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¿DOES RISK AVERSION AFFECTS EXPECTED STOCK RETURNS?

TESIS PARA OPTAR AL GRADO DE MAGISTER EN FINANZAS

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Abstract

We estimate an aggregate time-varying risk aversion function using option, stock return and macroeconomic data for a sample of 8 countries. We document that, in most of the countries, the degree of risk aversion is countercyclical. Moreover, we show that the estimated risk aversion function forecasts monthly stock index returns up to 12 months ahead. This effect is statistically significant in panel regressions, and it survives the inclusion of additional control variables.

Keywords: Option-implied risk aversion, forecast stock return, panel regression.
JEL Classification: G10, G11, G15.

1 Introduction

It is well known that investor's risk aversion plays a key role in most of the theoretical asset pricing and portfolio allocation models in Finance. For example, the Intertemporal-CAPM model of Merton (1973). However, this variable is not observable and difficult to estimate. Recent literature in empirical finance has studied the properties of some proxies such as Variance Risk Premium (VRP) (Bollerslev et al., 2009), investor's sentiment index (Schmeling, 2009), among others. In this paper, we estimate a time-varying risk aversion function following the parametric approach in Bollerslev et al. (2011), and prove if the estimated function can forecasts stock returns. The proposed method makes use of model-free realized volatility, model-free option-implied volatility and macroeconomic data to estimate the time-varying risk-aversion. In particular, the estimation method exploits a set of theoretical moments conditions from both the realized and the risk-neutral volatilities of stock returns, in order to implement a GMM-type of estimator. Then, a projection on a set of macro-finance variables provides variation through time.

Our empirical results, for a set of 8 countries (France, Germany, UK, China, Japan, Switzerland, US and South Korea), show that the estimated risk-aversion varies significantly through time, in a counter-cyclical manner, consistent with the C-CAPM model of Campbell and Cochrane (1999). We find that variables such as realized volatility, AAA bond spreads, and industrial production growth rates are the main drivers of aggregated risk aversion across countries. This evidence is consistent with reported results in Bollerslev et al. (2011) for the US. We also show that, in average, risk aversion is higher in Germany and Japan, and lower in France and the US during the analyzed period.

Using panel regression estimates, including country and time fixed-effects, we show that the estimated time-varying risk aversion function forecasts aggregate stock index returns, in the next 12 months. This results are robust to the inclusion of the VRP, an investor sentiment index and an economic uncertainty index. When these variables are included in the panel model, the TVRA metric remains statistically significant. This evidence shows that the information contained in the TVRA is valuable by its own and not necessarily reflects the same set of information of these variables that ex-ante we expect to be highly correlated. Moreover, our estimates of the control variables are align with previous evidence: the VRP predicts stock returns one quarter ahead (4 to 5 months) similar to Bollerslev et al. (2009, 2014), and the estimates of investor sentiment are negative and significant almost a year ahead as in Schmeling (2009). However, the relation of economic uncertainty with future stock return is weaker.

Following a country-by-country predictability regressions, we find that the estimated TVRA is a useful predictor of future stock returns in 5 out of 8 countries. Nevertheless, we face the same problem of heterogeneous effects at the country level as compared with the pool estimate, like Ang and Bekaert (2006) and Rapach et al. (2013).

This paper is organized as follows. In section 2, we review the literature. In section 3, we describe the methodology to compute the parametric time-varying risk aversion function. In section 4, we describe our data and report summary statistics. In section 5, we report the estimated constant and time-varying risk aversion functions for the countries in the sample, and we also study whether the estimated function is procyclical or not. In section 6, we study the predictive power of the estimated time-varying risk aversion function for country stock index returns using both panel and country-by-country regressions. Finally, we present our conclusions in section 7.

2 Literature Review

This study fits in the forecasting stock returns predictability literature. Among the most influential papers in this literature, we can mention the studies by Keim and Stambaugh (1986) and Campbell and Shiller (1988), that empirically documented in-sample predictability in stock returns using US data. However, more recent studies have challenged this view by showing that despite of evidence of in-sample predictability, the true test of predictability is out-of-sample. Where the empirical evidence is weaker. A representative study arguing in these lines is Welch and Goyal (2007), that examine the out-of-sample performance of a long list of economic and financial predictors, concluding that the historical mean has better out-of-sample performance than any of the single predictors considered. Following the standard bivariate predictive regression framework, Campbell and Thompson (2007) imposes economically restrictions on the out-of-sample forecasting exercise, showing that these economically motivated restrictions improves to some extent the out-of-sample performance of the models, both in statistical and in economic terms.

Ferreira and Santa-Clara (2011), propose forecasting the three components of stock market returns separately (the dividend–price ratio, the earnings growth, and the price–earnings ratio growth) in a sum-of-the-parts (SOP) approach. These authors show that the use of the SOP method substantially improves the out-of-sample explanatory power of several predictors relative to previous studies. Also, they show that this improvement in OOS predictability is economically significant for investors. Rapach et al. (2013) study the forecasting ability of the nominal interest rate and the dividend yield for a set of countries, finding evidence that both variables are statistically linked to future stock returns. They also document that stock returns in the US precede stock returns in international markets. Ang and Bekaert (2006) examine the predictive power of the dividend yield, cash-flows and interest rate in an international context as well, finding that at short horizons, the short rate negatively predicts excess returns. At longer horizons, the predictive power of the dividend yield is weak. Using a forecast combination approach, Guidolin and Timmermann (2007) also report empirical evidence supporting the OOS predictive power of several variables, both in a statistical and economic sense.

After the seminal contribution of Welch and Goyal (2007) in identifying and evaluating the predictive power of a set of 14 predictive financial and macro variables on stock returns, more recent studies have investigated the predictive power of new variables. For example, Schmeling (2009) examine if a consumer confidence index, used as proxy for individual investor sentiment, affects expected stock returns, for a sample of 18 industrialized countries. He finds that this sentiment variable negatively forecasts aggregate stock market returns on average across countries. Chung et al. (2012) complements the previous study by showing that the predictive power of sentiment is significant during economic expansions rather than economic recessions. Çakmaklı and van Dijk (2016) and Bai (2010) show that excess stock return predictions can be improved by exploiting factors, latent and non-latent, retrieved from a large set of macroeconomic variables. Neely et al. (2014), also use factor models to forecast the equity premium, but adding a set of technical indicators (e.g. moving averages, momentum, volume-based rules, etc.) to the information set. The economic policy uncertainty (EPU) index of Baker et al. (2016) has been used as predictor of stock returns by Brogaard and Detzel (2015). This study concludes that the EPU index forecasts (log) excess returns after two to three months.

Another related literature is the one that use stock option data to forecast the stock return. A well-know predictive variable in this literature is the variance risk premium (VRP), computed as the difference between an option-implied variance and expected realized variance. For example, Bollerslev et al. (2009) show that the VRP is able to explain a fraction of the time-series variation of stock market returns. The predictibility is concentrated at quarterly horizon. Bollerslev et al. (2014) study the predictibility of the VRP in an international setting. They document that VRP predicts future stock market returns over 3 to 5 months horizon for most of the countries in the sample. However, there is some heteregoneity in the level of statistical significance across countries. Last but not least, Bollerslev et al. (2011) also provide evidence of stock return predictability of a volatility risk premium built using option-implied volatility measures. They show that variables such as the P/E ratio, the industrial production and the non-farm Payroll employment drive this forecasting power.

3 Risk Aversion Estimation

In this section, we estimate a time-varying risk aversion function following Bollerslev et al. (2011). We start motivating from a theoretical point of view, the time-varying risk aversion using the model proposed by Heston (1993). Next, we estimate, using a GMM type of estimator, a static risk aversion function; then, we extend these results to a version, in which recursive projections of this function on a set of macroeconomic state variables, produces variation through time. Finally, as a consistency check, we verify how the estimated risk aversion function behaves across business cycles.

3.1 Theoretical Motivation

Consider the stochastic volatility model of Heston (1993), where the stochastic volatility of the logarithmic of the stock price ($p_t = logS_t$) follows a continuous-time process:

$$\begin{aligned} dp_t &= \mu_t()dt + \sqrt{V_t}dB_{1t} \\ dV_t &= \kappa(\theta - V_t)dt + \sigma_t()dB_{2t} \end{aligned} \tag{1}$$

with instantaneous correlation $corr(dB_t, dW_t) = \rho$ capturing the well-known leverage effect, and $\mu_t()$ and $\sigma_t()$ two functions that satisfy standard regularity conditions. Assuming no arbitrage and a linear volatility risk-premium, Bollerslev and Zhou (2002) show that the risk-neutral distribution associated to the stochastic process in (1) is given by:

$$\begin{aligned} dp_t &= r_t^* dt + \sqrt{V_t} dB_{1t}^* \\ dV_t &= \kappa^*(\theta^* - V_t)dt + \sigma_t() dB_{2t}^* \end{aligned} \tag{2}$$

with correlation $corr(dB_{1t}^*, dB_{2t}^*) = \rho$, with r_t^* the risk-free interest rate. The values of the risk-neutral parameters in (2) are mapped to the parameters of the actual price process in equation (1) by the functional relationships $\kappa^* = \kappa + \lambda$ and $\theta^* = \kappa\theta/(\kappa + \lambda)$. Here, the parameter λ is the stochastic volatility risk premium.

Following the notation in Bollerslev et al. (2011), let $\mathscr{V}^{\mathscr{N}}{}_{t,t+\Delta}$ denote the realized volatility introduced (9), computed as squared sum of daily returns between time t and $t + \Delta$. As we mentioned above, under mild conditions this model-free estimate has shown to be an accurate approximation of the unobserved integrated volatility, $\mathscr{V}_{t,t+\Delta}$.

Bollerslev and Zhou (2002) have shown that the first moment of the volatility process in (1) is given by:

$$\mathrm{E}(\mathscr{V}_{t+\Delta,t+2\Delta}|\mathfrak{F}_t) = \alpha_\Delta \mathrm{E}(\mathscr{V}_{t,t+\Delta}|\mathfrak{F}_t) + \beta_\Delta \tag{3}$$

where the coefficients $\alpha_\Delta = e^{-k\Delta}$ and $\beta_\Delta = \theta(1 - e^{-k\Delta})$ are functions of the underlying parameters k and θ of (1). Regarding the risk-neutral first moment of the integrated volatility, Britten-Jones and Neuberger (2000) proves that a volatility measure computed as the average of a continuum of Δ-maturity options,

$$IV*_{t,t+\Delta} = 2\int \frac{C(t+\Delta, K) - C(t+\Delta)}{K^2} dK, \tag{4}$$

where $C(t + \Delta, K)$ is the price of an European call option maturing at time t with strike price K, equals the true risk-neutral expectation of the integrated volatility:

$$IV_{t,t+\Delta}^* = \mathrm{E}^*(\mathscr{V}_{t,t+\Delta}|\mathfrak{F}_t). \tag{5}$$

Using these results, Bollerslev and Zhou (2006) show that there is a link between the risk-neutral volatility in (2) and the physical volatility under (1) given by:

$$E(\mathscr{V}_{t,t+\Delta}|\mathfrak{F}_t) = \mathscr{A}_\Delta \mathrm{IV}_{t,t+\Delta}^* + \mathfrak{B}_\Delta, \tag{6}$$

where $\mathscr{A}_{.} = \frac{(1-e^{-k\Delta})/k}{(1-e^{-k^{*}\Delta})/k^{*}}$ and $\mathfrak{B}_{\Delta} = \theta[\Delta - (1-e^{-k\Delta})/k] - A_{\Delta}\theta^{*}[\Delta - (1-e^{-k^{*}\Delta})/k^{*}]$ are functions of the parameters k, θ and λ. Bollerslev et al. (2011) show that the moment conditions (3) and (6) provides the necessary identification conditions of λ, the risk-premium parameter.

3.2 GMM Estimation

Given moments conditions in (3) and (6), it is natural to consider the GMM estimation method of Hansen (1982) as the appropriate way to recover the parameters of interest. Thus, considering moment conditions defined by (3) and (6), and adding lagged realized volatility as additional instrument to expand the set of moments conditions to allow for overidentifycation as in Garcia et al. (2011); Bollerslev et al. (2011), the final set of moment conditions to recover the vector of parameters $\xi = (\kappa, \theta, \lambda)$ is given by:

$$f_t(\xi) \equiv \begin{pmatrix} v_{t+\Delta,t+2\Delta} - \alpha_{\Delta} v_{t,t+\Delta} - \beta_{\Delta} \\ (v_{t+\Delta,t+2\Delta} - \alpha_{\Delta} v_{t,t+\Delta} - \beta_{\Delta})\, v_{t-\Delta,t} \\ v_{t,t+\Delta} - \mathscr{A}_{\Delta} iv^{*}_{t,t+\Delta} - \mathfrak{B}_{\Delta} \\ \left(v_{t,t+\Delta} - \mathscr{A}_{\Delta} iv^{*}_{t,t+\Delta} - \mathfrak{B}_{\Delta} \right) v_{t-\Delta,t} \end{pmatrix}. \tag{7}$$

By construction $\mathrm{E}(f_t(\xi)|\mathscr{G}_t) = 0$, and the GMM estimator is defined as:

$$\hat{\xi}_t = \arg\min_{\xi} g_t(\xi)' W g_t(\xi), \tag{8}$$

where $g_t(\xi)$ is the sample mean of the moment conditions, and W is a positive definite and symmetric $q \times q$ matrix that denotes the asymptotic covariance matrix of $g_t(\xi)$. The optimal matrix W can be estimated using an heteroskedastic and auto-correlation consistent (HAC) matrix with specific kernel and bandwidth. Bollerslev et al. (2011) point out that the complex lag structure in the moment conditions (3) and (6) impose a complex dependence, therefore, a HAC robust covariance matrix estimator with Bartlett-kernel and five lags are used in the estimation. Further details on the GMM estimation method used here could be found in Bollerslev et al. (2011).

4 Data and Summary Statistics

The key step of our study is the estimation of an aggregate time-varying risk aversion function. To estimate this function we follow the methodology proposed by Bollerslev et al. (2011), that combines stock index returns, option-implied stock index volatility, and a set of macroeconomic variables. The use of option-implied information enriches the analysis as it contains forward looking information, that complements the use of historical stock index returns and macroeconomic data.

The empirical analysis starts with the estimation of model-free realized volatilities (RV) and option-implied volatilities (IV) of each stock index in the sample, similarly to Bollerslev et al. (2009, 2011, 2014). Realized volatilities are computed for each month as the squared sum of daily stock index returns in that month:

$$RV_t \equiv \sum_{i=1}^{n} \left(p_{t+\frac{i}{n}} - p_{t+\frac{i-1}{n}} \right)^2. \tag{9}$$

Literature has shown that this model-free volatility estimator produces more accurate ex-post estimates of return variation, than a range of alternative volatility estimates (see, e.g., Andersen et al. 2001, 2003). Even though a number of studies have used high-frequency data to estimate (9), given our objective in this paper, we resort to daily returns to compute monthly volatilites, as in Bollerslev et al. (2014). We use option-implied volatility international indices akin to the VIX index as our observed implied volatility indices (IV). Stock index returns and related implied volatility indices are retrieved from Bloomberg, at a monthly frequency. Our sample contains information for France (CAC and VCAC), Germany (DAX 30 and VDAX), the UK (FTSE 100 and VFTSE), China (HSI and VHSI), Japan (NIKKEI 225 and VXJ), Switzerland (SMI 20 and VSMI), the US (S&P 500 and VIX), and South Korea (KOSPI and VKOSPI). The country selection is based on the sample used in Bollerslev et al. (2014). The initial date of the sample varies depending on the country, but most of the data are available from 2001 onward, except for the US, for which the data starts in 1990.[1]

In addition to option-implicit and realized volatilities, for each country/equity index, we also construct time series of Variance Risk Premium (VRP) measures, defined as the difference between implied volatility and realized volatility, $VRP \equiv IV_t - RV_t$. This variable is reported in monthly percentage-squared form. Appendix A shows time series plots of this variable. As commonly observed (see, e.g., Coudert and Gex, 2008), we observe that VRP increases during recessions.[2] We use a range of routinely monitored macro variables in the estimation of TVRA. Our selection of data to be included in the estimation follows Bollerslev et al. (2011). In particular, we collect data on AAA bond spreads over Treasuries of matching maturity (10-year when available), payroll employment, industrial production, producer price index, housing starts, and the unemployment rate. The data comes from different sources. Appendix B provides details of the data sources by country. We use a set of control variables in our panel regressions in section 6. In particular, we include proxies of investors sentiment and economic uncertainty. As in Lemmon and Portniaguina (2006); Schmeling (2009), investor sentiment is proxied by the consumer confidence index in each country: in the case of France, Germany, United Kingdom, China, United States, and South Korea, the consumer confidence index is obtained from the "Directorate Generale for Economic and Financial Affairs"; for Switzerland and Japan, we obtain sentiment data from Datastream. Economic uncertainty is proxied by the Economic and Political Uncertainty (EPU) indices of Baker et al. (2016). For all the countries except for Switzerland, we

[1] The sample dates for each country are: France (2001:01-2017:10), Germany (2001:01-2017:10), UK (2001:01-2017:09), China (2003:01-2014:11), Japan (2001:01-2017:10), Switzerland (2001:01-2017:10), US (1990:01-2017:10) and South Korea (2003:01-2017:10).

[2] Appendix C reports NBER recession dates of the countries in the sample

obtain the EPU indices from the web site http://www.policyuncertainty.com/. For Switzerland, we use an EPU index available at the Swiss Economic Institute.

Summary statistics for monthly realized and implied volatilities are reported in Table 1. As one would expect, for all countries/equity indices, the sample mean of implied volatility exceeds often substantially, like in the case of the KOSPI index (by 4.67% per year) or of the S&P500 (by 4.29% per year) realized volatility, which indicates that the variance risk premium is always on average negative. Interestingly, the ordering of the sample standard deviations of realized and implied volatilities are reversed, with the former always exceeding the latter for all our eight equity/implied volatility indices. Finally, all the series of both implied and realized volatility display large, positive (and statistically significant) skewness and excess kurtosis, which is however relatively unsurprising in light of the empirical literature on US data (see, e.g., Bandi and Perron, 2006), albeit less frequently documented with references to the remaining seven indices under investigation (but see Kourtis et al., 2016).

Table 1. Summary Statistics for Monthly Realized and Implied Volatility

	CAC 40		DAX 30		FTSE 100		HSI		NIKKEI 225		SMI 20		S&P 500		KOSPI	
	RV_t	IV_t	RV_t	IV_t	RV_t	IV_t	RV_t	IV_t	RV_t	IV_t	RV_t	IV_t	RV_t	IV_t	RV_t	IV_t
Mean	20.68	23.11	21.81	22.49	16.48	19.83	19.93	23.12	21.51	25.29	16.03	18.41	15.21	19.5	17.89	21.56
SD	11.01	8.40	11.43	8.41	9.57	8.31	11.49	9.73	10.57	8.79	9.52	7.46	9.05	7.5	10.12	9.26
Skew.	1.94	1.54	1.85	1.5	2.43	1.73	3.39	2.15	3.35	2.45	2.58	2.16	2.89	1.7	2.67	2
Kurt.	5.87	2.79	4.55	2.11	9.49	4.01	19.24	6.08	22.07	10.12	9.55	6.1	13.48	4.46	12.13	5.95
Min.	6.75	11.97	6.32	11.67	4.17	9.99	6.66	11.8	6.34	12.21	5.73	9.26	4.24	10.26	5.91	10.75
5 %	9.32	13.55	10.02	13.39	7.3	11.09	9.81	13.66	9.92	15.22	7.36	11.39	6.71	11.56	8.06	11.86
25 %.	13.07	17.46	14.58	16.89	10.27	13.94	13.48	16.63	15.39	19.61	10.44	13.77	9.66	13.75	11.69	15.03
50 %	18.62	21.41	18.57	20.74	14.12	17.6	16.87	20.36	19.33	24.07	13.31	16.14	12.86	17.66	15.61	19.51
75 %	24.32	25.77	25.31	25.65	19.22	23.26	22.53	26.2	25.64	28.31	18.15	20.2	17.61	23.52	20.58	24.92
95 %	45.35	41.49	42.65	41.14	35.28	36.58	41.76	43.23	40.58	37.72	37.01	34.49	30.18	32.04	37.76	36.48
Max.	84.61	59.09	80.62	52.78	79.29	59.98	110.26	71.97	109.61	78.9	77.64	56.92	82.92	59.89	86.8	70.29

Note: The table reports descriptive statistics for both realized (RV) and implied volatility (IV) for stock index returns in each of the countries in the sample. The countries (stock indices) consider are France (CAC 40), Germany (DAX 30), United Kingdom (FTSE 100), China (HSI), Japan (NIKKEI 225), Switzerland (SMI 20), US (S&P 500) and South Korea (KOSPI). Model-free realized volatility is the squared sum of daily stock returns within a month, $RV_t \equiv \sum_{i=1}^{n}\left(p_{t+\frac{i}{n}} - p_{t+\frac{i-1}{n}}\right)^2$ and implied volatility is the option-implied volatility index associated to each of the stock indices.

5 Constant and time-varying risk aversion

5.1 Country-by-country Estimation

It is worthy to establish under which assumptions the volatility risk premium coefficient, λ, as defined in Bollerslev, Gibson, and Zhou's model, may approximate the risk aversion coefficient of a representative investor in a standard endowment economy, see Cocharne (2005). Bollerslev et al. (2011), shows that the volatility risk premium is proportional to a representative investor's risk aversion coefficient under the assumptions of a linear volatility risk premium and of an affine stochastic volatility model, $\sigma(\cdot) = \sigma\sqrt{V_t}$. Assuming that the representative investor has a power utility function in terminal wealth,

$$U(W_t) = e^{-\delta t}\left(\frac{W_t^{1-\gamma}}{1-\gamma}\right) \tag{10}$$

where δ is a constant subjective time discount rate, in equilibrium the investor holds the market portfolio and it can be shown that the constant relative risk aversion coefficient, γ is proportional to the risk aversion coefficient. In particular, it holds that $\gamma = \lambda/(\rho\sigma)$. Here, $\rho < 0$ is the leverage effect parameter, and because $-1 < 1/(\rho\sigma) < 0$, then, $-\lambda$ is approximately equal to the representative investor's risk aversion.

In order to incorporate time variation, Bollerslev et al. (2011) propose to implement a simple augmented $AR(1)$ (or $ARX(1)$) process to be fitted to the volatility risk premium coefficient as follows:

$$\lambda_{t+1} = \alpha + b\lambda_t + \sum_{k=1}^{k} c_k \times state_{t,k} \tag{11}$$

where $x_{t,k}$ is a $K \times 1$ vector of state variables and u_{t+1} is a white noise shock capturing measurement error. Following Bollerslev et al. (2011), we consider as state variables a set of macro-finance variables available at monthly frequencies. In particular, we estimate the time-varying volatility risk premium specification in (11) by including in $x_{t,k}$ the series of lagged squared realized volatility, lagged implied volatility, and a set of macro-financial variables: Aaa corporate bond spreads, the annual (year-to-year) growth rate (computed as the change in logs) in housing starts, industrial production, producer price index, in total payroll employment, and finally, the price-earnings (PE) ratio of the respective stock exchange. All the macro-finance variables are standardized at the country level to have mean zero and unit variance so their marginal contribution to the time-varying risk premium are directly comparable. Moreover, this fact implies that:

$$E[\lambda_{t+1}] = \alpha + \beta\lambda_t + \sum_{k=1}^{K} c_k' x_{t,k} + u_{t+1} = \alpha + \beta E[\lambda_t] \Rightarrow E[\lambda_{t+1}] = \frac{\alpha}{1-\beta}.$$

Table 2 reports our GMM estimation results. For each country we report both a constant and a time-varying specification of the volatility risk premium, i.e., a constant λ and a time-varying λ_{t+1} one, the latter as specified in (11).[3] It is informative to start discussing estimation results for the US and compare them with the estimates in Bollerslev et al. (2011). Despite that, our estimates includes 10 additional years in the sample, our results are rather similar to those reported in Bollerslev et al. (2011), which is always comforting also with reference to the stationarity of the assumed joint process of the variables. The 2.50 estimate of the static variance risk premium, λ, is just slightly higher than what originally reported (1.79), but this value falls within a 90% confidence interval around the estimate reported for the US in Table 2. The same comment can be made with reference to the unconditional mean risk premium, that is estimated at -0.77 in Table 2 but appears to include in a 90% confidence interval the -1.82 in Bollerslev et al. (2011). λ_{t+1} is also somewhat persistent, with a precisely estimated $\beta = 0.74$. Moreover, similarly to Bollerslev et al. (2011), we find that the coefficients associated to most of the macro-finance variables in $x_{t,k}$ turn out to be precisely estimated, with the only exception being the changes in payroll employment.

In terms of the economic impact of the variables, past realized volatility plays the biggest role and with the expected sign (-0.42) in driving risk aversion. Next, the Aaa corporate bond spread and the rate of growth in housing starts do exercise relevant predictive influence, with significant coefficients of 0.25 and -0.21, respectively. Note that a higher credit quality spread is associated to a higher risk premium but lower risk aversion. The industrial production growth rate and the producer price inflation come at the bottom of the list with smaller and borderline significant coefficients. Overall, our results confirm previous evidence in Bollerslev et al. (2011) in terms of the magnitude of the estimates and their importance explaining the dynamic of the risk aversion through time.

The estimated results for the remaining countries show that a static version of the model is supported by the data. The estimated constant coefficient for λ varies between 1.77 for Germany and 4.71 in France. The estimated coefficient is significant in 7 out of 8 countries (Germany is the exception). In the case of Germany is rather odd to find that equity and options data would combine under stochastic volatility to deliver a risk aversion coefficient that cannot be distinguished from zero, which implies risk neutrality of investors in the aggregate. However, also for the remaining seven markets, the time-varying model seems more successful in generating plausible risk aversion. In this case, unconditional mean risk aversion varies between 1.33 for Switzerland and 3.58 for China (besides the rather low unconditional mean of 0.76 for the US).[4]

In general, estimated risk aversion coefficients between 1 and 3 appear to be highly plausible, in a comparative literature perspective. However, the most striking empirical findings concern the estimated coefficients associated with the factors collected in $x_{t,k}$. First, with very rare exceptions, all coefficients across markets carry the same sign and very similar values of the coefficients. For instance, in the case of the rate of growth

[3] When reading Table 2, it is useful to bear in mind that the risk aversion coefficient is given by $-\lambda$ so that, because of the minus sign, the sign of the estimated coefficients should interpreted as having the opposite effect on risk aversion as they have on λ; moreover, the economic significance of the estimated coefficients is directly observable because the variables are standardized to have mean zero and unit variance.

[4] Moreover, 90% confidence intervals for the unconditional mean computed using the delta method (to account for the non-linear way in which the estimated α and β enter the formula $E[\lambda_{t+1}] = \alpha/(1-\beta)$) reveal that all unconditional mean estimates are significant, with the only exception of France. This also derives from the fact that the estimators of α and β turn out to have a non-neglible negative correlation.

of housing starts, for seven countries the minimum estimated coefficient is -0.32 (France) and the maximum is -0.10 (Germany), with the only exception concerning the anyway negative and significant coefficient for Germany (-0.10). Second, lagged realized volatility remains the most important, negatively signed and highly statistically significant coefficient. Third, the ranking of variables across countries/markets is uniformly the same, in terms of the absolute values of the estimated coefficients, and approximately follows the order with which the predictors have been listed in Table 2, with the rate of growth of Payroll Employment hardly ever precisely estimated (but it is in the case of France and Germany, which justifies its inclusion into the research design).

Finally, at least in general, estimated coefficient signs are consistent with what is expected. Most of theses results seem to align with a cyclic story in which risk aversion increases during bear markets and decreases during bull markets. For example, higher levels of risk aversion are observed in periods of high realized volatility: the mechanism is that realized volatility is highly persistent and it raises the general level of risk aversion. Also, risk aversion is higher in periods where producer inflation and payroll employment growth are high, which are the more mature stages of the expansion cycles, when job creation occurs but also inflationary tensions set in, which typical lead to bear markets. We observe instead lower risk aversion when the Aaa bond spread the industrial production growth are high, which may be taken as indications of rapidly improving business cycle conditions typical of the early stages of expansions. Similar patterns are found in Bollerslev et al. (2011).

Table 2. GMM Estimates of Constant and Time-Varying Volatility Risk Premium Function

	France (CAC 40)		Germany (DAX 30)		UK (FTSE 100)		China (HSI)	
	Constant	Macro Finance	Constant	Macro Finance	Constant	Macro Finance	Constant	Macro Finance
λ	-4.705*		-1.776		-2.578***		-2.031**	
	(2.559)		(1.232)		(0.540)		(1.003)	
α		-0.527***		-0.435***		-0.526***		-0.527***
		(0.070)		(0.160)		(0.026)		(0.178)
β		0.812***		0.779***		0.818***		0.855***
		(0.035)		(0.038)		(0.012)		(0.061)
c_1 Realized Volatility		-0.323***		-0.319***		-0.317***		-0.319*
		(0.105)		(0.079)		(0.100)		(0.173)
c_2 Aaa Bond		0.190**		0.192***		0.187***		0.291**
		(0.086)		(0.036)		(0.061)		(0.127)
c_3 Housing Start		-0.325		-0.103**		-0.212***		-0.230
		(0.288)		(0.046)		(0.071)		(0.253)
c_4 Industrial Production		0.137		0.091***		0.069**		0.041
		(0.095)		(0.022)		(0.027)		(0.029)
c_5 Producer Price Index		-0.056		-0.034		-0.037***		-0.031
		(0.062)		(0.048)		(0.010)		(0.097)
c_6 Payroll Employment		-0.032***		-0.045***		-0.048		-0.052
		(0.011)		(0.007)		(0.052)		(0.127)
c_7 PE Ratio		0.440**		0.384***		0.393***		0.302**
		(0.190)		(0.086)		(0.129)		(0.152)
	Japan (NIKKEI 225)		**Switzerland (SMI 20)**		**US (S&P 500)**		**South Korea (KOSPI)**	
	Constant	Macro Finance	Constant	Macro Finance	Constant	Macro Finance	Constant	Macro Finance
λ	-3.118**		-3.153***		-2.504*		-3.382***	
	(1.565)		(0.756)		(1.347)		(0.986)	
α		-0.232*		-0.777***		-0.200		-0.320***
		(0.127)		(0.229)		(0.120)		(0.042)
β		0.931***		0.425***		0.740***		0.890***
		(0.019)		(0.087)		(0.222)		(0.017)
c_1 Realized Volatility		-0.319***		-0.362***		-0.423**		-0.216
		(0.055)		(0.076)		(0.194)		(0.166)
c_2 Aaa Bond		0.191***		0.210***		0.251***		0.192*
		(0.054)		(0.042)		(0.088)		(0.106)
c_3 Housing Start		-0.230***		-0.201***		-0.212***		-0.233**
		(0.088)		(0.062)		(0.063)		(0.112)
c_4 Industrial Production		0.037		0.079***		0.093***		0.056
		(0.118)		(0.029)		(0.023)		(0.073)
c_5 Producer Price Index		-0.052		-0.083***		-0.045***		-0.061*
		(0.093)		(0.028)		(0.011)		(0.036)
c_6 Payroll Employment		-0.030		0.018		-0.034		-0.052
		(0.096)		(0.049)		(0.031)		(0.062)
c_7 PE Ratio		0.302**		0.302***		0.114**		0.264
		(0.137)		(0.067)		(0.057)		(0.195)

Notes: The table presents GMM estimation results for the model in equation (11). The column "Constant" shows the case in which λ is constant ($\beta = c_k = 0$) and "Macro Finance" shows the case in which λ is predicted by to macro-finance variables and its own lagged value ($\beta \neq 0$ and $c_k \neq 0$). Macro-finance variables are standardized to have zero mean and unit variance. Newey-West adjusted errors with 5 lags are used. P-values are reported in parenthesis. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent.

Figure 1 shows plots of the estimated time-varying risk aversion functions when projected on the set of macro-finance variables as in (11). For each country, the shaded areas highlight recession periods according to the information reported by the NBER macroeconomic recessions database (see Appendix C).

Figure 1. Estimated Time-varying Risk Aversion Function ($-\hat{\lambda}$) Projected onto Macro-Finance Variables

graphics_tvra/TVRA_FR.png	graphics_tvra/TVRA_GE.png
graphics_tvra/TVRA_UK.png	graphics_tvra/TVRA_CH.png
graphics_tvra/TVRA_JP.png	graphics_tvra/TVRA_SW.png
graphics_tvra/TVRA_US.png	graphics_tvra/TVRA_KO.png

Note: The figures shows estimates of time-varying risk aversion from equation (11) by country. Shaded areas correspond to recession periods in each country as identified by the NBER. See appendix (C) for detailed information about the recession start and end dates.

5.2 Time-Varying Risk Aversion and the Business Cycle

Asset pricing models with habits predict a counter cyclical risk aversion. For example, the consumption CAPM of Campbell and Cochrane (1999) predicts that the existence of habits in the economy implies that investor risk aversion should increase during recessions, when real consumption is compressed close to the slow-moving habit, and decrease during expansions. Bekaert et al. (2009, 2019), consider asset pricing models with external habits to quantify the impact of economic uncertainty and risk aversion in asset prices and risk premium. The estimated time-varying risk aversion in these models is highly counter-cyclical as well.[5]. Bekaert and Hoerova (2016) provides a further discussion on these models. Finally, experimental empirical evidence in Cohn et al. (2015) shows that risk aversion is counter cyclical. This study faces a group of financial professionals to boom-bust scenarios to quantify their preferences for risk across the business cycle. Based on this evidence, both theoretical and empirical, in this subsection we verify whether our time-varying risk aversion estimates is counter-cyclical or not, and therefore, consistent or not with these theories.

Table 3 shows the sample correlations between our estimates of time-varying risk aversion and the unemployment rate, observed in each of the countries in our data set, and reports on their statistical accuracy in standard ways. As in Kim (2014), we report lagged, contemporaneous, as well as future correlations. In particular, we report correlations between months -5 and 5. Overall, our results show that the previously estimated time-varying risk aversion measure is counter-cyclical, as we observe a consistently declining pattern in the estimated correlations when moving from a -5 lag to a $+5$ lead. However, in some countries (e.g., the US) risk aversion clearly reacts to past recessionary conditions, in the sense that $Corr(-\lambda_t^i, Uempl_{t+k}^i)$ declines as k goes from -5 to $+5$ (here i is the country index). This the case of Germany (for instance, $Corr(-\lambda_t^{ger}, Uempl_{t-5}^{ger}) = 0.13 > Corr(-\lambda_t^{ger}, Uempl_{t+5}^{ger})) = 0.09$, and the difference is statistically significant at 10% at least), China ($0.38 > 0.05$), Japan ($0.26 > 0.02$), the US ($0.38 > 0$), and South Korea ($0.13 > 0.02$). In the case of France, the UK, and Switzerland, such a decline in $Corr(-\lambda_t^i, Uempl_{t+k}^i)$ as k goes from -5 to $+5$ is slower, for which risk aversion is predicted by past business cycle conditions but also predicts subsequent business cycle conditions. Interestingly, $Corr(-\lambda_t^i, Uempl_{t+k}^i)$ is positive and mostly statistically significant for all the 8 countries under examination.

Our results are align with those reported in Kim (2014) for the US. Such an empirical evidence validates our estimates but opens a further key question that lies at the heart of our project, i.e., whether time-varying risk aversion implicit in option prices may forecast future returns on equity indices or not. Especially for those countries/indices in which risk aversion predicts business cycles, our conjecture is that risk aversion may forecast equity index returns; such conjecture turns weaker for the cases, in which risk aversion is predicted by past business cycle conditions, even though there is a strong chance that $Unempl_{t+k}^i$ may represent a slowly-reacting business cycle indicator (as supported by the stylized fact that "jobless recoveries" may occur, see Shimer (2012)), which makes a direct test of the predictive power of $-\lambda_t^i$ for stock index returns.

[5]Bekaert et al., 2019 documents a correlation of 0.40 between their estimated risk aversion measure and NBER recession episodes.

Table 3. Correlation between Time-varying Risk Aversion and Unemployment Rate

Countries (Indices)	$t-5$	$t-4$	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
France (CAC 40)	0.412***	0.410***	0.406***	0.399***	0.389***	0.376***	0.360***	0.339***	0.317***	0.291***	0.261***
Germany (DAX 30)	0.125*	0.122*	0.119*	0.116*	0.113	0.108	0.103	0.099	0.094	0.090	0.086
UK (FTSE 100)	0.311***	0.327***	0.340***	0.347***	0.350***	0.350***	0.341***	0.330***	0.316***	0.301***	0.285***
China (HSI)	0.379***	0.333***	0.283***	0.232***	0.184**	0.140*	0.109	0.085	0.067	0.055	0.046
Japan (NIKKEI 225)	0.262***	0.234***	0.205***	0.175**	0.146**	0.117*	0.092	0.069	0.050	0.032	0.015
Switzerland (SMI 20)	0.449***	0.458***	0.454***	0.440***	0.412***	0.356***	0.326***	0.294***	0.260***	0.225***	0.188***
US (S&P 500)	0.376***	0.348***	0.318***	0.283***	0.247***	0.208***	0.164**	0.121*	0.080	0.039	0.001
South Korea (KOSPI)	0.132*	0.125	0.120	0.117	0.113	0.099	0.084	0.077	0.060	0.041	0.019

Notes: The table shows the correlation between the estimated time-varying risk averision $(-\lambda)$ from equation (11) and the unemployment rate in country i at time $t+k$, Corr($-\lambda_t, Unempl^i_{t+k}$). Unemployment data comes from different sources, see appendix B. *,**,*** indicates statistical significance at the 10, 5 and 1%, respectively.

6 Stock Return Predictability

In this Section, we examine whether the estimated time-varying risk aversion function helps to forecast stock returns. We run panel and country-by-country return predictability regressions.

6.1 Panel Estimates

In order to test if the TVRA measure estimated in Section (3) may forecasts stock returns, we estimate a set of panel regressions in which excess returns on equity indices under investigation are regressed on lagged values of the variable of interest and of additional control variables. Panel data techniques has been employed in the stock return predictability literature considering several countries by Ang and Bekaert (2006); Hjalmarsson (2010); Rapach et al. (2013); Brogaard and Detzel (2015), among others. The use of panel data regressions reduces data-mining problems usually observed in this type of regressions and enhances estimation efficiency due to the use of a set of countries in the analysis, instead of a single country as it generally the case in the literature.

Following Bollerslev et al. (2009) and Bollerslev et al. (2014), we estimate the following specification:

$$h^{-1} r^i_{t,t+h} = a(h) + b(h) TVRA^i_t + \gamma(h)' \mathbf{X}^i_t + \alpha_i + u^i_{t,t+h} \quad h = 1, 2, ..., 12, \tag{12}$$

where i is the country index (fr, ger, uk, china, jp, swtz, us, and sk), $r^i_{t,t+h}$ indicates to the $h = 1, 2, ..., 12$ horizon excess return, defined as the difference between the index stock gross total return between $t+1$ and $t+h$ and the cumulative, compounded riskless return over the same interval, $r^i_{t,t+h} \equiv \prod_{j=1}^{h}(1+R^i_{t+j}) - \prod_{j=1}^{h}(1+f_{t+j})$, where f_{t+j} indicates the risk-free return for a cash bond investment between $t+j-1$ and $t+j$. In (12), $TVRA^i_t$ represents the time-varying risk aversion index estimated discussed in section 3, and X^i_t represents a set of control variables. This empirical specification includes country-specific fixed effects, α_i to account for invariant unobservable heterogeneity at the country level (see Brogaard and Detzel, 2015). There is some discussion in the stock predictability literature regarding the inclusion of fixed effects in panel estimates. For example, Hjalmarsson (2010) argue that the inclusion of fixed effects may introduce some size distortion in the estimates. On the other hand, Menzly et al. (2004) include industry fixed-effects in their regressions between future stock return and dividend growth.

As it has been highlighted in the prior literature (see e.g. Stambaugh, 1999; Campbell and Yogo, 2006; Hjalmarsson, 2010), inference may be problematic when the predictor variable is persistent and its innovations are correlated with the dependent variable, which is indeed the case of the estimated TVRA. Significant biases may arise in this context. In order to cope with this problem in our empirical setup we follow Rapach et al. (2013) and use a wild bootstrap procedure to compute p-values. As argued by these authors, the wild-bootstrap procedure is robust to the Stambaugh (1999) bias for hypothesis testing, but it also account for conditional heteroskedasticity in stock returns. Rapach et al. (2016); Neely et al. (2014); Jiang et al. (2018) also use the wild bootstrap procedure for inference in stock predictability regressions. However, their estimates are for a single country (the US), not for a panel exercise as the one we perform here.[6]

As control variables collected in $\mathbf{X}_t^i$, we select the VRP, defined as the difference between the 1-month model-free implied volatility and the 1-month realized variance as in Bollerslev et al. (2009), $VRP_t^i \equiv IV_t^i - RV_t^i$. Similarly to Bollerslev et al. (2014), RV_t^i is the sum of the daily squared returns over a month for each of the countries. We also consider a proxy for investor sentiment as control variable. Recent evidence in the literature has shown that investor sentiment predict expected stock returns (see Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006; Schmeling, 2009; **?**; Huang et al., 2015; Zhou, 2018). In particular, we expect to find a negative predictive relationship between sentiment and subsequent stock returns. Following Lemmon and Portniaguina (2006); Schmeling (2009), we use consumer confidence index at the country level to proxy for investor sentiment.[7] We also control for economic uncertainty at the country level. We use the news-based Economic Policy Uncertainty (EPU) index introduced by Baker et al. (2016). The EPU index measures uncertainty based on the newspaper coverage of some key concepts associated to economic adversity and/or unexpected events. The index reflects precisely what its name indicates, information about uncertain, economic and policy relevant events. Pastor and Veronesi (2012) argues that economic uncertainty plays a first-order role in predicting the dynamics of stock returns. Brogaard and Detzel (2015) also highlight the role of EPU on affecting stock returns in the time series and in the cross-section.

Table 12 shows our results. We report the estimates of different specifications divided in several panels. We start by presenting models in which the TVRA measure is the single predictor; next, in Panels B-D, we present results from specifications in which we add each of the control variables considered in the analysis to the baseline models in Panel A, one at the time; finally, panel E deals with the case in which all the controls are included simultaneously. In panel A, we observe that the first-stage estimated TVRA helps to forecast future stock returns for all the horizons considered. The estimated coefficient of interest, $b(h)$, is positive, as expected, and highly significant. It goes from 1.21 at $h = 1$ to 0.11 for $h = 12$. It is interesting to note that the size of the estimated coefficient decreases as the time horizon moves further away from the one-month ahead case, possibly indicating a declining economic significance of current movements in TVRA as time passes. Yet, the adjusted R^2s are relatively low showing an average value of 0.23% only.

In Panel B, we estimate the same panel regressions but adding as control variable VRP, that has played a key role in recent, related literature. Our motivation to include this variable as control is that under some assumptions, it may be argued that VRP is either a measure of risk aversion or a measure of aggregate uncertainty (see, e.g., Bekaert et al., 2019; Bekaert and Hoerova, 2016), and therefore, our baseline result could just be a variation over the known empirical evidence that VRP predicts stock returns (see, e.g., Bollerslev et al., 2009, 2014). If this were the case, we would expect a loss of predictive significance of TVRA when the VRP is included in the specification. Our estimates shows that this is not the case, because

[6] As a robustness check we compute robust standard errors clustered by country. The results are quite similar to those obtained using the wild-bootstrap procedure.

[7] See Zhou (2018) for a detailed discussion on the measurement of investor sentiment using alternative metrics and data sources.

the estimated coefficient for TVRA remains highly significant across forecast horizons, despite the inclusion of VRP. We only observe a mild reduction in the magnitude of the estimated $b(h)$ coefficient. For instance, at $h = 1(12)$, $b(1) = 1.19(0.103)$ with a p-values of 0.01 at both horizons, while $\gamma(1) = 0.20(0.02)$ with a p-values below 0.10 in both cases as well.

The VRP variable shows forecasting ability as we find that the estimated $\gamma(h)$ coefficient is positive and statistically significant across time horizons. Because both TVRA and VRP have good in-sample forecasting power and none of them encompasses the predictive power of the other, the adjusted R^2s in panel B exceed all those in panel A, although they remain moderate, around 2%. Overall, the results in Panel B shows that TVRA and VRP provide different information for subsequent equity index returns, and both, predict them.

Under the widely spread intuition (see Huang et al., 2015) that a TVRA indicator may be capturing aggregate market sentiment, in Panel C, we replace VRP by an investor sentiment index as additional predictor. The estimates show that the estimated $\hat{b}(h)$ remain positive and highly significant for all the forecasting horizon considered, an indication that TVRA and the proxy of investor sentiment contain different information. The estimated coefficients of investor sentiment are negative, consistent with the evidence in Schmeling (2009), however, we do not find any statistical significance. Interestingly, the estimates of $\hat{b}(h)$ are not strongly affected by the fact that control predictors are added into our analysis. For instance, at a 1-month horizon, $\hat{b}(1) = 1.21$ in panel A, 1.19 in panel B, and 1.15 in panel C and this may be even consistent with a case in which the additional predictors are close to being orthogonal to TVRA. The precisely estimated, negative values for $\hat{\gamma}(h)$, for instance $\hat{\gamma}(12) = -0.013$, are expected in the light of the literature on the power of sentiment indices to predict return reversals (see, e.g., Da et al., 2014), even though in our case it is less easy to make sense of the absence of statistical significant. Interestingly, sentiment provided weaker in-sample predictions, in the sense that the adjusted R^2s in panel C are generally inferior to panel B.

In Panel D, we use as an additional, unique control variable a proxy of aggregate uncertainty, the EPU index. Prior literature has shown some predictive power of EPU index on future stock returns (see Brogaard and Detzel, 2015). Also in this case, we find that the TVRA measure survives, in terms of in-sample predictive power, the inclusion of the uncertainty proxy, remaining positive and statistically significant. However, we find that the estimated coefficient of the EPU index is positive across forecast horizons but not statistically significant. Brogaard and Detzel (2015) finds that contemporaneous EPU predicts negatively stock returns one-month in advance and positively two months in advance. When these authors use as dependent variable cumulative future returns in their regressions, they find that EPU affects (cumulative) stock returns positively, but this effect is statistically significant only between 14 and 18 months ahead. Note that the adjusted R^2s in panel D are similar to those in panels A and C, i.e., while VRP did provide forecasting power over and beyond the TVRA index, this does not seem to be the case for either investor sentiment or EPU.

Table 4. Panel Stock Return Predictability Regressions

Horizon	1	2	3	4	5	6	7	8	9	10	11	12
Panel A: Baseline												
TVRA	1.212***	0.621***	0.413***	0.312***	0.246***	0.206***	0.179***	0.157***	0.142***	0.126***	0.113***	0.105***
	(0.445)	(0.222)	(0.148)	(0.112)	(0.090)	(0.074)	(0.064)	(0.055)	(0.049)	(0.045)	(0.041)	(0.037)
%Adj. R^2	0.22	0.23	0.23	0.23	0.22	0.22	0.23	0.23	0.24	0.23	0.23	0.23
Obs.	1627	1619	1611	1603	1595	1587	1579	1571	1563	1555	1547	1539
Panel B: Baseline + Variance Risk Premium												
TVRA	1.191***	0.610***	0.406***	0.307***	0.242***	0.202***	0.176***	0.155***	0.139***	0.124***	0.112***	0.103***
	(0.421)	(0.209)	(0.139)	(0.105)	(0.084)	(0.070)	(0.059)	(0.052)	(0.046)	(0.042)	(0.038)	(0.035)
VRP	0.198*	0.099**	0.066**	0.050**	0.040*	0.033**	0.028**	0.025**	0.022**	0.020**	0.018**	0.016*
	(0.064)	(0.032)	(0.021)	(0.016)	(0.013)	(0.011)	(0.009)	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)
% Adj. R^2	2.07	2.08	2.09	2.1	2.09	2.1	2.11	2.11	2.11	2.09	2.08	2.07
Obs.	1627	1619	1611	1603	1595	1587	1579	1571	1563	1555	1547	1539
Panel C: Baseline + Investor Sentiment												
TVRA	1.147**	0.588**	0.391**	0.296**	0.234**	0.196**	0.170***	0.149***	0.135***	0.120***	0.108***	0.100***
	(0.463)	(0.229)	(0.152)	(0.115)	(0.093)	(0.077)	(0.065)	(0.057)	(0.050)	(0.046)	(0.042)	(0.038)
Sentiment	-0.131	-0.068	-0.046	-0.035	-0.028	-0.023	-0.021	-0.018	-0.017	-0.015	-0.014	-0.013
	(0.090)	(0.046)	(0.031)	(0.023)	(0.018)	(0.015)	(0.013)	(0.012)	(0.010)	(0.009)	(0.008)	(0.008)
% Adj. R^2	0.31	0.33	0.34	0.34	0.33	0.34	0.35	0.35	0.37	0.36	0.35	0.37
Obs.	1561	1553	1545	1537	1529	1521	1513	1505	1497	1489	1481	1473
Panel D: Baseline + Economic Uncertainty												
TVRA	1.161***	0.592***	0.394***	0.296***	0.234***	0.196***	0.170***	0.150***	0.136***	0.121***	0.110***	0.101***
	(0.431)	(0.214)	(0.142)	(0.107)	(0.086)	(0.071)	(0.061)	(0.053)	(0.047)	(0.043)	(0.040)	(0.036)
Uncertainty	0.035	0.017	0.011	0.009	0.007	0.006	0.005	0.004	0.003	0.003	0.002	0.002
	(0.022)	(0.011)	(0.008)	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
% Adj. R^2	0.39	0.4	0.4	0.4	0.41	0.41	0.39	0.38	0.37	0.36	0.32	0.31
Obs.	1428	1421	1414	1407	1400	1393	1386	1379	1372	1365	1358	1351
Panel E: Baseline + All controls variables												
TVRA	1.1684***	0.5950***	0.3946***	0.2973***	0.2337***	0.1950***	0.1690***	0.1478***	0.1337***	0.1193***	0.1082***	0.1005***
	(0.4294)	(0.2115)	(0.1405)	(0.1061)	(0.0860)	(0.0715)	(0.0601)	(0.0522)	(0.0465)	(0.0419)	(0.0386)	(0.0349)
VRP	0.2079**	0.1038**	0.0693**	0.0521**	0.0417**	0.0348**	0.0298***	0.0260***	0.0230**	0.0207***	0.0188***	0.0171**
	(0.0648)	(0.0324)	(0.0216)	(0.0162)	(0.0129)	(0.0108)	(0.0092)	(0.0080)	(0.0071)	(0.0064)	(0.0058)	(0.0053)
Sentiment	-0.0821	-0.0432	-0.0299	-0.0226	-0.0171	-0.0144	-0.0130	-0.0117	-0.0108	-0.0095	-0.0088	-0.0085
	(0.0648)	(0.0331)	(0.0223)	(0.0168)	(0.0132)	(0.0107)	(0.0094)	(0.0082)	(0.0074)	(0.0066)	(0.0059)	(0.0059)
Uncertainty	0.0530***	0.0263***	0.0176***	0.0135***	0.0112***	0.0092***	0.0077***	0.0065***	0.0057***	0.0052***	0.0045***	0.0040**
	(0.0201)	(0.0100)	(0.0068)	(0.0052)	(0.0042)	(0.0035)	(0.0031)	(0.0027)	(0.0025)	(0.0023)	(0.0022)	(0.0020)
% Adj. R^2	2.71	2.72	2.74	2.76	2.77	2.77	2.75	2.73	2.7	2.69	2.62	2.59
Obs.	1561	1553	1545	1537	1529	1521	1513	1505	1497	1489	1481	1473

Note: The table presents panel fixed effects regression estimates of :

$$h^{-1}r_{it,t+h} = a(h) + b(h)TVRA_{it} + \gamma(h)'\mathbf{X}_{it} + \alpha_i + u_{it,t+h},$$

where $r_{i,t,t+h}$ is the stock index excess return for an horizon of h months ahead. $TVRA$ represents the time-varying risk aversion function estimated in section 3 and α_i is a country fixed effect. We include several control variables in the $\mathbf{X}_{it}$. In Panel B, VRP is the Variance Risk Premium, defined as the difference between the implied and the realized volatilities, $IV - RV$. $Sentiment$, is a measure of investor sentiment proxied by the consumer confidence index as in Schmeling (2009), and $Uncertainty$ is the Economic Policy Uncertainty index (EPU) of Baker et al. (2016). Wild-boostrapped standard errors are reported in the parenthesis.*, ** and *** indicate significance at the 10, 5 and 1 percent, respectively.

Finally, in Panel E, we present estimates from a specification in which all the control variables are included simultaneously. We obtain confirmation of the results from the panel regressions based on the individual control variables, because the $\hat{b}(h)$ remain all positive and statistically significant for all the forecast horizons analyzed. The coefficient estimates of VRP are positive and significant similarly to the evidence in panel B. Bollerslev et al. (2009, 2014) find similar forecasting power of VRP, however, our results are stronger than theirs as we find significant coefficients for all horizons, while these authors only find significant effects around months 3-5. Again, the fact that both variables, TVRA and VRP, appear to be statistically significant in the predictive regressions confirm that both of them contain different information to forecast stock index returns. Similar to the results in panel D, investor sentiment remains negative but not significant. Finally, we find that higher economic uncertainty seems to predict a higher stock index return in the future. These results are consistent with the findings of Brogaard and Detzel (2015) in the sense of the positive effect, but stronger from an statistical point of view.

All in all, the panel regression estimates reported in this section provide evidence of a strong (in-sample) predictive link between TVRA and stock index returns, that it is not explained either by VRP, or by investor sentiment, or by aggregate economic uncertainty. Yet, this evidence, although necessary to our argument in this paper, is purely in-sample, and based on the simultaneous use of all available data. Therefore, it becomes of great importance to assess such predictive power of TVRA using a truly out-of-sample (henceforth, OSS) design.

6.2 Country level regressions

In section 6, we study whether the estimated TVRA measure has predictive power to forecast stock returns. Our evidence, based on a panel regression with country fixed effects, shows that this is the case indeed as the estimated TVRA precedes statistically stock returns in the next 12 months. The use of panel regressions in the previous analysis implied that the estimated effect is a sort of average across the countries in the sample as pointed out by Ang and Bekaert (2006); Hjalmarsson (2010); Rapach et al. (2013). Considering that one of our goals in this study is to exploit the heterogeneity associated to the fact of being working with a panel of countries instead of a single country, we report panel estimates as our baseline results. Nevertheless, it is also of interest to study the relationship between TVRA and stock returns at the country level. We conduct this analysis in this section.

Table 5 shows our estimation results. For each country in the sample, we report OLS estimates of stock return predictability regressions at different forecasting horizons (from 1 to 12) and its respective R^2. We include the same control variables used in the panel estimation in section (6) to make our inference more robust. Similar to Rapach et al. (2016), the t-statistics are computed using a wild bootstrapped procedure that account for persistent regressors, heteroskedasticity and autocorrelation of residuals.

We find that in all the countries but China (Hong-Kong) the estimated TVRA has predictive power in the next 12 months. The strongest effects are found in the UK, Switzerland and South Korea where the estimated TVRA coefficient is positive and highly significant in each of the 12 months analyzed. For the case of Germany and the US the predictability are slightly weaker but still significant in the month horizons considered. In France and Japan, the level of statistical significance is marginal but still significant at the 10% confidence. Finally, we do not find any evidence of predictability in Hong-Kong.

Overall, the evidence obtained from the country-by-country predictability regressions shows that the estimated TVRA is a useful predictor of future stock returns in most of the countries in the sample. Similar to Ang and Bekaert (2006) and Rapach et al. (2013), we find that country level regressions are consistent with pooling estimates. Thus, the evidence reported in this section, in line with the panel regression results reported in section 6, supports the estimatied TVRA function as significant predictor of future stock returns.

Table 5. Stock Return Predictability Regressions by Country

Horizon (h)		1	2	3	4	5	6	7	8	9	10	11	12
France	$\hat{\beta}_{TVRA}$	0.03*	0.05*	0.03*	0.03*	0.02*	0.01*	0.02*	0.03*	0.03*	0.02*	0.02*	0.02*
	R^2	5.29	5.33	5.34	5.36	5.32	5.33	5.19	5.13	5.12	5.14	5.10	5.02
Germany	$\hat{\beta}_{TVRA}$	2.97***	1.48**	0.99***	0.75***	0.60***	0.51***	0.43***	0.38***	0.33**	0.30***	0.28**	0.24**
	R^2	3.71	3.72	3.93	3.93	3.95	3.94	3.92	3.92	3.88	3.81	3.84	3.36
UK	$\hat{\beta}_{TVRA}$	1.46***	0.73***	0.48***	0.35***	0.27***	0.22***	0.20***	0.17***	0.15***	0.14***	0.14***	0.12***
	R^2	3.38	3.39	3.41	3.44	3.68	3.53	3.75	3.68	3.55	3.68	2.98	3.54
Hong-Kong	$\hat{\beta}_{TVRA}$	7.52	3.77	2.53	1.88	1.50	1.25	1.07	0.93	0.83	0.75	0.69	0.61
	R^2	5.02	5.02	5.17	5.20	5.21	5.10	5.13	5.04	5.04	5.30	5.23	5.29
Japan	$\hat{\beta}_{TVRA}$	0.19*	0.10*	0.08*	0.06*	0.04*	0.04*	0.03*	0.03*	0.03*	0.02*	0.02*	0.02*
	R^2	16.04	15.94	15.89	15.98	16.01	16.04	16.01	15.96	15.98	15.96	15.96	15.98
Switzerland	$\hat{\beta}_{TVRA}$	5.92***	3.04***	1.98***	1.57***	1.21***	0.99***	0.84***	0.71***	0.63***	0.53***	0.48***	0.47***
	R^2	6.11	6.08	6.01	6.12	6.01	5.92	5.88	5.64	5.61	5.31	5.30	5.38
US	$\hat{\beta}_{TVRA}$	0.62**	0.32***	0.22**	0.17**	0.13**	0.13***	0.12**	0.11**	0.11***	0.09**	0.08**	0.07***
	R^2	8.18	8.18	8.19	8.19	8.19	8.20	8.20	8.19	8.17	8.12	8.12	8.12
South Korea	$\hat{\beta}_{TVRA}$	5.34***	2.60***	1.73***	1.31***	1.04***	0.87***	0.72***	0.62***	0.58***	0.54***	0.50***	0.46***
	R^2	8.36	8.39	8.39	8.40	8.38	8.44	8.45	8.47	8.55	8.63	8.69	8.71

Note: The table presents OLS stock return predictability regression coefficients for each country in the sample and for several monthly time horizons (h). The estimated model is

$$h^{-1} r_{t,t+h} = a + \beta\, TVRA_t + \gamma' \mathbf{X}_t^i + u_{t,t+h},$$

where $r_{t,t+h}$ is the stock index excess return for an horizon of h months ahead, $TVRA$ is the time-varying risk aversion function estimated in section **??**, and $\mathbf{X}_t^i$ is a set of control variables including the variance risk premium (VRP), a sentiment index and the Economic Policy Uncertainty index (EPU). Wild-bootstrapped standard errors are computed to test the statistical significance of the parameter of interest, $\hat{\beta}_{TVRA}$. *, ** and *** indicate significance at the 10, 5 and 1 percent, respectively.

7 Conclusions

We estimate a time-varying risk aversion function for a set of 8 countries (France, Germany, UK, China, Japan, Switzerland, US and South Korea) using equity returns, equity option and macroeconomic data. Thereafter, we investigate whether this metric predicts stock index returns up to 12 months or not.

We find strong evidence of time variation in risk aversion across countries. Besides, the estimated function is counter-cyclical, consistent with theoretical predictions from asset pricing models with habits (e.g. Campbell and Cochrane, 1999). Our results show that variables such as corporate bond spreads, industrial production growth, and price-earnings ratios are the main drivers of risk aversion at the aggregate level in most of countries. We find that, on average, Japan, Switzerland and France are the most risk averse countries in the sample, while the US, China and the UK are the less risk averse.

Using both panel and country-by-country predictability regressions, we find that the estimated risk aversion function predicts stock returns in the next 12 months. This result is robust to control for variance risk premium, investor's sentiment, and economic uncertainty. This evidence confirm that the estimated risk-aversion function contains additional information to the one embedded in this set of control variables. Consistent with prior literature, we find that VRP and economic uncertainty helps to predict stock returns. On the other hand, we find that investor sentiment is negatively related to future stock returns but the effect is not statistically significant.

Overall, in this study we estimate a time-varying risk aversion function for a set of 8 countries and, consistent with asset pricing models with habits, we document significant predictability power of this variable on future stock returns in the following year.

References

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Ebens, H. (2001). The distribution of realized stock return volatility. *Journal of financial economics*, 61(1):43–76.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Labys, P. (2003). Modeling and forecasting realized volatility. *Econometrica*, 71(2):579–625.

Ang, A. and Bekaert, G. (2006). Stock return predictability: Is it there? *The Review of Financial Studies*, 20(3):651–707.

Bai, J. (2010). Equity premium predictions with adaptive macro indexes. *FRB of New York Staff Report*, (475).

Baker, M. and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The journal of finance*, 61(4):1645–1680.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636.

Bandi, F. M. and Perron, B. (2006). Long memory and the relation between implied and realized volatility. *Journal of Financial Econometrics*, 4(4):636–670.

Bekaert, G., Engstrom, E., and Xing, Y. (2009). Risk, uncertainty, and asset prices. *Journal of Financial Economics*, 91(1):59–82.

Bekaert, G., Engstrom, E. C., and Xu, N. R. (2019). The time variation in risk appetite and uncertainty. Technical report, National Bureau of Economic Research.

Bekaert, G. and Hoerova, M. (2016). What do asset prices have to say about risk appetite and uncertainty? *Journal of Banking & Finance*, 67:103–118.

Bollerslev, T., Gibson, M., and Zhou, H. (2011). Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities. *Journal of econometrics*, 160(1):235–245.

Bollerslev, T., Marrone, J., Xu, L., and Zhou, H. (2014). Stock return predictability and variance risk premia: statistical inference and international evidence. *Journal of Financial and Quantitative Analysis*, 49(3):633–661.

Bollerslev, T., Tauchen, G., and Zhou, H. (2009). Expected stock returns and variance risk premia. *The Review of Financial Studies*, 22(11):4463–4492.

Bollerslev, T. and Zhou, H. (2002). Estimating stochastic volatility diffusion using conditional moments of integrated volatility. *Journal of Econometrics*, 109(1):33–65.

Bollerslev, T. and Zhou, H. (2006). Volatility puzzles: a simple framework for gauging return-volatility regressions. *Journal of Econometrics*, 131(1-2):123–150.

Britten-Jones, M. and Neuberger, A. (2000). Option prices, implied price processes, and stochastic volatility. *The Journal of Finance*, 55(2):839–866.

Brogaard, J. and Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science*, 61(1):3–18.

Çakmaklı, C. and van Dijk, D. (2016). Getting the most out of macroeconomic information for predicting excess stock returns. *International Journal of Forecasting*, 32(3):650–668.

Campbell, J. Y. and Cochrane, J. H. (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of political Economy*, 107(2):205–251.

Campbell, J. Y. and Shiller, R. J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. *The Review of Financial Studies*, 1(3):195–228.

Campbell, J. Y. and Thompson, S. B. (2007). Predicting excess stock returns out of sample: Can anything beat the historical average? *The Review of Financial Studies*, 21(4):1509–1531.

Campbell, J. Y. and Yogo, M. (2006). Efficient tests of stock return predictability. *Journal of financial economics*, 81(1):27–60.

Chung, S.-L., Hung, C.-H., and Yeh, C.-Y. (2012). When does investor sentiment predict stock returns? *Journal of Empirical Finance*, 19(2):217–240.

Cohn, A., Engelmann, J., Fehr, E., and Maréchal, M. A. (2015). Evidence for countercyclical risk aversion: an experiment with financial professionals. *American Economic Review*, 105(2):860–85.

Coudert, V. and Gex, M. (2008). Does risk aversion drive financial crises? testing the predictive power of empirical indicators. *Journal of Empirical Finance*, 15(2):167–184.

Da, Z., Engelberg, J., and Gao, P. (2014). The sum of all fears investor sentiment and asset prices. *The Review of Financial Studies*, 28(1):1–32.

Ferreira, M. A. and Santa-Clara, P. (2011). Forecasting stock market returns: The sum of the parts is more than the whole. *Journal of Financial Economics*, 100(3):514–537.

Garcia, R., Lewis, M.-A., Pastorello, S., and Renault, É. (2011). Estimation of objective and risk-neutral distributions based on moments of integrated volatility. *Journal of Econometrics*, 160(1):22–32.

Guidolin, M. and Timmermann, A. (2007). Asset allocation under multivariate regime switching. *Journal of Economic Dynamics and Control*, 31(11):3503–3544.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society*, pages 1029–1054.

Heston, S. L. (1993). A closed-form solution for options with stochastic volatility with applications to bond and currency options. *The review of financial studies*, 6(2):327–343.

Hjalmarsson, E. (2010). Predicting global stock returns. *Journal of Financial and Quantitative Analysis*, 45(1):49–80.

Huang, D., Jiang, F., Tu, J., and Zhou, G. (2015). Investor sentiment aligned: A powerful predictor of stock returns. *The Review of Financial Studies*, 28(3):791–837.

Jiang, F., Lee, J., Martin, X., and Zhou, G. (2018). Manager sentiment and stock returns. *Journal of Financial Economics*.

Keim, D. B. and Stambaugh, R. F. (1986). Predicting returns in the stock and bond markets. *Journal of financial Economics*, 17(2):357–390.

Kim, K. H. (2014). Counter-cyclical risk aversion. *Journal of Empirical Finance*, 29:384–401.

Kourtis, A., Markellos, R. N., and Symeonidis, L. (2016). An international comparison of implied, realized, and garch volatility forecasts. *Journal of Futures Markets*, 36(12):1164–1193.

Lemmon, M. and Portniaguina, E. (2006). Consumer confidence and asset prices: Some empirical evidence. *The Review of Financial Studies*, 19(4):1499–1529.

Menzly, L., Santos, T., and Veronesi, P. (2004). Understanding predictability. *Journal of Political Economy*, 112(1):1–47.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica: Journal of the Econometric Society*, pages 867–887.

Neely, C. J., Rapach, D. E., Tu, J., and Zhou, G. (2014). Forecasting the equity risk premium: the role of technical indicators. *Management science*, 60(7):1772–1791.

Pastor, L. and Veronesi, P. (2012). Uncertainty about government policy and stock prices. *The journal of Finance*, 67(4):1219–1264.

Rapach, D. E., Ringgenberg, M. C., and Zhou, G. (2016). Short interest and aggregate stock returns. *Journal of Financial Economics*, 121(1):46–65.

Rapach, D. E., Strauss, J. K., and Zhou, G. (2013). International stock return predictability: what is the role of the united states? *The Journal of Finance*, 68(4):1633–1662.

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of empirical finance*, 16(3):394–408.

Shimer, R. (2012). Wage rigidities and jobless recoveries. *Journal of Monetary Economics*, 59:S65–S77.

Stambaugh, R. F. (1999). Predictive regressions. *Journal of Financial Economics*, 54(3):375–421.

Welch, I. and Goyal, A. (2007). A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, 21(4):1455–1508.

Zhou, G. (2018). Measuring investor sentiment. *Annual Review of Financial Economics*, 10:239–259.

A Variance Risk Premium Time Series by Country

graphics_vrp/Variance_risk_premia_FR.png graphics_vrp/Variance_risk_premia_GE.png

graphics_vrp/Variance_risk_premia_UK.png graphics_vrp/Variance_risk_premia_CH.png

graphics_vrp/Variance_risk_premia_JP.png graphics_vrp/Variance_risk_premia_SW.png

graphics_vrp/Variance_risk_premia_US.png graphics_vrp/Variance_risk_premia_KO.png

Note: This figure shows Variance Risk Premium (VRP) time series for each country in the sample. VRP is defined as the difference between implied (IV) and realized volatility (RV), $VRP \equiv IV - RV$. See section (4) for details on data sources and realized volatility estimation.

B Data Sources

	Countries (Indices)							
Macro-Finance Variables	France (CAC40)	Germany (DAX 30)	UK (FTSE 100)	China (HSI)	Japan (NIKKEI 225)	Switzerland (SMI 20)	US (S&P 500)	South Korea (KOSPI)
Realized Volatility	Bloomberg	Bloomberg	Bloomberg	Bloomberg	Bloomberg	Bloomberg	Bloomberg	Bloomberg
Implied Volatility	Bloomberg	Bloomberg	Bloomberg	Bloomberg	Bloomberg	Bloomberg	Bloomberg	Bloomberg
AAA Bond Index	Banque de France	Deutsche Bundesbank/Thomson Reuters	Bank of England	The People's Bank of China	Bank of Japan	SNB - Swiss National Bank	Federal Reserve Economic Data	The Bank of Korea
Payroll Employment	OECD	Bundesagentur fur Arbeit, Germany	OECD	National Bureau of Statistics of China	Ministry of Internal Affairs and Communications, Japan	OECD	Federal Reserve Economic Data	OECD
Industrial Production	INSEE - National Institute for Statistics and Economic Studies, France	Federal Statistical Office, Germany	ONS - Office for National Statistics, United Kingdom	National Bureau of Statistics of China	Federal Reserve Economic Data	Federal Statistical Office (FSO), Switzerland	Federal Reserve Economic Data	KOSTAT - Statistics Korea
Producer Price Index	INSEE - National Institute for Statistics and Economic Studies, France	Federal Statistical Office, Germany	ONS - Office for National Statistics, United Kingdom	National Bureau of Statistics of China	Bank of Japan	KOF - Swiss Economic Institute	Federal Reserve Economic Data	The Bank of Korea
Housing Start	Ministere de l'Ecologie du Developpement et de l'Amenagement durables, France	OECD	CLG - Communities and Local Government, United Kingdom	National Bureau of Statistics of China	Ministry of Land, Infrastructure, Transport and Tourism, Japan	OECD	Federal Reserve Economic Data	OECD
Unemployment Rate	DARES - Direction de l'animation de la recherche, des etudes et des statistiques, France	Federal Statistical Office, Germany	ONS - Office for National Statistics, United Kingdom	OECD	Ministry of Internal Affairs and Communications, Japan"	SECO - State Secretariat for Economic Affairs, Switzerland	Federal Reserve Economic Data	KOSTAT - Statistics Korea

Note: This table reports data sources for each macro-finance variable used in the empirical analysis.

C NBER Macroeconomic Recessions Dates

Macroeconomics Recessions					
Country (Index)	Peak	Trough	Countries	Peak	Trough
France (CAC 40)	2001-01-01	2003-06-01	Japan (NIKKEI 225)	2001-01-01	2001-12-01
	2008-02-01	2009-06-01		2004-03-01	2004-11-01
	2011-07-01	2013-01-01		2008-02-01	2009-03-01
	2014-10-01	2016-08-01		2010-09-01	2012-09-01
				2013-10-01	2015-11-01
Germany (DAX 30)	2001-07-01	2005-02-01	Switzerland (SMI 20)	2008-05-01	2009-06-01
	2008-04-01	2009-06-01		2011-04-01	2012-06-01
	2011-07-01	2013-03-01		2014-11-01	2015-07-01
	2014-03-01	2015-09-01			
UK (FTSE 100)	2001-01-01	2002-05-01	US (S&P 500)	1990-07-01	1991-03-01
	2003-11-01	2004-11-01		2001-03-01	2001-11-01
	2008-01-01	2009-06-01		2007-12-01	2009-06-01
	2014-11-01	2017-01-01			
China (HSI)	2001-04-01	2002-01-01	South Korea (KOSPI)	2008-07-01	2009-03-01
	2007-12-01	2009-02-01		2011-02-01	2013-01-01
	2011-08-01	2012-11-01		2014-04-01	2016-11-01
	2014-01-01	2016-10-01			

Note: This table reports NBER recession dates for the countries in the sample.