Master Thesis Finance

The Variance Risk Premium in an International Setting

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1. Introduction

Fluctuations in risk aversion levels have been frequently mentioned as a possible factor explaining financial (in)stability. One popular indicator of risk aversion is the so-called variance risk premium, which is defined as the difference between realized variance and implied volatility squared. In theory, an increase in investor risk aversion should coincide with increasing financial instability. Indeed, Coudert and Gex (2006,2008) show that risk aversion does tend to increase before financial crises.

The main purpose of this study is to show the relationship between the variance risk premium and financial instability. In principle, we would expect this relationship to be positive. I compute the variance risk premia for an international sample consisting of major stock market indices and test its predictive power on stock market crisis and financial stability. In this study, I start from the assumption that implied volatility indices contain information about risk aversion, once it is "cleansed" from the effect of physical volatility dynamics.

The measurement of the variance premium is not straightforward however, since it depends on an estimate of the conditional variance of stock returns. Multiple measures have been proposed in the literature (see, for example, Bekaert and Hoerova, 2014; Andersen, Bollerslev, Diebold and Labys, 2003; Londono, 2011; Bollerslev, Tauchen and Zhou, 2009), but none of them has been unanimously agreed upon to be the most efficient. I develop and test four different conditional variance estimates and select the best one in terms of forecasting efficiency. The variance risk premium is then calculated as the difference between the estimated conditional variance and the implied volatility. I then successively regress stock market returns, a stock market crisis dummy, and a financial instability indicator, on this measure of the variance risk premium. Besides, I also analyze the predictive power of the implied volatility and the realized variance on the same dependent variables. While I find a positive relation between the variance premium and returns on a monthly horizon, I find a negative relation between implied volatility and realized variance on the one hand and equity returns on the other. The implied volatility coefficient is significant up to a horizon of 1.5 years, while the realized variance coefficient predicts returns up to a horizon of five months. Additionally, I find the variance premium to be able to predict stock market crashes on a one-month horizon. The higher (lower) the variance risk premium in the current period, the lower (higher) the probability of a stock market crash in the next month. Finally, the variance premium is unable to predict any of the variation in the level of financial instability. The implied volatility on the other is a very strong predictor of financial instability.

The paper then continues with certain alternative regressions which analyze the role of the variance risk premium in predicting returns. For example, I find no evidence for the US variance premium to be a better predictor of returns than local variance premia. Nor do I find the global variance risk premium to outperform the simple local variance premia in terms of predicting stock returns. Nonetheless, the fact that I find similar results for all regressions, namely that the variance risk premium can predict equity returns for a one-month horizon, makes the results fairly robust. Even when I apply a different econometric methodology, in the form of a panel regression, to calculate the variance premium coefficient, I find it to be positive and significant at the monthly horizon.

The final section of the paper analyzes the cross-country moving variance premia correlations. It has been shown in the literature that correlations between markets increase during periods of crisis. Indeed, I do provide convincing evidence that cross-country VRP correlations are higher during crisis periods.

The remainder of the paper is organized as follows: section 2 studies and compares the existing literature on the topic. Section 3 provides a description of the data and analyzes its descriptive statistics. Section 4 sets out the econometric framework, in which it discusses various models to forecast the realized variance and points out potential econometric issues. The results of the regressions are also discussed in Section 4. Section 5 specifically analyzes the US variance premium. Section 6 looks at the global variance risk premium. Section 7 studies the moving cross-country variance premium correlations. Section 8 summarizes and concludes.

2. Related literature

Many authors have linked statistical measures of volatility to stock market returns. For example, it has become a general understanding that volatility increases as stock markets go down. French, Schwert and Stambaugh (1987) show that a positive shock in volatility causes future expected risk premiums to go up, resulting in lower stock prices. Schwert (2011) finds that stock volatility increases both during recessions and around major financial crises. Danielsson, Valenzuela, and Zer (2016) study the effects of volatility on financial crises. They find that relatively low volatility increases the likelihood of a banking crisis, while both relatively low and relatively high volatility increase the probability of a stock market crash. The effect of low volatility is particularly strong if it persists for a period of 5 years or more, while the effect of high volatility is significant only for much shorter lags, up to two or three years.

By comparing statistical and implied measures of volatility, researchers are able to determine the volatility risk premium. Some authors have interpreted the variance risk premium as a risk aversion indicator (Bakshi and Madan, 2006; Bollerslev, Gibson and Zhou, 2008). Bakshi and Madan (2006) argue that the desire of rational risk-averse investors to buy protection is what causes the volatility spreads. Rosenberg and Engle (2002) have also related variance risk premia to notions of aggregate market risk aversion. Another strand of literature interprets the variance risk premium as being a result of macroeconomic uncertainty risk. Drechsler and Yaron (2011) argue that market participants are willing to pay a premium for assets with high payoffs when return variation is large, causing the variance premium to be essentially always positive. They find that when the danger of big economic shocks is perceived to be high, the hedging premium increases, resulting in a large variance premium.

Typically, the volatility risk premium is calculated as the difference between implied volatility and a projection of realized volatility over the same horizon. Implied volatilities can be derived from a chain of option prices without using a specific pricing model, like the Black-Scholes formula (see, for example, Jiang and Tian, 2005; Britten-Jones and Neuberger, 2000). The use of model-free implied volatilities provides a superior estimate of risk-neutral future market volatility expectations than does the standard Black-Scholes model (Bollerslev, Gibson and Zhou, 2008; Carr and Wu, 2008).

Realized variance on the other hand, is measured as the sum of squared returns over a particular period, usually a month. Several authors (Andersen, Bollerslev, Diebold and Ebens, 2001; Andersen Bollerslev, Diebold and Labys, 2003; Barndorff-Nielsen and Shephard, 2002) have documented that intraday returns yield much more accurate ex post observations on the true return variation than the more traditional sample variances based on daily or coarser frequency return observations. Forecasting realized variance is not without controversy. Corsi (2004) proposes an HAR-RV model[1], in which one-month-ahead volatility is forecasted by a linear function of the current daily, weekly, and monthly realized volatilities. Bollerslev, Tauchen and Zhou (2009), rely on a similar reduced form HAR-RV model while Andersen, Bollerslev, and Diebold (2007) extent the HAR-RV model by including jump components. Bekaert and Hoerova (2014) combine continuous and jump volatility components and a potential leverage effect (see Bekaert and Wu, 2000) to forecast realized variance. Martens and van Dijk (2006) contribute to the econometric literature by developing the realized range, which uses intraday high and low observations in order to estimate realized variance. Finally, Carr and Wu (2008) quantify the variance risk premium as the difference between the realized variance and the variance swap rate. Essentially, the variance premium is the expected premium from selling variance swap contracts on the stock market.

Bollerslev, Tauchen and Zhou (2009) find empirical evidence that stock market returns are predictable by the variance risk premium, with the largest predictability at the quarterly horizon.

[1] "HAR-RV" stands for Heterogenous Autoregressive model of Realized Volatility and is based on the so called "Heterogenous Market Hypothesis".

Likewise, Zhou (2009) provides empirical evidence that the variance risk premium can significantly predict equity returns, bond returns, forward premiums, and credit spreads. The predictability is highest around one month and declines as the forecasting horizon increases. Bollerslev, Gibson and Zhou (2010) confirm the predictive power of the variance risk premium on stock returns and claim that it outperforms all other macro-finance variables, including the P/E ratio, as predictors of stock market returns up to 3 months. In contrast, Bekaert, Hoerova and Scheicher (2009) do not find any significant coefficients when they regress stock market returns on risk aversion[2]. Bekaert and Hoerova (2014) find that the variance premium is a significant predictor of stock returns, while the conditional variance mostly is not. However, they also conclude that the variance premium underperforms the conditional variance as a predictive indicator for financial instability. Ordinary stock volatility has been more extensively linked to financial stability in many settings (see, for example, Fornari and Mele, 2013; Danielsson, Valenzuela, and Zer, 2016).

Bekaert, Hoerova and Lo Duca (2013) link the variance premium to monetary policy and show that they are strongly related, suggesting that movements in the federal funds rate have an effect on risk aversion.

The vast majority of the literature that investigates the variance risk premium focuses on US data. The first reason is that the implied volatility index with the longest data history is the VIX index, which provides model-free implied volatility data based on S&P500 options. The second reason is that high frequency return data is more easily available for the S&P500 index than for other developed stock market indices. Bollerslev, Marrone, Xu, and Zhou (2014) and Londono (2011) extend the research on the variance risk premium to an international sample of eight different countries. Bollerslev, Marrone, Xu, and Zhou (2014) find that the relationship between stock market returns and variance risk premia also holds for the other countries, albeit with lower statistical significance than for the US. Moreover, they also claim that the global variance risk premium provides even stronger predictability for all countries in the sample. Londono (2011) on the other hand provides contradictory evidence, claiming that apart from the US and Belgium, local variance premiums do not predict local equity returns. What's more, he claims that the predictive power of the US variance premium over international equity returns outperforms local variance premia.

This paper adds to the literature not only that it extends the research on the variance premium to an international sample, it also links the variance risk premium to both stock market returns as well as financial instability indicators. Besides, it compares various realized variance forecasting methodologies from previous studies. Finally, whereas many papers focus solely on either the variance risk premium, realized variance or implied volatility, I aim to compare the predictive power of all of them.

3. Data description and summary statistics

In order to be able to estimate the realized variance I need return data for different financial markets. While the literature is rather confident as to the fact that high frequency data outperforms daily or sparser return data when it comes to estimating realized volatility (see, for example, Andersen, Bollerslev, Diebold, and Ebens, 2001; Barndorff-Nielsen and Shephard, 2002; Meddahi, 2002), I will use daily return data. High frequency data is available at a sufficiently long enough timespan only for the S&P500 index. I obtain daily return data from Datastream for the US S&P 500, the German DAX 30, the French CAC 40, the UK FTSE 100, the Dutch AEX 25, the Japanese Nikkei 225, and the Swiss SMI 20 index. Thus, my sample covers the three largest traditional economic regions in the world, namely Japan, the United States, and Western Europe. The sample spans the period from January 2000 to May 2017 and includes 4520 daily return observations. The sample includes both the crash of the dotcom bubble in 2001 and the global financial crisis in 2008. Table 1 includes the summary statistics on the daily return observations for all seven countries. The DAX 30 has the highest average daily return over the period (0.04%) while the NIKKEI shows the lowest average daily

[2] Bekaert, Hoerova and Scheicher (2009) refer to the difference between implied and conditional variance as "risk aversion"

return over the same period (0.005%). The daily return correlations are highest among the Western European countries. The Japanese NIKKEI index has very low correlations with the European indices and an even lower correlation with the S&P 500.

Table 1: Summary statistics daily return observations

	DAX	CAC40	FTSE100	AEX	NIKKEI	SMI	SP500
			Summary statistics				
Mean (%)	0.040	0.026	0.025	0.029	0.005	0.031	0.035
Std. Dev. (%)	1.41	1.36	1.08	1.30	1.47	1.14	1.09
Min (%)	-12.81	-9.04	-8.85	-9.14	-11.41	-10.54	-9.03
Max (%)	11.40	11.18	9.84	10.55	14.15	11.39	11.58
Skewness	-0.10	0.06	0.00	-0.02	0.03	-0.21	-0.09
Kurtosis	5.95	5.04	6.33	6.95	6.18	7.69	9.43
			Correlation matrix				
DAX	1.00	0.82	0.73	0.82	0.26	0.75	0.51
CAC40		1.00	0.82	0.87	0.27	0.77	0.50
FTSE100			1.00	0.82	0.28	0.74	0.49
AEX				1.00	0.28	0.79	0.49
NIKKEI					1.00	0.28	0.12
SMI						1.00	0.44
SP500							1.00

The table reports the summary statistics for the daily stock market returns for the seven countries considered for the sample period January 2000 to May 2017.

For the risk-neutral expectation of return variance, I use the corresponding implied volatility indices for each of the countries in the sample. The implied variance between time *t* and *t+1*, conditional on information available at time *t*, can be expressed as the following function in a model free fashion,

$$IV_{t,t+1} = 2\int_0^\infty \frac{C_t\left(t+1\frac{K}{B(t,t+1)}\right) - C_t(t,K)}{K^2} dK$$

where $C_t(t,K)$ denotes the price of a European call option with strike *K* and maturity *T*, and $B(t,T)$ denotes the price of a zero coupon bond at time *t* with maturity *T* (see Britten-Jones and Neuberger (2000); Demeterfi, Derman, Kamal, and Zou (1999); Carr and Madan (1998) for more detailed information on the model free implied volatility measurement). The model free approach is also a much more efficient and statistically more reliable method to estimate the variance risk premium than are estimates based on the Black-Scholes formula, as is demonstrated by Bollerslev, Gibson, Zhou (2010). The data for the implied volatility indices is obtained from Datastream and covers the period from January 2000 to May 2017. Euronext provides implied volatility indices for France, the UK and the Netherlands only from 2000 onwards. Even though the other markets have more extensive implied volatility data, I focus my empirical analysis on the period between January 2000 and May 2017 for comparative purposes. I collect implied volatility data for the S&P 500 (VIX), DAX 30 (VDAX), CAC 40 (VCAC), FTSE 100 (VFTSE), AEX 25 (VAEX), SMI 20 (VSMI), and NIKKEI 225 (VXJ). Table 2 provides summary statistics for each of the implied volatility indices. The Japanese VXJ shows the highest mean implied volatility (24.94%), while the Swiss SMI has the lowest average implied volatility (19,39%); a difference of more than 5%. The cross-country correlations show the same relationship as for the daily returns, with the correlations among the Western Europe countries being the highest, and the correlation between the German DAX and the Japanese VXJ being the lowest, albeit still rather high at 0.65.

Table 2: Summary statistics implied volatility indices

	VDAX	VCAC	VFTSE	VAEX	VXJ	VSMI	VIX
			Summary statistics				
Mean (%)	22.89	23.27	19.96	23.13	24.94	19.39	19.57
Std. Dev. (%)	9.41	8.82	8.57	10.39	8.50	8.05	7.83
Min (%)	9.35	0.43	6.19	5.77	7.99	8.81	9.31
Max (%)	83.23	78.05	75.54	81.22	92.03	84.9	80.86
Skewness	1.74	1.68	1.85	1.82	2.11	2.13	2.10
Kurtosis	3.89	4.02	5.04	3.84	9.26	6.59	7.64
			Correlation matrix				
VDAX	1.00	0.97	0.93	0.97	0.65	0.95	0.87
VCAC		1.00	0.95	0.96	0.73	0.94	0.90
VFTSE			1.00	0.94	0.79	0.96	0.94
VAEX				1.00	0.74	0.96	0.89
VXJ					1.00	0.79	0.72
VSMI						1.00	0.89
VIX							1.00

The table reports the summary statistics for the implied volatility indices for the seven countries considered for the sample period January 2000 to May 2017. All implied volatility indices are obtained from Datastream.

4. Econometric framework

In this section, I develop the econometric framework in which I first estimate and forecast the realized variance, based on four different models. I then calculate the variance risk premium as the difference between the implied variance and the estimated value of the realized variance. Finally, I investigate the relationship between the variance risk premium on the one hand, and stock market returns, a crisis dummy variable, and financial stability on the other hand.

As indicated before, high frequency data provides more accurate realized return estimates than does daily data. However, due to data restrictions for countries other than the US, I am constrained to using daily return data. I calculate realized variance as the sum of squared daily returns within a month (See Andersen et al 2003).

$$rv_{j,t} = \sum_{t_i=1}^{N_t} (r_j, t_i)^2$$

The variance risk premium is defined as the difference between the ex-ante risk neutral expectation of the future return variance and the statistical expectation of return variance from time *t* to time *t+1*.

$$VRP_t = E_t^Q\left(Var_{t,t+1}\right) - E_t^P\left(Var_{t,t+1}\right)$$

The ex-ante risk neutral expectation of realized variance can be observed through the implied volatility indices. The risk-neutral expectation of realized variance is determined as the end-of-month squared IV index de-annualized $\left(\frac{IV^2}{12}\right)$. The statistical expectation of return variance from time *t* to time *t+1*, however, has to be forecasted because it cannot be observed directly. Hence, I forecast the statistical expectation of return variation using four different forecasting models. This not only provides a robustness check, but it also makes the results more comparable to those in the existing literature. In this procedure, I follow Londono (2011). The advantage of the martingale assumption is that it does not actually require forecasting, because under the martingale assumption the expected realized variance can be observed directly.

The first model I test is a simple first order autoregressive forecast AR(1) as in the following equation:

$$rv_{j,t+1} = \gamma_0 + \gamma_1 rv_{j,t} + \epsilon_t$$

The second model is the martingale measure in which the expected realized variance is estimated as the current realized variance ($E_t(RV_{t+1}) = RV_t$). Bollerslev, Tauchen and Zhou (2009) measure stock return realized variance as a martingale model and Londono and Zhou (2017) use the martingale assumption to estimate currency variance risk premiums. That is, they calculate the variance risk premium by subtracting the squared IV index from the previous month's realized variance.

The third estimate of the forecasted realized variance includes the local IV index as in:

$$rv_{j,t+1} = \gamma_0 + \gamma_1 rv_{j,t} + \gamma_2 iv_{j,t} + \epsilon_t$$

Drechsler and Yaron (2011) have demonstrated that including the implied volatility index as a predictor variable increases the predictive power. Additionally, Busch et al. (2011) have also used implied volatilities as a predictive variable for similar forecasting exercises and show that it contains information with respect to future realized volatility. Since implied volatility itself also contains a risk premium, it is obviously not an unbiased predictor of future realized variance.

Finally, the fourth approximation of expected realized variance includes the range-based variance for each country as in the following equation:

$$rv_{j,t+1} = \gamma_0 + \gamma_1 rv_{j,t} + \gamma_2 RangeV_{j,t} + \epsilon_t$$

where $RangeV_{j,t}$ is the range-based variance calculated as:

$$RangeV_{j,t} = \frac{1}{4\ln 2}\sum_{t_i=1}^{N_t} range_{t_i}^2$$

The realized range measures realized variance by summing high-low ranges at intra-day level. In theory, the realized range should improve the realized variance estimate (see Parkinson, 1980 and Martens and van Dijk, 2006 for a more detailed description of the realized range).[3]

When forecasting the realized variance, I take into account the possible statistical problems of autocorrelation and heteroscedasticity. The ACF for the realized variance series of each country reveals that there is autocorrelation between one and five lags, with an average of three lags. Hence, I opt to use heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimation with five lags for all countries. In order to determine the most accurate forecasting model I examine three different criteria. I compute the root-mean-squared error (RMSE), the mean absolute error (MAE), and the R^2 in the regression of the observed values on their forecasted values. Table 3 shows the different measures of forecasting performance. The indicator that includes the local implied volatility, henceforth called the "IV estimate", shows by far the best results in terms of forecasting performance. The superiority of the IV measure is consistent across all seven indices and across all three measures of forecasting performance. The martingale method performs the worst as it has the highest errors and lowest R^2. The AR(1) model and the realized range model perform rather similar, although the realized range indicator has slightly better results. In general, the forecasting performance is highest for the US SP500 and lowest for the Japanese NIKKEI index. For the rest of the paper, I will continue to report the results based on the IV estimate, as this proves to be the most accurate estimator of realized variance. For the other VRP estimators any noteworthy findings will be briefly discussed in the text.[4]

As previously explained, the variance risk premium is defined as the difference between the realized variance and the implied volatility squared. Based on the four different realized variance estimations, the variance risk premium can be estimated. Table 4 shows the summary statistics for the variance premium as measured by the IV estimate and the other three measures. On average, I find the variance premium to be positive for all countries in the sample, which is consistent with the existing literature (e.g., Bollerslev, Tauchen and Zhou, 2009; Zhou, 2009; Drechsler and Yaron, 2011). The average variance risk premium ranges from 4.54% for the French CAC40 index to 10.06% for the Japanese NIKKEI index. Furthermore, I find the variance premium to be negatively skewed. The large

[3] Intra-day high and low data for each country is obtained from Datastream.

[4] Tables and graphs for the other three realized variance forecasting measures are available upon request from the author.

Table 3: Forecasting performance for realized variance[5]

	AR(1)			IV			Martingale			Range		
	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2
DAX	50.16	26.00	0.39	**31.16**	**16.41**	**0.76**	55.73	26.14	0.24	50.14	25.88	0.39
CAC40	48.48	25.95	0.38	**35.46**	**17.66**	**0.67**	53.97	26.76	0.23	47.83	25.05	0.40
FTSE100	38.81	19.15	0.36	**27.82**	**13.39**	**0.67**	43.43	19.68	0.20	38.65	18.38	0.36
AEX	54.13	27.21	0.42	**37.23**	**17.52**	**0.73**	59.62	27.36	0.30	53.72	26.40	0.43
NIKKEI	72.14	29.54	0.11	**32.10**	**17.66**	**0.82**	88.65	31.49	-0.35[6]	64.56	31.64	0.28
SMI	43.57	21.12	0.20	**27.69**	**13.42**	**0.68**	51.15	21.90	-0.10[6]	41.94	19.49	0.26
SP500	39.99	19.19	0.50	**29.45**	**14.11**	**0.73**	43.29	19.52	0.42	39.93	19.04	0.50
Average	49.61	24.02	0.34	**31.56**	**15.74**	**0.72**	56.55	24.69	0.13	48.11	23.70	0.37

The table shows the forecasting performance of the realized variance forecasts for the seven countries in the sample for the period from January 2000 to May 2017. For each country, the highest value for the R^2 and the lowest values for the RMSE and MAE are reported in bold.

negative minimal values as well as the large positive excess kurtosis, indicate that certain negative outliers have a large weight in the sample. The graphs in Figure 1 suggest that these large negative values for the variance risk premium all occurred during the global financial crisis in 2008 and 2009. For all three other estimates considered, all variance risk premia are positive on average as well. The characteristics of large positive excess kurtosis and negative skewness also hold under the other VRP estimates. Under all four measures, the mean VRP is highest for the NIKKEI. At the same time, the NIKKEI also has the largest kurtosis, the largest negative skew and the largest negative minimum VRP value. Finally, it is worth noting that all variance risk premium estimates display significant deviation from normality. On average, there is a large difference between the mean and median, skewness is predominantly negative, and kurtosis is much larger than 3.

The realized variance (blue), calculated according to the forecast which includes the local implied volatility index, the implied volatility indices squared (green), and the variance risk premia (red) are plotted in Figure 1 for each country separately. Several spikes in the level of the VRP can be observed. The first one occurs during the bear market in 2002-2003, the second one occurs around the global financial crisis in 2008, and the third and last one happened in response to the European sovereign debt crisis in late 2011. Just from observing the graphs it seems that the correlations with respect to the realized variance and the implied volatility squared are particularly large among the European markets.

[5] Forecasting performance is based on in-sample testing.

[6] Negative r-squared values can occur when the regression doesn't have an intercept and when the model performs arbitrarily worse.

Table 4: Summary statistics variance risk premium

Panel A: IV estimate

	VRP-DAX	VRP-CAC	VRP-FTSE	VRP-AEX	VRP-NIKKEI	VRP-SMI	VRP-SP500
Summary statistics							
Mean (%)	6.60	4.54	7.79	8.21	10.06	5.29	8.38
Median (%)	10.76	9.36	10.31	12.49	14.39	8.50	11.78
Std. Dev. (%)	31.63	33.51	26.05	37.77	58.14	23.43	36.16
Min (%)	-176.60	-187.29	-171.88	-222.86	-667.93	-158.44	-244.68
Max (%)	130.29	117.22	88.15	166.63	316.60	82.05	254.46
Skewness	-1.70	-1.83	-2.25	-1.63	-7.05	-2.82	-1.13
Kurtosis	9.04	8.95	13.74	11.62	93.71	15.81	24.7
Correlation matrix							
VRP-DAX	1.00	0.94	0.92	0.93	0.57	0.89	0.85
VRP-CAC		1.00	0.93	0.96	0.48	0.84	0.87
VRP-FTSE			1.00	0.95	0.65	0.93	0.90
VRP-AEX				1.00	0.53	0.89	0.84
VRP-NIKKEI					1.00	0.72	0.53
VRP-SMI						1.00	0.79
VRP-SP500							1.00

Panel B- AR(1)

	VRP-DAX	VRP-CAC	VRP-FTSE	VRP-AEX	VRP-NIKKEI	VRP-SMI	VRP-SP500
Summary statistics							
Mean (%)	6.60	4.54	7.79	8.21	10.06	5.29	8.38
Median (%)	2.56	1.34	2.97	2.47	1.49	-0.85	5.45
Std. Dev. (%)	46.72	44.25	37.84	54.63	60.50	35.49	45.77
Min (%)	-324.65	-344.99	-284.90	-394.47	-305.91	-214.55	-385.09
Max (%)	199.65	203.87	146.32	259.37	621.44	186.71	296.99
Skewness	-1.07	-1.83	-1.40	-1.20	5.01	0.40	-1.92
Kurtosis	15.29	21.23	19.49	18.06	55.34	13.23	34.65
Correlation matrix							
VRP-DAX	1.00	0.95	0.94	0.94	0.66	0.92	0.84
VRP-CAC		1.00	0.94	0.96	0.58	0.88	0.84
VRP-FTSE			1.00	0.95	0.72	0.94	0.88
VRP-AEX				1.00	0.61	0.90	0.83
VRP-NIKKEI					1.00	0.77	0.64
VRP-SMI						1.00	0.79
VRP-SP500							1.00

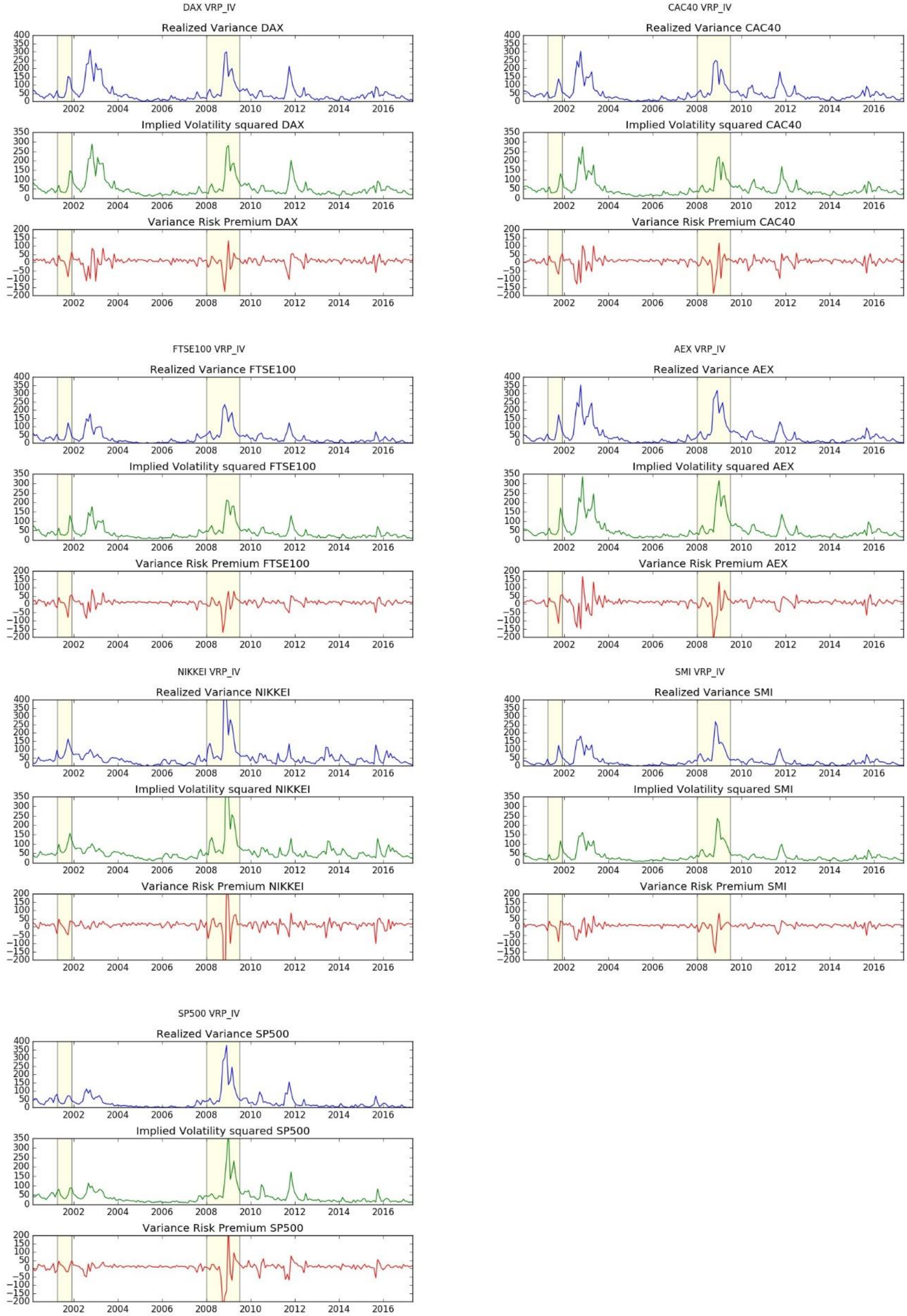
The table reports the variance risk premium summary statistics for the seven countries in the sample for the period from January 2000 to May 2017. The variance premia are calculated using four different realized variance forecasting measures as explained in section 4 and the summary statistics for each of them are divided over four panels.

Table 4: continued

Panel C - Martingale							
	VRP-DAX	VRP-CAC	VRP-FTSE	VRP-AEX	VRP-NIKKEI	VRP-SMI	VRP-SP500
Summary statistics							
Mean (%)	6.90	4.83	8.02	8.40	10.13	5.40	8.52
Median (%)	12.96	10.25	10.55	13.77	15.60	9.18	11.16
Std. Dev. (%)	59.83	59.48	49.79	69.41	87.97	51.95	56.20
Min (%)	-515.22	-555.97	-479.78	-605.49	-941.07	-477.42	-545.32
Max (%)	181.01	190.23	140.15	243.45	547.27	166.87	271.42
Skewness	-4.00	-4.59	-4.91	-3.95	-5.16	-4.42	-4.85
Kurtosis	30.70	39.69	46.04	32.51	72.81	38.87	49.96
Correlation matrix							
VRP-DAX	1.00	0.94	0.93	0.93	0.74	0.93	0.85
VRP-CAC		1.00	0.95	0.96	0.72	0.90	0.86
VRP-FTSE			1.00	0.95	0.81	0.94	0.90
VRP-AEX				1.00	0.71	0.93	0.84
VRP-NIKKEI					1.00	0.79	0.76
VRP-SMI						1.00	0.84
VRP-SP500							1.00

Panel D - Realized range							
	VRP-DAX	VRP-CAC	VRP-FTSE	VRP-AEX	VRP-NIKKEI	VRP-SMI	VRP-SP500
Summary statistics							
Mean (%)	6.60	4.54	7.79	8.21	10.06	5.29	8.38
Median (%)	3.08	2.42	3.61	3.69	6.32	1.47	5.58
Std. Dev. (%)	46.52	42.88	36.61	53.22	66.53	33.71	46.00
Min (%)	-320.13	-310.68	-276.83	-350.43	-223.54	-151.36	-396.93
Max (%)	197.28	194.85	141.40	249.11	614.50	168.34	296.06
Skewness	-1.08	-1.85	-1.58	-1.12	3.77	0.03	-2.12
Kurtosis	14.99	17.38	19.67	14.48	35.79	9.75	36.91
Correlation matrix							
VRP-DAX	1.00	0.95	0.94	0.94	0.58	0.89	0.85
VRP-CAC		1.00	0.93	0.95	0.46	0.86	0.82
VRP-FTSE			1.00	0.94	0.58	0.87	0.87
VRP-AEX				1.00	0.49	0.88	0.81
VRP-NIKKEI					1.00	0.59	0.60
VRP-SMI						1.00	0.71
VRP-SP500							1.00

Figure 1: Estimated realized variances, implied volatilities squared, and variance risk premia



The figures show the realized variance as forecasted by the IV estimator, the implied volatility squared, and the variance risk premium for the sample of seven countries for the period from January 2000 to May 2017. The variance premium is defined as the difference between the realized variance forecast and the implied volatility, as $vp_{j,t} = iv_{j,t}^2 - \left(\widehat{rv}_{j,t+1}\right)^2$*. The shaded areas represent the US recession periods as defined by the NBER.*

4.1 Predicting equity returns

The main interest of this paper is to examine the predictive power of the variance risk premium. The stylized fact that local variance premia can predict local stock market returns has been confirmed mostly for the US stock market[7]. I extend this research and investigate whether the local variance premia in other markets are also able to predict local equity returns. The following regression analyzes the predictive power of the variance risk premium on stock market returns:

$$r_{j,t,t+h} = \gamma_{0,j} + \gamma_{1,j,t} vp_{j,t} + \epsilon_{j,t,t+h}$$

where $r_{j,t}$ is defined as the monthly stock market return for country *j* at time *t* for *h*-months ahead, and $vp_{j,t}$ is the variance risk premium. By using Newey-West standard errors, I correct for the serial correlation in the error terms, which is due to the overlap in the monthly data series. Since the data is at monthly frequency, I opt to include 12 lags. Figure 2 reports the regression coefficients along with the 95% confidence intervals and the adjusted R^2 for a horizon of up to 24 months.[8]

For all countries, the coefficient of the variance risk premium is positive and significant at the one-month horizon. This positive coefficient implies that the larger the variance risk premium, the higher will be the return in the next month. This result is consistent with the findings of Bollerslev, Tauchen and Zhou (2009), who conclude that high (low) variance risk premia predict high (low) future stock market returns. However, in their research they find the predictability to be the strongest at the quarterly return horizon, while I find significance only at the monthly horizon. For longer horizons, the slope coefficient is predominantly insignificant at the 5% confidence level. The adjusted R-squared also peaks at the one-month horizon and then declines toward zero. These results are somewhat comparable to the findings of Zhou (2009), who also finds that the predictive power of the variance risk premium peaks at a one-month horizon and dies out for longer horizons. Overall, I find little evidence for the variance premium to predict equity returns at longer horizons for any of the seven countries in the sample. Londono (2015) shares a similar conclusion as he finds that the local variance premium plays an insignificant role in predicting equity returns, except for the US. While numerous papers, including Londono (2015), Bollerslev, Tauchen and Zhou (2009) and Bollerslev, Gibson, Zhou (2010), find that the US variance premium does predict US equity returns, especially for horizons between three and six months, I find significance only at the one-month horizon. Zhou (2009) on the other hand finds the return predictability to peak around one month.

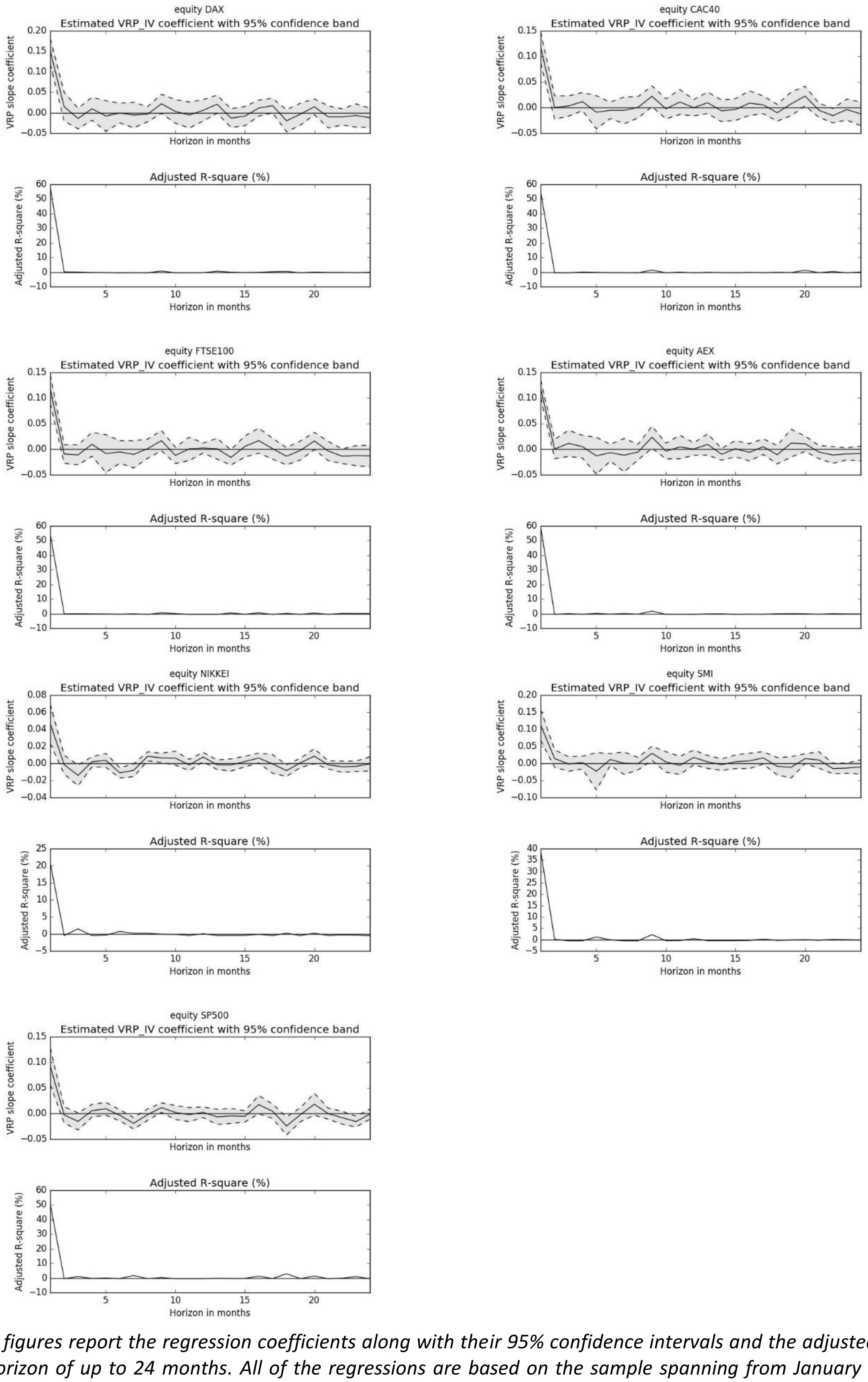
The slope coefficients for the variance premium when the simple autoregressive forecast method, the realized range method, and the martingale method are used, are very similar to those under the IV estimate. That is, all countries show significant coefficients at the one-month horizon.

In addition to the variance risk premium, the local implied volatility index and the realized variance have also been considered as potential predictors of stock market returns. For example, Giot (2005) shows that there is a negative and statistically significant relationship between stock returns and implied volatility indices. Hence, I run the same regression using the implied volatility index and the realized variance as predictor variables instead of the variance premium. Figure 3 reports the coefficients of the implied volatility indices. Clearly, there is a negative relationship between the level of the implied volatility and future stock market returns. Hence, the higher (lower) the implied volatility, the lower (higher) the stock market returns in the next months. For most countries, this relationship is statistically significant at the 5% level up to a horizon of approximately 14 months. The relationship is strongest at the one-month horizon and then slowly decreases toward zero. Similarly, the adjusted R^2 peaks at the one-month horizon and reaches values between 15% and 20%, after which it declines toward zero. At the monthly horizon, the magnitude of the implied volatility coefficient is between -0.2 and -0.3, implying that an increase (decrease) in implied volatility of 1% leads to a decrease (increase) in equity returns for the next month of between 0.2% and 0.3%. At the annual horizon, the magnitude declines to about 0.1%. Overall, there seems to be a

[7] See, for example, Bollerslev, Tauchen and Zhou (2009), Zhou (2009), Bekaert and Hoerova (2014), and Drechsler and Yaron (2011).

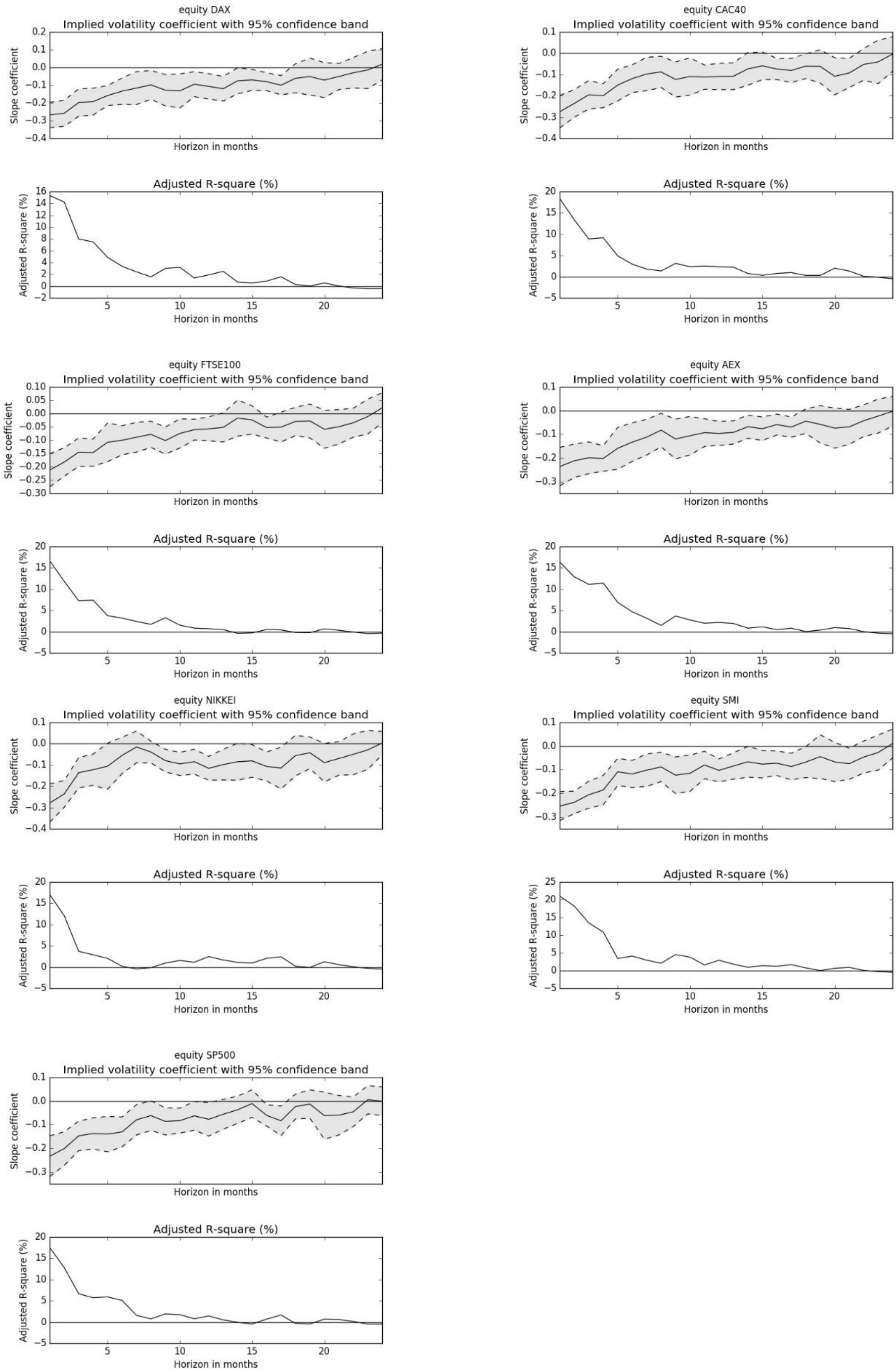
[8] For the interpretation of the results in this section I assume the VRP coefficients to be significant if they have a t-statistic below 5%.

Figure 2: Predictive power of VRP on equity returns



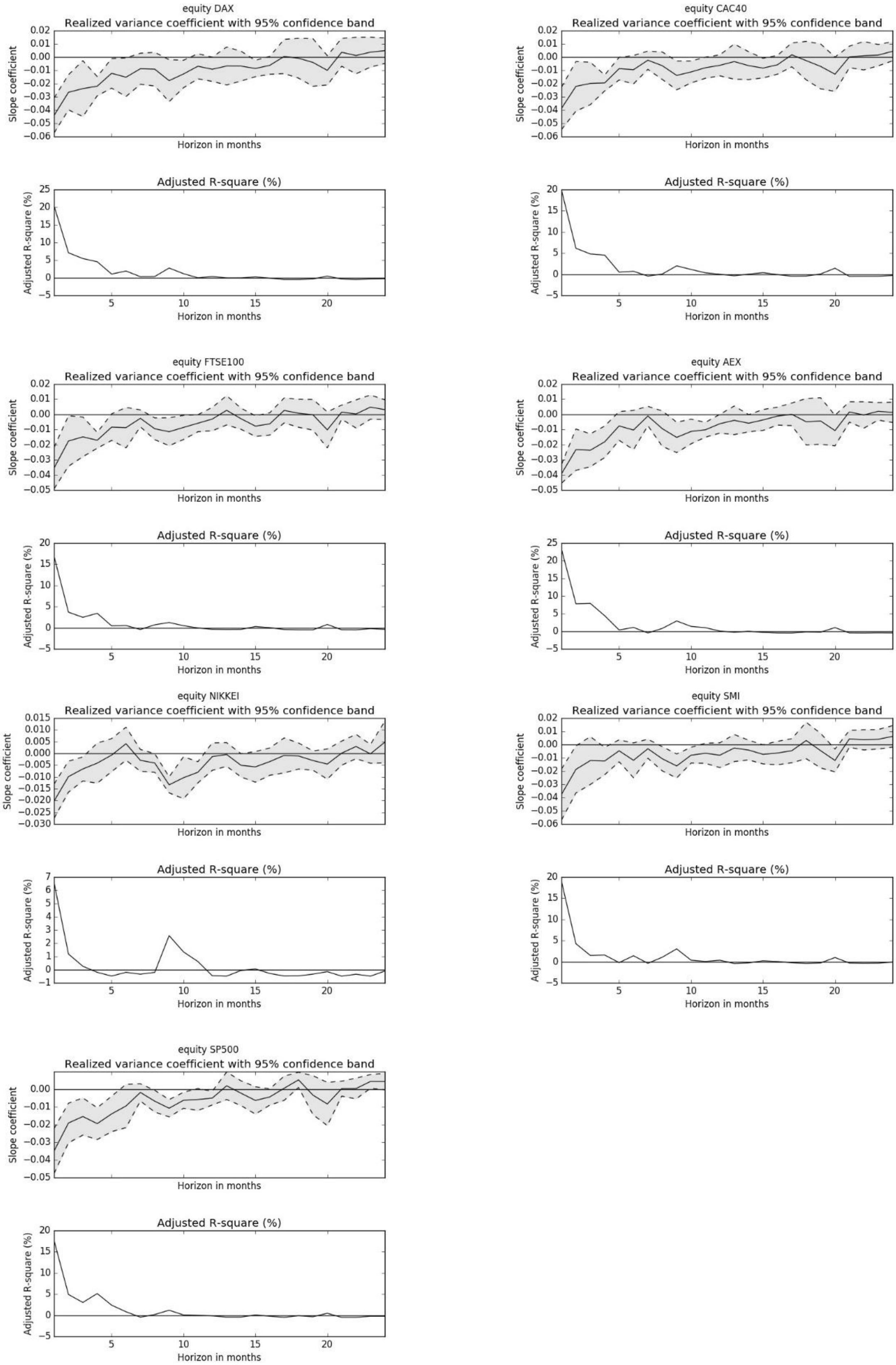
The figures report the regression coefficients along with their 95% confidence intervals and the adjusted R^2 for a horizon of up to 24 months. All of the regressions are based on the sample spanning from January 2000 to May 2017. The VRP is measured as the difference between realized variance, as estimated using the IV measure, and the implied volatility.

Figure 3: Predictive power of implied volatility on equity returns



The figures report the regression coefficients along with their 95% confidence intervals and the adjusted R^2 for a horizon of up to 24 months. All of the regressions are based on the sample spanning from January 2000 to May 2017.

Figure 4: Predictive power of realized variance on equity returns



The figures report the regression coefficients along with their 95% confidence intervals and the adjusted R^2 for a horizon of up to 24 months. All of the regressions are based on the sample spanning from January 2000 to May 2017. The realized variance is calculated as the sum of squared daily returns within a month (See Andersen et al 2003).

much stronger relationship between the implied volatility and equity returns, than between the variance risk premium and equity returns. Similar regressions with implied variance as independent variable yields rather identical results. This stands in contrast to the findings of Bekaert and Hoerova (2014), who claim that the squared VIX fails to predict equity returns.

The regression coefficients of the realized variance are reported in Figure 4. There is a significant negative relationship between the current realized variance and stock returns on a one-month horizon for all countries. On a longer horizon, the realized variance coefficient is significant up to a horizon of 12 months, with some insignificant months in between. The adjusted R-squared peaks at the one-month horizon and then rapidly declines toward zero. Bekaert and Hoerova (2014) come to the same conclusion as they find negative and significant realized variance coefficients at monthly and quarterly horizons. Although the predictive power of the realized variance is less than the predictive power of the implied volatility, it exceeds, on average, the predictive power of the variance risk premium. Where the VRP is statistically significant only at the monthly horizon, both the implied volatility and the realized variance are significant at much longer horizons. In general, implied volatility is a stronger predictor of stock market returns than its two components, the realized variance and the variance risk premium.

4.2 Predicting market crashes

In a second regression, I investigate the predictive power of the variance premium on financial crises, where I take a crisis dummy as the dependent variable. This crisis dummy variable takes a value of 1 if the monthly stock return is below -5%. That is, I define a month with an aggregate stock market return below -5% as a crisis month. The analysis entails the period between January 2000 and May 2017, and the number of crisis months for each country are reported in table 5[9]. The UK index has the lowest number of crisis months (22), while the Japanese index has almost twice as many crisis months (41). Since the dependent variable in this equation is a binary variable, a linear model is not the most efficient. Hence, instead of using OLS, I opt to use a logistic regression model based on the maximum likelihood estimation. The following logistic regression examines the relationship between the variance risk premium and the crisis dummy:

$$Crisis_{j,t,t+h} = \Phi(\gamma_{0,j} + \gamma_{1,j,t} vp_{j,t} + \epsilon_{j,t,t+h})$$

Table 5: Number of crisis months per country

	DAX	CAC	FTSE	AEX	NIKKEI	SMI	SP500
Crisis months (-5%)	32	30	22	32	41	25	24
Crisis months (-10%)	13	11	4	12	10	4	4

The table reports the number of crisis months for each country in the sample during the period between January 2000 and May 2017. A crisis month is defined as a month in which the return is lower than -5%, or lower than 10%.

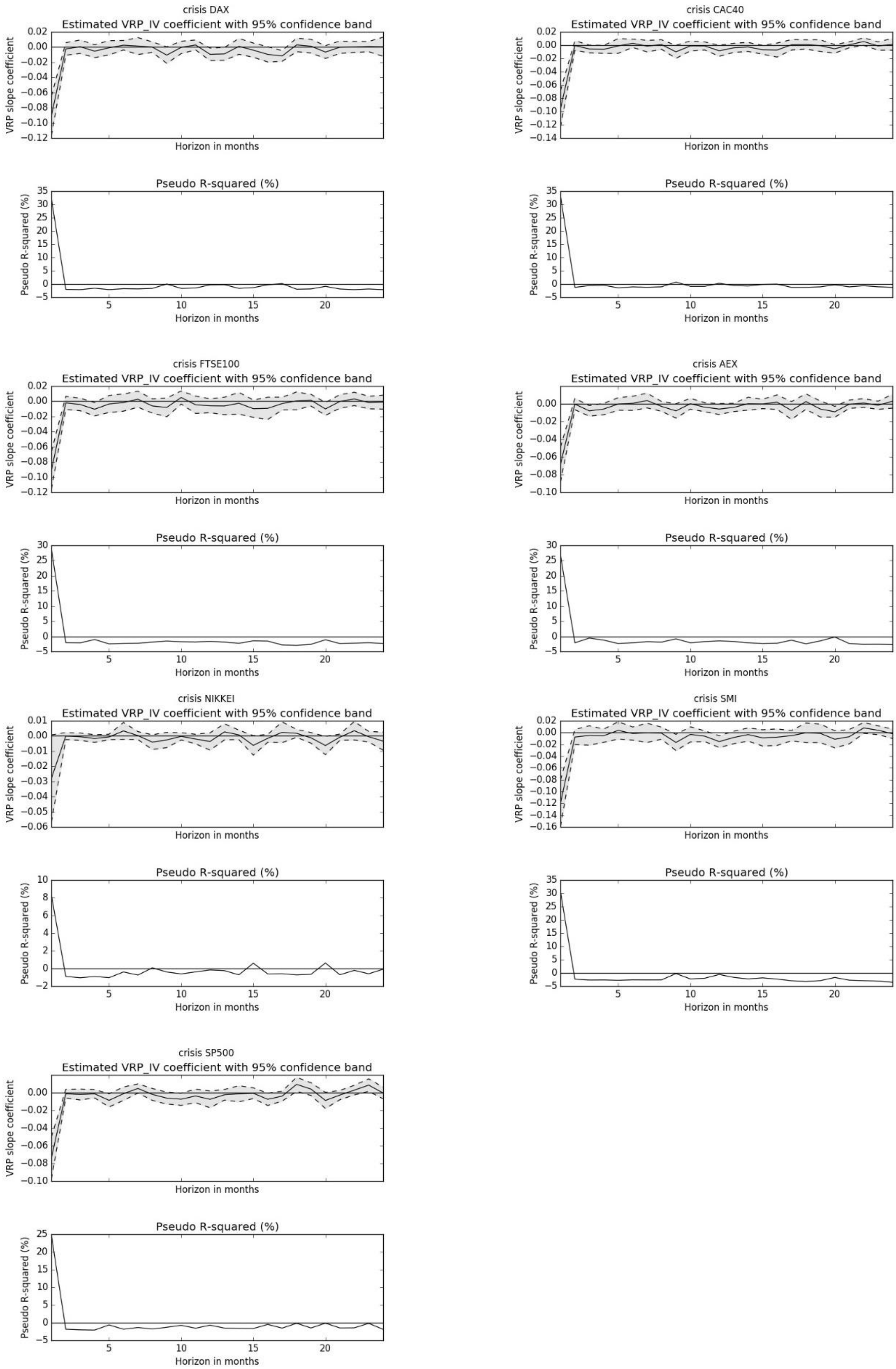
The VRP coefficients, along with their 95% confidence intervals are reported in Figure 5. The standard errors used to determine the confidence interval are heteroscedasticity and autocorrelation robust (HAC) using 12 lags (Newey and West, 1987). In addition, Figure 5 reports the McFadden's R-squared values for the logistic regression.[10] For all countries, the VRP coefficient is statistically significant at the one-month horizon, but not at longer horizons. The negative coefficient at the one-month horizon indicates that the higher (lower) the variance risk premium in the current period, the lower (higher) the probability of a stock market crash of more than 5% in the next month.

When the VRP is measured using either the simple AR(1) method, martingale method, or realized range method, I find significantly negative coefficients at the monthly horizon for all countries except Japan. However, the magnitude of the coefficients and the pseudo R-squared are smaller than under the IV estimate. For the Japanese and Swiss index I find significantly positive

[9] The entire period consists of 207 months.

[10] Refer to McFadden (1974) for further details on the econometric computation of McFadden's R-squared.

Figure 5: Predictive power of variance risk premia on stock market crisis



The figures report the logistic regression coefficients along with their 95% confidence intervals and the Pseudo R^2 for a horizon of up to 24 months. All of the regressions are based on the sample spanning from January 2000 to May 2017. The variance premium is calculated according to the IV estimate, as explained in section 4.

coefficients at the two- and three-month horizon respectively, when the AR(1) method is used.

Like I did in section 4.1, I replace the variance premium with the implied volatility and realized variance and rerun the regression. Again, I use a logistic regression with robust standard errors. With respect to the implied volatility I find negative and significant coefficients for the FTSE100, AEX, and SMI, but only at horizons between 20 and 24 lags. Contrarily, when the crisis dummy is regressed on realized variance I find positive and statistically significant coefficients at the monthly horizon for all countries except Japan.

The results are robust when the threshold value for the crisis dummy is set at -10% instead of -5%. The results are very much similar, even though the standard errors are larger for the -10% crisis dummy because it has fewer crisis observations (see Table 5).

4.3 Predicting financial stability

The main interest of this paper lies in the relationship between the variance risk premium and financial stability. Previously, I have found little evidence for variance risk premia being able to predict either equity returns or stock market crashes. Stock market crashes however, are not a very good proxy for financial instability. A much better indicator of financial instability is the Composite Indicator of Systemic Stress (CISS), which was developed by the European Central Bank. The CISS indicator is based on data from the European Monetary Union and it includes information from the equity, bond, money, and foreign exchange markets, plus some financial intermediaries-related information (see Hollo, Kremer and Lo Duca (2012) for further details on the CISS methodology). It must be noted that the CISS is a European financial stress indicator, which might cause issues when regressing it on non-European measures of the VRP. The following regression estimates the predictive power of the variance premium on financial stability:

$$CISS_{t,t+h} = \gamma_{0,j} + \gamma_{1,j,t} vp_{j,t} + \epsilon_{j,t,t+h}$$

Figure 6, again, plots the regression coefficients, along with their 95% confidence intervals, and adjusted R^2.

The variance risk premium coefficient is not significant at any horizon in any country. The results indicate that the VRP does not predict financial instability as measured by the CISS. The adjusted R-squared peaks at 3% for the Swiss index at the one-month horizon. Apart from that, it is very close to zero for all countries at all horizons. Overall, the variance risk premium as measured by the IV estimate has no predictive power with respect to the CISS indicator. The VRP as measured by the martingale method also doesn't show any significant results.

When the simple autoregressive forecast is used, I find the VRP coefficient to be positive across all countries. However, only for the Swiss SMI and, surprisingly, the Japanese NIKKEI, I find statistically significant VRP coefficients. For both countries, they are significant up to a horizon of 18 months, with some insignificant months in between. The realized range method shows equivalent results to the simple AR method, with significant VRP coefficients up to 18 months for the Swiss and Japanese indices. Especially for the NIKKEI it is noteworthy that there is such a strong predictive power of the Japanese VRP on a European financial stress indicator. For both the AR(1) and realized range methods, the adjusted R-squared ranges between 5% and 25% in the first four months, which is substantially higher than under the IV estimate. The results support the findings of Bekaert and Hoerova (2014) to the extent that they do not find the VRP coefficient for the US to be significant at the quarterly or annual frequency.[11] However, they do find significance at the monthly horizon.

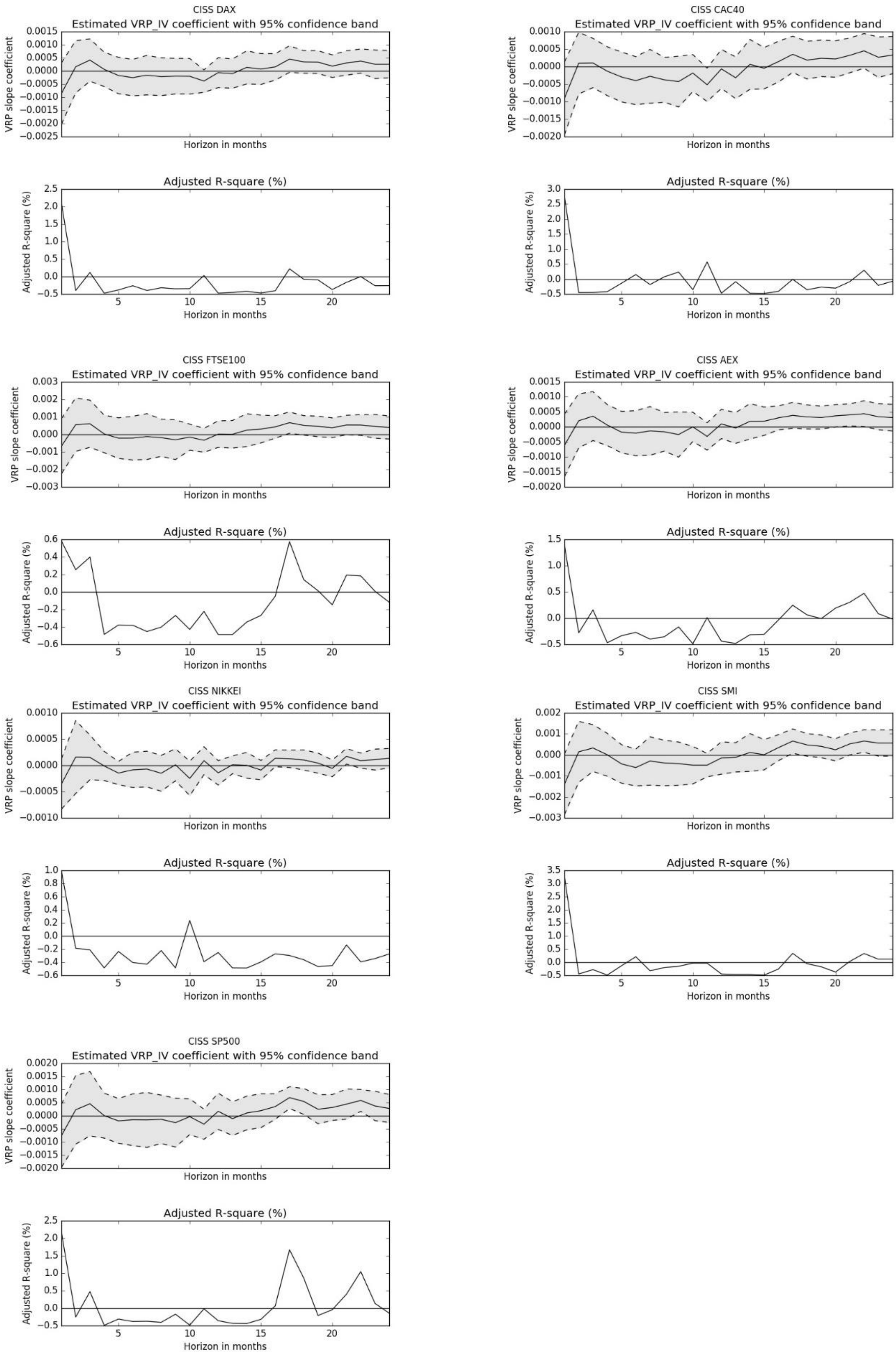
In section 4.1 I found both the implied volatility and the realized variance to be much stronger predictors of equity returns than the variance risk premium. Hence, I investigate to what extent financial instability can be predicted by implied volatility and the realized variance. The following equation estimates the predictive power of the implied volatility on financial instability:

$$CISS_{t,t+h} = \gamma_{0,j} + \gamma_{1,j,t} IV_{j,t} + \epsilon_{j,t,t+h}$$

where $IV_{j,t}$ is the implied volatility index of country *j* at time *t*.

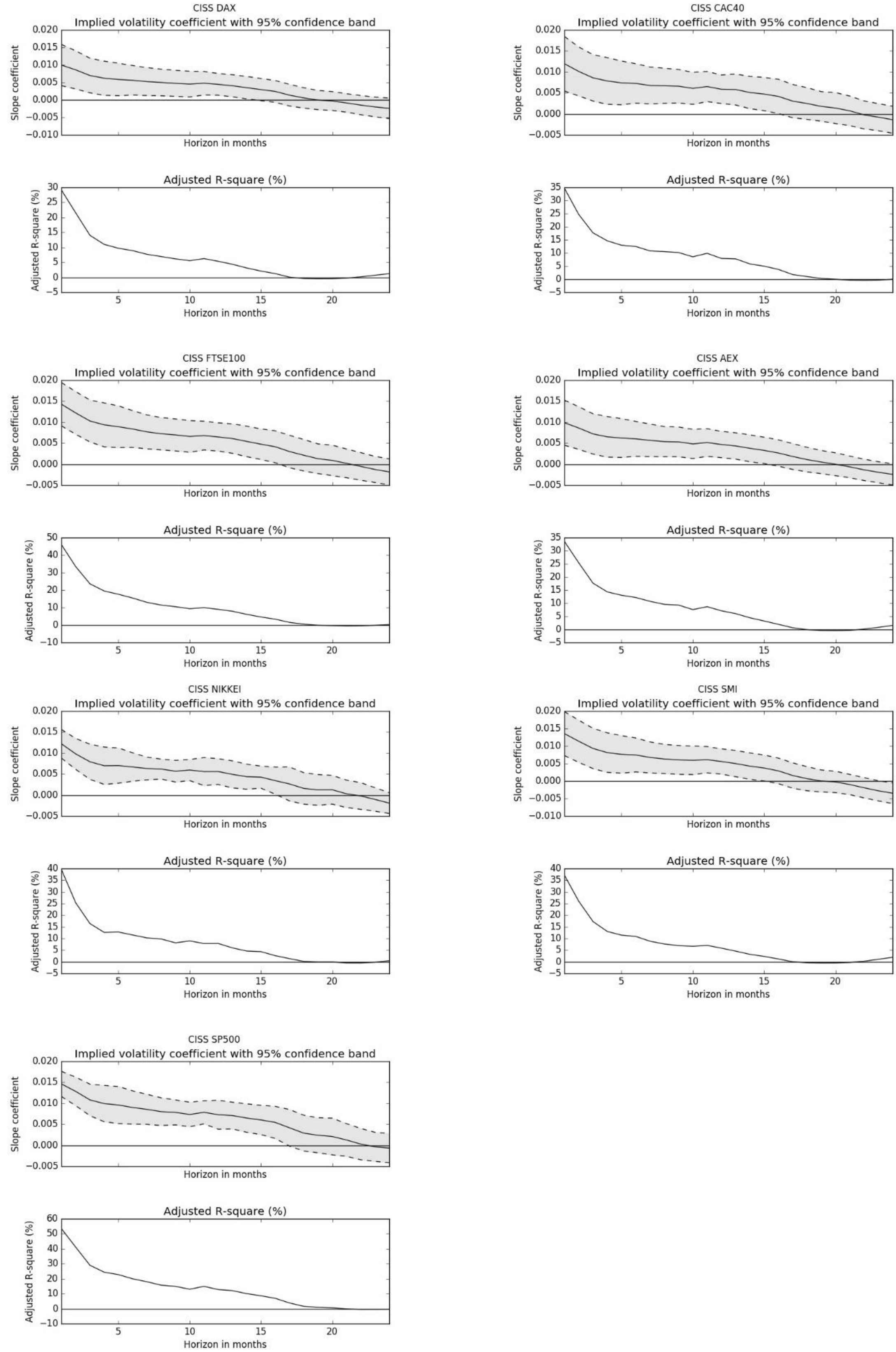
[11] Bekaert and Hoerova (2014) use five-minute intraday returns to estimate the realized variance.

Figure 6: Predictive power of variance risk premia on financial stability



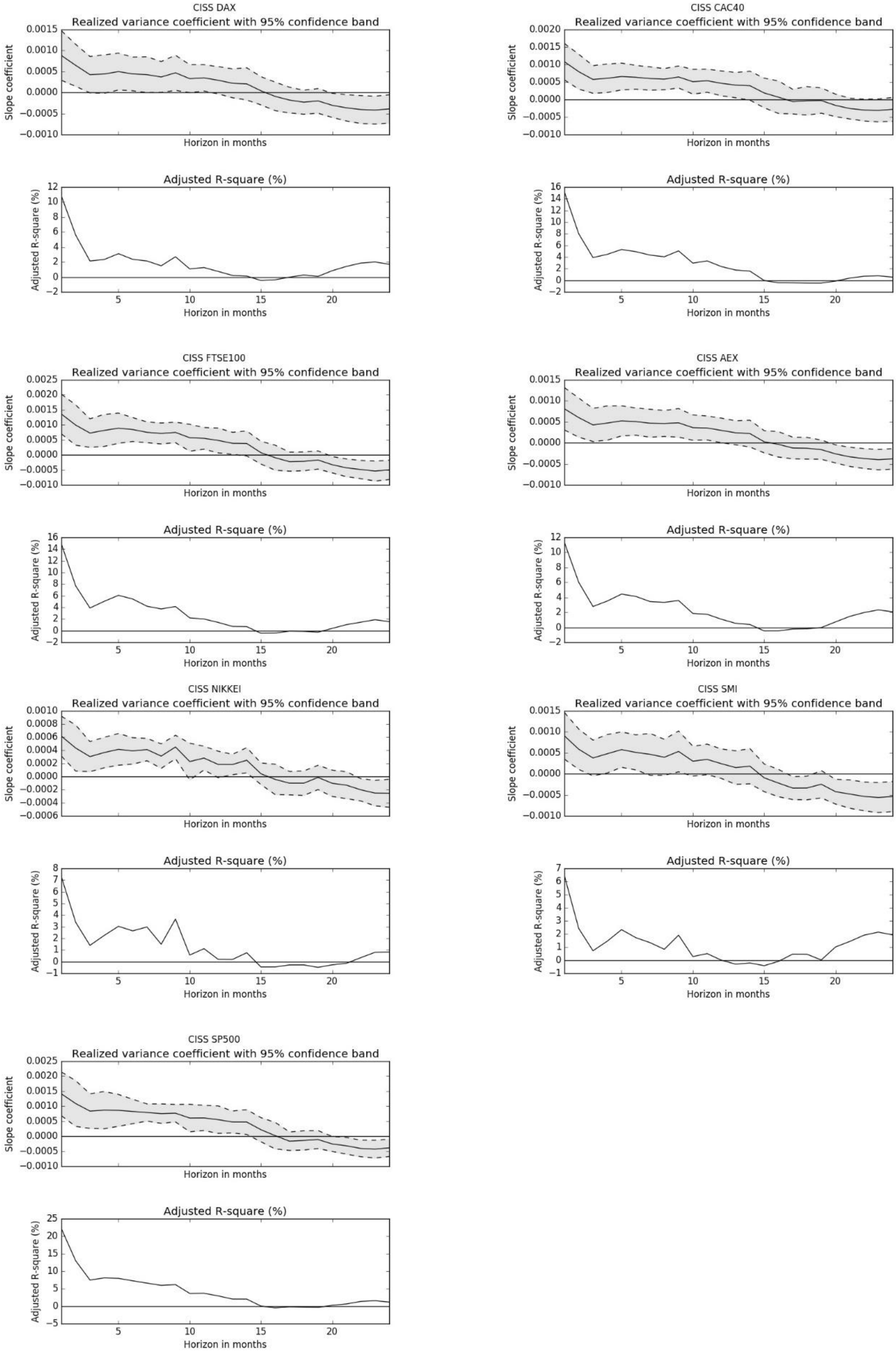
The figures report the regression coefficients along with their 95% confidence intervals and the adjusted R^2 for a horizon of up to 24 months. All of the regressions are based on the sample spanning from January 2000 to May 2017. The variance risk premium is calculated according to the IV estimate, as explained in section 4.

Figure 7: Predictive power of implied volatility on financial stability



The figures report the regression coefficients along with their 95% confidence intervals and the adjusted R^2 for a horizon of up to 24 months. All of the regressions are based on the sample spanning from January 2000 to May 2017.

Figure 8: Predictive power of realized variance on financial stability



The figures report the regression coefficients along with their 95% confidence intervals and the adjusted R^2 for a horizon of up to 24 months. All of the regressions are based on the sample spanning from January 2000 to May 2017. The realized variance is calculated as the sum of squared daily returns within a month (See Andersen et al 2003).

The results of the regression, which are reported in Figure 7, clearly indicate that the implied volatility is a strong predictor of financial stability. There is a positive and statistically significant relationship between implied volatility and the CISS for a horizon of up to 15 months. It is remarkable that even the implied volatility indices of the Non-European countries, the SP500 and the NIKKEI, have a large predictive power on a European financial stress indicator. The implied volatility coefficient of the US is even among the highest of all countries considered. The adjusted R-squared ranges from 30% for Germany to 52% for the US at the monthly horizon, after which it gradually declines toward zero. The magnitude of the regression coefficient is between 0.010 and 0.015 at the monthly horizon for all seven countries. Hence, an increase (decrease) in implied volatility of 1% leads to an increase (decrease) in the Composite Indicator of Systemic Stress (CISS) of between 0.010 and 0.015 points. This is a rather sizeable effect, taking into account that the average value of the CISS between January 2000 and May 2017 is approximately 0.2.

The relation between realized variance and financial instability is estimated by the following regression:

$$CISS_{t,t+h} = \gamma_{0,j} + \gamma_{1,j,t} rv_{j,t} + \epsilon_{j,t,t+h}$$

where $rv_{j,t}$ is the realized variance in country *j* at time *t*, calculated as the sum of squared daily returns within a month. Figure 8 reports the regression coefficients and adjusted R-squared. The confidence intervals in Figure 8 show that the realized variance coefficient is statistically significant at the 5% level up to a horizon of about one year. The magnitude and significance of the realized variance coefficient is lower than for implied volatility. The same holds true for the level of the adjusted R-squared. It is noteworthy that for both the implied volatility and realized variance regressions, the regression coefficients as well as the adjusted R-squared are highest for the US index, since the financial instability indicator is based on European data.

5. US variance risk premium

In section 4, little evidence was found for local variance premia being able to predict local equity returns. This section examines whether the US variance premium is able to predict equity returns for other countries in the sample. The US stock market has been and still is the largest stock market in the world, both in terms of size and importance to the global financial markets.[12] Its implicit variance premium may therefore convey information for other stock markets as well. Indeed, both Londono (2011) and Bollerslev, Marrone, Xu, and Zhou (2014) find that the US variance premium predicts equity returns for all other countries in their sample.[13]

The results of the regression

$$r_{j,t,t+h} = \gamma_{0,j} + \gamma_{1,j,t} VRP_t^{SP500} + \epsilon_{j,t,t+h},$$

are reported in Figure 9. The US VRP coefficient is significant at the monthly horizon for all countries in the sample, but not at longer horizons. Londono (2011) on the other hand, finds the US VRP coefficient to be significant for all countries at the three-month horizon. In general, the graphs in Figure 9 look very much like the graphs in Figure 2, which reports the regression coefficients of the local VRPs. However, the magnitude of the regression coefficient and the adjusted R-squared both are lower for the US variance premium than for the local variance premia. This indicates that the predictive power of the US variance premium is inferior to the predictive power of the local variance premia.

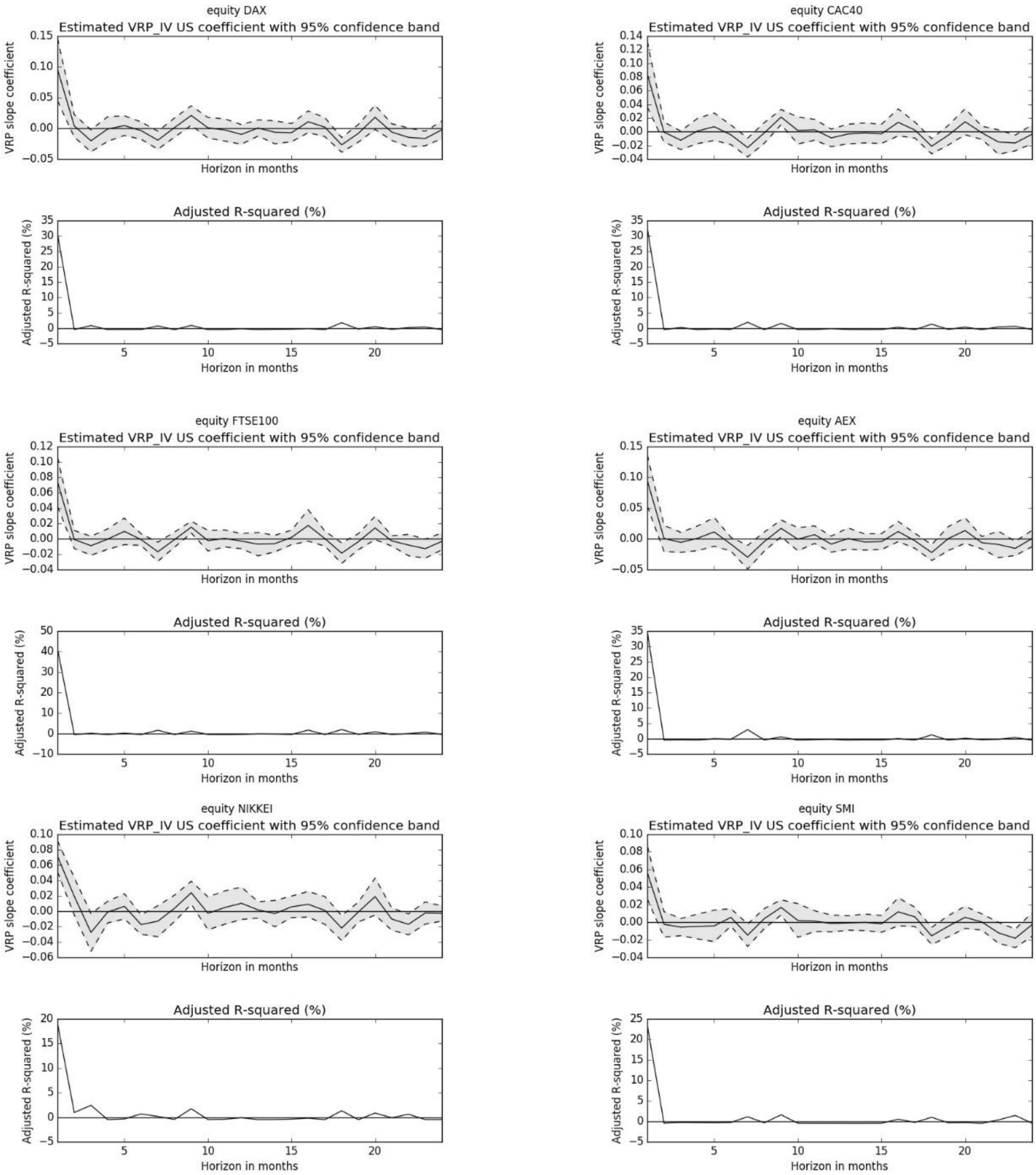
When the US variance risk premium, VRP_t^{SP500}, is measured according to the other three methods as discussed in section 4.1, I do not find many noteworthy differences. The adjusted R-squared is generally lower at the one-month horizon, but higher at longer horizons. Also, the magnitude of the coefficients is lower, and in some occasions even becomes significantly negative at

[12] The two largest stock exchanges in the world, the New York Stock Exchange and the NASDAQ, are both located in the United States.

[13] The sample of both papers consists of eight countries, including the Netherlands, Belgium, France, Japan, Germany, Switzerland, the UK, and the US.

horizons longer than one month. This result is remarkable since both Londono (2011) and Bollerslev et al. (2014), who have used similar techniques to calculate the VRP, find the opposite.

Figure 9: Predictive power of US variance premium on international equity returns



The figures report the regression coefficients along with their 95% confidence intervals and the adjusted R^2 for a horizon of up to 24 months. All of the regressions are based on the sample spanning from January 2000 to May 2017. The variance risk premium is calculated according to the IV estimate as explained in section 4.1.

6. Global variance risk premium

6.1 Country specific regressions

In this section, I compute a global variance risk premium and test whether it has predictive power on local equity returns. The proxy for the global variance risk premium is based on a simple equally-weighted average of the country-specific variance risk premia. As opposed to Bollerslev, Marrone, Xu, and Zhou (2014), who use a capitalization-weighted average, I choose an equally-weighted average to reduce the dominance of the US market in the global VRP. The following equation estimates the global VRP,

$$VRP_t^{GLOBAL} = \sum_{j=1}^{7} \frac{1}{7} VRP_t^j,$$

where j = 1,2,...,7 refers to each of the seven indices included in the study and the country-specific variance risk premia, VRP_t^j, are measured according to the IV estimate as explained in section 4.1. Replacing the local variance premium with the global variance premium in the equation of section 4.1 yields the following regression:

$$r_{j,t,t+h} = \gamma_{0,j} + \gamma_{1,j,t} VRP_t^{GLOBAL} + \epsilon_{j,t,t+h}$$

The results in Figure 10 show that for all seven countries the global variance risk premium coefficient is statistically significant at the monthly horizon.[14] The adjusted R-squared is also very high at the monthly horizon, ranging from 30% for Japan to 52% for the Netherlands. For horizons from two months and longer, the global VRP coefficient becomes insignificant and the adjusted R-squared is virtually zero. The results are very similar to the regressions with the local variance premia as independent variables (see Figure 2), in terms of both size and significance of the coefficients. For most countries, the regression coefficient at the monthly horizon is marginally higher for the global VRP than for the local VRP. The reason for the exceptionally high values of the adjusted R-squared in the first month remain puzzling.

When the global VRP is calculated based on the local variance premia as measured according to the alternative methods[15], I do not find any noteworthy differences[16]. The size and significance of the coefficients, as well as the adjusted R-squared values, are very similar for the global VRP and the local VRP.

6.2 Panel regressions

In addition to the country-specific regressions based on the global variance risk premium, this section analyzes the relationship between the variance risk premium and equity returns by means of a panel regression. The panel regression restricts the variance risk premium coefficients to be the same across all countries, thereby generating additional power in estimating the variance premium coefficient γ_1. The panel regression thus assumes that the stock returns in all countries respond to the variance premium in the same way. The results of the panel regression

$$r_{j,t,t+h} = \gamma_0 + \gamma_1 VRP_t^j + \epsilon_{j,t,t+h},$$

where VRP_t^j is the variance risk premium in country *j* at time *t,* are reported in Figure 11.

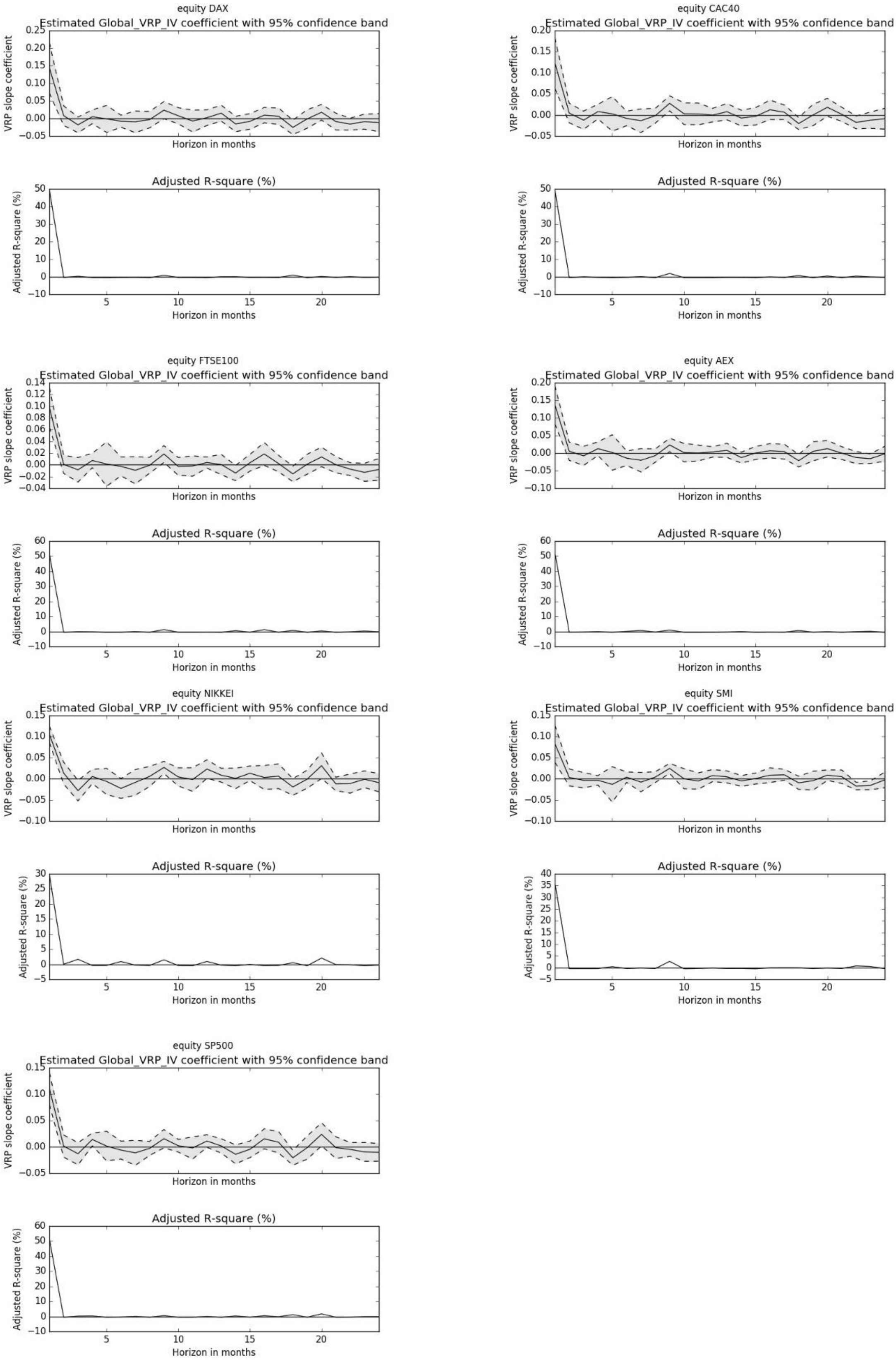
Like in the previous regressions, the VRP is calculated according to the IV estimate as explained in section 4.1. The regression coefficients along with their Newey-West based 95% confidence intervals and adjusted R^2 are presented in Figure 11. Again, the coefficient is statistically significant only at the monthly horizon. Even at the one-month horizon the adjusted R-squared is extremely low with a peak at 0.4%. Thus, I conclude that, in contrast to Bollerslev et al. (2014), the panel regression does not lead to efficiency gains relative to the country-specific regressions.

[14] The standard errors of the regression coefficients are corrected using the Newey-West HAC (heteroskedasticity and autocorrelation correction) with 12 monthly lags (Newey and West, 1987).

[15] The simple autoregressive method, the martingale method, and the realized range method as explained in section 4.1.

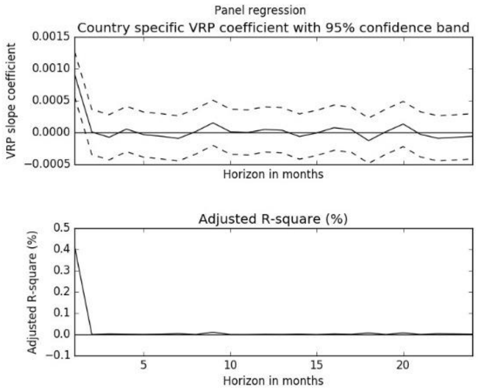
[16] The regression results for the alternative global VRP estimates are available upon request from the author.

Figure 10: Predictive power of global variance risk premium on equity returns



The figures report the regression coefficients along with their 95% confidence intervals and the adjusted R^2 for a horizon of up to 24 months. All of the regressions are based on the sample spanning from January 2000 to May 2017. The global variance premium is calculated as an equally-weighted average of the country-specific variance risk premia, as measured by the IV estimate.

Figure 11: Panel regression coefficients of variance risk premium on equity returns

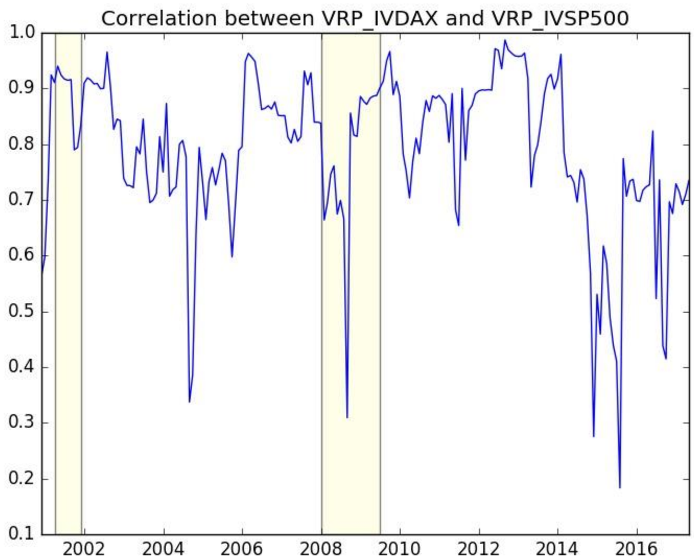


The figure reports the regression coefficients along with their 95% confidence intervals and the adjusted R^2 for a horizon of up to 24 months. The regression is based on the sample spanning from January 2000 to May 2017. The variance premium is calculated according to the IV estimate.

7. Cross-country variance risk premium correlations

The graphs in Figure 1 show that there is substantial fluctuation in the level of the variance risk premium over time. Moreover, there is a large correlation between the variance risk premia of different countries (see Table 4). The literature has demonstrated that correlations across markets increase during market crashes. For example, Sandoval and Franca (2012) investigate the correlation of financial markets in times of crisis and find that correlations tend to increase during crisis periods. To analyze whether the cross-country VRP correlations peak during crisis periods, I compute the moving correlation coefficients based on a moving window size of 10 periods. The graph in Figure 12 provides an illustrative example of the moving correlation coefficient between the VRP of the DAX and the VRP of the SP500.[17]

Figure 12: Rolling VRP correlation between DAX and SP500



The figure shows the moving correlation coefficient between the variance risk premia of Germany and the US as forecasted by the IV estimator. The shaded areas represent the US recession periods as defined by the NBER.

[17] The graphs for the cross-country moving correlations for each country combination are available from the author upon request.

In order to test whether the variance premium correlations peak during crisis periods, I split the sample and calculate the mean moving correlation coefficient during crisis periods and non-crisis periods, again using a moving window size of 10 periods. Table 6 reports the average VRP correlation coefficients during crisis and non-crisis periods. A one-sided Welch's t-test[18] is performed to test econometrically whether the mean correlation coefficient is significantly higher during crisis periods. The p-values of the Welch's test are also included in Table 6.

Table 6: Variance premium correlations during crisis periods

	DAX						
Crisis mean	0.913						
Non-crisis mean	**0.916**	CAC40					
P-value	0.423						
Crisis mean	**0.895**	**0.959**					
Non-crisis mean	0.877	0.897	FTSE100				
P-value	0.129	0.000***					
Crisis mean	**0.916**	**0.970**	**0.958**				
Non-crisis mean	0.910	0.916	0.893	AEX			
P-value	0.317	0.000***	0.000***				
Crisis mean	**0.827**	**0.692**	**0.715**	**0.692**			
Non-crisis mean	0.611	0.572	0.550	0.595	NIKKEI		
P-value	0.000***	0.002***	0.000***	0.022**			
Crisis mean	**0.920**	**0.848**	**0.863**	**0.876**	**0.894**		
Non-crisis mean	0.887	0.848	0.856	0.874	0.598	SMI	
P-value	0.012**	0.486	0.366	0.430	0.000***		
Crisis mean	**0.805**	**0.846**	**0.849**	**0.854**	0.534	0.702	
Non-crisis mean	0.786	0.806	0.829	0.804	**0.537**	**0.704**	SP500
P-value	0.256	0.030**	0.105	0.024**	0.469	0.480	

*The table shows the mean variance risk premium correlation coefficients between the seven countries in the sample. Crisis mean reports the mean VRP correlation coefficient during crisis periods, where the crisis periods are defined by the NBER. Non-crisis mean reports the mean VRP correlation coefficient during non-crisis periods. The sample spans the period from January 2000 to May 2017 and includes a total of 26 crisis months. The highest mean correlation is reported in bold. The p-values for a Welch's t-test are reported, with *, ** and *** representing significance at the standard 1, 5 and 10% confidence levels.*

For 11 of the 21 cross-country combinations, the VRP correlation coefficient is significantly higher during crisis periods than during non-crisis periods. The largest difference in VRP correlations during crisis and non-crisis periods is between the Swiss SMI index and the Japanese NIKKEI index. In just 3 out of the 21 occasions, the average VRP correlation coefficient is higher during non-crisis periods than during crisis periods, however, none of these are statistically significant. The results thus predominantly indicate that the cross-country variance premium correlations peak during crisis periods. Forbes and Rigobon (2002) show that actual stock market correlations will be biased upward during crisis periods, due to increased stock market volatility. This problem of heteroskedasticity leads us to be cautious in interpreting the variance risk premium correlations. It must also be

[18] The Welch's t-test is more efficient than a Student's t-test when the two samples have unequal variance and unequal sample sizes.

mentioned that Table 6 only produces mean values, and does not provide any further information about the dynamics of the variance risk premium over time.

While all evidence in this section points towards higher variance risk premium correlations during crisis periods, the limitations of the analysis make it difficult to make any inferences from them.

8. Conclusion

This paper studies the relationship between the variance risk premium and financial instability. The variance risk premium is defined as the difference between implied volatility squared and future realized variance. I test four different realized variance forecasting measures and find that including the implied volatility as a predictor variable yields the best results.

Secondly, I provide evidence that the variance risk premium can significantly predict equity returns on a monthly horizon. The US variance risk premium also predicts equity returns in other countries on a monthly horizon, but is not a superior predictor to local equity returns. The same holds true for the global variance premium. The results are robust to different econometric techniques, in the form of a panel regression. I also provide evidence that both the implied volatility index and the realized variance estimate are superior predictors of stock returns compared to the variance risk premium. The implied volatility index predicts equity returns up to a horizon of 14 months.

Thirdly, I find the variance premium to be able to predict stock market crashes one month ahead. However, the variance premium fails to predict financial instability as measured by the CISS indicator. This is remarkable since both the realized variance and the implied volatility are very strong predictors of financial instability. Hence, splitting the implied volatility squared into a realized variance and a risk premium component does not seem to add value in terms of predicting equity returns or financial instability. Practitioners are therefore recommended to concentrate on implied volatility itself, instead of its two components.

Finally, I provide new evidence that the cross-country variance risk premium correlations are significantly higher during crisis periods than during non-crisis periods. For 11 of the 21 cross-country combinations, the VRP correlation coefficient is significantly higher during crisis periods than during non-crisis periods.

When comparing the results in this paper to the findings in other papers, it seems that the predictive power of the variance risk premium to a large extent depends on the way future realized variance is estimated. For example, my results are generally different from papers that use intraday return data to calculate realized variance[19].

[19] See, for example, Bekaert and Hoerova (2014) and Bollerslev, Tauchen and Zhou (2009).

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