coefficient on VIX_{t-1} in the final regression is statistically significant with a t-statistic of -8.47 (with robust standard errors) and an R-squared of 8.9%. For the U.S.-U.K. stock-stock case, the estimated coefficient on VIX_{t-1} in the final regression has a t-statistic of 5.22 and an R-squared is 6.7%. Thus, at least in FKO's framework, it seems likely that the comovement-IV relation would have economic value.

Finally, our forward-looking findings and subsequent regime-switching work (in Section 6) suggest that the economic value analysis in Ang and Bekaert (2002) may be an interesting avenue to pursue, with the addition of long-term bond returns in their analysis. We do not pursue this avenue with our sample, primarily because their model (fit to monthly data) calculates optimal portfolio weights based on estimated mean returns as well as the covariance matrix. We believe the FKO assumption of unpredictable mean returns is more appropriate for our daily return sample of 11 years.

5 Comovement variation and the change in stock implied volatility

Next, we report how return comovements vary contemporaneously with a period's change in stock implied volatility (IV). Section 5.1 reports on stock-bond return comovements, Section 5.2 reports on cross-country stock comovements, and Section 5.3 discusses the statistical significance of the comovement variations. In this section, we calculate subset correlations using the unconditional mean return over the entire sample as the subset mean return. We make this choice for simplicity and because this leads to a clear interpretation of the resulting correlations; the correlations depict how returns co-move relative to their overall sample mean (which is essentially zero for daily returns).

5.1 Stock-bond return correlations and a period's IV change

In Table 6, Panel A, we report on the stock-bond correlations for subsets of observations sorted by the day's change in VIX or VDAX. We find that the stock-bond correlations vary substantially with a day's change in stock IV. On days when the IV changes appreciably, either up or down, the correlations are negative or near zero. On the other hand, on days when the IV changes relatively little, the stock-bond correlations are modestly to substantially positive.

For example, for the U.S. on days with a large decrease in VIX (the low quintile ΔVIX observations), the correlation is -0.110. On days with a large increase in VIX (the top decile ΔVIX observations), the correlation is -0.200. However, for the ΔVIX quintiles two through four, the average correlation is 0.219. The German and U.K. returns exhibit similar patterns. We also note that the average stock return is negatively and substantially related to the day's ΔIV in all cases. To conclude, variation in the stock-bond comovements with the day's change in stock IV exhibits a clear 'inverted U' or frown shape. Figure 3, Panel A, depicts this relation graphically.

5.2 Cross-country stock return correlations and a period's IV change

In Table 6, Panel B, we report on cross-country stock correlations for subsets of observations sorted by the day's change in VIX or VDAX. We find that the stock comovements are higher on days with substantial changes in IV (both up or down) and lower on days with little change in IV. For example, on days with a large decrease in VDAX (the low quintile ΔVDAX), the German:U.K. stock correlation is 0.793. On the days with large increases in VDAX (the top decile ΔVDAX), the German:U.K. stock correlation is 0.847. By contrast, the average German:U.K. stock correlation for ΔVDAX quintiles two through four is 0.468. Thus, the cross-country stock correlations vary with the day's ΔIV in the shape of a 'standard U' or smile shape. Figure 3, Panel B, exhibits this relation.

Overall, a period's change in IV is related to variations in stock-bond comovements, cross-country stock comovements, and mean stock returns in a manner that seems consistent with flight-to-quality (flight-from-quality) pricing influences as stock uncertainty increases (decreases). Given that times of high IV level are also times with high IV variability in the near future, this interpretation seems consistent with the forward-looking results in Tables 2, 3, and 5 (also see Section 6.3).

5.3 Evaluating the differences in return comovements

Here, we evaluate whether the correlations reported in Table 6 are reliably different for the ΔIV subsets. As in Section 4.3, we rely on bootstrap methods that make draws with replacement over 1000 cycles to generate a bootstrapped distribution. We make random draws, with replacement, of the actual return pairs that correspond to the ΔIV criteria. For each cycle, the number of drawn return-pairs is equal to the number of observations in the actual ΔIV subset. We then calculate the correlation for the set of drawn return pairs. Then we calculate the difference in the subset correlations for each drawn set of return observations and repeat 1000 cycles to generate a distribution of the respective "difference in correlations".

For the stock-bond cases in Table 6, Panel A, bootstrap distributions indicate that the stock-bond correlations for the extreme ΔIV observations are statistically significantly different than the stock-bond correlation for the modest ΔIV observations at a 1% p-value for all three countries (in this subsection, extreme means the low quintile, high quintile, and high decile of the ΔIV distribution and modest means the inner 60^{th} percentile). Similarly, for the cross-country stock cases in Table 6, Panel B, the bootstrapped distributions indicate that the stock correlations for the extreme ΔIV observations are statistically significantly different than the stock correlation for the modest ΔIV observations at a 1% p-value for all three pairwise stock combinations.

A second, more complex question is whether the correlations vary more than expected relative to some model or assumed distribution. This question is difficult to evaluate because sorting return observations on the day's ΔIV tends to sort stock returns from high to low (because of the negative correlation between stock returns and ΔIV, see Fleming, Ostdiek, and Whaley (1995)). This means that some variation in correlations across the ΔIV subsets is expected (if the two return series have a non-zero correlation); see, e.g., Ang and Chen (2002). For our sample, we note that this is primarily a concern for the cross-country stock correlations. This is because the unconditional correlation for the stock-bond daily returns is close to zero in our sample. Under the assumption that the stock and bond returns are uncorrelated, the predicted stock-bond correlation should be zero for the different ΔIV subsets. From this perspective, the observed variations in the stock-bond correlations with ΔIV in Table 6 are greater than expected.

6 Regime-shifting analysis

In this section, we further explore the nature of time-series variation in both the stock-bond return relations and the cross-country stock relations by examining a regime-shifting approach to modeling shifts in return comovements. There is considerable evidence of regime switching in both stock and bond returns.[19] Our purposes in this section are fivefold: (1) to examine whether a simple regime-switching model also picks up statistically reliable time-variation in the return relations, (2)

[19]There is a relatively large literature applying variants of Hamilton's regime-switching model in financial economics, see Hamilton (1994) for an overview of the method and early literature. More recent related literature includes Gray (1996), Boudoukh, Richardson, Smith, and Whitelaw (1999), Ang and Bekaert (2002a, 2002b), Whitelaw (2000), the earlier-cited Veronesi papers, and Connolly, Stivers, and Sun (2003).

to examine whether the probability of switching from one regime to another depends on the lagged stock IV, (3) to examine, for a given country, to what extent that the country's stock-bond regime movements correspond to the country's regime movements in the cross-country stock relations, (4) to examine to what extent regime movements are common across countries, and (5) to examine what the implied regime durations suggest about the nature of the return dynamics and about implications for asset allocation between stocks and bonds and across stock markets.

6.1 The empirical regime-switching models

We estimate the following two-state, regime-switching model for the stock-bond return relations.

$$B^r_{x,t} = \alpha_s S^r_{x,t} + \epsilon_t \tag{10}$$

where $B^r_{x,t}$ (S^r_t) is the bond return-residual (stock return-residual) for country x with the superscript r indicating the residual retained after estimating the 4-lag VAR system in Section 4.4; α_s is an estimated regime-dependent coefficient that indicates the comovement, either α_0 for regime-zero or α_1 for regime-one where the subscript s indicates the regime; and ϵ_t is the residual. The variable s can be regarded as an unobserved state variable that follows a two-state, first-order Markov process.

We model s_t with time-varying transition probabilities (Pr) as follows:

$$Pr(s_t = j | s_{t-1} = j) = \frac{e^{c_j + d_j \ln(IV_{t-1})}}{1 + e^{c_j + d_j \ln(IV_{t-1})}}, \tag{11}$$

where j = 0 (regime-zero) or j = 1 (regime-one), $\ln(IV_{t-1})$ is the natural log of the lagged implied volatility (either VIX or VDAX), and the c_js, and d_js are estimated coefficients (see Diebold, Lee, and Weinbach (1994)). Since we are concerned with stock uncertainty (with the stock implied volatility), we use the stock return-residual as the explanatory variable in the regime-shifting estimation.

We estimate the following two-state, regime-switching model for the cross-country stock relations:

$$S^r_{y,t} = \beta_s S^r_{x,t} + \epsilon_t \tag{12}$$

where $S^r_{y,t}$ ($S^r_{x,t}$) is the stock return-residual for country y (country x) with the superscript r indicating the residual retained after estimating the 4-lag VAR system in Section 4.4; β_s is an estimated coefficient that indicates the comovement, either β_0 for regime-zero or β_1 for regime-one where the subscript s indicates the regime, as in the stock-bond case above. For the cross-country stock cases, we also allow for time-varying transition probabilities per equation (11). As we noted in footnote 13 for equations (2) and (6), equations (10) and (12) are meant to describe contemporaneous comovements between the unexpected component of daily returns, not econometric causality.

6.2 Empirical results

In Table 7, we report the results from estimating the stock-bond regime-shifting model for each of our three primary countries over the 1992 to 2002 period. We find strong evidence of regime-shifting behavior with substantial contrast between the regimes. The stock-bond return relations for regime-zero, represented by the α_0 coefficient, are 0.305, 0.276, and 0.439, for the U.S., Germany, and the U.K., respectively. In contrast, the stock-bond return relations for regime-one, represented by the α_1 coefficient, are -0.110, -0.032, and -0.069, for the U.S., Germany, and the U.K., respectively. These estimated coefficients are all highly statistically significant.

We also find that it is important to allow the transition probabilities to vary with IV_{t-1}. For all three countries, the estimated d_0 is negative, sizable, and statistically significant. This indicates that the probability of staying in regime-zero decreases with IV_{t-1}. This feature is further depicted in Table 7, Panel B, which presents the expected duration of staying in each regime at roughly the 25^{th} and 75^{th} percentile values of the VIX/VDAX. Note that the expected duration of staying in regime-zero is sizable at a stock IV of 15%. However, the expected duration of staying in regime-zero drops dramatically when the stock IV increases to 25%. For regime-one, the estimated d_1 is positive for all three countries and is positive and statistically significant for the U.K. The estimated d_1 coefficients suggest a modest positive relation between the expected duration of staying in regime-one and the stock implied volatility.

Figure 4, Panels A through C, plot the filtered probability of being in regime-one over time for the U.S., Germany, and the U.K. stock-bond return relations, respectively. Inspection of each figure indicates an obvious relation between the regime movements across the countries.

Next, in Table 8, we report the results for the regime-shifting model for the cross-country stock return relations. With three countries, there are three possible pairwise combinations when considering simple correlations. However, in equation (12), the choice of which stock return-residual to use as the explanatory variable and which to use as the dependent variable is arbitrary. We elect to examine both possibilities to ensure that our findings do not depend upon which return-residual is the explanatory variable. Thus, there are six total regime-shifting cases for the cross-country stock comovement evaluation. We estimate each of the six cases with transition probabilities that may vary with either VIX or VDAX, alternately, for 12 total estimations. Table 8 reports on the VIX or VDAX choice, for each case, which yields the highest estimated likelihood function value.

To summarize, we find evidence of regime-shifting behavior with substantial contrast between the regimes. (In Table 8 and the following discussion, the stock return-residual from the first country listed is the explanatory variable in equation (12).) The cross-country stock return relations for regime-zero, represented by the β_0 coefficient, are 0.36, 0.44, 0.23, 0.67, 0.29, and 0.49, for the U.K:German case, German:U.K. case, German:U.S. case, U.S.:German case, U.K.:U.S. case, and U.S.:U.K. case, respectively. In contrast, the cross-country stock return relations for regime-one, represented by the β_1 coefficient, are 1.10, 0.86, 0.74, 1.96, 1.06, and 1.39, for the U.K:German case, German:U.K. case, German:U.S. case, U.S.:German case, U.K.:U.S. case, and U.S.:U.K. case, respectively. These estimated coefficients are all highly statistically significant.

Further, we find that it is important to allow the transition probabilities to vary with IV_{t-1}. For all six cases, the estimated d_0 is negative, sizable, and statistically significant. This indicates that the probability of staying in regime-zero decreases with increasing IV. The expected durations in Table 8, Panel B, further illustrate this point. For regime-one, the estimated d_1 is positive for all six model variations, but positive and statistically significant at the 10% level for only two cases. Overall, as shown by the expected durations in Panel B, there is little relation between the transition probabilities when in regime-one and IV_{t-1}. Figure 5, Panels A through F, shows the filtered probability of being in regime-one for the six cases.

6.3 Discussion of regimes and expected regime durations

The two regimes depicted from the regime-shifting results seem consistent with our correlation results in Tables 2 and 3. Regime-zero may be described as a lower uncertainty regime where the stock-bond relations are sizably positive, the cross-country stock relations are relatively weak, and IV tends to be low. On the other hand, regime-one is less frequent and may be described as a higher uncertainty regime, where the stock-bond relations are modestly negative, the cross-country stock relations are relatively stronger, and IV tends to be higher. The expected durations of the stock-bond regimes seem long enough to suggest a potential application in asset allocation for investors who are concerned with short horizon diversification and risk management.

On the other hand, we note that the expected durations of regime-one are quite short for the cross-country stock cases.[20] Certainly, our regime-one results do not depict stable long-term regimes, where regime changes are infrequent and are associated with variations in the business cycle or other long-term economic conditions. However, when viewing the collective regime-shifting results depicted in Figures 4 and 5, the regime-shifting representation does appear useful. Specifically, there are sustained periods when the estimation indicates almost exclusively regime-zero and other sustained periods when there are frequent episodes of regime-one. Further, the time-variation in the stock-bond regimes seems to be substantially related across countries and substantially related to the cross-country stock regimes.

Since the regime-one episodes are of longer duration for the stock-bond relations (as compared to regime-one for the cross-country stock relations), we evaluate the following question. What proportion of the regime-one days for the cross-country stock regimes for a particular country occur when that country's stock-bond regime is in regime-one? For this evaluation, we categorize a day as regime-one if the filtered probability of being in regime-one is 80% or more. For example, for the German stock-bond case (Figure 4, Panel B), about 43% of the days are categorized as regime-one. For the German:U.K. stock relation (Figure 5, Panel A), about 19% of the days are categorized as regime-one and over 92% of these regime-one days occur when the German stock-bond relation is also in regime-one. Second, for the U.S. stock-bond case (Figure 4, Panel A), about 32.5% of the days are categorized as regime-one. For the U.K.:U.S. stock relation (Figure 5, Panel E), about 4.1% of the days are categorized as regime-one and over 93% of these regime-one days occur when the U.S. stock-bond relation is also in regime-one. This same evaluation for the other possible combinations in Figures 4 and 5 indicates that the regime-one days for the cross-country stock relations overlap with the regime-one days for the respective country's stock-bond relations for over 90% of the cross-country stock regime-one days.

Next, we also evaluate the commonality across the three countries for the regime-one stock-bond days, as depicted in Figure 4. Using the U.S. (with the largest economy and the largest financial markets) as the base case, we evaluate the following question: When the U.S. stock-bond relation is estimated to be in regime-one, then what proportion of the time are the U.K. and German stock-

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

bond relations also in regime-one? The answer is 96.6% of the time for the U.K. and 92.4% of the time for Germany. (As before, we consider a day to be in regime-one if the filtered probability is greater than 80%.) Recall that the transition probabilities are a function of the lagged VIX for the U.S. and the lagged VDAX for Germany, which makes this commonality even more striking.

We also note that transitions to regime-one tend to be associated with sizable increases in IV. For example, for the U.S. stock-bond relation, there are 36 episodes when the filtered probability of being in regime-one goes from a value of 0.7 or lower (on day t-1) to a value of 0.8 or higher (on day t). On 15 of these 36 transitional days, the daily VIX change exceeds the top 10^{th} percentile of its distribution. Similarly, for the U.S.:U.K. stock relation, there are 71 episodes when the filtered probability of being in regime-one goes from a value of 0.7 or lower (on day t-1) to a value of 0.8 or higher (on day t). On 41 of these 71 transitional days, the daily VIX change exceeds the top 10^{th} percentile of its distribution.

One interpretation of our regime-shifting results is the following. First, we note that when the IV level is relatively high then the IV variability in the near future also tends to be high. In our sample, the correlation between the VIX volatility (measured by the 22-trading-day average of absolute daily VIX changes over periods t to $t + 21$) and the VIX level at $t - 1$ is 0.698 (0.703 for VDAX). See Figure 1 for a graphic display of this behavior. Thus, when the stock IV level is relatively high (such as during the Asian financial crisis of 1997 or the Russian default crisis in 1998), then the "volatility of uncertainty" is also higher. During these high IV times, it is more likely that there will be news or market reactions that result in a spike upward in implied volatility on certain days. Following these IV upward spikes, the uncertainty typically falls over the next few days as the uncertainty is somewhat resolved (but IV still remains high compared to long-term averages). This process in such times could induce a short-term negative return correlation in stock and bond returns with an initial flight-to-quality and subsequent flight-from-quality as uncertainty fluctuates. Further, if the dynamic movements in IV are informative about the uncertainty and risk of a global stock common-factor, then stock prices across countries should move together more during the periods with a substantial change in IV (both upward and downward), and the stock-bond regime movements should be substantially linked across countries. Such a dynamic process seems consistent with our regime-shifting results and the return patterns documented in Tables 2 through 6.

7 Conclusions

We investigate commonality in the time-variation of stock-bond return comovements within country and stock-stock return comovements across countries by analyzing asset returns from the U.S. and Europe over 1992 to 2002. Our focus is on how return comovements vary with stock market uncertainty, as measured by the implied volatility (IV) from equity index options.

To support our primary empirical goal, we first extend work on stock-bond comovements and document two strong, pervasive comovement patterns over our 1992 to 2002 sample period. We find that stock-bond correlations tend to be negative following high IV days and tend to be positive following low IV days, which reinforces results in Connolly, Stivers, and Sun (2003). Further, the stock-bond correlations following high IV days tend to be more negative for stock portfolios of high market-beta stocks. Next, we find that stock-bond correlations vary with a day's IV change in a "frown shape", where correlations are negative or near zero for days with either sizable increases or decreases in stock IV and are sizably positive for days with little change in IV.

Next, we also contribute by characterizing how cross-country stock comovements vary with IV. We find that cross-country stock correlations tend to be more positive following high IV days and tend to be less positive following low IV days. Further, we find that the cross-country stock correlations vary with a day's IV change in a "smile shape", where the correlations are stronger for days with either sizable increases or decreases in IV and are weaker for days with little change in IV.

We then contribute by conducting a regime-shifting analysis that indicates substantial linkages between the stock-bond and stock-stock comovement patterns. Our specification allows the transition probabilities to vary with the lagged IV. Our regime-shifting results also depict sizable comovement variations and indicate that stock IV has an important role in understanding comovement variations.

Our collective evidence supports the ideas that: (1) implied volatilities from equity index options are useful as state variables that provide information about the uncertainty of a global stock common factor, and (2) time-varying uncertainty with associated cross-market asset revaluations is important in understanding daily return dynamics. Thus, our findings support the empirical relevance of intuition from theoretical work such as Kodres and Pritsker (2002) (that cross-market rebalancing or hedging during market shocks influences short horizon returns), and Ribeiro and Veronesi (2002) and other related Veronesi papers (that time-varying uncertainty is important in price formation).

Our results also suggest that times with high stock uncertainty are also likely to have higher variability about the perceived uncertainty in the near future with an associated higher volatility in the relative attractiveness of stocks versus bonds (flight-to and flight-from quality pricing influences). See the time-series behavior of IV (Figure 1), the forward-looking comovement patterns (Tables 2 through 5), and the regime-shifting results (Tables 7 and 8, and Figures 4 and 5). Future theory that more formally explains our series of comovement findings would be interesting and would likely yield additional empirical implications.

Our findings also bear on understanding variations in the risk-premia of stock and long-term bond returns. Since our work examines daily government bond returns in periods with modest and stable inflation, it seems unlikely that the bond's expected cash flows (in real terms) would vary appreciably over the 22-trading-day horizons used in our study. This suggests that risk-premium adjustments must largely explain the daily bond price movements related to stock IV (since short-term risk-free rates vary little compared to bond price volatility). Thus, our results suggests a high frequency variation in risk premia, related to time-varying stock IV, that is likely to be important during times of international financial crisis and liquidity shocks.

Finally, the economic benefits of diversifying across stock and bond markets and across countries are fundamental issues in asset allocation and risk management. Our work bears on these issues by promoting a better understanding of how diversification benefits vary with time-varying stock uncertainty. From the perspective of Fleming, Kirby, and Ostdiek (2001), incorporating our findings into asset allocation decisions seems likely to provide economic benefit.

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Table 1: Descriptive statistics

This table reports basic descriptive statistics for the data used in this article. The stock returns for each country are from Datastream's total stock market index. The bond returns are from Datastream's 10-year benchmark government bond index. The returns are in daily percentage units. Std. Dev. denotes standard deviation and ρ_i refers to the ith autocorrelation. The VIX is the Chicago Board Option Exchange's Volatility Index, which provides a standardized implied volatility from S&P 100 equity index options. Similarly, VDAX provides a standardized implied volatility from options on the German DAX stock index. Panel A reports univariate return statistics. Panel B reports on the distribution of the VIX and VDAX, in annualized standard deviation percentage units. Panel C reports on rolling 22-trading-day correlations between daily stock and bond returns. Finally, Panel D reports on rolling 22-trading-day cross-country correlations between the stock markets. These correlations are calculated assuming that the daily mean returns are zero for each 22-trading-day period. For the U.S.:German and U.S.:U.K. stock-stock correlations, the returns are calculated from open-open S&P 500 prices for the U.S. and 2PM-2PM Greenwich Mean Time for the U.K. and Germany to give approximately contemporaneous returns. The sample period is 1992 to 2002, except for the cross-country stock correlations involving the U.S. where the sample period is 7/16/92 through 12/31/02.

Panel A: Univariate daily return statistics

	Mean	Std. Dev.	Skewness	Excess Kurtosis	ρ_1	ρ_2
U.S. Stock	0.042	1.07	-0.048	4.07	0.024	-0.035
U.S. Bond	0.027	0.431	-0.39	2.08	0.071	-0.008
German Stock	0.029	1.17	-0.30	3.09	0.061	-0.028
German Bond	0.031	0.323	-0.67	3.92	0.004	0.034
U.K. Stock	0.038	0.989	-0.13	3.10	0.053	-0.047
U.K. Bond	0.038	0.422	-0.03	4.24	0.037	0.011

Table 1: (continued)

Panel B: VIX and VDAX univariate statistics

	Mean	Std. Dev.	10^{th} pctl	25^{th} pctl	Median	75^{th} pctl	90^{th} pctl
VIX	21.02	7.74	12.19	14.12	20.79	25.56	31.11
VDAX	21.75	8.89	12.48	15.04	20.20	25.40	34.13

Panel C: Rolling 22-trading-day stock-bond correlations

	Percentage of Correlations<0	Mean	Std. Dev.	10^{th} pctl	25^{th} pctl	Median	75^{th} pctl	90^{th} pctl
U.S.	32.4%	0.180	0.432	-0.489	-0.137	0.282	0.534	0.688
German	28.2%	0.229	0.402	-0.390	-0.076	0.292	0.563	0.705
U.K.	33.1%	0.203	0.428	-0.399	-0.162	0.303	0.547	0.705

Panel D: Rolling 22-trading-day cross-country stock correlations

	Mean	Std. Dev.	10^{th} pctl	25^{th} pctl	Median	75^{th} pctl	90^{th} pctl
Germany-U.K.	0.590	0.216	0.279	0.456	0.626	0.756	0.848
Germany-U.S.	0.503	0.210	0.233	0.362	0.509	0.653	0.794
U.K.-U.S.	0.498	0.198	0.244	0.377	0.497	0.638	0.771

Table 2: Stock implied volatility and subsequent stock-bond return correlations

This table reports on the relation between stock implied volatility and the subsequent 22-trading-day correlations between stock and 10-year government bond returns. The VIX criterion refers to the percentile range of 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 mean daily returns for both stocks and bonds are zero, rather than the respective sample means for each 22-trading-day period. For column three, the standard error of the average correlation is in parentheses, calculated with bootstrap methods per Section 4.3. For comparison, the final column reports the average correlations for VDAX criterion rather than VIX. Panels A through C report on the U.S., Germany, and the U.K., respectively. The sample period is January 1992 through December 2002.

Panel A: U.S. 22-trading-day stock-bond return correlations

VIX Criterion	Proportion of Correlations < 0	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.	VDAX Criterion Average Corr.
Low Quintile	2.7%	0.475 (0.009)	0.504	0.341	0.636	0.425
Quintile 2	4.2%	0.432 (0.011)	0.441	0.275	0.647	0.428
Quintile 3	29.1%	0.224 (0.018)	0.376	-0.097	0.539	0.257
Quintile 4	52.9%	0.001 (0.018)	-0.030	-0.328	0.309	-0.003
Top Quintile	73.0%	-0.230 (0.017)	-0.265	-0.530	0.019	-0.205
Top Decile	85.5%	-0.361 (0.019)	-0.409	-0.660	-0.076	-0.354

Panel B: German 22-trading-day stock-bond return correlations

VIX Criterion	Proportion of Correlations < 0	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.	VDAX Criterion Average Corr.
Low Quintile	0.4%	0.492 (0.009)	0.540	0.297	0.677	0.520
Quintile 2	2.2%	0.499 (0.010)	0.525	0.360	0.675	0.455
Quintile 3	25.7%	0.279 (0.017)	0.376	-0.004	0.612	0.243
Quintile 4	47.7%	0.027 (0.015)	0.023	-0.267	0.299	0.027
Top Quintile	64.7%	-0.148 (0.014)	-0.173	-0.437	0.125	-0.096
Top Decile	73.8%	-0.248 (0.018)	-0.320	-0.502	0.011	-0.216

Panel C: U.K. 22-trading-day stock-bond return correlations

VIX Criterion	Proportion of Correlations < 0	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.	VDAX Criterion Average Corr.
Low Quintile	2.0%	0.539 (0.008)	0.556	0.400	0.694	0.493
Quintile 2	2.0%	0.503 (0.009)	0.522	0.350	0.675	0.498
Quintile 3	29.8%	0.220 (0.016)	0.316	-0.063	0.522	0.172
Quintile 4	58.4%	-0.025 (0.015)	-0.075	-0.308	0.253	0.035
Top Quintile	72.9%	-0.220 (0.016)	-0.287	-0.509	0.020	-0.179
Top Decile	87.3%	-0.372 (0.018)	-0.411	-0.617	-0.237	-0.360

Table 3: Stock implied volatility and subsequent cross-country stock correlations

This table reports on the relation between stock implied volatility and the subsequent 22-trading-day correlations between the stock indices of Germany, the U.K., and the U.S. The VIX criterion refers to the percentile range of the VIX level in period $t-1$. The subsequent 22-trading-day correlation refers to the correlation between the stock indices over days t through $t+21$, following the respective VIX_{t-1}. In this table, the correlations are calculated assuming that the mean daily return for each 22-trading-day period is zero. For column two, the standard error of the average correlation is in parentheses, calculated with bootstrap methods per Section 4.3. For comparison, the final column reports the average correlations for VDAX criterion rather than VIX. Panels A through C report on the German:U.K, German:U.S., and U.K.:U.S. cases, respectively. The sample period is January 1992 through December 2002 for the German:U.K. case and 7/16/92 through December 2000 for the German:U.S. and the U.K.:U.S. cases.

Panel A: German:U.K. 22-trading-day stock-stock return correlations

VIX Criterion	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.	VDAX Criterion Average Corr.
Low Quintile	0.430 (0.009)	0.480	0.261	0.601	0.467
Quintile 2	0.491 (0.008)	0.499	0.380	0.615	0.454
Quintile 3	0.578 (0.008)	0.603	0.444	0.722	0.583
Quintile 4	0.686 (0.007)	0.712	0.599	0.779	0.714
Top Quintile	0.763 (0.006)	0.805	0.692	0.863	0.729
Top Decile	0.800 (0.007)	0.824	0.762	0.870	0.791

Panel B: German:U.S. 22-trading-day stock-stock return correlations

VIX Criterion	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.	VDAX Criterion Average Corr.
Low Quintile	0.377 (0.009)	0.409	0.268	0.520	0.408
Quintile 2	0.431 (0.009)	0.428	0.293	0.577	0.428
Quintile 3	0.545 (0.008)	0.549	0.411	0.705	0.533
Quintile 4	0.546 (0.008)	0.550	0.425	0.660	0.550
Top Quintile	0.616 (0.009)	0.610	0.469	0.810	0.596
Top Decile	0.668 (0.013)	0.756	0.483	0.846	0.658

Panel C: U.K.: U.S. 22-trading-day stock-stock return correlations

VIX Criterion	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.	VDAX Criterion Average Corr.
Low Quintile	0.423 (0.007)	0.439	0.327	0.550	0.400
Quintile 2	0.432 (0.009)	0.430	0.310	0.555	0.471
Quintile 3	0.536 (0.010)	0.564	0.408	0.687	0.517
Quintile 4	0.526 (0.008)	0.521	0.414	0.635	0.525
Top Quintile	0.573 (0.008)	0.553	0.439	0.763	0.578
Top Decile	0.638 (0.012)	0.702	0.459	0.813	0.635

Table 4: Stock implied volatility and the subsequent means and volatility of the daily returns

This table reports on the relation between the VIX and VDAX level and the subsequent mean, volatility, and Sharpe ratio of daily excess returns for the stock market and 10-year government bonds (excess refers to the return above a 3-month risk-free return). For this table, the VIX (VDAX) criterion refers to the percentile range of the VIX (VDAX) level in period $t-1$. The subsequent means (μ) and standard deviations (σ) refer to the sample statistics for the subset of daily returns that follow the respective VIX_{t-1} (VDAX_{t-1}) percentile range. The return statistics are in daily percentage units. The sample period is January 1992 through December 2002.

VIX (VDAX)		Stock returns			Bond returns		
Criterion		U.S.	German	U.K.	U.S.	German	U.K.
Low Quintile VIX:	μ	0.050	0.045	0.077	0.035	0.022	0.021
	σ	0.503	0.703	0.645	0.383	0.329	0.490
Low Quintile VDAX:	μ	0.029	0.026	0.004	0.016	0.014	0.012
	σ	0.637	0.604	0.614	0.405	0.285	0.396
Quintile 2 VIX:	μ	0.031	0.004	-0.001	-0.008	0.004	-0.005
	σ	0.621	0.657	0.676	0.429	0.313	0.441
Quintile 2 VDAX:	μ	0.061	0.025	0.063	0.026	0.024	0.026
	σ	0.627	0.732	0.635	0.408	0.280	0.427
Quintile 3 VIX:	μ	-0.020	0.128	0.068	-0.008	0.022	0.024
	σ	0.876	0.884	0.755	0.419	0.313	0.408
Quintile 3 VDAX:	μ	-0.047	-0.059	-0.057	-0.010	-0.020	-0.003
	σ	0.885	0.900	0.794	0.417	0.364	0.480
Quintile 4 VIX:	μ	-0.015	0.029	-0.003	0.014	-0.011	0.009
	σ	1.156	1.231	0.942	0.402	0.325	0.385
Quintile 4 VDAX:	μ	0.024	0.053	0.054	-0.004	0.017	0.004
	σ	1.249	1.231	1.014	0.424	0.344	0.413
Top Quintile VIX:	μ	0.092	-0.135	-0.058	0.016	0.024	0.018
	σ	1.738	1.890	1.572	0.517	0.340	0.385
Top Quintile VDAX:	μ	0.072	0.025	0.019	0.019	0.025	0.029
	σ	1.620	1.897	1.538	0.500	0.340	0.395
Top Decile VIX:	μ	0.223	-0.116	-0.033	0.019	0.044	0.025
	σ	1.988	2.163	1.869	0.536	0.356	0.388
Top Decile VDAX:	μ	0.099	0.027	0.051	0.024	0.034	0.036
	σ	1.770	2.087	1.796	0.547	0.365	0.409

Table 5: Comovement variation and implied volatility in a GARCH model

This table reports estimated coefficients for the GARCH systems given by equations (2) and (3) for the stock-bond relations within country and by equations (6) and (7) for the stock-stock relations across countries (see Section 4.4). Panel A reports on the stock-bond return relation with the following conditional mean equation:

$$B^r_{x,t} = (\beta_0 + \beta_1 ln(IV_{t-1}))S^r_{x,t} + \epsilon_t,$$

where $B^r_{x,t}$ ($S^r_{x,t}$) is the bond-return (stock-return) residual from country x obtained from first estimating a 4-lag VAR model on the pair of returns, $\ln(IV_{t-1})$ is the natural log of the lagged implied volatility (either VIX or VDAX), and the β's are estimated coefficients. Panel B reports on the cross-country stock relations with the following conditional mean equation, where the y and x return series are identified in column one:

$$S^r_{y,t} = (\beta_0 + \beta_1 ln(IV_{t-1}))S^r_{x,t} + \epsilon_t,$$

where $S^r_{y,t}$ ($S^r_{x,t}$) is the stock-return residual from country x (country y) obtained from first estimating a 4-lag VAR on the pair of returns, and other terms are defined above. Column one in each panel identifies whether VIX or VDAX is used for the model in that row. The coefficient of interest is β_1. The GARCH system is estimated with a conditional normal density with T-statistics in parentheses, calculated with standard errors that are robust to departures from conditional normality per Bollerslev and Wooldridge (1992). The sample period is 1992 to 2002, except for the cross-country stock relations with the U.S where the sample period is July 16, 1992 through December 2002. For Panel B, we estimate variations of the model with VIX and VDAX separately and the table reports on the model variation with the highest likelihood function value. The final two columns for each model report the total relation between the two series implied by the estimated β_1 with the IV_{t-1} at its 5^{th} and 95^{th} percentile value.

Panel A: Stock-bond return comovements

Country (IV)	β_0	β_1	$(\beta_0 + \beta_1 ln(IV_{t-1})$ (IV=5^{th} pctl)	$(\beta_0 + \beta_1 ln(IV_{t-1})$ (IV=95^{th} pctl)
U.S. (VIX)	1.389 (14.52)	-0.422 (-14.32)	0.355	-0.116
Germany (VDAX)	0.717 (12.80)	-0.212 (-12.44)	0.198	-0.071
U.K. (VIX)	1.326 (14.03)	-0.395 (-14.02)	0.361	-0.080

Panel B: Cross-country stock return comovements

Country y:x (IV)	β_0	β_1	$(\beta_0 + \beta_1 ln(IV_{t-1})$ (IV=5^{th} pctl)	$(\beta_0 + \beta_1 ln(IV_{t-1})$ (IV=95^{th} pctl)
Germany:U.K. (VIX)	-0.989 (-5.62)	0.560 (10.09)	0.381	1.007
U.K.:Germany (VIX)	-0.285 (-2.32)	0.263 (6.81)	0.360	0.655
Germany:U.S. (VDAX)	-0.705 (-3.18)	0.474 (6.60)	0.476	1.067
U.S.:Germany (VIX)	-0.382 (-4.02)	0.243 (7.78)	0.214	0.489
U.K.:U.S (VDAX)	-0.184 (-1.16)	0.244 (4.78)	0.422	0.726
U.S.:U.K. (VIX)	-0.515 (-3.88)	0.318 (7.22)	0.267	0.627

Table 6: Daily changes in stock implied volatility and variation in return correlations

This table reports how daily return correlations vary with the day's change in stock implied volatility. Panel A reports on stock-bond correlations within country and Panel B reports on cross-country stock correlations. For this table, the ΔVIX (ΔVDAX) criterion means the subset of daily return observations where the day's change in VIX or VDAX falls within the stated percentile range. For every subset of returns, the subset correlation and standard deviations are calculated with the mean return for each series set to its unconditional mean return over the entire sample. The low (top) quintile refers to the observations with the largest daily decreases (increases) in implied volatility. Return statistics are in daily percentage units. For the correlations in column-two, standard errors are reported in parentheses, calculated with bootstrap methods per Section 5.3. The sample period is January 1992 through December 2002; except for the U.S.:German and U.S.:U.K cases in Panel B, where the sample period is 7/16/92 through 2000 due to intraday data availability.

Panel A: Stock-bond daily return correlations

ΔVIX / ΔVDAX Criterion	Correlation	Average Bond Return	Std. Dev. Bond Return	Average Stock Return	Std. Dev. Stock Return
		U.S. stock and bond returns			
Low Quintile ΔVIX	-0.110 (0.055)	0.034	0.459	1.120	1.484
Quintile 2 ΔVIX	0.206 (0.055)	0.074	0.396	0.335	0.643
Quintile 3 ΔVIX	0.184 (0.050)	0.018	0.372	0.076	0.524
Quintile 4 ΔVIX	0.268 (0.042)	-0.004	0.401	-0.169	0.614
Top Quintile ΔVIX	-0.109 (0.051)	0.016	0.514	-1.141	1.584
Top Decile ΔVIX	-0.200 (0.065)	0.066	0.571	-1.652	2.028
		German stock and bond returns			
Low Quintile ΔVDAX	0.039 (0.046)	0.051	0.327	0.996	1.464
Quintile 2 ΔVDAX	0.305 (0.055)	0.082	0.291	0.349	0.784
Quintile 3 ΔVDAX	0.104 (0.076)	0.038	0.294	0.058	0.846
Quintile 4 ΔVDAX	0.185 (0.044)	-0.008	0.293	-0.194	0.730
Top Quintile ΔVDAX	0.036 (0.046)	-0.007	0.396	-1.083	1.687
Top Decile ΔVDAX	-0.035 (0.064)	0.013	0.430	-1.570	2.075
		U.K. stock and bond returns			
Low Quintile ΔVDAX	-0.064 (0.051)	0.033	0.397	0.737	1.195
Quintile 2 ΔVDAX	0.425 (0.074)	0.105	0.442	0.247	0.708
Quintile 3 ΔVDAX	0.162 (0.071)	0.047	0.398	0.055	0.744
Quintile 4 ΔVDAX	0.310 (0.043)	-0.018	0.404	-0.124	0.688
Top Quintile ΔVDAX	0.022 (0.048)	0.019	0.462	-0.726	1.373
Top Decile ΔVDAX	-0.116 (0.062)	0.053	0.459	-1.069	1.664

Table 6: (continued)

Panel B: Cross-country stock-to-stock daily return correlations

ΔVIX / ΔVDAX Criterion	Correlation	Average Stock Return	Std. Dev. Stock Return	Average Stock Return	Std. Dev. Stock Return
	German:U.K.	German returns		U.K. returns	
Low Quintile ΔVDAX	0.793 (0.019)	1.005	1.470	0.745	1.205
Quintile 2 ΔVDAX	0.420 (0.041)	0.355	0.782	0.246	0.703
Quintile 3 ΔVDAX	0.537 (0.046)	0.055	0.861	0.067	0.744
Quintile 4 ΔVDAX	0.446 (0.036)	-0.202	0.731	-0.136	0.689
Top Quintile ΔVDAX	0.784 (0.023)	-1.071	1.686	-0.735	1.382
Top Decile ΔVDAX	0.847 (0.021)	-1.567	2.083	-1.100	1.67
	U.S.:German	U.S. returns		German returns	
Low Quintile ΔVIX	0.661 (0.036)	0.875	1.429	1.170	1.904
Quintile 2 ΔVIX	0.344 (0.050)	0.328	0.771	0.339	1.210
Quintile 3 ΔVIX	0.261 (0.046)	0.114	0.673	0.001	1.015
Quintile 4 ΔVIX	0.390 (0.046)	-0.123	0.692	-0.079	1.145
Top Quintile ΔVIX	0.680 (0.030)	-1.010	1.586	-1.263	2.241
Top Decile ΔVIX	0.740 (0.035)	-1.454	1.957	-1.883	2.760
	U.S.:U.K.	U.S. returns		U.K. returns	
Low Quintile ΔVIX	0.626 (0.039)	0.869	1.420	0.889	1.466
Quintile 2 ΔVIX	0.283 (0.059)	0.324	0.760	0.266	0.884
Quintile 3 ΔVIX	0.280 (0.045)	0.110	0.678	0.063	0.791
Quintile 4 ΔVIX	0.320 (0.049)	-0.107	0.686	-0.090	0.914
Top Quintile ΔVIX	0.669 (0.029)	-1.015	1.602	-0.996	1.679
Top Decile ΔVIX	0.730 (0.030)	-1.456	1.988	-1.455	2.043

Table 7: A two-state regime-shifting model of changing stock-bond return relations

This table reports the results for the following regime-switching model of stock-bond return relations:

$$B^r_{x,t} = \alpha_s S^r_{x,t} + \epsilon_t,$$

where $B^r_{x,t}$ ($S^r_{x,t}$) is the bond return-residual (stock return-residual) for country x with the superscript r indicating the residual retained after estimating the 4-lag VAR system in Section 4.4; α_s is an estimated regime-dependent coefficient, either α_0 for regime-zero or α_1 for regime-one where the subscript s indicates the regime; and ϵ_t is the residual. The s regime variable is modeled with time-varying transition probabilities (Pr) as follows:

$$Pr(s_t = j | s_{t-1} = j) = \frac{e^{c_j + d_j \ln(IV_{t-1})}}{1 + e^{c_j + d_j \ln(IV_{t-1})}},$$

where j = 0 (regime-zero) or j = 1 (regime-one), $\ln(IV_{t-1})$ is the log of the lagged implied volatility (either VIX or VDAX), and the c_js, and d_js are estimated coefficients. The sample period is 1992 to 2002. Panel A reports the coefficient estimates, with standard errors in parentheses, and Panel B reports the expected durations of each regime for different values of VIX/VDAX.

Panel A: Parameter estimates

Coeff.	U.S. (VIX)	German (VDAX)	U.K. (VIX)
α_0	0.305 (0.022)	0.276 (0.029)	0.439 (0.019)
α_1	-0.110 (0.011)	-0.032 (0.007)	-0.069 (0.009)
c_0	23.80 (10.31)	21.67 (7.32)	17.72 (4.50)
d_0	-6.68 (3.27)	-6.23 (2.27)	-4.89 (1.46)
c_1	-0.021 (5.04)	0.588 (3.39)	-2.11 (2.80)
d_1	1.05 (1.63)	0.956 (1.05)	1.91 (0.92)

Panel B: Expected durations for each regime and VIX/VDAX

Regime, VIX/VDAX	U.S. (VIX)	German (VDAX)	U.K. (VIX)
Regime-zero, 15%	305.9	123.6	89.0
Regime-zero, 25%	11.1	6.1	8.2
Regime-one, 15%	17.7	25.0	22.4
Regime-one, 25%	29.5	40.1	57.7

Table 8: A two-state regime-shifting model of changing cross-country stock return relations

This table reports the results for the following regime-switching model of cross-country stock return relations:

$$S^r_{y,t} = \beta_s S^r_{x,t} + \epsilon_t,$$

where $S^r_{y,t}$ is the stock return-residual for country y and $S^r_{x,t}$ is the stock return-residual from country x with the superscript r indicating the residual retained after estimating the 4-lag VAR system in Section 4.4; β_s is an estimated regime-dependent coefficient, either β_0 for regime-zero or β_1 for regime-one where the subscript s indicates the regime variable. The s regime variable is modeled with time-varying transition probabilities (Pr) as follows:

$$Pr(s_t = j | s_{t-1} = j) = \frac{e^{c_j + d_j \ln(IV_{t-1})}}{1 + e^{c_j + d_j \ln(IV_{t-1})}},$$

where j = 0 (regime-zero) or j = 1 (regime-one), $\ln(IV_{t-1})$ is the log of the lagged implied volatility (either VIX or VDAX), and the c_js, and d_js are estimated coefficients. The sample period is January 1992 to December 2002 for the German:U.K. case, and July 16, 1992 to December 2002 for the U.S.:German and U.S.:U.K. cases. Panel A reports the coefficient estimates, with standard errors in parentheses, and Panel B reports the expected durations of each regime for different values of VIX/VDAX.

Panel A: Parameter estimates

x:	U.K.:	German:	German:	U.S.:	U.K.	U.S.
y:	German	U.K.	U.S.	German	U.S.	U.K.
	(VIX)	(VIX)	(VIX)	(VDAX)	(VIX)	(VDAX)
β_0	0.36 (0.044)	0.44 (0.020)	0.23 (0.022)	0.67 (0.029)	0.29 (0.022)	0.49 (0.025)
β_1	1.10 (0.029)	0.86 (0.039)	0.74 (0.037)	1.96 (0.090)	1.06 (0.038)	1.39 (0.077)
c_0	17.67 (3.82)	26.72 (9.34)	8.46 (2.58)	18.61 (2.63)	9.13 (1.71)	15.36 (2.88)
d_0	-5.51 (1.21)	-7.66 (2.72)	-2.15 (0.73)	-4.96 (0.736)	-2.42 (0.51)	-3.96 (0.81)
c_1	-3.48 (2.71)	0.322 (9.10)	-3.74 (5.65)	-16.17 (10.79)	-9.26 (5.94)	-7.911 (5.20)
d_1	1.44 (0.80)	0.02 (2.49)	1.25 (1.54)	4.15 (2.79)	2.69 (1.62)	1.97 (1.39)

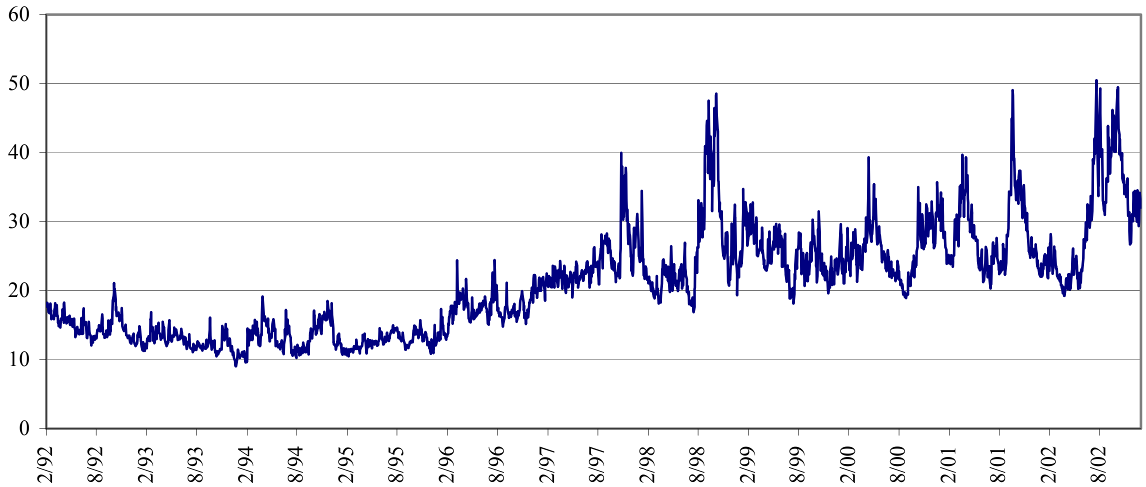
Panel B: Expected durations for each regime and VIX/VDAX

	x:	U.K.:	German:	German:	U.S.:	U.K.:	U.S.:
	y:	German	U.K.	U.S.	German	U.S.	U.K.
Regime, VIX/VDAX		(VIX)	(VIX)	(VIX)	(VDAX)	(VIX)	(VDAX)
Regime-zero, 15%		16.5	395.0	15.1	178.3	14.2	104.1
Regime-zero, 25%		1.9	8.9	5.7	15.1	4.8	14.6
Regime-one, 15%		2.5	2.4	1.7	1.0	1.1	1.1
Regime-one, 25%		4.2	2.5	2.3	1.1	1.6	1.2

Figure 1: The implied volatility from U.S. and German equity index options

This figure displays the time-series of implied volatility from equity index options from the U.S. and Germany. Panel A exhibits the time-series of the CBOE's Volatility Index (VIX). Panel B exhibits the time-series of the German VDAX. The sample period is 1992 to 2002 with the month and year denoted on the horizontal axis for each panel. January 1992 is omitted from the figure to match the sample periods in Figures 4 and 5.

Panel A: U.S. VIX

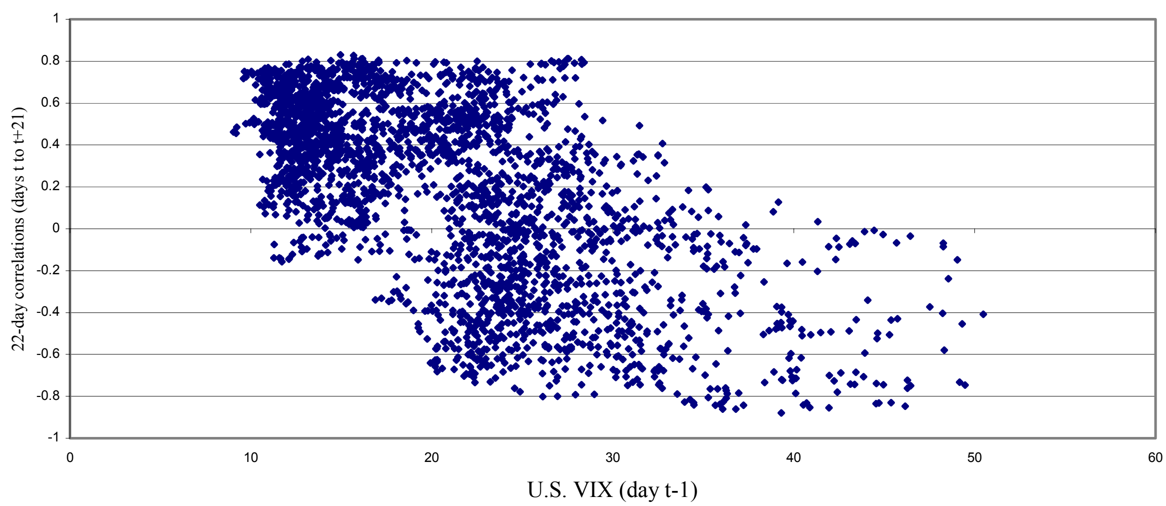


Panel B: German VDAX

Figure 2: Stock implied volatility and subsequent return correlations

This figure displays how return correlations vary with the lagged VIX/VDAX value. Here, 22-trading-day rolling correlations (calculated with returns from days *t* to *t+21*) are plotted against the VIX/VDAX value from the end-of-day *t-1*. The correlations are calculated assuming that the daily mean return is zero for each 22-trading-day period. Panel A displays how the U.S. stock-bond correlations vary with lagged VIX. Panel B displays how the U.S.:German cross-country stock correlations vary with the lagged VIX. Panel C displays how the German stock-bond correlations vary with lagged VDAX. Finally, Panel D displays how the German:U.K. cross-country stock correlations vary with the lagged VDAX. The sample period is 1992 to 2002.

Panel A: U.S. stock-bond correlation with VIX



Panel B: U.S.:German cross-country stock correlations and the lagged U.S. VIX

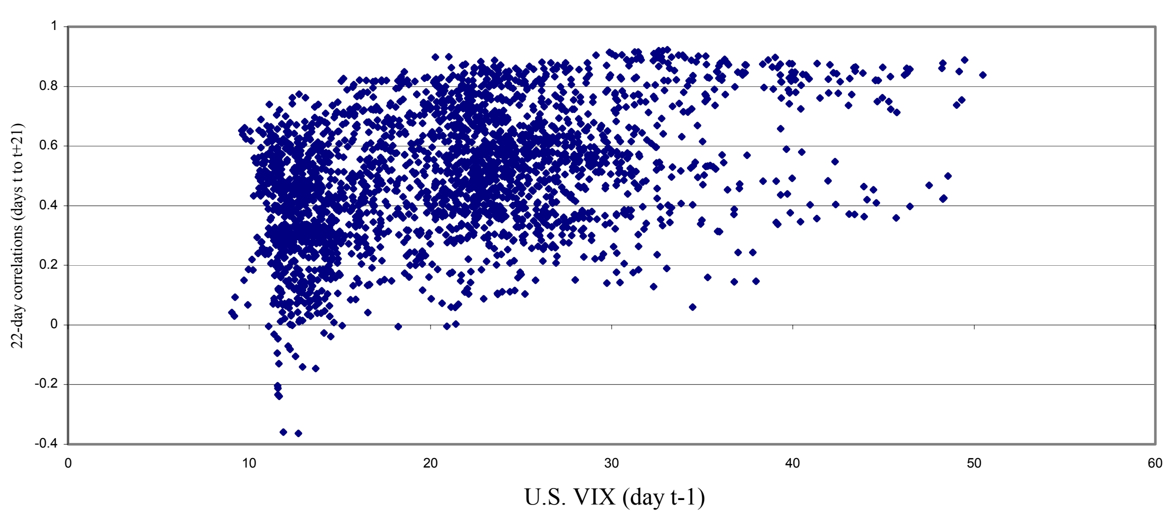
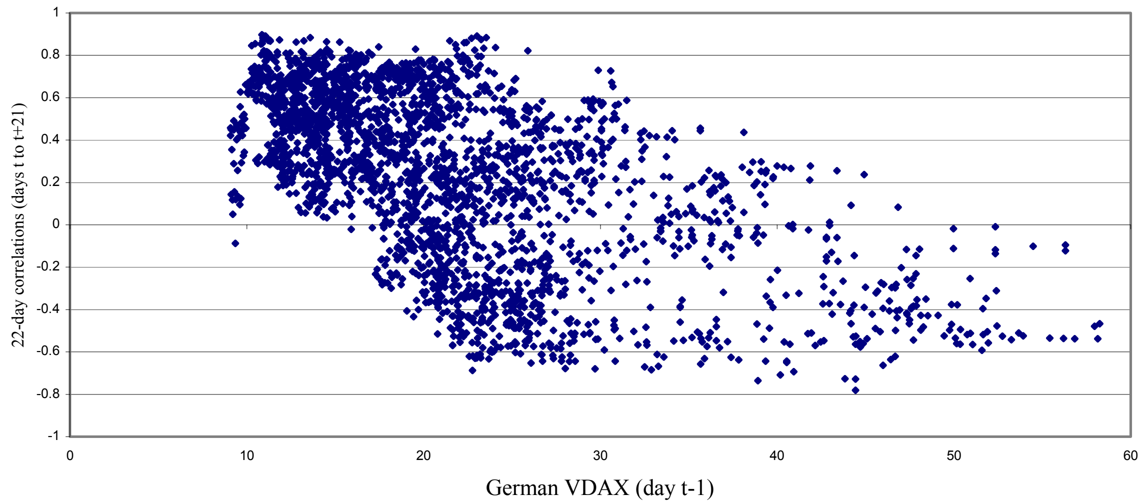


Figure 2: (continued)

Panel C: German stock-bond correlations and lagged VDAX



Panel D: German:U.K. cross-country stock correlations and lagged VDAX

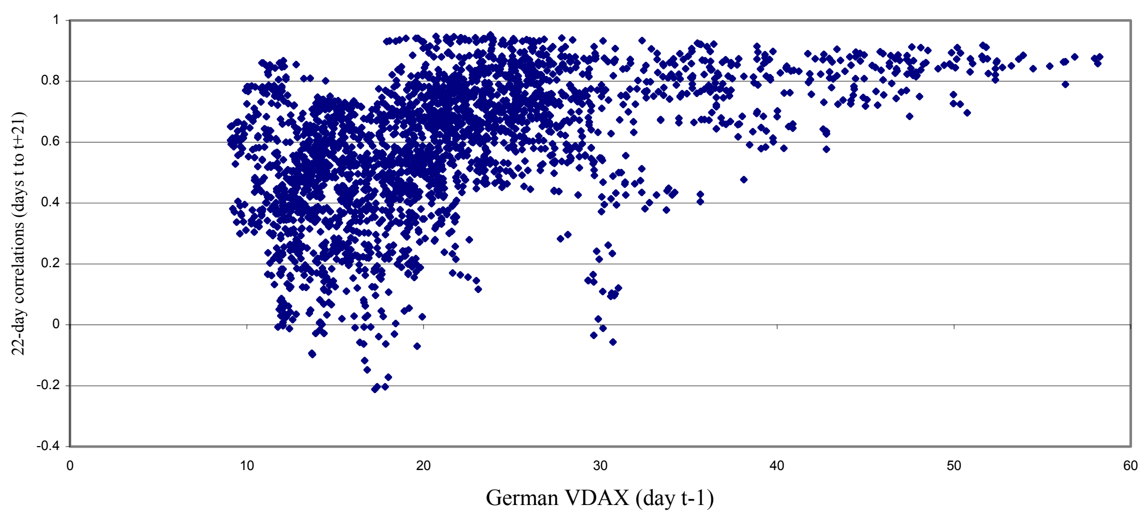
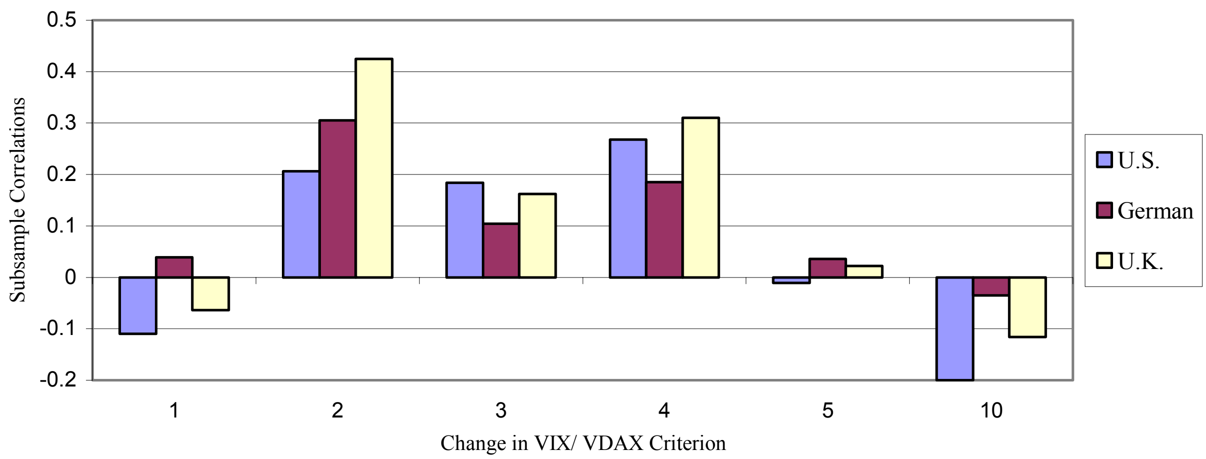


Figure 3: Correlation variations with the day's change in stock implied volatility

This figure displays how the correlations in daily returns vary with the day's change in VIX/VDAX. Panel A presents the variation in daily stock-bond correlations and Panel B presents the variation in daily cross-country correlations between stock markets. For both panels, 1 through 5 on the horizontal axis denote quintile-subsets of return observations, sorted by the day's VIX/VDAX change. The quintile-one days have the largest decreases in VIX/VDAX and the quintile-five days have the largest increases in VIX/VDAX. The 10 on the horizontal axis denotes the days with the largest decile of VIX/VDAX increases. As in Table 6, for each subset of returns, the correlation is calculated with the mean return for each series set to its unconditional mean return over the entire sample. The VIX-change criterion is used for the U.S. stock-bond case and the U.S.:German stock-stock case. The other return pairs use the VDAX-change criterion.

Panel A: Stock-bond correlations and daily VIX/VDAX changes



Panel B: Cross-country stock correlations and daily VIX/VDAX changes

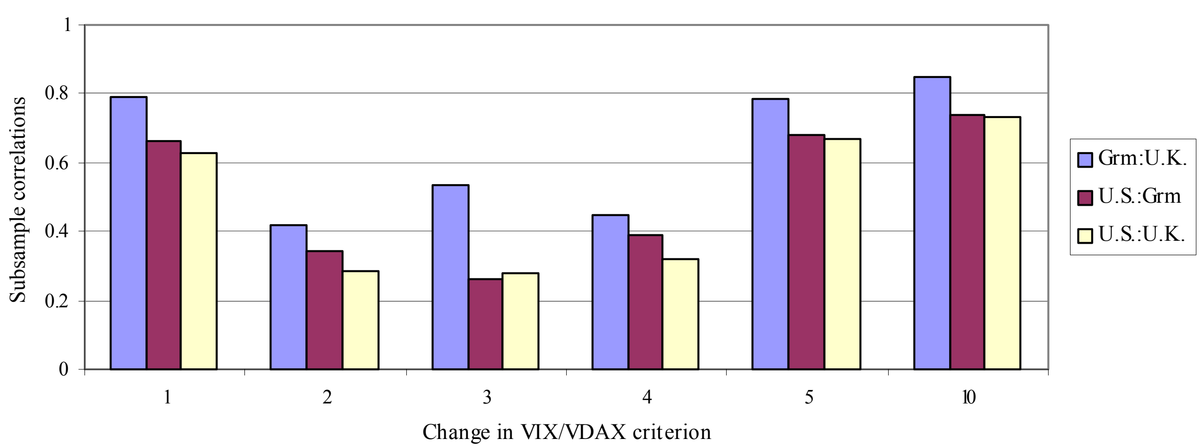
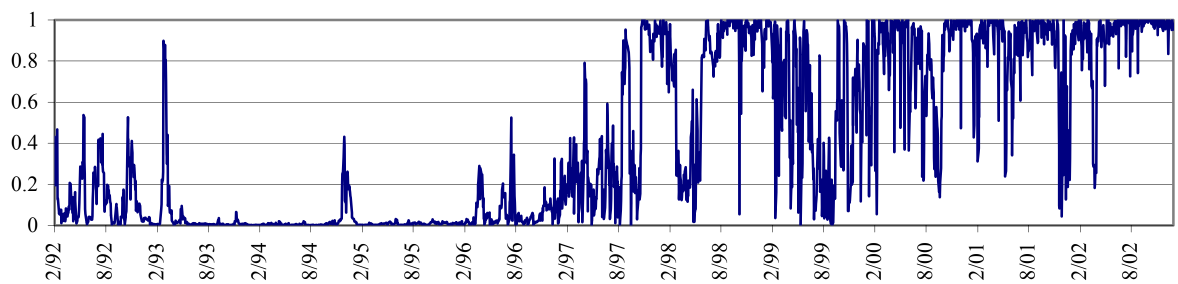


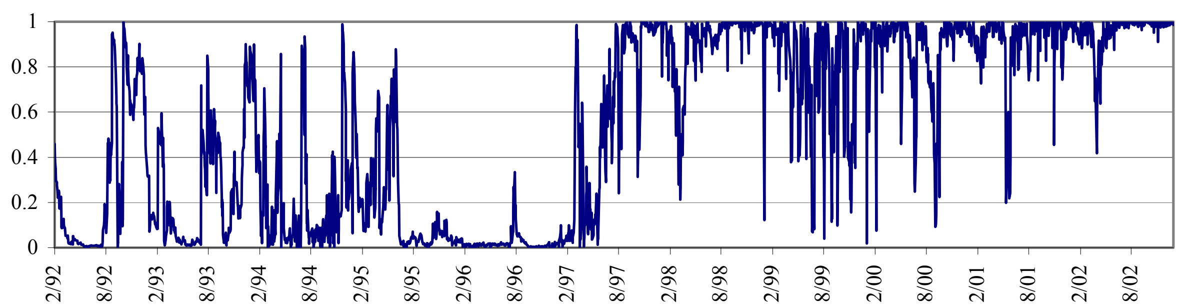
Figure 4: Regime-shifting results for the stock-bond return relations

This figure displays filtered probabilities of being in regime-one for the stock-bond regime-shifting model, as detailed in Section 6 and Table 7. The transition probabilities are dependent upon either VIX or VDAX, as noted in each panel. Panels A through C exhibit the results for the U.S., Germany, and the U.K., respectively. The sample period is 1992 to 2002 with the month and year denoted on the horizontal axis for each panel. January 1992 is omitted from the figure to omit early filtered probabilities that are more sensitive to starting value assumptions.

Panel A: The U.S. stock-bond return relation and VIX



Panel B: The German stock-bond return relation and VDAX



Panel C: The U.K. stock-bond return relation and VIX

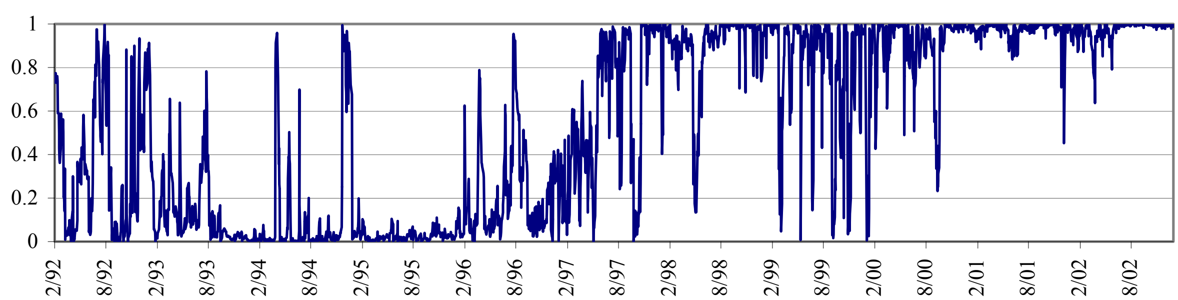
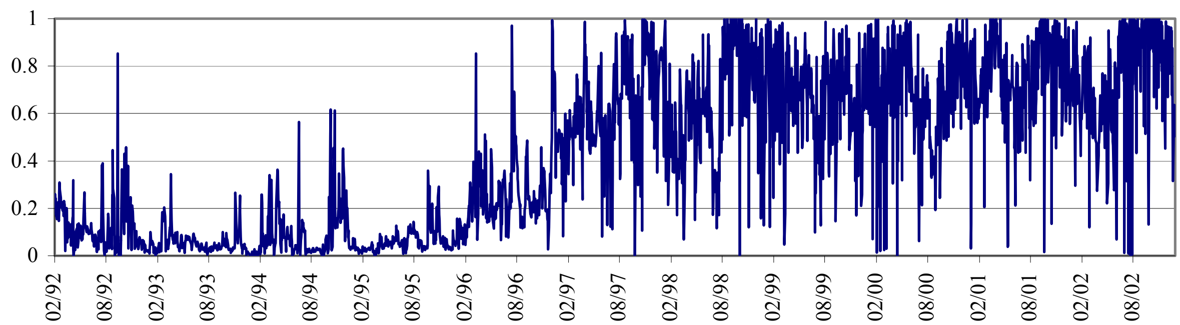


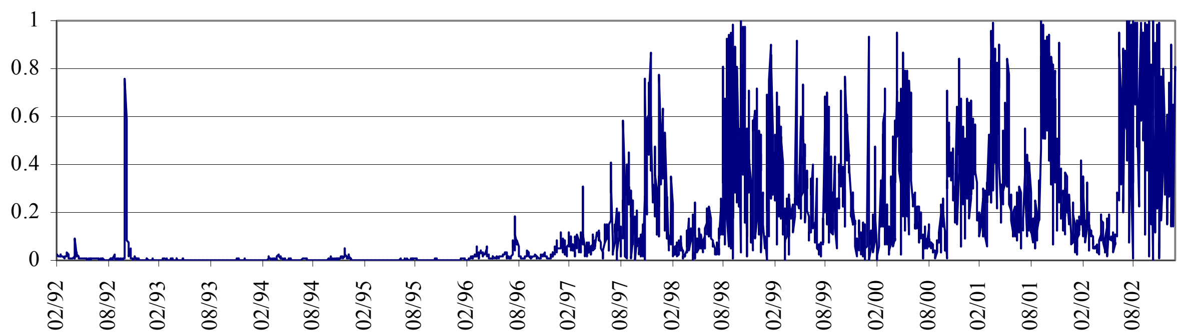
Figure 5: Regime-shifting results for the cross-country stock return relations

This figure displays the filtered probabilities of being in regime-one for the cross-country stock return regime-shifting model in Section 6 and Table 8. The transition probabilities are dependent upon either VIX or VDAX, as noted in each panel. Panels A through F display all possible pairwise combinations for the stock returns of Germany, the U.S., and the U.K. The sample period is 1992 to 2002 with the month and year on the horizontal axis. The first month for each estimation is omitted because the first few days may be sensitive to starting value assumptions.

Panel A: German stock returns as a function of U.K. stock returns with VIX



Panel B: U.K. stock returns as a function of German stock returns with VIX



Panel C: U.S. stock returns as a function of German stock returns with VIX

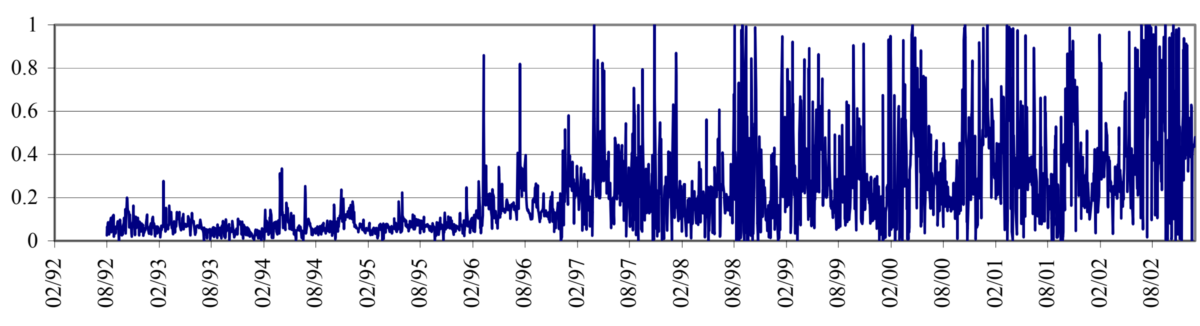
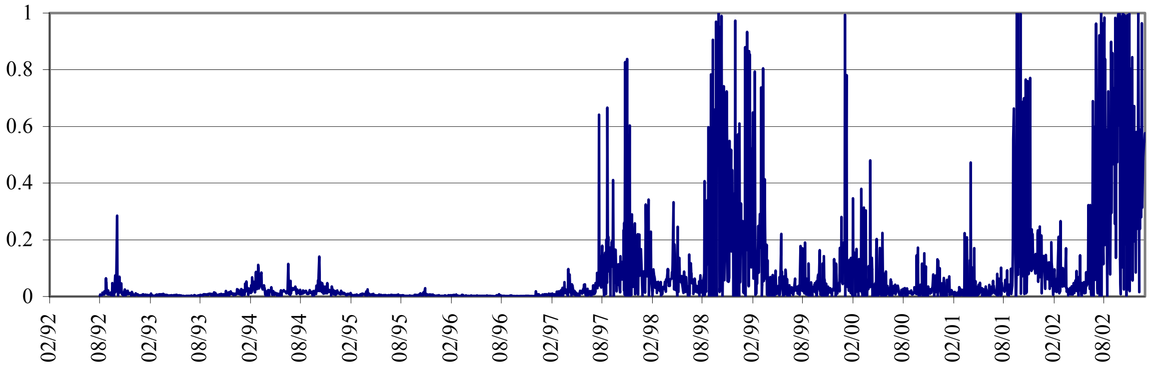
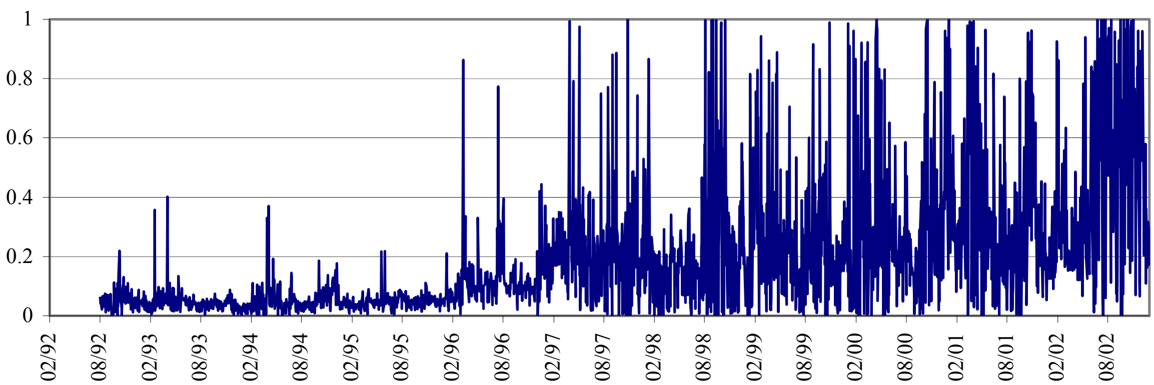


Figure 5: (continued)

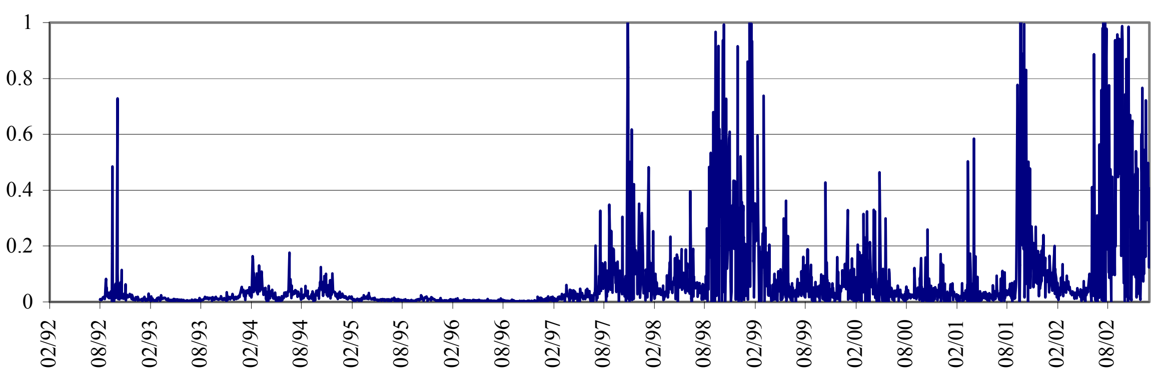
Panel D: German stock returns as a function of U.S. stock returns with VDAX



Panel E: U.S. stock returns as a function of U.K. stock returns with VIX



Panel F: U.K. stock returns as a function of U.S. stock returns wiith VDAX



Appendix A: Stock-Bond Subperiod Results

Table A1: Stock implied volatility and subsequent stock-bond return correlations: 7/97 to 12/02

This table reports on the relation between the stock implied volatility and the subsequent 22-trading-day correlation between stock and 10-year government bond returns within country. The VIX criterion refers to the percentile range of 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 mean daily returns for both stocks and bonds are zero. For column three, the standard error of the average correlation is in parentheses, calculated with bootstrap methods per Section 4.3. For comparison, the final column reports the average correlations for VDAX criterion rather than VIX. The sample period is July 1997 through December 2002. Panels A through C report on the U.S., Germany, and the U.K., respectively.

Panel A: U.S. 22-trading-day stock-bond return correlations

VIX Criterion	Proportion of Correlations < 0	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.	VDAX Criterion Average Corr.
Low Quintile	51.2%	-0.018 (0.025)	-0.019	-0.0392	0.370	0.003
Quintile 2	54.4%	-0.031 (0.023)	-0.055	-0.337	0.242	-0.120
Quintile 3	58.8%	-0.050 (0.023)	-0.079	-0.341	0.199	-0.028
Quintile 4	59.9%	-0.101 (0.024)	-0.095	-0.414	0.174	-0.055
Top Quintile	85.7%	-0.361 (0.020)	-0.409	-0.664	-0.077	-0.357
Top Decile	95.6%	-0.451 (0.025)	-0.473	-0.724	-0.161	-0.498

Panel B: German 22-trading-day stock-bond return correlations

VIX Criterion	Proportion of Correlations < 0	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.	VDAX Criterion Average Corr.
Low Quintile	46.7%	0.046 (0.021)	0.022	-0.253	0.341	0.015
Quintile 2	52.7%	-0.015 (0.020)	-0.045	-0.309	0.253	-0.093
Quintile 3	48.7%	-0.005 (0.019)	0.011	-0.282	0.252	0.001
Quintile 4	55.3%	-0.048 (0.020)	-0.059	-0.303	0.228	0.020
Top Quintile	74.0%	-0.248 (0.018)	-0.312	-0.499	0.010	-0.215
Top Decile	85.4%	-0.348 (0.022)	-0.422	-0.527	-0.239	-0.352

Panel C: U.K. 22-trading-day stock-bond return correlations

VIX Criterion	Proportion of Correlations < 0	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.	VDAX Criterion Average Corr.
Low Quintile	54.0%	-0.016 (0.018)	-0.019	-0.281	0.232	-0.094
Quintile 2	61.2%	-0.045 (0.021)	-0.102	-0.304	0.233	-0.133
Quintile 3	63.0%	-0.057 (0.020)	-0.100	-0.334	0.188	0.030
Quintile 4	58.6%	-0.072 (0.023)	-0.104	-0.343	0.191	-0.004
Top Quintile	87.3%	-0.372 (0.018)	-0.411	-0.618	-0.236	-0.360
Top Decile	96.4%	-0.466 (0.019)	-0.501	-0.641	-0.330	-0.483

Appendix B: Cross-country Stock Subperiod Results

Table B1: Stock implied volatility and subsequent cross-country stock correlations: 7/97 - 12/02

This table reports on the relation between stock implied volatlity and the subsequent 22-trading-day correlation between the stock indices of Germany, the U.K., and the U.S. The VIX criterion refers to the percentile range of the VIX level in period $t-1$. The subsequent 22-trading-day correlation refers to the correlation between the stock indices over days t through $t+21$, following the respective VIX_{t-1}. In this table, the correlations are calculated assuming that the mean daily returns for the stock returns are zero. For column two, the standard error of the average correlation is in parentheses, calculated with bootstrap methods per Section 4.3. For comparison, the final column reports the average correlations for VDAX criterion rather than VIX. The sample period is July 1997 through December 2002. Panels A through C report on the German:U.K, German:U.S., and U.S.:U.K. cases, respectively.

Panel A: German:U.K. 22-trading-day stock-stock return correlations

VIX Criterion	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.	VDAX Criterion Average Corr.
Low Quintile	0.676 (0.007)	0.680	0.578	0.773	0.662
Quintile 2	0.695 (0.008)	0.713	0.622	0.771	0.728
Quintile 3	0.694 (0.010)	0.725	0.618	0.806	0.743
Quintile 4	0.725 (0.007)	0.751	0.656	0.848	0.667
Top Quintile	0.801 (0.007)	0.824	0.762	0.871	0.791
Top Decile	0.831 (0.005)	0.846	0.805	0.874	0.821

Panel B: German:U.S. 22-trading-day stock-stock return correlations

VIX Criterion	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.	VDAX Criterion Average Corr.
Low Quintile	0.529 (0.012)	0.543	0.420	0.703	0.558
Quintile 2	0.548 (0.010)	0.532	0.433	0.678	0.568
Quintile 3	0.540 (0.011)	0.557	0.409	0.641	0.528
Quintile 4	0.563 (0.010)	0.564	0.446	0.675	0.533
Top Quintile	0.663 (0.013)	0.749	0.484	0.844	0.661
Top Decile	0.687 (0.018)	0.790	0.483	0.847	0.698

Panel C: U.S.:U.K. 22-trading-day stock-stock return correlations

VIX Criterion	Average Corr.	Median Corr.	25^{th} Pctl Corr.	75^{th} Pctl Corr.	VDAX Criterion Average Corr.
Low Quintile	0.516 (0.014)	0.537	0.403	0.687	0.520
Quintile 2	0.539 (0.011)	0.546	0.419	0.652	0.534
Quintile 3	0.517 (0.011)	0.512	0.408	0.614	0.507
Quintile 4	0.510 (0.009)	0.511	0.411	0.627	0.519
Top Quintile	0.636 (0.012)	0.685	0.458	0.810	0.638
Top Decile	0.681 (0.016)	0.785	0.471	0.821	0.680

Appendix C: Heteroskedasticity Discussion

In this appendix, we consider our findings from the perspective of the numerical example on pages 2230-2231 in Forbes and Rigobon (2002). Their example assumes the economic relation between two return series is constant, which means (in their context) that $E(r_{y,t}|r_{x,t})$ is a fixed proportion of the given $r_{x,t}$. When market x has a shock with accompanying higher return volatility, then the measured correlation between the two series should increase.

First, consider the following for the U.S. stock-bond relation. Since VIX measures the stock's expected volatility, we initially evaluate the stock market as the shocked market. Using the observed average 22-trading-day correlation of 0.180 (see Table 1, Panel C) and the unconditional volatility of the stock and bond returns (see Table 1, Panel A), we can calculate an implied regression beta of 0.073 (with the stock return as the explanatory variable and the bond return as the dependent variable, $\beta = \rho \frac{\sigma_{bond}}{\sigma_{stock}}$). Then, we calculate different implied return correlations where $E(r_{B,t}|r_{S,t})$ is a fixed proportion of the period's stock return and the volatilities of the stock and bond returns change to the values depicted in Table 4 for the low (high) VIX values. For the low VIX quintile, the implied correlation is 0.096 (as compared to an observed average correlation of 0.475 in Table 2). For the upper VIX decile, the implied correlation is 0.245 (as compared to an observed average correlation of -0.361 in Table 2). Thus, the observed variation in correlations is in the *opposite* direction to that predicted by this Forbes-Rigobon perspective.

Next, we also consider the opposite perspective where the bond return is the explanatory variable and the stock return is the dependent variable. This case assumes that the heteroskedasticity in the stock market is primarily stock-specific volatility, rather than volatility common to both assets. Using the average 22-trading-day correlation of 0.180 and the unconditional return volatilities, we calculate an implied regression beta of 0.447 (with the bond return as the explanatory variable and the stock return as the dependent variable). Then, we calculate different implied correlations where $E(r_{S,t}|r_{B,t})$ is a fixed proportion of the period's bond return and for the volatility for the return observations following the low (high) VIX values in Table 4. In this case, the implied correlation is 0.340 for the low VIX quintile and 0.133 for the high VIX quintile. While these variations in correlations are now in the same direction as that observed in the data, the implied variations are still much smaller than the variations in correlations reported in Table 2.

Next, we evaluate the cross-country stock correlations from the perspective of the Forbes-Rigobon example. For example, consider the German:U.K. stock-stock relation. We use VDAX variation and evaluate the German stock return as the shocked market. Using the average correlation of 0.590 and the unconditional volatility of the stock returns in Table 1, we calculate an implied regression beta of 0.499. Then, we calculate different implied correlations where $E(r_{UK,t}|r_{GM,t})$ is a fixed proportion of the German stock return and for the volatility of the stock returns following the low (high) VDAX groupings per Table 4. For this beta and the observed return volatilities in the low VDAX quintile, the implied correlation is 0.490 (as compared to an observed average correlation of 0.476). For this beta and the observed return volatilities for the upper VDAX decile, the implied correlation is 0.580 (as compared to an observed average correlation of 0.820). Thus, while the observed variation in correlations is in the same direction as that predicted by the heteroskedasticity perspective in Forbes-Rigobon, the difference in the two observed correlations is much greater.

We also perform this exercise for the other cases and find similar results. Thus, under the perspective of the Forbes-Rigobon example, the observed heteroskedasticity is unable to fully explain the observed variation in correlations.

Appendix D: Additional Analysis

We also examine seven other European countries: Belgium, Denmark, France, Italy, the Netherlands, Spain, and Switzerland. For these countries, we find that the negative relation between the future correlation of stock and bond returns and the value of VIX/VDAX is also readily apparent. For these seven countries, the average 22-trading-day correlation is 0.373 (0.377), conditional on the lagged VIX (VDAX) being in the lowest quartile of its distribution. In contrast, the average stock-bond correlation is -0.174 (-0.038), conditional on the lagged VIX (VDAX) being in the top decile of its distribution. The sign reversal and the magnitude of the difference in the correlations, 0.547 for VIX and 0.415 for VDAX, compare closely with the results for Germany and the U.K.

Results for these other countries also confirms the positive relation between cross-country stock correlations and lagged implied volatility. We examine the 22-trading-day correlations of German stock returns with the stock returns from each of these seven countries, conditional on the lagged VDAX. When the value of VDAX is in its lowest quartile, the average subsequent cross-country stock correlation is 0.478. The average correlation is 0.723 when the lagged VDAX is in its top decile. Since the inflation behavior over our sample period varies somewhat across countries and the correlation patterns are consistent across the different countries, these findings further suggest that inflation does not have a material role in understanding our findings.

We also analyze the magnitude of the correlation variations in Tables 2 and 3 using the H-statistic proposed by Ang and Chen (2002) in their study of asymmetric stock correlations during market declines. The H-statistic is a weighted average of the squared differences between correlations predicted by a model (or assumed distribution) and correlations observed in the data. In our sample, the H-statistics are sizable and further suggest substantial time-variation in comovements.

First, consider the stock-bond correlations as a function of lagged IV. The unconditional stock-bond correlation in our sample is about zero (0.004 for the U.S., 0.121 for the U.K., and 0.094 for Germany). This is convenient because under the assumption that the true correlation is zero, the observed correlation should not vary with heteroskedasticity across the two return series. We estimate H-statistics by equally-weighting the squared difference between the average correlation for each IV quintile and the overall average correlation (see Tables 1 and 2). The estimated H-statistics are sizable at 0.266, 0.294, and 0.256, for the U.S., U.K., and German, respectively.

On the other hand, the cross-country stock correlations are substantially positive over the entire sample. Thus, from the perspective in Forbes and Rigobon, times with a volatility spike in a shocked market should also be associated with differing cross-country correlations. To mitigate this concern, we report an H-statistic for the U.K.:German stock comovements as a function of the lagged VIX, because the volatility of each market largely moves together with movement in VIX. Here, note that the return standard deviation of both the German and U.K. stock market each increases by roughly 2.5 times when comparing the low-quintile VIX sample to the high-quintile VIX sample (see Table 4). Thus, the variances move similarly with VIX and neither market is obviously a shocked market relative to the other market. Accordingly, we compute an H-statistic for the U.K.:German stock correlations, using the average 22-trading-day correlation for each VIX-quintile from Table 3 as the observed value and the average 22-trading-day correlation over the entire sample as the expected value. The computed H-statistic is sizable at 0.122, which reinforces the notion of stronger stock comovements following higher VIX values.