Commonality in the Time-variation of Stock-Stock and Stock-Bond Return Comovements¹

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Abstract

We jointly investigate time-varying comovements between stock returns across countries and between long-term government bond and stock returns within countries. Our focus is on how daily return comovements vary with stock uncertainty, as measured by the implied volatility (IV) from equity index options. We contribute with the following primary findings. Cross-country stock return comovements tend to be stronger (weaker) following high (low) IV days and on days with large (small) changes in IV. Consistent with earlier work, stock-bond return comovements tend to be substantially positive (negative) following low (high) IV days and on days with small (large) changes in IV. Further, a regime-switching analysis indicates a striking temporal commonality in the stock-stock and stock-bond comovement variations. Our findings bear on understanding the influence of time-varying uncertainty on price formation across asset classes, and on understanding the benefits of stock-bond and cross-country stock diversification.

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 (2005), Forbes and Rigobon (2002), Kodres and Pritsker (2002), Ang and Bekaert(2002), Ang and Chen (2002), Ribeiro and Veronesi (2002), and Corsetti, Pericoli, and Sbracia (2005)) and stock-bond comovement (see, e.g., Fleming, Kirby, and Ostdiek (1998) and (2001), Scruggs and Glabadanis (2003), Hartmann, Straetmans, and Devries (2001), Connolly, Stivers, and Sun (2005), Gulko (2002), and Li (2002)).

In this study, we jointly investigate time-variation in stock-stock return comovements across countries and in stock-bond return comovements within countries. We conduct a comprehensive investigation of how return dynamics vary with a measure of stock market uncertainty, the implied volatility (IV hereafter) 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.

We examine stock index returns and long-term government bond returns for the U.S. and European countries over 1992 to 2002. We choose these markets because they are economically sizable and substantially integrated, and because U.S. and German stock IV indices are available from 1992.

Our work is most closely related to Connolly, Stivers, and Sun (2005) (CSS hereafter), who show how the U.S. stock-bond return relation varies with the IV from U.S. equity index options. We contribute by extending this literature in three primary dimensions. First, we show how cross-country stock return comovements vary with IV. Second, we contribute by extending the stock-bond comovement work. Specifically, we examine more countries over a more recent period and also evaluate stock-bond comovements for stock portfolios of different systematic risk. Re-examining the stock-bond comovements is also necessary to support our third primary contribution, which is to evaluate the temporal commonality in

the stock-stock and stock-bond comovement variations.

CSS only consider how stock-bond comovements vary with stock IV. In this study, we also document how cross-country stock-stock comovements vary with IV. We find that cross-country stock correlations tend to be substantially more positive following high values of IV and tend to be less positive following low values of IV. 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.

Next, we corroborate the CSS findings about the relation between stock-bond comovement and lagged IV. Consistent with their evidence, we find that the stock-bond correlations tend to be negative following high levels of stock IV and tend to be positive following low IV.¹ The stock-bond correlations following high IV periods tend to be more negative for portfolios of high market-beta stocks. We also find that the stock-bond correlations are negative 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. In other words, there is a “frown shape” in the variation in return correlations as a function of the daily IV change. This frown shape is stronger than the comparable findings in CSS.

Finally, we conduct a two-state, regime-switching analysis which depicts a commonality in the comovement variations over time, both across countries and across assets. We estimate separate regime-switching 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.

We find the following. In one regime, the lagged IV tends to be low, the comovement between stocks and bonds is sizably positive, and the comovement between cross-country stock returns is weaker. An increase in IV dramatically decreases the probability of staying in the first regime. In the other regime, the lagged IV tends to be high, the comovement between stocks and bonds is modestly negative, the comovement between cross-country stock returns is much stronger, and average bond returns are high relative to the stock-bond comovement. The probability of staying in the second regime tends to increase

¹The correlations are monthly correlations, calculated from rolling 22-trading-day windows under the assumption that the mean daily returns are zero.

with IV, but the effect is marginal.

Traditional long-term, present-value models of asset prices do not seem well suited to explain the comovement patterns. Further, the correlation variations appear well in excess of the variation that could be attributed to heteroskedasticity in the sense of Forbes and Rigobon (2002). 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-factor, rather than a country-specific stock factor (in the sense of King and Wadwhani (1990)). Further, the observations that stock-stock (stock-bond) return linkages are stronger (weaker) following high IV and during large IV changes seem consistent with the notion of flight-to-quality pricing influences with increased uncertainty. 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-switching 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 IV from equity-index options as a proxy for stock market uncertainty in the sense of CSS (2005). IV may contain information about several aspects of uncertainty, which are briefly reviewed here. First, under the assumptions of the Black-Scholes option pricing model, IV indicates the expected volatility over the life of the option. A large literature shows that IV contains reliable information about the subsequent realized volatility (see, e.g., Blair, Poon, and Taylor (2001), Christensen and Prabhala (1998), and Fleming (1998)). Second, IV may be influenced by the uncertainty about

the subsequent expected volatility (or the volatility of volatility). See, e.g., Coval and Shumway (2001) and Bakshi and Kapadia (2003), who suggest that option prices may contain a premium attributed to stochastic volatility. If so, then 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).

2.2 Return comovement literature

What factors and pricing influences might be important for understanding the daily comovements that we investigate? Here, we review 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 excess returns over 1952 to 1987 and identify three key economic factors that contribute to explaining the correlation. Factors that promote a positive correlation are variation in real interest rates (since the prices of both assets are negatively related to the discount rate) and common movements in future expected returns (Fama and French (1989)). On the other hand, a negative correlation can result from time-variation in expected inflation since inflation impacts bonds differently than stocks. 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.

Note that this fundamental approach assumes that only changes in inflation expectations can generate a negative stock-bond correlation. However, recent times have exhibited both relatively low, stable inflation and lengthy periods with a negative stock-bond correlation, which suggests other important pricing influences exist.

Our study fits better with the comovement literature that considers short-term uncertainty fluctuations may influence price formation across asset classes. For example, Fleming, Kirby, and Ostdiek (1998) 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 uncertainty. Here, international financial and political crises of modest duration may increase stock uncertainty and lead to frequent cross-market asset revaluations with flight-to and flight-from quality pricing influences as uncertainty fluctuates.² This effect could temporarily induce more negative stock-bond return correlations and more positive cross-country stock correlations. 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 CSS (2005)).

Findings in Chordia, Sarkar, and Subrahmanyam (2001) also suggest a link between time-varying uncertainty and dynamic cross-asset rebalancing. They compare stock and bond bid-ask spreads, trading volume, and mutual fund flows during financial crises, relative to normal times. Their findings suggest that increased investor uncertainty may lead 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.

Our empirical analysis is also motivated by the recent literature on economic-state uncertainty (Veronesi, 1999 and 2001; David and Veronesi, 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

²By 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. The time-series behavior of IV seems to support this conjecture, see our data description in Section 3.

a rational expectations model where higher economic-state uncertainty promotes higher stock return correlations across markets.

Finally, Ang and Bekaert (2002) provide additional motivation for the regime-switching 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.

3 Data Description

Our empirical work relies on total return indices for the U.S. and European countries from 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 analyze daily returns from these total return indices over the January 1, 1992 to December 31, 2002 period.³

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 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, and summarize the results in Appendix A.

³These indices are representative of the aggregate markets and include cash distribution in the returns. For comparison, U.S. daily stock returns from the DataStream index and from the CRSP value-weighted index are correlated at 0.995, with practically the same daily standard deviation. U.S. long-term daily bond returns from the Datastream index and from the prices implied by the 10-year constant maturity yield from the Federal Reserve are correlated at 0.982, with practically the same daily standard deviation.

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 5, 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 focus on stock market uncertainty.

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.

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.⁴

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). We note that our work features the original VIX series, now denoted as VXO by the CBOE. This VIX estimates the IV of a hypothetical at-the-money option on the S&P 100 index with 30 calendar days until expiration. The CBOE constructs this IV index as a weighted average of the IV extracted from eight options, controlling

⁴In 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 4 and 7.

for dividend payments and the possibility of early exercise; see Fleming, Ostdiek, and Whaley (1995). The VDAX index is based on the IV 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 VIX, but with a longer 45 day maturity. Summary statistics for VIX and VDAX are in Table 1, Panel B.

As one would expect, the VIX and VDAX level tend to move together and have a simple correlation of 0.83 over our sample. Figure 1 depicts the substantial time-series variability in the VIX and VDAX series. We also explore the dynamics of the daily changes in VIX and VDAX, which have a simple correlation of 0.44.⁵ A standard vector-autoregression (VAR) analysis indicates that each “daily IV-change” series Granger-causes the other. The contemporaneous and lagged relations between the two “daily IV-change” series vary little when conditioning upon either a high IV level or a high IV change.

Thus, the VIX and VDAX move substantially together, both in terms of their levels and their daily changes. However, the comovement also reflects a substantial country-specific component. These two observations are consistent with the notions that: (1) both VIX and VDAX contains information about the volatility or uncertainty of a “global stock common factor,” and (2) country-specific volatility and measurement noise also generate substantial country-specific variability in the IV indices. Further, to foreshadow our paper’s major results, our analysis indicates that both the VIX and VDAX level and the VIX and VDAX daily changes perform similarly in terms of what they imply about stock-bond and cross-country stock return comovements. To conclude, our paper’s joint use of the VIX and VDAX, as distinct but highly related series, seems reasonable when taking into account both the VIX/VDAX joint dynamics and our subsequent main results.

We also 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

⁵We note that there is substantial overlap between extreme IV changes in VIX and VDAX. For example, when the absolute IV change in one index is in its top 5%, then about half the time the absolute IV change in the other index will be in its top 10%. Details are available by request from the authors.

$t - 1$ is 0.698 (0.703 for VDAX). This IV behavior suggests that the subsequent “volatility of expected volatility” is higher when the IV level is high and supports the notion that a higher IV level suggests relatively strong flight-to and flight-from quality pricing influences in stocks and bonds in the near future. We further discuss IV behavior in subperiod analysis in Section 4.1.2.

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 observations within the month, and (3) allows us to capture short-term comovement variations that may arise from short-lived financial crises.

Following from Fleming, Kirby, and Ostdiek (2001) and CSS (2005), 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 a 22-trading-day period. Specifically, for a given IV at the end of day $t-1$, 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 (cross-country stock correlations) and Panel D (stock-bond correlations).

4 Comovement variation with the stock IV level

In this section, we report how return comovements vary with the lagged level of stock IV. We first report on stock-bond correlations (Section 4.1) and then cross-country stock correlations (Section 4.2). We present our stock-bond results first in order to link our investigation to the earlier stock-bond findings in CSS (2005). Section 4.3 reports how the mean and volatility of the daily returns vary with the lagged IV level. In Section 4.4, we evaluate the correlation differences and argue that the variations

appear statistically significant. Finally, in Section 4.5, we argue that heteroskedasticity, by itself, seems incapable of explaining the correlation patterns.

4.1 Variations in stock and bond return correlations

4.1.1. Overall sample. Table 2 reports on the distribution of 22-trading-day stock-bond correlations (calculated from returns over days t to $t + 21$) following days when IV_{t-1} falls within the stated percentile range of the IV distribution. The 22-trading-day correlations are calculated as in equation (1).

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%.⁶ However, when VIX_{t-1} is at its 80th (90th) percentile or greater, then the subsequent correlations are negative 72.9% (87.4%) of the time. In contrast, when VIX_{t-1} is below its 20th percentile, the subsequent correlations are negative only 2.0% of the time. The mean (median) correlations vary substantially from 0.570 (0.609) for the low-decile VIX to -0.373 (-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, exhibits these correlation results graphically for the U.S. and Germany, respectively. Our results here reinforce and extend findings in CSS (2005).

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

⁶The 33.1% is the number of negative rolling-22-trading-day correlations in our sample divided by the total number of rolling-22-trading-day correlations in our sample.

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 IV-related correlation are also evident when separately evaluating the one-half subperiods. 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 -0.409 following the largest quintile of VIX observations. In contrast, we find little variation in stock-bond correlations with IV over our first-half subperiod. Detailed subperiod results are available from the authors, by request.

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.

4.1.3. Stock-bond comovements with stock portfolios of different systematic risk. We also examine whether the stock-bond comovement patterns are different for stock portfolios with different systematic risk, as 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 (DAX) [FTSE-100] into three beta-sorted groupings to form U.S. (German) [U.K.] portfolios with different systematic risk.

We then repeat the exercise in Table 2 with beta-based portfolios used in place of the stock indices. Table 3 provides more details and reports the results. We find that the stock-bond correlations following the higher VIX observations tend to be more negative for the high-beta portfolios. For the U.S. (German) [U.K.] following the largest quintile of VIX observations, the median correlation is -0.310 (-0.210) [-0.333]

for the high-beta stock portfolio and -0.112 (-0.109) [-0.102] for the low-beta stock portfolio. Also, for all three countries, note that the difference between the VIX quintile-1 correlations and the VIX quintile-5 correlations is greater for the high-beta portfolio than for the low-beta portfolio. These results seem consistent with 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. In Table 4, we report on the distribution of 22-trading-day cross-country stock correlations (formed from returns over 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 0.415 (0.445) following the low-decile 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 exhibits how the cross-country stock correlations vary with lagged IV for the U.S.:German and German:U.K. case, respectively. Thus, these findings suggest that our IV indices reflect uncertainty at an international level and that the stock-stock comovements are stronger during times with more negative stock-bond correlations.

4.2.2. Subperiod results. We are also interested in whether the cross-country stock comovement patterns are evident across subperiods (for reasons discussed in Section 4.1.2). We find that the stock correlation patterns are also evident in our second-half subperiod for all three pairwise cases, but the patterns are somewhat more modest as compared to the overall sample. For example, for the U.S.:German case, the median 22-trading-day correlation following the low (high) VIX-quintile is 0.527 (0.756). 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. We find little variation in the German:U.K. stock correlations with IV in our first-half period.

4.3 Lagged IV and the subsequent means and volatilities of daily returns

We also evaluate other return patterns associated with the lagged IV. Specifically, 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 5. We make three primary observations. First, 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. Second, the mean returns 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. Third, Sharpe ratios also seem to convey little information because they rely on the imprecise mean returns (so we do not report the Sharpe ratios in Table 5).

4.4 Evaluating differences in the correlations

We use bootstrap methods to evaluate statistical significance for the differences in correlations. Specifically, we make draws with replacement to generate a bootstrapped distribution and then use the distribution to evaluate whether the average 22-trading-day correlations are reliably different across the different lagged IV conditions.⁷ Appendix B fully describes our bootstrap methods and results.⁸

For the stock-bond cases in Table 2, this bootstrap method indicates that the average stock-bond correlations following each extreme IV quintile are statistically significantly different than the overall average 22-trading-day correlation for the entire sample at a 0.1% p-value for all three countries. For the cross-country stock cases in Table 4, this bootstrap method also indicates that the average stock

⁷Bootstrap methods are well developed in statistics and econometrics. See Efron and Tibshirani (1993) and Horowitz (2002) for an introduction to bootstrap methods. We gratefully acknowledge Roberto Rigobon's suggestion in this regard.

⁸Note 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 4.5.

correlations following each extreme IV quintile are statistically significantly different than the average correlation over the entire sample for all three pairwise combinations (although only at the 10% level for the UK:US case). In all cases, the correlations following the high IV quintiles are different than the correlations following the low IV quintile at a 1.1% p-value or less.

Next, recall that our results in Tables 2 and 4 are for 22-trading-day correlations. It is an interesting question whether the covariance structure varies appreciably within the 22 day period. For example, are the correlations in days $t + 1$ to $t + 5$ following an extreme IV condition substantially different than the correlations in days $t + 16$ to $t + 20$ following an extreme IV condition? We investigate this question and report results in Appendix A. To summarize, the correlation patterns reported in Tables 2 and 4 are evident across the entire 22-day period with only modest decay as time passes from the IV event.

4.5 The correlation variations and heteroskedasticity

Forbes and Rigobon (2002) (FR hereafter) 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.

4.5.1. Perspective of FR (2002) example. First, we consider our findings from the perspective of the simple numerical example in FR (pp. 2230-2231). 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 should increase.⁹

First, consider the U.S. stock-bond relation. Since VIX measures the stock's expected volatility,

⁹Our limited purpose here is to address whether heteroskedasticity, by itself, appears capable of explaining our principal results. The FR perspective is a well known approach. Corsetti, Pericoli, and Sbracia (forthcoming, 2005) point out that the FR perspective is likely to overstate the correlation variation attributed to heteroskedasticity because of the FR assumptions about common-factor versus idiosyncratic volatility. If so, then the heteroskedasticity-related variations in correlation, suggested by our illustrations in this subsection, may be considered to err on the high side.

we initially evaluate the stock market as the shocked market. Using the overall average 22-trading-day correlation of 0.180 and the unconditional volatility of the stock and bond returns, we can calculate an implied OLS coefficient of 0.073 with the stock return as the explanatory variable and the bond return as the dependent variable. Then, we calculate different implied correlations where $E(r_{B,t}|r_{S,t})$ is equal to 0.073 times the given stock return and where the volatilities change to the values depicted in Table 5 for the low (high) VIX values. For the low VIX quintile, the implied correlation is 0.096 (as compared to the observed average correlation of 0.475). For the upper VIX quintile, the implied correlation is 0.245 (as compared to the observed average correlation of -0.232). Thus, the observed variation in correlations is in the *opposite* direction suggested by this FR perspective.

Next, we also consider the opposite perspective where the expected stock return, given the bond return, can be expressed as a constant proportion of the bond return. This case assumes that the heteroskedasticity in the stock market is stock-specific volatility. Using the overall average correlation and the unconditional return volatilities, we calculate an implied OLS coefficient 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 equal to 0.447 times the given bond return and where the volatilities change to the values depicted in Table 5 for the low (high) VIX values. In this case, the implied correlation is 0.340 for the low VIX quintile and 0.133 for the high VIX quintile. While these correlation variations are in the same direction as that observed in the data, the implied variations are still much smaller than those in Table 2.

Next, we evaluate the cross-country stock correlations from the perspective of the FR example. We consider the German:U.K. stock-stock relation and use the VDAX variation with Germany as the shocked market. Using the average correlation of 0.590 and the unconditional stock volatilities, we calculate an implied OLS coefficient of 0.499 with the German stock return as the explanatory variable and the U.K. stock return as the dependent variable. Then, we calculate different implied correlations where $E(r_{UK,t}|r_{GM,t})$ is equal to 0.499 times the given German stock return and where the volatilities change to the values depicted in Table 5 for the low (high) VIX values. In this case, for the low VDAX

quintile, the implied correlation is 0.490 (as compared to an observed average correlation of 0.467). In this case, for the upper VDAX decile, the implied correlation is 0.615 (as compared to an observed average correlation of 0.729). Thus, while the observed variation in correlations is in the same direction as that predicted by the FR heteroskedasticity perspective, the actual correlation differences are over twice as great. Thus, from this FR perspective, the observed heteroskedasticity is unable to explain the observed variation in correlations.

4.5.2. Comovement variations in a GARCH system. Next, we also evaluate comovements in a GARCH system that directly models the heteroskedasticity 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 4.

For the stock-bond return relations within country, we follow from CSS (2005) and estimate the following GARCH system.¹⁰

$$B_{x,t} = \beta_0 + (\beta_1 + \beta_2 \ln(IV_{t-1}))S_{x,t} + \epsilon_t \quad (2)$$

$$h_t = \frac{\gamma_0 + \gamma_1 \epsilon_{t-1}^2}{1 - \gamma_2 L} + \gamma_3 IV_{t-1}^2 \quad (3)$$

where $B_{x,t}$ ($S_{x,t}$) is the daily 10-year bond return (stock return) from country x , $\ln(IV_{t-1})$ is the natural log of the lagged IV (either VIX or VDAX), h_t is the conditional variance of the residual ϵ_t from (2), IV_{t-1}^2 is the lagged implied variance from either the VIX or VDAX series, L is the lag operator, and the β 's and γ 's are coefficients to be estimated.¹¹ The coefficient of interest is β_2 . The GARCH system is estimated with a conditional normal density. For inference, we calculate standard errors that are robust

¹⁰It 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.

¹¹Note that this specification for the conditional variance is a simplified version of the Blair, Poon, and Taylor (2001) model with their α_2 , γ , β_I , and β_V coefficients restricted to zero. Note that our specification has only the most recent lagged IV (IV_{t-1}^2) as an explanatory variable since the older IV terms fall out of the expression if one substitutes in the preceding h terms into the conditional variance equation.

to departures from conditional normality, see Bollerslev and Wooldridge (1992). We use the log of IV in (2) to reduce the positive skewness of the raw IV series and make it closer to normally distributed (the skewness for the log(series) is 0.11 (0.34) for VIX (VDAX) versus 0.82 (1.33) for the raw series).

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

$$S_{y,t} = \beta_0 + (\beta_1 + \beta_2 \ln(IV_{t-1}))S_{x,t} + \epsilon_t \quad (4)$$

$$h_t = \frac{\gamma_0 + \gamma_1 \epsilon_{t-1}^2}{1 - \gamma_2 L} + \gamma_3 IV_{t-1}^2 \quad (5)$$

where $S_{y,t}$ ($S_{x,t}$) is the stock return from country y (country x) and the other terms and model estimation details are the same as for (2) and (3). The coefficient of interest is β_2 .

Table 6 presents the results from estimating the model in equations (2) and (3) for the stock-bond relations and equations (4) and (5) for the cross-country stock-stock relations. First, for the stock-bond case in Panel A, the estimated β_2 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 0.359 at the 5th percentile of VIX_{t-1} and -0.079 at the 95th percentile of VIX_{t-1} .

Next, for the cross-country stock cases, we find that the estimated β_2 is sizably positive for all cases (see Table 6, Panel B). This indicates that the stock comovements increase with increasing stock IV. For example, for the German stock return as a function of the U.K. stock return, the implied relation between the two series is 0.394 at the 5th percentile value of VIX_{t-1} and 1.005 at the 95th percentile value of VIX_{t-1} . For the reverse case (the U.K. stock return as a function of the German stock return), the implied relation between the two series is 0.361 at the 5th percentile value of VIX_{t-1} and 0.653 at the 95th 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 (4), which is inconsistent with the comovement variations being driven by heteroskedasticity in a single shocked stock market. Thus, the Table 6 results reinforce the comovement results depicted in Tables 2 and 4.¹²

¹²For the conditional variance equations in the Table 6 models (equations (3) and (5)), we find standard GARCH behavior. All of the estimated γ_1 and γ_2 coefficients are positive and statistically significant with an average γ_1 of 0.062

We also estimate the models given by equations (2) through (5), for one-half subperiods for each case reported in Table 6. For our second-half period, the estimated β_2 's depict the same relations as in Table 6 for all cases and the β_2 's are statistically significant for all cases except the U.S.:German stock case. However, for our first-half period, the same patterns are reliably evident only for 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.

5 Comovement variation and the daily change in stock IV

This section reports our analysis of how daily return comovements vary with the contemporaneous change in stock IV. Here, we calculate correlations for subsets of return observations that occur when the day's IV change falls within a particular percentile range of the sample IV-change distribution. We compute the subset correlations as the deviation from the overall sample mean, rather than as the deviation from the respective subset mean. 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 unconditional mean (which is essentially zero for daily returns). Section 5.1 covers 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.

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

In Table 7, Panel A, we report how the stock-bond correlations vary with the contemporaneous IV change. 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. On the other hand, on days when the IV changes relatively little, the stock-bond correlations are modestly to substantially positive.

and an average γ_2 of 0.852. For the lagged IV term, the estimated γ_3 coefficients are positive and statistically significant for all six of the stock cases in Panel B and for two of the three stock-bond cases in Panel A.

For example, for the U.S. on days with a large decrease in VIX (the low decile ΔVIX observations, where Δ refers to the daily change), the correlation is -0.183. 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. Germany and the U.K. exhibit similar patterns. Thus, variation in the stock-bond comovements with the day’s change in stock IV exhibits a clear ‘inverted U’ or frown shape. We also note that the average stock return is negatively and substantially related to the day’s ΔIV in all cases. Further, average bond returns are high, relative to the stock returns, on day’s with substantial increases in ΔIV .

CSS (2005) perform a similar investigation for the U.S. stock and bond returns only, over the 1986 to 2000 period. Their findings suggest only a modest frown or skew shape in the correlation variations with the days’ IV change. The frown shape is more pronounced for our more recent U.S. sample and for our U.K. and German samples, perhaps because our later sample period has a greater proportion of its time associated with identifiable financial crises.

5.2 Cross-country stock return correlations and a day’s IV change

In Table 7, Panel B, we report how cross-country stock correlations vary with the contemporaneous IV change. Here, to match the return timing for the UK:US and US:German cases, the daily ΔVIX is equal to the opening-VIX for day t minus the opening-VIX for day $t - 1$.

We find that the stock comovements are more positive 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 decile ΔVDAX), the German:U.K. stock correlation is 0.848. 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 0.467. Thus, the cross-country stock correlations vary with the day’s ΔIV in the shape of a ‘standard U’ or smile shape.

Our perspective is that a day’s change in IV is related to variations in stock-bond comovements, cross-country stock comovements, and mean stock returns in a manner 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 (see the data description in Section 3), this view fits with the results in Section 4.

5.3 Evaluating the differences in return comovements

As in Section 4.3, we rely on bootstrapped distributions for inference when trying to evaluate whether the correlation variations with the contemporaneous IV change are statistically significant. To summarize, the bootstrap distributions indicate that the correlations for each extreme ΔIV quintile subset are reliably greater than the inner 60th percentile ΔIV subset at a 1% p-value. See Appendix B for details.

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 7 are greater than expected.

6 Regime-switching analysis

In this section, we further explore the time-varying return comovements by examining a regime-switching approach.¹³ Our approach builds from CSS's (2005) regime-switching analysis of the U.S. stock-bond

¹³There 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 (2002), Whitelaw (2000), Veronesi (1999), and CSS (2005).

return relation. We extend their regime-switching analysis by also examining the U.K. and German stock-bond return relations and all the possible pairwise stock-stock relations between the three countries. In addition to examining whether a regime-switching approach indicates sizable time-variation in the return comovements and whether the regime switching is related to the lagged stock IV, we are also interested in commonality questions, such as: For a given country, how are the country's stock-bond regime movements related to the country's regime movements in the cross-country stock relations? Across countries, to what extent are the stock-bond regime movements related?

Our exploration appeals to the following intuition. Consider two regimes of return comovements where the first regime is the predominant regime associated with a typical level of uncertainty. In this regime, our prior results suggest more positive stock-bond return comovements (with little flight-to-quality pricing influences) and modestly positive cross-country stock-stock comovement. Next, consider a second, more transient regime that is associated with relatively high uncertainty, presumably during times of economic crisis or duress. In this relatively transient regime, our earlier results suggest more negative stock-bond return comovements (with sizable flight-to and flight-from quality as the perceived uncertainty varies) and strongly positive cross-country stock-stock correlations (with increased volatility in a global stock common factor and with more variation in the attractiveness of stocks as an asset class). Here, we assume that two regimes are reasonable for this approach in order to keep the model parsimonious and the interpretation simple.

6.1 The empirical regime-switching models

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

$$B_{x,t} = \delta_j + \theta_j S_{x,t} + \epsilon_t, \quad (6)$$

where $B_{x,t}$ ($S_{x,t}$) is the 10 year government bond return (stock market return) for country x ; δ_j and θ_j are regime-dependent coefficients to be estimated where j denotes the regime, and ϵ_t is the residual. Since we focus on stock uncertainty (with the stock IV), we use the stock return as the explanatory variable in the regime-switching estimation.

The regime, s , is modeled with time-varying transition probabilities (Pr) as follows:

$$Pr(s_t = j | s_{t-1} = j) = \frac{e^{c_j + d_j \ln(IV_{t-1})}}{1 + e^{c_j + d_j \ln(IV_{t-1})}}, \quad (7)$$

where $j = 0$ (regime-zero) or $j = 1$ (regime-one), $\ln(IV_{t-1})$ is the log of the lagged IV (either VIX or VDAX), and the c_j 's, and d_j 's are regime-dependent coefficients to be estimated (see Diebold, Lee, and Weinbach (1994)). As in the models given by equations (2) through (5), we use the log of IV to reduce the skewness of the raw IV series. The regime s can be regarded as an unobserved state variable that follows a two-state, first-order Markov process.

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

$$S_{y,t} = \kappa_j + \lambda_j S_{x,t} + \epsilon_t, \quad (8)$$

where $S_{y,t}$ is the stock return for country y and $S_{x,t}$ is the stock return from country x ; κ_j and λ_j are regime-dependent coefficients to be estimated where j denotes the regime, and ϵ_t is the residual. The regime, s , is modeled with time-varying transition probabilities as in equation (7), where $j = 0$ (regime-zero) or $j = 1$ (regime-one).¹⁴

6.2 Empirical results

In Table 8, we report the results from estimating the stock-bond regime-switching model for each of our three primary countries over the 1992 to 2002 period. The estimations indicate strong regime-switching behavior. The stock-bond return comovements for regime-zero, represented by the θ_0 coefficient, are 0.314, 0.289, 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 θ_1 coefficient, are -0.109, -0.032, and -0.070, for the same respective cases. These estimated coefficients are all highly statistically significant. Also note that the estimated intercepts for regime-one are all positive and highly statistically significant, versus the negative and insignificant intercepts for regime-zero. This indicates that average bond returns are high, relative to the stock-bond return comovement, in regime-one.

¹⁴As we noted in footnote 10 for equations (2) and (4), equations (6) and (8) are meant to describe contemporaneous comovements between the daily returns, not economic causality.

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 8, Panel B, which presents the expected duration of staying in each regime at roughly the 25th and 75th 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 IV.¹⁵

Next, in Table 9, we report the results for the regime-switching model for the cross-country stock return relations. With three countries, there are three possible pairwise combinations when considering simple correlations. However, in equation (8), the choice of which stock return 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 is the explanatory variable. Thus, there are six total regime-switching 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 9 reports on the VIX or VDAX choice, for each case, which yields the highest estimated likelihood function value.

To summarize, our estimates indicate substantial regime-switching behavior. (In Table 9 and the following discussion, the stock return from the first country listed is the explanatory variable in equation (8).) The cross-country stock return relations for regime-zero, represented by the λ_0 coefficient, are 0.380, 0.435, 0.212, 0.677, 0.284, and 0.446, 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 λ_1 coefficient, are 1.13, 0.846, 0.715, 1.82, 1.07,

¹⁵We also estimate a restricted model with constant transition probabilities. We then evaluate the importance of allowing for time-varying transition probabilities by performing a Likelihood Ratio Test. For all cases in Tables 8 and 9, the LRT rejects a null of constant transition probabilities at a 0.001 p-value.

and 1.28, for the same respective cases. These 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 9, Panel B, further illustrate this point. For regime-one, the estimated d_1 is positive for five of the six model variations, but positive and statistically significant at the 10% level for only one case. 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} .

6.3 Discussion of regimes and expected regime durations

The regime behavior appears consistent with our motivating conjecture at the beginning of this section and reinforces our prior results in Tables 2 and 4. Specifically, regime-zero is the predominant regime and 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 transient 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. Also, the estimated intercepts in the model indicate that the average bond returns tend to be higher in regime-one, after controlling for the comovement with the stock return. 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. 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, the regime-switching representation does appear useful. When examining the probabilities of being in each regime over time, we find that 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 is substantially

related across countries and substantially related to the cross-country stock regimes.

Specifically, we evaluate the temporal commonality across the three countries for the regime-one stock-bond days, as follows. 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-bond relations also in regime-one? We consider a day to be in regime-one if the filtered probability is greater than 80%. The answer is 95.6% of the time for the U.K. and 92.0% of the time for Germany. 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.

Next, for a given country, we evaluate the commonality between the stock-bond regime-one days and the stock-stock regime-one days. Since the regime-one episodes are of longer duration for the stock-bond relations (as compared to stock-stock regime-one episodes), we evaluate the following question. What proportion of the cross-country stock-stock regime-one days occur when the respective country's stock-bond regime is also in regime-one? The overlap is very substantial. For example, for the German stock-bond case, about 44% of the days are categorized as regime-one. For the U.K.:German stock relation, about 16% 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, about 33% of the days are categorized as regime-one. For the U.K.:U.S. stock relation, about 4% of the days are categorized as regime-one and over 89% 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 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.

Given the positive relation between the IV level and subsequent IV volatility noted in Section 3, one interpretation of our regime-switching results is the following. When the stock IV level is relatively high, 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 IV on certain days. Following

these IV upward spikes, the uncertainty tends to fall somewhat over the next few days as the uncertainty is partially 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 flights to and from quality as uncertainty fluctuates. Further, if the dynamic movements in IV are informative about the risk of a global stock common-factor and the relative attractiveness of stocks versus bonds, 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-switching results and the return patterns documented in Tables 2 through 7.

7 Conclusions

We jointly investigate time-variation in stock-stock return comovements across countries and in stock-bond return comovements within countries. Our focus is on how return comovements vary with stock market uncertainty, as measured by the IV from equity index options. Our study analyzes daily stock index returns and long-term government bond returns for the U.S. and European countries over 1992 to 2002. We contribute to the comovement literature in three dimensions.

First, we contribute by showing how cross-country stock comovements vary with stock 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, contemporaneously, 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 IV increases or decreases and are weaker for days with little IV change.

Next, we extend the stock-bond comovement work in CSS (2005) by analyzing more countries, by examining a more recent period, and by examining stock portfolios with different systematic risk. Consistent with CSS, we find that stock-bond correlations tend to be negative following high IV days and tend to be positive following low IV days. Further, we find that the stock-bond correlations following high IV days tend to be more negative for stock portfolios of high market-beta stocks. Contempora-

neously, we find that stock-bond correlations vary with a day's IV change in a "frown shape", where correlations are negative for days with either sizable IV increases or decreases and are sizably positive for days with little IV change. This frown pattern is stronger in our samples than comparable results in CSS.

We also contribute by conducting a regime-switching analysis to further examine the temporal commonality in the comovement variations. The regime-switching results depict sizable comovement variations and indicate that stock IV has an important role in understanding comovement variations. Further, our results indicate a substantial temporal linkage between the stock-bond and stock-stock comovement variations.

Collectively, our evidence supports the idea that uncertainty fluctuations with associated cross-market asset revaluations are important in understanding daily return dynamics. More specifically, the notion of flight-to-quality (flight-from-quality) pricing influences with increased (decreased) uncertainty is supported by the joint observations that: (1) stock-stock return linkages are stronger following high IV and during large IV changes, (2) stock-bond return linkages are weaker following high IV and during large IV changes, and (3) the IV level and subsequent IV volatility are positively related.

Thus, our evidence supports the empirical relevance and intuition of theoretical work such as Kodres and Pritsker (2002) (that cross-market 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). Future theory that more formally explains our collective comovement findings would be interesting and would likely yield additional empirical implications.

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.

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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 i th autocorrelation. The VIX is the Chicago Board Option Exchange's original Volatility Index (now denoted as VXO), which provides a standardized IV from S&P 100 equity index options. Similarly, VDAX provides a standardized IV 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 cross-country correlations between the stock markets. Finally, Panel D reports on rolling 22-trading-day correlations between daily stock and bond returns. These correlations are calculated assuming that the daily mean returns are zero for each 22-trading-day period. 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

	Excess					
	Mean	Std. Dev.	Skewness	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

			10 th	25 th		75 th	90 th		Excess
	Mean	Std. Dev.	pctl	pctl	Median	pctl	pctl	Skewness	Kurtosis
VIX	21.02	7.74	12.19	14.12	20.79	25.56	31.11	0.823	0.473
VDAX	21.75	8.89	12.48	15.04	20.20	25.40	34.13	1.33	1.86

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

			10 th	25 th		75 th	90 th
	Mean	Std. Dev.	pctl	pctl	Median	pctl	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

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

	Percentage of			10 th	25 th		75 th	90 th
	Correlations<0	Mean	Std. Dev.	pctl	pctl	Median	pctl	pctl
U.S.	32.4%	0.180	0.432	-0.489	-0.137	0.282	0.534	0.688
Germany	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

Table 2: Equity index IV and subsequent stock-bond return correlations

This table reports on the relation between stock IV 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 day $t - 1$. The 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} (see Section 3). For column three, the standard error of the average correlation is in parentheses, calculated with bootstrap methods. The final column reports the average correlations for VDAX criterion rather than VIX. The sample period is January 1992 through December 2002.

VIX Criterion	Proportion of Correlations < 0	Average Corr.	Median Corr.	25 th Pctl Corr.	75 th Pctl Corr.	VDAX Crit. Average Corr.
Panel A: U.S. 22-trading-day stock-bond return correlations						
Low 5 Pctl	1.5%	0.524 (0.018)	0.594	0.435	0.681	0.339
Low Decile	2.6%	0.495 (0.013)	0.524	0.365	0.667	0.383
Low Quintile	2.7%	0.475 (0.009)	0.505	0.342	0.636	0.426
Quintile 2	4.2%	0.432 (0.010)	0.441	0.276	0.646	0.428
Quintile 3	29.2%	0.224 (0.017)	0.376	-0.099	0.539	0.254
Quintile 4	53.1%	-0.001 (0.018)	-0.031	-0.328	0.300	-0.003
Top Quintile	73.0%	-0.232 (0.016)	-0.266	-0.529	0.018	-0.206
Top Decile	85.5%	-0.361 (0.020)	-0.409	-0.660	-0.076	-0.355
Top 5 Pctl	95.7%	-0.453 (0.025)	-0.473	-0.725	-0.163	-0.498
Panel B: German 22-trading-day stock-bond return correlations						
Low 5 Pctl	0.0%	0.530 (0.018)	0.625	0.314	0.694	0.573
Low Decile	0.0%	0.496 (0.013)	0.539	0.290	0.684	0.532
Low Quintile	0.4%	0.492 (0.009)	0.540	0.297	0.677	0.519
Quintile 2	2.2%	0.499 (0.010)	0.524	0.365	0.675	0.457
Quintile 3	26.0%	0.277 (0.017)	0.372	-0.007	0.616	0.241
Quintile 4	47.6%	0.028 (0.015)	0.023	-0.272	0.304	0.028
Top Quintile	64.8%	-0.150 (0.013)	-0.174	-0.437	0.125	-0.099
Top Decile	73.8%	-0.248 (0.018)	-0.320	-0.502	0.011	-0.217
Top 5 Pctl	85.5%	-0.348 (0.023)	-0.422	-0.527	-0.242	-0.354
Panel C: U.K. 22-trading-day stock-bond return correlations						
Low 5 Pctl	0.0%	0.601 (0.012)	0.636	0.512	0.691	0.437
Low Decile	0.7%	0.570 (0.009)	0.609	0.458	0.680	0.464
Low Quintile	2.0%	0.538 (0.009)	0.556	0.400	0.694	0.493
Quintile 2	2.0%	0.504 (0.010)	0.522	0.351	0.675	0.496
Quintile 3	30.1%	0.218 (0.016)	0.315	-0.080	0.521	0.172
Quintile 4	58.5%	-0.025 (0.015)	-0.075	-0.308	0.253	0.035
Top Quintile	72.9%	-0.222 (0.016)	-0.288	-0.512	0.019	-0.183
Top Decile	87.4%	-0.373 (0.017)	-0.411	-0.619	-0.238	-0.361
Top 5 Pctl	95.7%	-0.462 (0.019)	-0.501	-0.641	-0.330	-0.485

Table 3: Equity index IV and stock-bond correlations for stocks with different market-betas

This table reports on the relation between stock IV and the subsequent 22-trading-day correlations between stock and 10-year government bond returns, as in Table 2, except we examine beta-based stock portfolios. Beta-based, equally-weighted portfolios are formed from individual stocks in major stock indices for the firms that have daily returns available over our entire 1992 through 2002 sample period. We use firms in the U.S. S&P 100, the U.K. FTSE-100, and the German DAX to form separate beta-based portfolios for each country. High-beta (low-beta) refers to stocks which have market-betas in the top third (bottom third) of the cross-sectional beta distribution for the individual firms that comprise each respective index over our sample period. 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					
Beta	VIX	Median	25 th Pctl	75 th Pctl	Difference in Median Corr.
Criterion	Criterion	Corr.	Corr.	Corr.	Quintile-1 minus Quintile-5
Low Beta	Quintile 1	0.491	0.326	0.623	0.603
	Quintile 5	-0.112	-0.434	0.072	
High Beta	Quintile 1	0.338	0.171	0.521	0.648
	Quintile 5	-0.310	-0.549	0.004	
Panel B: German 22-trading-day stock-bond return correlations					
Beta	VIX	Median	25 th Pctl	75 th Pctl	Difference in Median Corr.
Criterion	Criterion	Corr.	Corr.	Corr.	Quintile-1 minus Quintile-5
Low Beta	Quintile 1	0.461	0.287	0.606	0.570
	Quintile 5	-0.109	-0.344	0.092	
High Beta	Quintile 1	0.473	0.275	0.600	0.683
	Quintile 5	-0.210	-0.436	0.106	
Panel C: U.K. 22-trading-day stock-bond return correlations					
Beta	VIX	Median	25 th Pctl	75 th Pctl	Difference in Median Corr.
Criterion	Criterion	Corr.	Corr.	Corr.	Quintile-1 minus Quintile-5
Low Beta	Quintile 1	0.476	0.340	0.629	0.578
	Quintile 5	-0.102	0.371	0.112	
High Beta	Quintile 1	0.530	0.381	0.644	0.863
	Quintile 5	-0.333	-0.524	0.023	

Table 4: Equity index IV and subsequent cross-country stock correlations

This table reports on the relation between stock IV 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 day $t - 1$. 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} (see Section 3). For column two, the standard error of the average correlation is in parentheses, calculated with bootstrap methods. The final column reports the average correlations for VDAX criterion rather than VIX. 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.

VIX Criterion	Average Corr.	Median Corr.	25 th Pctl Corr.	75 th Pctl Corr.	VDAX Crit. Average Corr.
Panel A: German:U.K. 22-trading-day stock-stock return correlations					
Low 5 Pctl	0.426 (0.020)	0.454	0.263	0.638	0.565
Low Decile	0.415 (0.015)	0.445	0.239	0.614	0.485
Low Quintile	0.430 (0.010)	0.481	0.261	0.601	0.467
Quintile 2	0.491 (0.007)	0.498	0.381	0.615	0.454
Quintile 3	0.579 (0.009)	0.606	0.447	0.726	0.584
Quintile 4	0.686 (0.007)	0.713	0.599	0.779	0.714
Top Quintile	0.763 (0.006)	0.805	0.692	0.863	0.729
Top Decile	0.800 (0.006)	0.824	0.762	0.870	0.791
Top 5 Pctl	0.831 (0.005)	0.848	0.805	0.874	0.821
Panel B: German:U.S. 22-trading-day stock-stock return correlations					
Low 5 Pctl	0.428 (0.017)	0.486	0.283	0.572	0.472
Low Decile	0.378 (0.013)	0.433	0.242	0.542	0.440
Low Quintile	0.378 (0.009)	0.412	0.256	0.523	0.409
Quintile 2	0.429 (0.009)	0.424	0.294	0.569	0.427
Quintile 3	0.542 (0.008)	0.546	0.409	0.701	0.533
Quintile 4	0.553 (0.008)	0.557	0.438	0.673	0.550
Top Quintile	0.615 (0.009)	0.612	0.463	0.813	0.597
Top Decile	0.667 (0.013)	0.758	0.491	0.844	0.657
Top 5 Pctl	0.692 (0.019)	0.789	0.495	0.847	0.700
Panel C: U.K.: U.S. 22-trading-day stock-stock return correlations					
Low 5 Pctl	0.461 (0.012)	0.469	0.395	0.583	0.414
Low Decile	0.433 (0.010)	0.449	0.363	0.541	0.412
Low Quintile	0.424 (0.007)	0.442	0.327	0.551	0.401
Quintile 2	0.430 (0.009)	0.424	0.303	0.547	0.471
Quintile 3	0.534 (0.009)	0.562	0.406	0.687	0.517
Quintile 4	0.531 (0.008)	0.527	0.425	0.640	0.525
Top Quintile	0.574 (0.008)	0.552	0.434	0.761	0.579
Top Decile	0.638 (0.012)	0.703	0.468	0.813	0.636
Top 5 Pctl	0.682 (0.018)	0.784	0.481	0.821	0.684

Table 5: Equity index IV 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 and volatility 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). 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, in percentage units, that follow the respective VIX $_{t-1}$ (VDAX $_{t-1}$) percentile range. 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 Decile VIX:	μ	0.061	0.053	0.074	0.020	0.012	0.009
	σ	0.451	0.680	0.628	0.386	0.320	0.493
Low Decile VDAX:	μ	0.005	0.013	-0.039	0.019	0.028	0.010
	σ	0.598	0.599	0.573	0.373	0.229	0.320
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 6: Comovement variations with IV 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 (4) and (5) for the stock-stock relations across countries (see Section 4.5.2). Panel A reports on the stock-bond cases with the following conditional mean equation:

$$B_{x,t} = \beta_0 + (\beta_1 + \beta_2 \ln(IV_{t-1}))S_{x,t} + \epsilon_t$$

where $B_{x,t}$ ($S_{x,t}$) is the daily 10-year bond return (stock return) from country x , $\ln(IV_{t-1})$ is the natural log of the lagged IV, and the β 's are estimated coefficients. Panel B reports on the stock-stock cases with the following conditional mean equation, where the y and x return series are identified in column one:

$$S_{y,t} = \beta_0 + (\beta_1 + \beta_2 \ln(IV_{t-1}))S_{x,t} + \epsilon_t,$$

where $S_{y,t}$ ($S_{x,t}$) is the stock return from country x (country y) 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 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. ***, **, and * indicate statistical significance at 0.001, 0.01, and 0.05 p-values, calculated with robust standard errors. The final two columns for each model report the total relation between the two series implied by the estimated β_2 with the IV_{t-1} set at its 5th and 95th percentile value.

Panel A: Stock-bond return comovements					
Country (IV)	β_0	β_1	β_2	$(\beta_1 + \beta_2 \ln(IV_{t-1}))$ (IV=5 th pctl)	$(\beta_1 + \beta_2 \ln(IV_{t-1}))$ (IV=95 th pctl)
U.S. (VIX)	0.026**	1.388***	-0.422***	0.357	-0.114
Germany (VDAX)	0.038***	0.714***	-0.211***	0.198	-0.070
U.K. (VIX)	0.030***	1.320***	-0.393***	0.359	-0.079

Panel B: Cross-country stock return comovements					
Country y:x (IV)	β_0	β_1	β_2	$(\beta_1 + \beta_2 \ln(IV_{t-1}))$ (IV=5 th pctl)	$(\beta_1 + \beta_2 \ln(IV_{t-1}))$ (IV=95 th pctl)
Germany:U.K. (VIX)	0.026*	-0.941***	0.546***	0.394	1.005
U.K.:Germany (VIX)	0.026*	-0.278*	0.261***	0.361	0.653
Germany:U.S. (VDAX)	0.027	-0.582**	0.427***	0.483	1.014
U.S.:Germany (VIX)	0.036**	-0.359***	0.236***	0.220	0.487
U.K.:U.S (VDAX)	0.009	-0.080	0.205***	0.430	0.685
U.S.:U.K. (VIX)	0.038*	-0.438**	0.292***	0.280	0.608

Table 7: Daily changes in stock IV and variation in return correlations

This table reports how comovements vary with the contemporaneous daily change in stock IV. Panel A reports on the stock-bond correlations and Panel B reports on cross-country stock correlations. The ΔVIX ($\Delta VDAX$) criterion means the subset of daily return observations where the day's IV change falls within the stated percentile range. The subset correlations and standard deviations are calculated as the deviation from the overall sample mean, rather than the respective subset mean. The low (top) percentiles refer to the largest IV decreases (increases). Return statistics are in daily percentage units. For the correlations in column-two, bootstrapped standard errors are reported in parentheses. The sample period is 1992 through 2002; except for the U.S.:German and U.S.:U.K cases, where the sample starts in 7/16/92.

Panel A: Stock-bond daily return correlations					
ΔVIX / $\Delta VDAX$		Average	Std. Dev.	Average	Std. Dev.
Criterion	Correlation	Bond Return	Bond Return	Stock Return	Stock Return
U.S. stock and bond returns					
Low 5 Pctl ΔVIX	-0.323 (0.092)	-0.089	0.523	2.054	2.323
Low Decile ΔVIX	-0.183 (0.075)	-0.024	0.500	1.530	1.864
Low Quintile ΔVIX	-0.109 (0.054)	0.035	0.459	1.118	1.483
Quintile 2 ΔVIX	0.205 (0.060)	0.073	0.396	0.337	0.643
Quintile 3 ΔVIX	0.188 (0.051)	0.017	0.373	0.075	0.525
Quintile 4 ΔVIX	0.264 (0.042)	-0.004	0.401	-0.172	0.614
Top Quintile ΔVIX	-0.109 (0.048)	0.017	0.512	-1.147	1.581
Top Decile ΔVIX	-0.200 (0.066)	0.066	0.572	-1.652	2.028
Top 5 Pctl ΔVIX	-0.249 (0.095)	0.129	0.629	-2.110	2.448
German stock and bond returns					
Low 5 Pctl $\Delta VDAX$	-0.092 (0.092)	0.009	0.318	1.598	2.136
Low Decile $\Delta VDAX$	-0.032 (0.065)	0.010	0.335	1.389	1.850
Low Quintile $\Delta VDAX$	0.037 (0.045)	0.050	0.326	0.997	1.466
Quintile 2 $\Delta VDAX$	0.305 (0.053)	0.082	0.293	0.351	0.786
Quintile 3 $\Delta VDAX$	0.108 (0.080)	0.040	0.292	0.061	0.845
Quintile 4 $\Delta VDAX$	0.184 (0.042)	-0.008	0.296	-0.199	0.730
Top Quintile $\Delta VDAX$	0.036 (0.049)	-0.008	0.397	-1.065	1.692
Top Decile $\Delta VDAX$	-0.034 (0.064)	0.016	0.435	-1.561	2.100
Top 5 Pctl $\Delta VDAX$	-0.081 (0.090)	0.056	0.457	-1.926	2.508
U.K. stock and bond returns					
Low 5 Pctl $\Delta VDAX$	-0.253 (0.088)	-0.026	0.419	1.215	1.712
Low Decile $\Delta VDAX$	-0.151 (0.068)	0.001	0.403	1.018	1.474
Low Quintile $\Delta VDAX$	-0.064 (0.046)	0.034	0.397	0.737	1.195
Quintile 2 $\Delta VDAX$	0.425 (0.073)	0.105	0.442	0.247	0.708
Quintile 3 $\Delta VDAX$	0.165 (0.071)	0.049	0.398	0.059	0.745
Quintile 4 $\Delta VDAX$	0.307 (0.043)	-0.019	0.404	-0.127	0.686
Top Quintile $\Delta VDAX$	0.022 (0.049)	0.019	0.462	-0.726	1.373
Top Decile $\Delta VDAX$	-0.116 (0.065)	0.053	0.459	-1.069	1.664
Top 5 Pctl $\Delta VDAX$	-0.200 (0.087)	0.092	0.444	-1.406	1.956

Table 7: (continued)

Panel B: Cross-country stock-to-stock daily return correlations					
$\Delta VIX / \Delta VDAX$		Average	Std. Dev.	Average	Std. Dev.
Criterion	Correlation	Stock Return	Stock Return	Stock Return	Stock Return
	German:U.K.	German returns		U.K. returns	
Low 5 Pctl $\Delta VDAX$	0.883 (0.019)	1.615	2.150	1.246	1.721
Low Decile $\Delta VDAX$	0.848 (0.019)	1.398	1.860	1.035	1.475
Low Quintile $\Delta VDAX$	0.793 (0.019)	1.005	1.470	0.745	1.205
Quintile 2 $\Delta VDAX$	0.421 (0.039)	0.356	0.783	0.248	0.704
Quintile 3 $\Delta VDAX$	0.536 (0.046)	0.054	0.861	0.064	0.743
Quintile 4 $\Delta VDAX$	0.445 (0.037)	-0.200	0.732	-0.135	0.688
Top Quintile $\Delta VDAX$	0.784 (0.021)	-1.072	1.685	-0.736	1.383
Top Decile $\Delta VDAX$	0.847 (0.021)	-1.567	2.083	-1.100	1.670
Top 5 Pctl $\Delta VDAX$	0.885 (0.018)	-1.904	2.492	-1.413	1.959
	U.S.:German	U.S. returns		German returns	
Low 5 Pctl ΔVIX	0.734 (0.053)	1.498	2.226	2.122	2.861
Low Decile ΔVIX	0.709 (0.043)	1.237	1.809	1.617	2.329
Low Quintile ΔVIX	0.661 (0.034)	0.876	1.429	1.171	1.905
Quintile 2 ΔVIX	0.343 (0.054)	0.328	0.771	0.338	1.209
Quintile 3 ΔVIX	0.263 (0.045)	0.112	0.673	-0.002	1.018
Quintile 4 ΔVIX	0.387 (0.046)	-0.123	0.692	-0.079	1.141
Top Quintile ΔVIX	0.680 (0.031)	-1.012	1.586	-1.259	2.242
Top Decile ΔVIX	0.740 (0.036)	-1.454	1.957	-1.883	2.760
Top 5 Pctl ΔVIX	0.760 (0.041)	-1.896	2.399	-2.621	3.403
	U.S.:U.K.	U.S. returns		U.K. returns	
Low 5 Pctl ΔVIX	0.705 (0.053)	1.492	2.222	1.655	2.234
Low Decile ΔVIX	0.681 (0.043)	1.211	1.793	1.228	1.804
Low Quintile ΔVIX	0.626 (0.038)	0.870	1.419	0.890	1.465
Quintile 2 ΔVIX	0.281 (0.056)	0.326	0.765	0.264	0.882
Quintile 3 ΔVIX	0.281 (0.045)	0.106	0.670	0.061	0.792
Quintile 4 ΔVIX	0.326 (0.052)	-0.112	0.689	-0.096	0.915
Top Quintile ΔVIX	0.669 (0.028)	-1.017	1.599	-0.996	1.675
Top Decile ΔVIX	0.731 (0.032)	-1.453	1.985	-1.452	2.040
Top 5 Pctl ΔVIX	0.762 (0.038)	-1.914	2.417	-1.941	2.516

Table 8: A two-state regime-switching model of the stock-bond return relation

This table reports on the following regime-switching model of the stock-bond return relation:

$$B_{x,t} = \delta_j + \theta_j S_{x,t} + \epsilon_t,$$

where $B_{x,t}$ ($S_{x,t}$) is the 10-year government bond (stock market) return for country x in percentage units; δ_j and θ_j are regime-dependent coefficients to be estimated where j denotes the regime, and ϵ_t is the residual. The regime, s , 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 $j = 0$ or 1 , $\ln(IV_{t-1})$ is the log of the lagged IV (VIX or VDAX), and the c_j 's, and d_j 's are coefficients to be estimated. The sample period is 1992 to 2002. Panel A reports the coefficient estimates, with asymptotic standard errors in parentheses. Panel B shows how the expected regime duration varies with IV, where the expected duration is: $E(D) = \frac{1}{1-p_{ii}}$, $p_{ii} = Pr(s_t = i | s_{t-1} = i)$.

Panel A: Coefficient estimates

Coeff.	U.S. (VIX)		German (VDAX)		U.K. (VIX)	
δ_0	-0.0115	(0.0117)	-0.0012	(0.0106)	-0.0006	(0.0102)
δ_1	0.0506	(0.0125)	0.0429	(0.0080)	0.0413	(0.0111)
θ_0	0.314	(0.0201)	0.289	(0.0260)	0.439	(0.0178)
θ_1	-0.109	(0.0090)	-0.0319	(0.0074)	-0.0702	(0.0093)
c_0	20.32	(4.95)	19.99	(4.13)	17.71	(4.55)
d_0	-5.59	(1.56)	-5.70	(1.34)	-4.91	(1.47)
c_1	-0.174	(3.04)	1.94	(2.53)	-1.86	(2.87)
d_1	1.09	(0.96)	0.501	(0.810)	1.80	(0.944)

Panel B: Expected durations for each regime, in trading days, and VIX/VDAX

Regime, VIX/VDAX	U.S. (VIX)	German (VDAX)	U.K. (VIX)
Regime-zero, 15%	174	96	84
Regime-zero, 25%	11	6	8
Regime-one, 15%	17	28	21
Regime-one, 25%	29	36	52

Table 9: A two-state regime-switching model of the cross-country stock return relations

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

$$S_{y,t} = \kappa_j + \lambda_j S_{x,t} + \epsilon_t,$$

where $S_{y,t}$ is the stock return for country y and $S_{x,t}$ is the stock return from country x in percentage units; κ_j and λ_j are regime-dependent coefficients to be estimated where j denotes the regime, and ϵ_t is the residual. The regime, s , 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 $j = 0$ or 1 , $\ln(IV_{t-1})$ is the log of the lagged IV (VIX or VDAX), and the c_j s, and d_j s 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 asymptotic standard errors in parentheses. Panel B shows how the expected regime duration varies with IV, where the expected duration is: $E(D) = \frac{1}{1-p_{ii}}$, $p_{ii} = Pr(s_t = i | s_{t-1} = i)$.

Panel A: Coefficient 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)
κ_0	0.040 (0.023)	0.032 (0.017)	0.044 (0.025)	0.080 (0.026)	0.037 (0.022)	0.034 (0.025)
κ_1	-0.018 (0.028)	0.003 (0.049)	-0.025 (0.056)	-1.37 (0.202)	0.028 (0.064)	-0.183 (0.140)
λ_0	0.380 (0.044)	0.435 (0.021)	0.212 (0.022)	0.677 (0.026)	0.284 (0.021)	0.446 (0.026)
λ_1	1.13 (0.032)	0.846 (0.040)	0.715 (0.028)	1.82 (0.077)	1.07 (0.043)	1.28 (0.061)
c_0	16.57 (3.80)	29.05 (13.42)	8.12 (1.91)	25.72 (3.40)	9.08 (1.56)	13.79 (3.06)
d_0	-5.14 (1.22)	-8.25 (3.86)	-2.18 (0.56)	-6.96 (0.957)	-2.42 (0.46)	-3.59 (0.84)
c_1	-3.06 (2.63)	4.66 (12.68)	-5.88 (3.96)	-18.17 (12.57)	-10.70 (5.73)	-12.44 (5.53)
d_1	1.26 (0.78)	-1.11 (3.47)	1.79 (1.10)	4.28 (3.25)	3.03 (1.56)	3.20 (1.46)

Panel B: Expected durations for each regime, in trading days, 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%		15	820	10	965	14	59
Regime-zero, 25%		2.0	13	4.0	29	4.6	10
Regime-one, 15%		2.4	6.2	1.4	1.0	1.1	1.0
Regime-one, 25%		3.7	4.0	1.9	1.1	1.4	1.1

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 original VIX series (currently denoted as VXO by the CBOE). 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.

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

Appendix A: 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 IV level and the subsequent stock-bond correlation 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 confirm the positive relation between cross-country stock correlations and lagged IV. 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.

Next, we also analyze the magnitude of the correlation variations in Tables 2 and 4 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.

We estimate H-statistics for the stock-bond correlations as a function of lagged IV, as follows. 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. Using bootstrapping to estimate standard errors for the differences between the quintile correlations and the overall correlations, we can reject a null of “no difference in correlations” at a 0.1% p-value.

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. Thus, we choose to estimate an H-statistic for the U.K.:German stock comovements as a function of the lagged VIX, because neither market is a “shocked market” relative to the other. (Note that in Table 5 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.) We compute an H-statistic using the average 22-trading-day correlation for each VIX-quintile from Table 4 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. Using bootstrapping to estimate standard errors for the differences between the quintile correlations and the overall correlations, we can reject a null of “no difference in correlations” at a 0.1% p-value.

Next, recall that our results in Tables 2 and 4 report on 22-day rolling correlations. Here, we investigate whether the correlation-IV relation is fairly uniform across the 22-day period, or whether the correlations exhibit substantial reversion over the 22-day period to their overall average value (as time passes from the IV observation). To investigate this question, we repeat the exercise depicted in Tables 2 and 4, except we use shorter rolling periods to calculate the correlation that follows the respective IV value. We calculate five different rolling 5-day correlations using days $t + 1$ to $t + 5$, $t + 6$ to $t + 10$, $t + 11$ to $t + 15$, $t + 16$ to $t + 20$, and $t + 21$ to $t + 25$, where day t has the respective IV observation that is used in the sort. We calculate the 5-day correlations using equation (1), except with only five return observations.

We find the following. First, for the stock-bond correlations, the correlations following the IV condition revert very modestly towards the overall average 22-trading-day correlation. For example, following the highest 20% of VIX observations, the average of the three countries’ 5-day stock-bond average correlations is -0.230 for the “day $t + 1$ to $t + 5$ ” correlations and -0.171 for the “day $t + 21$ to $t + 25$ ” correlations. Following the lowest 20% of VIX observations, the average of the three countries’ 5-day average correlations varies little, within a narrow range of 0.469 to 0.496.

For the cross-country stock-stock correlations, the correlations following the IV condition revert modestly towards the overall average 22-trading-day correlation (but with more reversion than the comparable stock-bond correlation reversion). For example, following the highest 20% of VIX observations, the average of the three countries’ 5-day average correlations is 0.649 for the “day $t + 1$ to $t + 5$ ” correlations and 0.562 for the “day $t + 21$ to $t + 25$ ” correlations. Following the lowest 20% of VIX observations, the average of the average 5-day correlations across the three countries is 0.348 for the “day $t + 1$ to $t + 5$ ” correlations and 0.403 for the “day $t + 21$ to $t + 25$ ” correlations.

To conclude, the correlation differences following high and low IV events are evident for all the five different 5-day rolling periods following the IV event. There is only a modest reversion towards the overall 22-trading-day average correlation as time passes from the IV event in day t . These results suggest that the 22-trading-day period is a good choice for our main empirical work reported in Tables 2 and 4.

Appendix B: Bootstrap Methods

B.1. Differences in average 22-trading-day correlations. We use bootstrapped distributions for inference when analyzing the differences in the 22-trading-day correlations with IV (Tables 2 and 4). We analyze whether the average 22-trading-day correlations following extreme IV conditions are reliably different than the overall average 22-trading-day correlation. In the discussion here, we focus on each extreme IV quintile.

Our bootstrap method proceeds as follows. To begin with, we calculate non-overlapping 22-trading-day correlations by stepping through the data in 22-trading-day steps with the first correlation calculated from days 2 to 23 with the IV condition at day 1 (the second correlation covers days 24 to 45 with the IV condition at day 23, etc). Next, we sort the resulting set of correlations on the preceding day’s IV. Then, from the respective set of correlations following the high IV quintile (low IV quintile), we randomly draw correlations with replacement until the number of correlations equals the number of correlations in the original IV subset. Then, we calculate the average of the drawn correlations. Likewise, we make draws from the entire set of the non-overlapping 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 quintile (low IV quintile) and the average correlation for the entire sample and retain the difference. We then repeat this cycle 100 times to generate 100 different observations of the “difference in the average correlations”.

Next, we repeat this above process, except we move the starting day for the first correlation to day 3 so the first correlation covers days 3 to 24 with the IV condition at day 2 (the second correlation covers days 25 to 46 with the IV at day 24, etc). This step also yields 100 observations of the “difference in the average correlations.”

We then repeat the basic process for the remaining 20 different starting days for the measured 22-trading-day correlations, where each different starting day yields 100 observations of the “difference in the average correlations”. Thus, when we are finished, we have 2200 observations of the “difference in the average correlations”. Note that this makes the process a “block bootstrap” process, in the sense that each cycle that generates an observed “difference in the average correlations” has only one IV event and one subsequent correlation per month (22-trading-day period).

We then use the distribution of the 2200 observations for inference. For example, for the U.S. stock-bond

case, the inner 98th percentile of the “difference in average correlations” is 0.160 to 0.429 (-0.611 to -0.155) when comparing the low IV quintile (high IV quintile) average 22-trading-day correlation to the overall average 22-trading-day correlation. Our bootstrapped distributions indicates that the average stock-bond correlation for each IV quintile is different than the overall average correlation at a 0.1% p-value for all three countries.

For the cross-country stock-stock 22-trading day correlations, our bootstrapped distributions indicate that the average correlations for each extreme IV quintile is different than the overall average correlation at a 1% p-value for the U.K:German case, 5% p-value for the GM:US case, and 10% p-value for the U.S.:U.K. case. We perform a similar bootstrap but analyze whether the average correlation for the high IV decile is different than the average correlation for the low IV decile. For this case, our results indicates that the average correlations are statistically significantly different at a 0.1% p-value for the UK:GM and GM:US case and a 1.1% p-value for the UK:U.S. case.

We also use bootstrap methods to calculate the standard errors for the different average 22-trading-day correlations, as reported in Tables 2 and 4. We make draws with replacement from the available IV subset of 22-trading-day correlations until we have drawn n correlations where n is the number of correlations in the particular IV subset. We then compute the average of the drawn correlations. We repeat this cycle 500 times to come up with a distribution of average correlations and compute the standard error of this set of 500 “average correlation” observations. The standard errors for the average correlations seem modest, ranging from 0.009 to 0.025 for the stock-bond cases and from 0.005 to 0.020 for the stock-stock cases.

B.2. Differences in correlations for different IV-change observations. We also use bootstrap methods for inference to analyze the differences in correlations for the different IV-change conditions (Table 7). We investigate whether the correlation for each extreme ΔIV quintile is different than the correlation for the inner 60th percentile ΔIV condition. To begin with, we make random draws, with replacement, of the actual return pairs for a given ΔIV criteria. 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 correlation between each extreme ΔIV quintile set and the inner 60th percentile ΔIV set. We repeat this process for 1000 cycles to generate a distribution of the respective “difference in correlations”.

We find the following. For the three stock-bond cases and the three stock-stock cases in Table 7, the bootstrapped distributions indicate that the correlations for each extreme ΔIV quintile are statistically significantly different than the correlation for the inner 60th percentile ΔIV observations at a 1% p-value or better.