Time-Varying Risk Aversion and International Stock Returns *

Massimo Guidolin † Erwin Hansen ‡ Gabriel Cabrera §

December 22, 2023

Abstract

We estimate aggregate, time-varying risk aversion inferred from options, stock returns and macroeconomic data for a panel of 8 countries. We document that, for most countries, the estimated risk aversion measure is counter-cyclical. Moreover, we show that estimated risk aversion 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, such as an estimated of the variance risk premium, an investors' sentiment index, and a measure of economic uncertainty. Finally, we show that risk aversion provides useful information to an investor who aims at timing the market. An investment strategy that uses the estimated time-varying risk aversion measure to solve a mean-variance asset allocation problem, delivers significantly positive returns.

Keywords: Implied risk aversion, stock return predictions, market timing, mean-variance asset allocation.

JEL Classification: G10, G11, G15.

1 Introduction

While classical finance theory has traditionally interpreted risk aversion as a parameter constant over time, starting with the seminal papers by Campbell and Cochrane (1999), Gordon and St-Amour (2000), Brandt and Wang (2003) and Brunnermeier and Nagel (2008), modern asset pricing theory has been moving towards actively considering risk aversion as a time-varying attribute characterizing investors, often

*We thank comments from seminar participants at York Asset Pricing Workshop (UK,2019), the 26th Forecasting Financial Markets Conference (Venice, 2019), Universidad Adolfo Ibanez (Chile, 2019), and FMA Annual Meeting (Virtual, 2020). Massimo Guidolin acknowledges the financial support of Ministero dell Universita e della Ricerca PRIN 2017 Prot. 2017TA7TYC (Hi-Di NET. Econometric Analysis of High Dimensional Models with Network Structures in Macroeconomics and Finance).

†Departament of Finance, BAFFI-CAREFIN, and IGIER, Bocconi University, Milan, Italy. Email: massimo.guidolin@unibocconi.it.

‡Department of Business Administration, Faculty of Economics and Business, University of Chile. Email: ehansen@fen.uchile.cl.

§Alliance Manchester Business School, University of Manchester. Email: gabriel.cabreraguzman@postgrad.manchester.ac.uk

using some notion of an average, representative investor.[1] However, while the standard state variables that are assumed to drive asset prices (such as consumption, firms' dividends and cash flows, aggregate economic activity, interest rates, etc.) are easy to measure or at least to approximate across data revisions (this also applies to the quantity of risk, that can be approximated by option-implied risk-neutral variance estimates), risk aversion remains an exquisitely latent factor that is recalcitrant to easy-to-implement, back-of-the-envelope inferential approaches (see Bekaert et al., 2019; Bekaert and Hoerova, 2016; Cuesdeanu and Jackwerth, 2018; Bekaert et al., 2009).[2] Nonetheless, the practical value of the estimates of such latent risk aversion remains largely unexplored. In this paper, we exploit the methodology in Bollerslev et al. (2011) to produce estimates of country-specific, aggregate risk aversion that turn out not only to be sensible when interpreted as proxies as the relative risk aversion of a representative agent, but also to successfully forecast national stock market returns over horizons of up to 12 months. The result holds not only in a statistical sense, but also using classical, portfolio-based gauges of economic value.

Overcoming the challenges posed by the unobservable nature of risk aversion is crucial: if risk aversion is time-varying, then the very way in which the stochastic discount factor (henceforth, SDF) is shaped by its systematic, unidentifiable drivers may change over time. For instance, under power utility, how random future consumption growth translates into the discounting of uncertain asset cash flows, depends on a random, time-varying curvature parameter which turns out to be the opposite of the relative risk aversion coefficient. Moreover, if this phenomenon is to be structural, such time-varying features of the SDF should impact all asset classes and all markets, including all key national equity indices. Indeed, a growing literature has deployed a range of empirical proxies of unobservable risk aversion—such as the variance risk premium (henceforth, VRP, see Bollerslev et al., 2009; Drechsler and Yaron, 2010), a range of investor sentiment indices (see Lemmon and Portniaguina, 2006; Baker and Wurgler, 2006; Gai and Vause, 2006; Baker and Wurgler, 2007; Schmeling, 2009, among others), and risk-neutral measures of risk (such as the VIX, see Coudert and Gex, 2008)—to try and pin down its role in asset pricing. In our paper, we pursue a different avenue and exploit both options and stock returns information to extract implied aggregate risk aversion by adopting the parametric approach in Bollerslev et al. (2011).

One of the additional challenges concerning TVRA is that it is easy to proceed to its estimation by imposing tight parametric assumptions concerning preferences (hence, the functional form of the SDF) and the state variables driving the SDF. However, this routinely makes the resulting TVRA estimates non-robust

[1] This shift in sensitivity has also been supported by considerable experimental (see, e.g., Cohn et al., 2015) and micro-economic data evidence (see, e.g., Guiso et al., 2018 and Paravisini et al., 2016). For instance, in their seminal paper, Bliss and Panigirtzoglou (2004) assume constant parameters for the assumed utility functions and yet report strong time variability in the estimated relative risk aversion of the marginal investor.

[2] This is also the case as time-variation in risk aversion to gambles with respect to wealth may derive from complex non-linearities in the value function.

and plagued by model specification error. Therefore, in this paper we build on a method that makes use of model-free realized volatility, model-free option-implied volatility, and of commonly observable international macroeconomic data series, to estimate TVRA functions on a country-by-country basis. In particular, the estimation method exploits a set of theoretical moment conditions derived from both the realized and the risk-neutral volatilities of stock returns in order to implement a GMM-type estimator that separates the market expectations from the shape of preferences without imposing overly strong restrictions on either expectations or utility functions. In an extension of the standard GMM approach to estimate risk aversion in Bollerslev et al. (2011)'s approach, in this paper we estimate the coefficients of a parametric projection of risk aversion on a set of macro-finance variables provides a flexible specification of the variation in risk aversion through time, which is what we define a *TVRA function*. Such a TVRA function is what subsequently allows to predict risk aversion and hence aggregate stock market returns.

Under the assumption that TVRA affects the shape of the SDF, TVRA must explain and even predict the returns on all assets, and in particular of all major stock market indices. This is consistent with the empirical evidence in Faccini et al. (2018) that TVRA forecasts future growth in real economic activity in a number of countries.[3] Therefore, we estimate TVRA functions and use their values in forecasting exercises with reference to equity index returns for eight major, developed countries (France, Germany, Hong Kong, Japan, South Korea, Switzerland, the US, and the UK). We show that estimated risk aversion varies significantly through time in a counter-cyclical manner, consistent with the consumption CAPM model of Campbell and Cochrane (1999) as well as New Keynesian models including a monetary policy function, such as the one in Pflueger and Rinaldi (2022). We find that variables such as realized volatility, the Aaa-Bbb credit yield spread, industrial production growth rates and the price-earnings ratio are the main drivers of aggregate risk aversion across countries. This evidence is consistent with but extends the results in Bollerslev et al. (2011) for the US to an international context and corroborates the hypothesis that the shape of the SDF is time-varying and driven by local TVRA functions. We also report that, on average, during our sample period, risk aversion is higher in Germany and Japan, and lower in France and in the US, although in all countries the hypothesis that TVRA is a driver of aggregate stock returns cannot be rejected.

Our key contribution is to investigate the genuine out-of-sample (OOS) predictive power of TVRA for international equity returns when risk aversion is related to business cycle conditions. Using panel regression methods, we show that the estimated TVRA function forecasts aggregate stock index returns over the subsequent 12 months. This result is robust to the inclusion of the VRP, an investor sentiment index, and a

[3]Empirical evidence for the US in fact shows that TVRA affects the price of other financial assets such as options written on the S&P 500 index (see Hansen and Tong, 2022), government bond returns (see Çepni et al., 2020), and the riskless yield curve (see Bouri et al., 2021).

measure of economic uncertainty. When these variables are included in the panel model, the TVRA metric remains statistically significant. Therefore the information contained in the TVRA is valuable on its own and does not necessarily reflect the same information as these additional variables that—in the light of the literature (see, e.g., Bali and Hovakimian, 2009; Bekaert et al., 2010; Brogaard and Detzel, 2015; Pyun, 2019)—are expected be highly correlated with TVRA and that have been used in earlier papers to proxy for time-varying risk preferences (see, e.g., Bekaert and Hoerova, 2014; Bekaert et al., 2019; Londono, 2015). Moreover, our estimates of the predictive regression coefficients associated with the *control* variables are reassuring because they are in line with previous evidence: the VRP predicts stock returns at several horizons similarly to what is reported by Bollerslev et al. (2009, 2014); the estimates of investor sentiment negatively forecast stock returns as in Lemmon and Portniaguina (2006) and Schmeling (2009); the relationship between economic uncertainty and future stock returns is positive and significant in line with Brogaard and Detzel (2015). We complement the panel regression approach with a rolling OOS approach similar to Welch and Goyal (2007), to assess stock return predictability in a genuine, standard time series framework. Our results reveal strong OOS forecasting power of TVRA for national equity markets. In sample and for half of the countries under analysis, we find that a model the uses the estimated, lagged TVRA as single predictor of future stock returns outperforms a benchmark that assumes no predictability. Out-of-sample, we find even stronger evidence that the predictive accuracy of TVRA is superior to a no-predictability benchmark.

Also because misalignments between statistical predictability and the market value from economic timing have been often reported in the literature (see, e.g., Kandel and Stambaugh, 1996; Welch and Goyal, 2007; Cenesizoglu and Timmermann, 2012; Timmermann, 2018; Dal Pra et al., 2018), we further examine whether the estimated TVRA function may generate economic value to an investor. We apply a set of market timing tests and investigate the OOS performance of a portfolio tracking the signals revealed by the TVRA estimates, relative to a benchmark portfolio. Our results suggest that the estimated TVRA considerably helps to time the market. First, the probability of correctly forecasting the direction of change in equity returns (the realized hit ratio) exceeds on average 60 percent for most of the country indices and prediction horizons considered. Second, we find that the Direction Accuracy (DA) test of Pesaran and Timmermann (1992) and the Excess Predictability (EP) test of Anatolyev and Gerko (2005) give results consistent with the hypothesis of market timing ability of the model that includes the TVRA. This evidence supports the existence of timing ability associated to our TVRA measure for most countries and forecast horizons.

Finally, in line with the literature (see, e.g., Kostakis et al. 2011; Pyun 2019), in addition to market timing tests, we evaluate the economic value of the estimated TVRA by comparing the performance of a mean-variance portfolio that exploits predictability signals from the TVRA model relative to a benchmark just based on historical sample means. We find that in most countries, the portfolio rule backed by TVRA outperforms the benchmark: both the Sharpe ratio and the Certainty Equivalent measures are considerably higher vs. the historical sample mean, which has been shown to be hard to outperform by Welch and Goyal (2007). We also compute the performance fee an investor would be willing to pay to switch from a portfolio based on the historical mean to one based on TVRA predictive signals. We find that investors ought to be willing to pay a positive performance fee in all the countries in our sample but Germany, and that such fee is generally in excess of a rather sizeable 100 bps per year.

This article fits in different strands of the literature on the estimation of TVRA and predictability. First, we contribute to the research aiming at estimating risk aversion at the aggregate level using stock return and option data (see, e.g., Jackwerth, 2000; Rosenberg and Engle, 2002; Bliss and Panigirtzoglou, 2004; Bollerslev et al., 2011; Faccini et al., 2018; Liao and Sung, 2020, and Kosolapova et al., 2023). This literature has provided considerable evidence of predictable time variation in risk preferences for US data. We provide evidence for broader set of countries and compare to what extent risk aversion across countries co-moves. A second literature investigates aggregate stock return predictability (see, e.g., Welch and Goyal, 2007; Wachter and Warusawitharana, 2009; Rapach and Zhou, 2013). Our contribution consists of the evidence that an important theoretical determinant of expected stock returns, TVRA, is statistically linked to future realized stock returns and represents a useful indicator to an investor who times the market. Even though we show that TVRA predicts stock returns after controlling for well know predictors such as VRP, sentiment, and economic uncertainty indices, our goal is not to perform a fully-fledged horse race among potential equity return predictors, but to empirically validate the theoretical link between risk aversion and expected stock returns. Of course, there is also a literature that investigates stock return predictability in an international context (see, e.g., Ang and Bekaert, 2006; Hjalmarsson, 2010; Rapach et al., 2013; Bollerslev et al., 2014; Bali et al., 2011; Londono and Xu, 2019; Chiang, 2021). To the best of our knowledge, ours is the first paper that examines the predictive power of TVRA in an international context and provides novel results which relate to recent papers that have estimated variance risk premia and total uncertainty implicit in asset prices (see Drechsler, 2013; Bekaert et al., 2019, 2009; Bekaert and Hoerova, 2014).

The remainder of the paper is organized as follows. In section 2, we describe the methodology to estimate parametric time-varying risk aversion. In section 3, we describe our data and report preliminary estimation results on constant vs. time-varying risk aversion. In section 4, we study the predictive power of the estimated TVRA function for stock index returns using both panel regressions and a time series out-of-sample forecast evaluation design. In section 5, we assess the economic value of using the TVRA estimates in timing the market. Section 6 presents robustness checks. Section 7 concludes.

2 Estimation of Time-Varying Risk Aversion

In this section, we estimate a time-varying risk aversion function following Bollerslev et al. (2011). We start by providing the theoretical motivations of time-varying risk aversion using the empirical framework proposed by Heston (1993). Using a GMM-type estimator, we then proceed to estimate a static risk aversion function, i.e., when risk aversion boils down to be a fixed, estimable coefficient; next, we extend these empirical 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.

2.1 A Formal Framework

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

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

with instantaneous correlation between shocks to stock returns (dp_t) and shocks to variance denoted as $\rho = corr(dB_{1t}, dB_{2t})$, which captures the well-known leverage effect; $\mu_t(\cdot)$ and $\sigma_t(\cdot)$ are two functions that satisfy standard regularity conditions (see, e.g., Bollerslev and Zhou, 2002). Assuming no arbitrage and a linear volatility risk-premium, Bollerslev and Zhou (2002) shows that the risk-neutral distribution associated to the stochastic process in (1) is given by

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

with the same correlation $\rho = corr(dB_{1t}^*, dB_{2t}^*)$ characterizing the physical process and r_t^* being the risk-free interest rate. The values of the risk-neutral parameters in (2) are mapped into the parameters of the physical log-price process in (1) by the functional relationships $\kappa^* = \kappa + \lambda$ and $\theta^* = \kappa\theta/(\kappa + \lambda)$, where λ is the constant risk premium associated to stochastic volatility.

Following the notation in Bollerslev et al. (2011), let $\mathcal{V}^{\mathcal{N}}{}_{t,t+\Delta}$ denote the realized volatility, computed as the squared sum of daily returns between time t and $t + \Delta$. Under mild conditions, such a model-free estimate provides an accurate approximation of the unobserved integrated volatility, $\mathcal{V}_{t,t+\Delta}$. In fact, Bollerslev and

Zhou (2002) show that the risk-neutral distribution associated to the stochastic process in (1) is given by

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

where the coefficients $\alpha_\Delta = e^{-\kappa\Delta}$ and $\beta_\Delta = \theta(1 - e^{-\kappa\Delta})$ are functions of the underlying parameters κ and θ in (1). As for the risk-neutral first moment of integrated volatility, Britten-Jones and Neuberger (2000) proves that volatility computed as the (continuous) 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 a European call option maturing at time $t+\Delta$ with strike price K, equals the true risk-neutral expectation of the integrated volatility, $IV^*_{t,t+\Delta} = E^*(\mathcal{V}_{t,t+\Delta}|\mathfrak{F}_t)$. Finally, using these resul,. 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

$$E(\mathcal{V}_{t,t+\Delta}|\mathfrak{F}_t) = \mathcal{A}_\Delta \mathrm{IV}^*_{t,t+\Delta} + \mathfrak{B}_\Delta, \tag{5}$$

where $\mathcal{A}_{\cdot} = \frac{(1-e^{-\kappa\Delta})/\kappa}{(1-e^{-\kappa^*\Delta})/\kappa^*}$ and $\mathfrak{B}_\Delta = \theta[\Delta - (1 - e^{-\kappa\Delta})/\kappa] - A_\Delta\theta^*[\Delta - (1 - e^{-\kappa^*\Delta})/\kappa^*]$ are functions of the parameters κ, θ and λ. Bollerslev et al. (2011) shows that the moment conditions (3) and (5) jointly provide the necessary identification conditions for λ, the risk-premium parameter.

2.2 GMM Estimation

Given the moments conditions in (3) and (5), it is natural to consider GMM as the appropriate method to infer the parameters of interest from the data. Thus, considering (3) and (5), and adding lagged realized volatility as additional instrument to expand the set of moments conditions to allow for over-identification as in Garcia et al. (2011); Bollerslev et al. (2011), the final set of conditions to recover the vector of parameters $\xi = (\kappa, \theta, \lambda)'$ is given by:

$$\mathbf{f_t}(\xi) \equiv \begin{pmatrix} \nu_{t+\Delta,t+2\Delta} - \alpha_\Delta \nu_{t,t+\Delta} - \beta_\Delta \\ (\nu_{t+\Delta,t+2\Delta} - \alpha_\Delta \nu_{t,t+\Delta} - \beta_\Delta)\, \nu_{t-\Delta,t} \\ v_{t,t+\Delta} - \mathcal{A}_\Delta iv^*_{t,t+\Delta} - \mathfrak{B}_\Delta \\ \left(v_{t,t+\Delta} - \mathcal{A}_\Delta iv^*_{t,t+\Delta} - \mathfrak{B}_\Delta\right) v_{t-\Delta,t} \end{pmatrix}. \tag{6}$$

By construction $E(\mathbf{f_t}(\xi)|\mathcal{G}_t) = \mathbf{0}$, where $\mathcal{G}_t$ is the available set of information up to time t, and the GMM estimator is defined as

$$\hat{\xi}_t = \arg\min_{\xi} \mathbf{g}(\xi)'\mathbf{W}\mathbf{g}(\xi), \tag{7}$$

where $\mathbf{g}(\xi)$ is the sample mean of the moment conditions, $\mathbf{g}(\xi) = \sum_{t=1}^{T} \mathbf{f_t}(\xi)$, and $\mathbf{W}$ is a positive definite and symmetric 4×4 matrix that denotes the asymptotic covariance matrix of $\mathbf{g_t}(\xi)$. The optimal matrix $\mathbf{W}$ can be estimated using an heteroskedastic and auto-correlation consistent (HAC) matrix with appropriate kernel and bandwidth choices.[4] In our application, these by now standard estimation methods are extended to estimate not a vector of constant structural parameters $\xi = (\kappa, \theta, \lambda)'$ but instead the parameters of a TVRA function that besides κ and θ, maps λ into a vector of predictive instruments (see below for details).

3 Data, Summary Statistics and Preliminary Empirical Results

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 data on 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.

3.1 Data and Summary Statistics.

The empirical analysis starts with the estimation of time series of model-free realized volatilities (RV) and option-implied volatilities (IV) for each national stock index/market in our sample. The realized volatilities are computed on each month as the squared sum of daily stock continuously compounded index returns in that month:

$$RV_t \equiv \sum_{i=1}^{n} \left(p_{t+\frac{i}{n}} - p_{t+\frac{i-1}{n}} \right)^2 . \tag{8}$$

The literature has shown that this model-free volatility estimator produces more accurate ex-post estimates of return variation than a range of alternative volatility estimators (see, e.g., Andersen et al. 2001, 2003). Even though a number of studies have used high-frequency data to estimate (8), given our objectives in this paper, we simply resort to daily returns to compute monthly volatilities, as in Bollerslev et al. (2014). We also use option-implied volatility on international equity indices akin to the VIX index as our observed

[4] Bollerslev et al. (2011) point out that the complex lag structure in the moment conditions (3) and (5) imposes a complex dependence, therefore, a HAC robust covariance matrix estimator with Bartlett-kernel and five lags is used in the estimation.

implied volatility indices (IV).[5] Stock index returns and related implied volatility indices are retrieved from Bloomberg, at a monthly frequency. Given a need for sufficiently long time series in our empirical tests and forecasting exercises, our sample contains information for eight countries, i.e., France (CAC and VCAC indices are used), Germany (DAX 30 and VDAX), the United Kingdom (FTSE 100 and VFTSE), Hong Kong (HSI and VHSI), Japan (NIKKEI 225 and VXJ), South Korea (KOSPI and VKOSPI), Switzerland (SMI 20 and VSMI), and the United States (S&P 500 and VIX). The country selection matches the sample used in Bollerslev et al. (2014) but it remains hard to find sufficiently long time series for a wider cross section. 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 start in 1990.[6]

In addition to option-implicit and realized volatilities, for each country/equity index, we also construct time series of the estimated variance risk premium (VRP), defined as the difference between implied volatility and realized volatility, $VRP_t \equiv RV_t - IV_t$. This additional variable is compiled in monthly percentage-squared form. Appendix A shows time series plots of VRP_t. As commonly observed (see, e.g., Coudert and Gex, 2008), we find that VRP increases during recessions.[7] We use a range of routinely monitored macro variables in the estimation of TVRA. In particular, we collect data on Aaa bond spreads over Treasuries of matching maturity (both at 10-year when available), payroll employment, industrial production, producer price index, housing starts, the unemployment rate, and the price-earning (PE) ratio. The data come from different sources, all described in Appendix C.

In the panel regressions in section 4, we use a set of additional control variables to rule out omitted variable bias. In particular, we include proxies for investors' sentiment and for 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 Hong-Kong, France, Germany, South Korea, the UK, and the US, the consumer confidence index is obtained from the Directorate Generale for Economic and Financial Affairs of the European Commission; in the case of Japan and Switzerland, we obtain sentiment data from Datastream. Economic uncertainty is proxied by the Economic and Political Uncertainty (EPU) indices of Baker et al. (2016).[8]

[5]Similar to Bakshi and Madan (2006) and Kosolapova et al. (2023), we use non-overlapping time periods and focus on short-term, 1-month option contracts to extract IV indices.

[6]The sample dates for each country are: France (2001:01-2017:10), Germany (2001:01-2017:10), the UK (2001:01-2017:09), Hong Kong (2003:01-2017:10), South Korea (2003:01-2017:10), Japan (2001:01-2017:10), Switzerland (2001:01-2017:10), and the US (1990:01-2017:10).

[7]Appendix D reports recession dates for countries in the sample. For the US, we use NBER recession dates, and for the remaining countries (but Hong-Kong) OECD recession indicators. For Hong Kong, we use quarterly GDP growth rates (from the Hong Kong Monetary Authoriry) to identify recession episodes.

[8]For all the countries but Switzerland, we obtain the EPU indices from the web site http://www.policyuncertainty.com/. For Switzerland, we use an EPU index available at the data repository of the Swiss Economic Institute.

Summary statistics for monthly realized and implied volatilities are reported in Table 1.[9] As one would expect, for all countries/indices, the sample mean of implied volatility exceeds realized volatility and often substantially. For instance, this is the case of the KOSPI index (by 4.67% per year) or of the S&P500 (by 4.29% per year). This fact indicates that the variance risk premium is always negative, on average. Interestingly, the ordering of the sample standard deviations of realized and implied volatilities are reversed vs. the means, with the former always exceeding the latter for all our eight equity/volatility indices. Finally, all the series of both implied and realized volatilities display large, positive (and statistically significant) skewness and excess kurtosis, which is relatively non surprising in light of the empirical literature concerning US data (see, e.g., Bandi and Perron, 2006), albeit less frequently documented with reference to the remaining seven countries under investigation (but see Kourtis et al., 2016). Appendix B reports descriptive statistics of index stock returns.

3.2 Constant vs. Time-varying Risk Aversion Functions

To provide a theoretical background to our empirical work, 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 Cochrane (2009). Bollerslev et al. (2011) show 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 of terminal wealth (as in Bliss and Panigirtzoglou, 2004)

$$U(W_t) = e^{-\delta t}\left(\frac{W_t^{1-\gamma}}{1-\gamma}\right), \tag{9}$$

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 volatility risk premium. In particular, it turns out that $\gamma = \lambda/(\rho\sigma)$. Here, on the basis of typical empirical results, $\rho < 0$ is the leverage effect parameter, and because $-1 < 1/(\rho\sigma) < 0$, as a result λ is approximately equal to the negative of the representative investor's relative risk aversion.[10]

In this setup, in order to capture any time variation in estimated risk aversion, we implement a simple

[9] Countries are sorted alphabetically based on its stock index name. We keep this order in the rest of the paper.

[10] Note that even though $\rho\sigma$ = -1 is unlikely to hold exactly in all data samples, what matters to our empirical goals is that λ turns out to equal the negative of relative risk aversion, apart from a proportionality constant.

Table 1. Summary Statistics for Monthly Realized and Implied Volatility

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

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), the United Kingdom (FTSE 100), Hong Kong (HSI), South Korea (KOSPI), Japan (NIKKEI 225), Switzerland (SMI 20), and the US (S&P 500). 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.

augmented $AR(1)$ (or $ARX(1)$) process to be fitted to the volatility risk premium coefficient as follows,

$$\lambda_{t+1} = \alpha + \beta\lambda_t + \sum_{k=1}^{k} c_k' x_{t,k} + u_{t+1}, \tag{10}$$

where $\mathbf{x}_t$ 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 series observable at monthly frequencies. In particular, we estimate the time-varying volatility risk premium specification in (10) by including in $\mathbf{x}_t$ the series of lagged squared realized volatility, lagged implied volatility, and a set of macro-finance indicators: Aaa corporate bond spreads, the annual (year-to-year) growth rate (computed as the change in logs) in housing starts, the rate of growth of industrial production, producer price inflation, the change in total payroll employment, and finally, the price-earnings (PE) ratio of the corresponding national stock market under consideration. Importantly, in the time-varying case, the functional equation (10) replaces the individual risk aversion parameter θ, so that the GMM estimation routine delivers an extended set of parameters $\xi^* = (\kappa, \theta, \alpha, \beta, \mathbf{c}_k')'$. However, the parameters featured in 10 allow us to subsequently re-construct the implied (GMM) time series of estimated TVRA, λ_t.

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 the unconditional mean of the TVRA coefficient is:

$$E[\lambda_{t+1}] = E[\alpha + \beta\lambda_t + \mathbf{c}'\mathbf{x_t} + u_{t+1}] = \alpha + \beta E[\lambda_t] \Rightarrow E[\lambda_{t+1}] = \frac{\alpha}{1-\beta}.$$

Table 2 reports the 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}, the latter as specified in (10).[11] It is informative to start discussing estimation results for the US and compare them with typical estimates in earlier literature. Despite the fact 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 clearly encouraging 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 latter value falls within a 90% confidence interval around our estimate 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

[11] With reference to 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.

somewhat persistent, with a precisely estimated autoregressive coefficient $\hat{\beta} = 0.74$. Moreover, as typical in the literature, we find that the coefficients associated to most of the macro-finance variables in $\mathbf{x_t}$ 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 on risk aversion, past realized volatility plays the biggest role and with the expected sign (-0.42), i.e., higher perceived risk foster an increased aversion to future risks. Next, the Aaa corporate bond spread and the rate of growth in housing starts do exercise economically 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 hence with lower risk aversion. It is easier to understand—especially in the light of its dynamics during the Great Financial Crisis—why lower housing starts predict higher risk aversion. The industrial production growth rate and producer price inflation come at the bottom of the list with smaller and borderline significant coefficients. Overall, our results confirm previous evidence in terms of the magnitude of the estimates and their importance explaining the dynamic of the risk aversion over time.

The estimation outputs for the remaining countries show that a static version of the model is supported by the data, in terms of generating significant and economically plausible estimates of risk aversion. The estimates of the constant coefficient for λ vary between -1.77 for Germany and -4.71 in the case of France. The estimated coefficient is significant in 7 out 8 countries (Germany is the exception).[12] However, in the case of the remaining seven markets, the time-varying model seems more successful in generating plausible risk aversion estimates. In this case, the unconditional mean risk aversion varies between 1.33 for Switzerland and 3.58 for Hong Kong (besides the rather low unconditional mean of 0.76 for the US).[13]

In general, estimated risk aversion coefficients between 1 and 3 appear to be highly plausible, in a comparative literature perspective (see, e.g., Bliss and Panigirtzoglou, 2004 and Alan et al., 2009). However, the most striking empirical findings concern the estimated coefficients associated with the factors collected in $\mathbf{x}_t$. First, with rare exceptions, all coefficients across markets carry the same sign and reveal very similar estimated values. For instance, in the case of the rate of growth of housing starts, for seven countries the minimum estimated coefficient is -0.32 (France) and the maximum is -0.20 (Switzerland), i.e., a rather tight range, with the only exception concerning the anyway negative and significant coefficient for Germany (-0.10). Second, lagged realized volatility keeps returning the most important, negatively signed

[12] In the case of Germany, it is harder to make sense for why equity and options data may combine under a SV framework to deliver a risk aversion coefficient that cannot be distinguished from zero, which implies risk neutrality of investors in the aggregate. Yet, we need to recall that in the presence of non-linearities such as those implied by our model, even modest misspecification errors may combine into large standard errors for the estimated coefficients.

[13] 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 mostly derives from the fact that the estimators of α and β turn out to have a non-neglible negative correlation.

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 (yet it is in the case of France and Germany, which justifies its inclusion in our research design).

Finally, at least in general, the signs of the estimated coefficients are consistent with what is expected. Most of these seem to align with a counter-cyclical story in which risk aversion increases during bear markets and decreases during bull markets (see, e.g., Coudert and Gex, 2008). 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 price 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, often spurred by policy-induced (but potentially unintentional) recessions (see, e.g., Blanchard et al., 2015). We observe instead lower risk aversion when the Aaa bond spread and 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 were reported by Bollerslev et al. (2011).

Figure 1 shows plots of the estimated time-varying risk aversion functions when projected on the set of macro-finance variables as in (10). For each country, the shaded areas highlight recession periods according to the information reported by the NBER macroeconomic recessions database for the US and OECD recession indicators for the remaining countries (see Appendix D).

3.3 Time-Varying Risk Aversion and the Business Cycle

As it is well known, asset pricing models that include habit formation predict a counter cyclical risk aversion dynamics. 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 to fall close to the slow-moving habit index, 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, see for instance the discussion in Bekaert and Hoerova, 2016.[14]. Experimental empirical evidence in Cohn et al. (2015) shows that risk

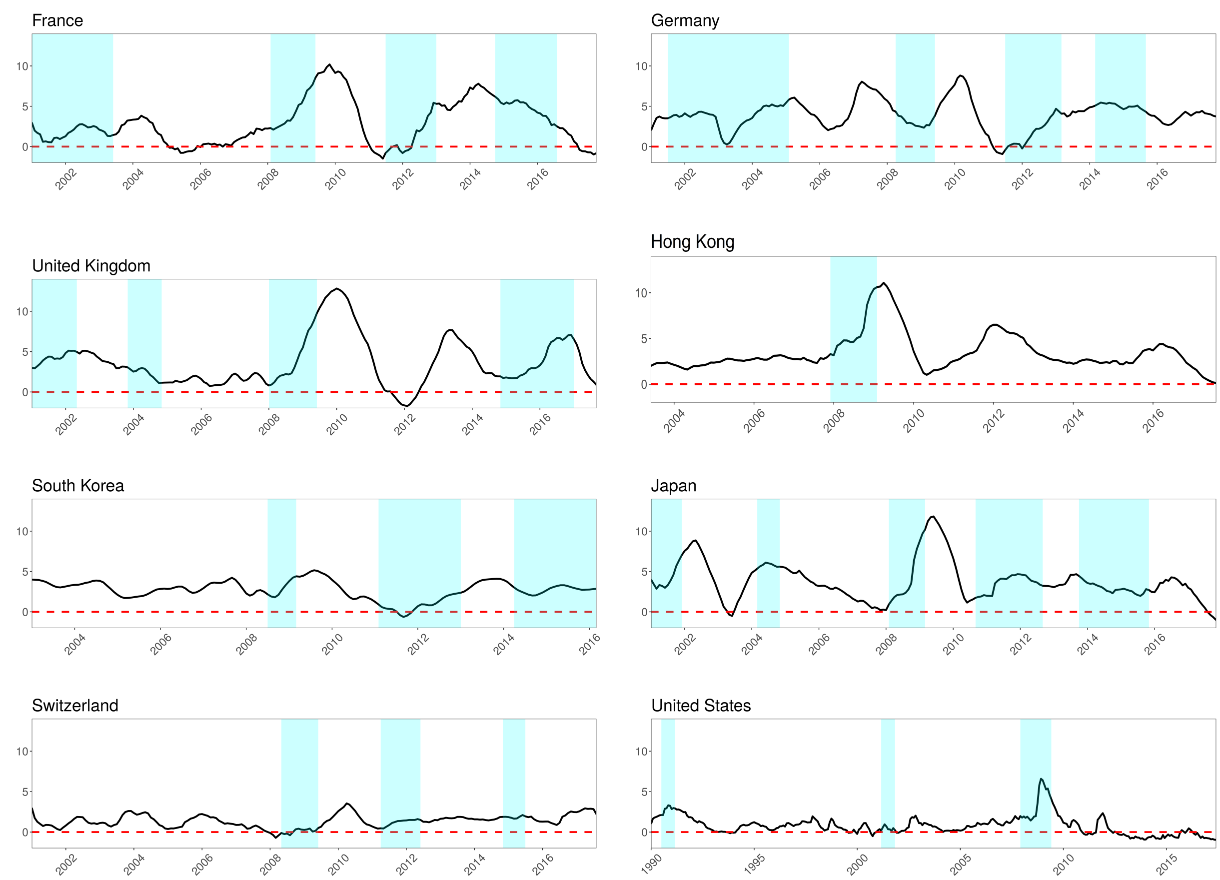
[14] Bekaert et al. (2019) documents a correlation of 0.40 between their estimated risk aversion measure and NBER recession episodes in the US.

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

	France (CAC 40)		Germany (DAX 30)		UK (FTSE 100)		Hong Kong (HSI)	
	Constant	Time-varying	Constant	Time-varying	Constant	Time-varying	Constant	Time-varying
λ	-4.705*		-1.776		-2.578***		-2.415**	
	(2.559)		(1.232)		(0.540)		(1.365)	
α		-0.527***		-0.435***		-0.526***		-0.528**
		(0.070)		(0.160)		(0.026)		(0.215)
β		0.812***		0.779***		0.818***		0.845***
		(0.035)		(0.038)		(0.012)		(0.054)
c_1 Realized volatility		-0.323***		-0.319***		-0.317***		-0.319***
		(0.105)		(0.079)		(0.100)		(0.054)
c_2 Aaa bond spread		0.190**		0.192***		0.187***		0.291
		(0.086)		(0.036)		(0.061)		(0.195)
c_3 Housing starts growth rate		-0.325		-0.103**		-0.212***		-0.230***
		(0.288)		(0.046)		(0.071)		(0.059)
c_4 Ind. production growth rate		0.137		0.091***		0.069**		0.043***
		(0.095)		(0.022)		(0.027)		(0.012)
c_5 Producer price growth rate		-0.056		-0.034		-0.037***		-0.031
		(0.062)		(0.048)		(0.010)		(0.035)
c_6 Payroll employment		-0.032***		-0.045***		-0.048		-0.054**
		(0.011)		(0.007)		(0.052)		(0.023)
c_7 PE Ratio		0.440**		0.384***		0.393***		0.306***
		(0.190)		(0.086)		(0.129)		(0.116)
Unconditional λ		-2.803		-1.968		-2.890		-3.406
	South Korea (KOSPI)		Japan (NIKKEI 225)		Switzerland (SMI 20)		US (S&P 500)	
	Constant	Time-varying	Constant	Time-varying	Constant	Time-varying	Constant	Time-varying
λ	-3.382***		-3.118**		-3.153***		-2.504*	
	(0.986)		(1.565)		(0.756)		(1.347)	
α		-0.320***		-0.232*		-0.777***		-0.200
		(0.042)		(0.127)		(0.229)		(0.120)
β		0.890***		0.931***		0.425***		0.740***
		(0.017)		(0.019)		(0.087)		(0.222)
c_1 Realized volatility		-0.216		-0.319***		-0.362***		-0.423**
		(0.166)		(0.055)		(0.076)		(0.194)
c_2 Aaa bond spread		0.192*		0.191***		0.210***		0.251***
		(0.106)		(0.054)		(0.042)		(0.088)
c_3 Housing starts growth rate		-0.233**		-0.230***		-0.201***		-0.212***
		(0.112)		(0.088)		(0.062)		(0.063)
c_4 Ind. production growth rate		0.056		0.037		0.079***		0.093***
		(0.073)		(0.118)		(0.029)		(0.023)
c_5 Producer price growth rate		-0.061*		-0.052		-0.083***		-0.045***
		(0.036)		(0.093)		(0.028)		(0.011)
c_6 Payroll Employment		-0.052		-0.030		0.018		-0.034
		(0.062)		(0.096)		(0.049)		(0.031)
c_7 PE Ratio		0.264		0.302**		0.302***		0.114**
		(0.195)		(0.137)		(0.067)		(0.057)
Unconditional λ		-2.909		-3.364		-1.351		-0.769

Notes: the table presents GMM estimation results for the model in equation (10). The column "Constant" shows the case in which λ is constant ($\beta = c_k = 0$) and "Time-varying" 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. Estimated Time-varying Risk Aversion ($-\hat{\lambda}_t$) Projected onto Macro-Finance Variables



Note: the plots show estimates of time-varying risk aversion from equation (10), by country. Shaded areas correspond to recession periods. See appendix (D) for detailed information about the recession start and end dates, and sources.

aversion is counter cyclical. This study faces a group of financial professionals to boom-bust scenarios to quantify their preferences for risk across such a lab-induced notion of business cycle. Finally, Guiso et al. (2018) also provides evidence along these lines by combining survey information and portfolio holdings data from a commercial bank in Italy. However, there is also a set of studies showing that risk aversion, estimated combining option data and different functional form for the marginal aggregate investor's utility function, is pro-cyclical (see, Bliss and Panigirtzoglou, 2004; Kosolapova et al., 2023). 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 the theories described above.

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 contemporaneous as well as cross-serial (using both leads and lags) correlations; in particular, we report correlations between months -5 and 5. Overall, our results show that the time-varying risk aversion measure displayed in Figure (1) is counter-cyclical as we observe a consistently declining pattern in the estimated correlations when moving from a -5 lag to a $+5$ lead. Indeed, in some countries, 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 Hong Kong ($Corr(-\lambda_t^{hk}, Uempl_{t-5}^{hk}) = 0.25 > Corr(-\lambda_t^{hk}, Uempl_{t+5}^{hk})) = 0.082$, and the difference is statistically significant at 5%), Germany ($0.13 > 0.09$), Japan ($0.26 > 0.02$), South Korea ($0.13 > 0.02$), and the US ($0.38 > 0$). In the case of France, Switzerland, and the UK, such a decline in $Corr(-\lambda_t^i, Uempl_{t+k}^i)$ as k goes from -5 to $+5$ is slower, so that risk aversion is predicted by past business cycle conditions but also predicts subsequent business cycle conditions. Crucially, $Corr(-\lambda_t^i, Uempl_{t+k}^i)$ is positive and mostly statistically significant for all the 8 countries under examination, i.e., all around the world, risk aversion does grow during recessions.

Our results are in line with those reported in Kim (2014) for the US. Such empirical evidence validates the economic meaningfulness of our estimates but opens a further, key question that lies at the hart of our project, i.e., whether the time-varying risk aversion implicit in the joint time series of equity spot and option prices may forecast future returns on equity indices. Especially for those countries/indices in which it is risk aversion that predicts business cycles, our conjecture is that risk aversion may forecast equity index returns; such a conjecture turns weaker for the cases in which risk aversion is predicted by past business cycle conditions but the opposite does not hold, 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 be occurring with an increasing frequency, see Shimer, 2012), which makes a direct test of the predictive power of $-\lambda_t^i$ for stock index returns compelling.

4 Stock Return Predictability from Time-Varying Risk Aversion

In this section, we examine whether the estimated time-varying risk aversion function helps to forecast stock returns. We perform two empirical exercises. First, we estimate panel regressions with country fixed effects in which our time-varying risk aversion function predicts future stock returns up to 12 months ahead. Second, following Welch and Goyal (2007), we compute the out-of-sample R^2 from forecast regressions in which the key predictor is the inferred time-varying risk aversion and we test whether this predictor outperforms a natural benchmark, the rolling, historical mean of equity index returns.

4.1 Panel Estimates and In-Sample Predictions

In order to test whether the TVRA measure estimated in Section (2) may forecasts stock returns, we estimate a set of panel regressions in which the excess returns of the equity indices under investigation are regressed on lagged values of the TVRA indicator and additional control variables. Panel data techniques have been employed in the stock return predictability literature when several countries have been jointly analyzed by Ang and Bekaert (2006); Hjalmarsson (2010); Rapach et al. (2013); Brogaard and Detzel (2015), among others. The use of panel regressions reduces the data mining problems commonly plaguing time series predictive regressions because to mine predictors for a set of heterogenous countries is harder and it enhances estimation efficiency due to the use of a set of countries in the analysis instead of a single country. In practice, we estimate the following specification

$$\frac{1}{h} r_{t,t+h}^i = a(h) + b(h) TVRA_t^i + \gamma(\mathbf{h})' \mathbf{z}_t^i + \alpha_i + \delta_t + u_{t,t+h}^i \quad h = 1, 2, ..., 12, \tag{11}$$

where i is the country index (in our case, i = fr, ger, uk, hkg, sk, jp, swtz, and us), $r_{t,t+h}^i$ indicates to the h-horizon cumulative 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, i.e., $r_{t,t+h}^i \equiv \prod_{j=1}^h (1 + R_{t+j}^i) - \prod_{j=1}^h (1 + f_{t+j})$, where f_{t+j} indicates the risk-free return for a cash bond investment between $t + j - 1$ and $t + j$. In (11), $TVRA_t^i$ represents the time-varying risk aversion index estimated in section 2, and $\mathbf{z_t^i}$ represents a set of control variables specific to each country. This empirical specification includes country-specific fixed effects, α_i to account for invariant unobservable heterogeneity at the country

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***
Hong Kong (HSI)	0.252***	0.225***	0.197**	0.171**	0.152**	0.142*	0.123	0.107	0.094	0.085	0.082
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
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

Notes: The table shows the correlation between the estimated time-varying risk averision $(-\lambda_t)$ from equation (10) 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 C. *,**,*** indicates statistical significance at the 10, 5 and 1%, respectively.

level (see the discussion in Brogaard and Detzel, 2015) as well as time-specific effects, captured by δ_t.[15] Importantly, the coefficients $b(h)$ and $\gamma(\mathbf{h})$ are homogenous across countries as they just depend on the horizon and therefore represent common effects of time-varying risk aversion and other macro-finance style predictors on subsequent (per-period) excess returns, $h^{-1} r^i_{t,t+h}$. Note that even though TVRA at time *t* is used to predict subsequent, h-horizon equity index retuns, such predictability is purely in-sample.

Previous literature (see e.g. Stambaugh, 1999; Campbell and Yogo, 2006; Hjalmarsson, 2010) has discussed the fact that inference may be problematic and lead to biased estimates when the predictor variable is persistent and the innovations to the predictors are correlated with the dependent variable, which is indeed the case of the estimated TVRA. To cope with this problem in our empirical set up, we follow Rapach et al. (2013) and use a wild bootstrap procedure to compute p-values. The wild bootstrap procedure is robust to the Stambaugh (1999) bias for hypothesis testing purposes and it also accounts for conditional heteroskedasticity in stock returns.[16]

As for the control variables collected in $\mathbf{z^i_t}$, 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) ($VRP^i_t \equiv IV^i_t - RV^i_t$). We also consider a proxy for investors' sentiment: recent evidence in the literature has shown that sentiment predicts 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 the consumer confidence index at the country level to proxy for investor sentiment.[17] We also control for economic uncertainty at the country level and use the news-based Economic Policy Uncertainty (EPU) index introduced by Baker et al. (2016).[18]

Table 4 shows the main results. We report the estimates of different specifications organized in several panels. We start in panel A by presenting models in which the TVRA measure is the single predictor; next, in panels B through D, we present results from specifications in which we add, one at the time, each of the control variables considered in the analysis to the baseline models in panel A; finally, panel E deals

[15]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 sizes distortion in the estimates. However Menzly et al. (2004) include industry fixed-effects in their regressions of excess stock returns on lagged dividend growth rates.

[16]Rapach et al. (2016); Neely et al. (2014); Jiang et al. (2018) use the wild bootstrap procedure for inferences in stock predictability regressions even though their exercise just concerns US data and not a panel application. As a robustness check, we also compute robust standard errors clustered by country. The results are quite similar to those obtained using the wild-bootstrap procedure and available upon request.

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

[18]The EPU index measures uncertainty based on the newspaper coverage of some key concepts associated to economic adversities and/or unexpected events. Hence the index reflects information about uncertain, economic and policy relevant events. Pastor and Veronesi (2012) have argued that economic uncertainty plays a first-order role in predicting the dynamics of stock returns. Empirically, Brogaard and Detzel (2015) has emphasized the role of EPU in predicting stock returns both in the time series and in the cross-section in the U.S. Rehman et al. (2021) show similar evidence at the U.S. sectoral level, and Xu et al. (2021) in the Chinese stock market.

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, $\hat{b}(h)$, is positive, as expected, and highly significant. It ranges from 1.21 at $h = 1$ to 0.11 for $h = 12$, i.e., higher risk aversion forecasts higher global equity risk premia and—as one would conjecture—the predictive relationship is stronger, the shorter is the forecast horizon. It is also interesting to note that the size of the estimated coefficient decreases as the time horizon moves further away from the one-month case, which is expected as the relationship between past risk aversion and business cycle ought to weaken as the number of lags increases. Yet, the adjusted R^2s are relatively modest, with 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 the 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 Li and Zinna, 2018). If this were the case, we would expect a loss of predictive significance of TVRA when the VRP is included in the specification. Crucially, despite that VRP_t^i is an instrument implicitly used to calculate $TVRA_t^i$, note that VRP_t^i is not necessarily highly collinear with $TVRA_{t+1}^i$ projected from (10). On the one hand, this moves the focus on the role played by the parametric specification in (10); on the other hand, given the reasonable empirical evidence provided by our estimates of (10), this is a key step of our contribution. Our estimates shows that this is not the case, because 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 $\hat{b}(h)$ coefficients. For instance, at $h = 1$ (12, respectively), $\hat{b}(1) = 1.19\,(0.103)$ with a p-values of 0.01 at both horizons, while $\hat{\gamma}(1) = 0.20$ (0.02) with p-values below 0.10 in both cases, where $\gamma(h)$ is the coefficient associated with lags of VRP. Nonetheless, VRP does show forecasting power for excess stock returns, as we find that the estimated $\gamma(h)$ coefficient is positive and generally significant across all VRP 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 all exceed those in panel A, although they remain moderate (for daily returns), around 2%. Overall, the results in panel B shows that TVRA and VRP provide different information for subsequent equity index returns but they can both predict them.

Under the common intuition (see Huang et al., 2015) that a TVRA indicator may be simply capturing aggregate market sentiment, in panel C, we replace VRP by an investor sentiment index, also used as an

Table 4. Panel Predictability Regressions

Horizon	1	2	3	4	5	6	7	8	9	10	11	12
Panel A: Baseline												
$TVRA$	1.614***	0.827***	0.558***	0.422***	0.337***	0.282***	0.245***	0.215***	0.195***	0.173***	0.157***	0.144***
	(0.179)	(0.089)	(0.062)	(0.047)	(0.038)	(0.032)	(0.028)	(0.024)	(0.022)	(0.020)	(0.018)	(0.017)
%Adj. R^2	0.39	0.40	0.41	0.42	0.42	0.42	0.43	0.43	0.45	0.44	0.43	0.44
Obs.	1660	1652	1644	1636	1628	1620	1612	1604	1596	1588	1580	1572
Panel B: Baseline + Variance Risk Premium												
$TVRA$	1.552***	0.796***	0.537***	0.406***	0.324***	0.272***	0.236***	0.208***	0.188***	0.167***	0.151***	0.139***
	(0.146)	(0.069)	(0.047)	(0.036)	(0.029)	(0.025)	(0.021)	(0.018)	(0.016)	(0.015)	(0.013)	(0.013)
VRP	0.211**	0.105**	0.070**	0.053**	0.042**	0.035**	0.030**	0.026**	0.023**	0.021**	0.019**	0.017**
	(0.063)	(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	2.33	2.35	2.36	2.37	2.37	2.38	2.39	2.39	2.4	2.38	2.36	2.35
Obs.	1660	1652	1644	1636	1628	1620	1612	1604	1596	1588	1580	1572
Panel C: Baseline + Investor Sentiment												
$TVRA$	1.521***	0.780***	0.526***	0.398***	0.318***	0.267***	0.232***	0.204***	0.184***	0.164***	0.148***	0.137***
	(0.182)	(0.087)	(0.059)	(0.045)	(0.037)	(0.031)	(0.026)	(0.022)	(0.020)	(0.018)	(0.016)	(0.015)
$Sentiment$	-0.136	-0.070	-0.048	-0.037	-0.029	-0.025	-0.022	-0.019	-0.018	-0.016	-0.014	-0.013
	(0.088)	(0.045)	(0.031)	(0.023)	(0.018)	(0.015)	(0.013)	(0.012)	(0.010)	(0.009)	(0.009)	(0.008)
% Adj. R^2	0.49	0.52	0.53	0.54	0.54	0.55	0.56	0.57	0.59	0.58	0.57	0.59
Obs.	1594	1586	1578	1570	1562	1554	1546	1538	1530	1522	1514	1506
Panel D: Baseline + Economic Uncertainty												
$TVRA$	1.593***	0.815***	0.549***	0.414***	0.330***	0.276***	0.240***	0.210***	0.191***	0.170***	0.154***	0.143***
	(0.173)	(0.084)	(0.058)	(0.044)	(0.037)	(0.031)	(0.026)	(0.023)	(0.021)	(0.019)	(0.017)	(0.016)
$Uncertainty$	0.038*	0.019*	0.013*	0.010*	0.008*	0.007*	0.005*	0.004	0.004	0.003	0.003	0.002
	(0.023)	(0.012)	(0.008)	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
% Adj. R^2	0.6	0.61	0.63	0.63	0.65	0.64	0.63	0.6	0.59	0.59	0.54	0.53
Obs.	1660	1652	1644	1636	1628	1620	1612	1604	1596	1588	1580	1572
Panel E: Baseline + All controls variables												
$TVRA$	1.4560***	0.7448***	0.5016***	0.3785***	0.3018***	0.2526***	0.2186***	0.1917***	0.1739***	0.1550***	0.1409***	0.1304***
	(0.2032)	(0.0942)	(0.0627)	(0.0477)	(0.0408)	(0.0346)	(0.0274)	(0.0231)	(0.0205)	(0.0182)	(0.0165)	(0.0141)
VRP	0.2217**	0.1107**	0.0739**	0.0555**	0.0444**	0.0371**	0.0317**	0.0277**	0.0245**	0.0220**	0.0200**	0.0182**
	(0.0629)	(0.0315)	(0.0210)	(0.0157)	(0.0126)	(0.0105)	(0.0090)	(0.0078)	(0.0069)	(0.0063)	(0.0057)	(0.0052)
$Sentiment$	-0.0967	-0.0503	-0.0349	-0.0263	-0.0202	-0.0173	-0.0154	-0.0139	-0.0129	-0.0113	-0.0105	-0.0100
	(0.0591)	(0.0308)	(0.0212)	(0.0159)	(0.0125)	(0.0102)	(0.0090)	(0.0080)	(0.0073)	(0.0064)	(0.0059)	(0.0058)
$Uncertainty$	0.0503***	0.0249***	0.0169***	0.0128***	0.0107***	0.0088***	0.0073***	0.0061***	0.0052***	0.0048***	0.0041*	0.0036
	(0.0215)	(0.0106)	(0.0071)	(0.0055)	(0.0044)	(0.0037)	(0.0033)	(0.0030)	(0.0028)	(0.0025)	(0.0024)	(0.0022)
% Adj. R^2	2.95	2.97	3	3.01	3.03	3.03	3.02	2.98	2.96	2.95	2.88	2.85
Obs.	1594	1586	1578	1570	1562	1554	1546	1538	1530	1522	1514	1506

Note: The table presents panel fixed effects regression estimates of

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

where $r^i_{t,t+h}$ is the stock index excess return for an horizon of h months ahead. $TVRA$ represents time-varying risk aversion estimated in section 2 and α_i is a country fixed effect. We include several control variables in $\mathbf{z}^i_t$. 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 parenthesis.*, ** and *** indicate significance at 10, 5 and 1 percent, respectively.

additional predictor. The estimates show that $\hat{b}(h)$ remains positive and highly significant at all the forecasting horizon considered, an indication that TVRA and the proxy of investor sentiment contain different information. The estimated coefficients for the investors' sentiment are negative, consistent with the evidence in Schmeling (2009); however, we cannot find any evidence of 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. This may be consistent with a case in which the additional predictors are close to being orthogonal to TVRA. The precisely estimated, negative values for $\gamma(h)$ associated to sentiment in panel C, e.g., $\hat{\gamma}(12) = -0.013$, are expected in the light of the literature on the power of sentiment indices to predict return reversal (see, e.g., Da et al., 2014). Interestingly, when combined with TVRA, sentiment provides less accurate in-sample predictions vs. VRP, in the sense that the adjusted R^2s in panel C are generally inferior vs. panel B.

In panel D, we use as an additional, sole 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, as the associated $\hat{b}(h)$ coefficients remain positive and precisely estimated. We find that the estimated coefficient for 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 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.

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 individual control predictors, because the $\hat{b}(h)$ remain all positive and statistically significant for all the horizons. The coefficient estimates for VRP are positive and precisely estimated, 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 at all horizons while they only report accurately estimated effects for horizons of 3-5 months. Again, the fact that both variables, TVRA and VRP, appear to be statistically significant in the predictive regressions confirm that they both contain different information to forecast stock index returns. Similar to the results in panel D, the coefficient associated to investor sentiment remains negative but it is not significant. Finally, we find that higher economic uncertainty forecasts higher stock index excess returns. These results are consistent with the findings in Brogaard and Detzel (2015), but once more they appear stronger in Table 4.[19]

All in all, the panel regression estimates reported in this section provide evidence of a strong (in-sample) predictive link between TVRA and global stock excess returns that is not explained either by VRP, by investor sentiment, or by aggregate economic uncertainty. Yet, this evidence—although certainly necessary to our argument in this paper—is purely in-sample, and based on the simultaneous use of all available data. It becomes therefore of the essence to assess the predictive power of TVRA using a truly out-of-sample research design.

4.2 Out-of-Sample Predictive Performance

Panel estimation results show that our TVRA measure helps to forecast stock returns *in-sample*. Here we turn to a complementary analysis of the predictive, *out-of-sample* power of TVRA following Welch and Goyal (2007) and Campbell and Thompson (2007). They propose a forecast evaluation set up that in our case is based on the recursive comparison of the relative root mean square forecast errors from a predictive model in which TVRA is the single predictor ($\mathcal{M}$) vs. a benchmark strategy that assumes no predictability and it is hence based on historical mean returns ($\mathcal{M}_{mean}$). The exercise is performed using a rolling window approach and, as typical of the equity premium forecasting literature, on a country-by-country basis. We select a window length of 60 months, which tends to be classical in this literature. Thus, both models are estimated on an initial window of 60 months, then the OOS forecasts are computed and saved. Next, we move the window forward by one-month, re-estimate the models—both the one delivering the TVRA only based on available data and the historical sample mean return—and compute OOS forecasts again. We repeat this procedure until the last observation available in the sample has been predicted h-step ahead. Using the set of OOS forecast errors ($e^2_{\mathcal{M},t}$) obtained for both models and saved for each estimation/prediction window, overall Mean Square (forecast) Errors (henceforth, MSE) are computed.

In particular, we follow Welch and Goyal (2007) who have proposed the use of the following statistics (in

[19] As a robustness check, we also estimate these panel regressions including country-specific macroeconomic variables (the GDP growth and inflation rates) as additional control variables. In unreported results (available upon request), we find that our results are essentially unchanged, suggesting that our baseline estimates are not explained by a possible omited-variable bias.

what follows, the country index i is dropped for simplicity),

$$R^2_{OOS} \equiv 1 - (MSE_{\mathcal{M}}/MSE_{\mathcal{M}_{mean}}), \quad \bar{R}^2 = R^2 - (1 - R^2)\left(\frac{T-k}{T-1}\right) \tag{12}$$

$$MSE\text{-}F \equiv (P - h + 1)\frac{P^{-1}\left(\sum_t e^2_{\mathcal{M}_{mean},t+1} - \sum_t e^2_{\mathcal{M},t+1}\right)}{P^{-1}\sum_t e^2_{\mathcal{M}_{mean},t+1}} \tag{13}$$

$$= (P - h + 1)\frac{MSE_{\mathcal{M}_{mean}} - MSE_{\mathcal{M}}}{MSE_{\mathcal{M}_{mean}}} \tag{14}$$

$$= (P - h + 1)\frac{\Delta MSE}{MSE_{\mathcal{M}_{mean}}} = (P - h + 1)R^2_{OOS} \tag{15}$$

where T is the sample size and k is the number of variables included in the predictive regression. Clearly, $R^2_{OOS} > 0$ implies that the model under investigation delivers a stronger forecasting performance vs. the historical sample mean; this implies a larger MSE-F test statistic, which carries a classical TR^2 flavor. MSE-F represents the test statistic of forecast accuracy proposed by McCracken (2007). The null hypothesis of this F-type test is that when the two competing forecasting models have identical MSE, or equivalently, $\Delta MSE = 0$. In (13), P is the number of OOS forecasts that have been recursively obtained, and h is the degree of overlap ($h = 1$ for no overlap), $h = P - 1$. The MSE-F statistic is non-standard and therefore the bootstrapped critical values provided by Clark and McCracken (2001) are used in what follows.

Table 5 shows our results. We find evidence of strong predictive ability of the TVRA measure, in terms of R^2_{OOS}. Given 8 countries and 12 forecast horizons, for a total of 96 possible cells, we observe that $R^2_{OOS} > 0$ in 86 cases out of 96, which is quite impressive. In particular, $R^2_{OOS} > 0$ for all tested horizons in the case of France, Germany, UK, Japan and Switzerland. Only for Hong Kong, South Korea, and the US, we observe some cases of $R^2_{OOS} < 0$. R^2_{OOS} turns out to be large, on average, in the order of 1-2.5 percent, which implies reductions in MSE in the order of 1-3%, which appears to be important in light of the typical values reported in the literature. Particularly, large R^2_{OOS} are observed in South Korea, where the estimated values range between 4.3 and 6.5 percent. In most cases, the estimated R^2_{OOS}s are statistical significant at standard confidence levels according to the MSE-F test with bootstrapped p-values. Indeed, in around two third of the cells, the estimated R^2_{OOS} are statistically significant and positive. In the few cases in which we find $R^2_{OOS} < 0$, such estimates are not statistically significant according to the MSE-F test. Overall, the finding of OOS R-squares indicating superior predictive accuracy vs. the historical sample mean in most of the possible combinations, encourages us to further examine whether trading strategies may exist that exploit such forecasting power.

Table 5. Out-of-Sample Predictability R^2 Ã¡ la Welch and Goyal (2007)

Country (Index)	1	2	3	4	5	6	7	8	9	10	11	12
France (CAC 40)	1.476	2.077*	1.878*	1.841*	1.994*	2.145*	1.866*	1.960*	2.143*	2.338*	2.123*	2.244*
Germany (DAX 30)	0.841*	0.986*	0.109	0.448	0.628	0.738	0.722	0.804	0.884	1.144*	1.231*	1.179*
UK (FTSE 100)	0.508	1.616	2.269*	2.350*	2.412*	2.436*	2.567*	2.495*	2.701*	2.558*	2.507*	2.546*
Hong Kong (HSI)	-0.608	0.052	0.107	0.178	-0.023	-0.045	0.134	-0.152	-0.199	-0.097	0.077	0.250
South Korea (KOSPI)	-5.015	1.729	2.659	3.366	3.081	5.348**	6.455**	4.790**	6.482**	6.385**	3.955**	4.245*
Japan (NIKKEI 225)	1.395*	1.401*	1.352*	1.322*	1.435*	1.489*	1.303*	1.350*	1.525*	1.645**	1.518*	1.514*
Switzerland (SMI 20)	1.360	1.761*	1.864*	2.014**	1.990**	2.030**	1.979**	2.200**	2.402**	2.204**	2.093*	1.915*
US (S&P 500)	-1.306	-0.252	0.672*	0.942*	0.465	0.313	0.749*	1.149**	0.730	1.252**	0.552	0.774*

Notes: The table reports out-of-sample (OOS) R^2 estimates from stock index excess return predictability regressions as in Welch and Goyal (2007) considering the economic restrictions suggested by Campbell and Thompson (2007). h is the forecast horizon . $R^2_{OOS} \equiv 1 - (MSE_{\mathcal{M}}/MSE_{\mathcal{M}_{mean}})$ where $MSE_{\mathcal{M}}$ is the Mean Squared Forecast Error from the regression using the estimated $TVRA$ as predictor and $MSE_{\mathcal{M}_{mean}}$ is the analogous using the historical mean instead. Statistical significance is established using the F-statistics proposed in McCracken (2007) with bootstrapped critical values from Clark and McCracken (2001). The F-test statistics is defined as MSE-F $\equiv (P - h + 1)R^2_{OOS}$ and $pvalue$ is the p-value of the test. R^2_{oos} are reported in percentage. *, ** and *** indicate significance at the 10, 5 and 1 percent, respectively.

5 Economic Evaluation

In this section, we evaluate to which extent the estimated TVRA provides useful information to an investor seeking (ex-ante as well as ex-post) optimal portfolio risk-adjusted performance. We perform two alternative empirical exercises to study any potential, realized portfolio gains. First, we compute a range of alternative market timing tests; second, we evaluate the performance of a mean-variance optimal portfolio that uses TVRA as leading predictor of mean excess returns of the equity indices of the countries under examination.

5.1 Market Timing Tests

We evaluate the market timing power of TVRA by computing the hit ratio (PCS, the percentage of correct signs, defined as the percentage of times the sign of excess stock return is predicted correctly by a TVRA-based predictive regression), the directional accuracy (DA) test of Pesaran and Timmermann (1992), and the excess predictability (EP) test of Anatolyev and Gerko (2005).

Pesaran and Timmermann (1992) proposed a market timing test statistic based on the directional accuracy of the forecasts. The test provides a statistical evaluation of the predictive quality of a set of recursive forecasts. The null hypothesis of the DA test is the absence of market timing ability. The test is computed using the hit ratio, defined as the proportion of the months in which the sign of the predicted excess return equals the observed sign,

$$DA_P \equiv \frac{\hat{\pi} - \hat{\pi}_{ind}}{\sqrt{\widehat{Var}[\hat{\pi}] - \widehat{Var}[\hat{\pi}_{ind}]}} \tag{16}$$

where $\hat{\pi}$ is the actual, sample hit ratio, that is,

$$\hat{\pi} \equiv \frac{1}{P}\sum\nolimits_{t=0}^{P-1} I\left\{r_{t+1}\hat{r}_{\mathcal{M},t+1} > 0\right\},$$

where $I\{\cdot\}$ an indicator function that takes the value one if the condition in brackets is satisfied and it is zero otherwise, and P is the number of months in the recursive OOS exercise. Similarly, $\hat{\pi}_{ind}$ is the expected hit ratio under the assumption of independence of excess returns (i.e., when they are not predictable), computed as $\hat{\pi}_{ind} = \hat{\pi}_r\hat{\pi}_{\mathcal{M}} + (1-\hat{\pi}_r)(1-\hat{\pi}_{\mathcal{M}})$, where $\hat{\pi}_r \equiv P^{-1}\sum_{t=0}^{P-1} I\left\{r^i_{t+1} > 0\right\}$ and $\hat{\pi}_{\mathcal{M}} = (1/P)\sum_{t=0}^{P-1} I(\hat{r}^i_{\mathcal{M},t+1} > 0)$ are the proportions of months in which the actual and the predicted excess returns, respectively, are positive. Under the null hypothesis of no market timing ability, the DA statistics is asymptotically standard normally distributed.

An alternative test of market timing is the excess predictability (EP) test statistic developed by Anatolyev and Gerko (2005). This test is based on the idea that a trading strategy can be used to test for predictability rather than to only consider the directional accuracy of a forecasting model as in (16). The excess predictability statistic is defined as

$$EP_P \equiv \frac{Active_P^{\mathcal{M}} - BuyHold_P}{\sqrt{\hat{V}_{EP}}}, \tag{17}$$

where $Active_P^{\mathcal{M}}$ is the expected return of an active trading strategy that takes long (short) positions when positive (negative) excess returns are predicted from model $\mathcal{M}$ over a recursive OOS period of length P, and $BuyHold_P$ are the returns of a passive buy-and-hold investment strategy that always takes long positions in the stock index (of a country under analysis). Let r_{t+1} be the stock index return and $\hat{r}_{\mathcal{M},t+1}$ the predicted value of r_{t+1}. The active trading rule is given by:

$$\begin{cases} \text{buy shares for a worth equal to all of current wealth, if } \hat{r}_{\mathcal{M},t+1} \geq 0 \\ \text{sell shares for a worth equal to all of current wealth, otherwise.} \end{cases}.$$

As a result, the investor potentially changes her position on each trading period, closing it at the last period of the OOS evaluation period. The one-period return of this strategy is $r_{rule,t+1} = sign(\hat{r}_{\mathcal{M},t+1})r_{t+1}$, where $sign(\cdot)$ takes a value of -1 when the argument is negative and $+1$ when it is non-negative. Under the null hypothesis of no market timing, the expected one-period return of this trading strategy can be estimated as:

$$\widehat{Active}_P^{\mathcal{M}} \equiv \frac{1}{P}\sum_{t=0}^{P-1} r_{rule,t+1} \quad and\ BuyHold_P \equiv \left(\frac{1}{P}\sum_{t=0}^{P-1} r_{M,t+1}\right)\left(\frac{1}{P}\sum_{t=0}^{P-1} sign(r_{t+1})\right).$$

$\widehat{Active}_P^{\mathcal{M}}$ is the sample mean return from the use of the trading strategy and $\widehat{BuyHold}_P$ is an estimate of the average return of a benchmark strategy that issues/sell at random with probabilities corresponding to the proportion of "buys"and "sells"implied ex post by the trading strategy, see
citetanatolyev2005trading for a full discussion. The required, estimated variance to perform the test, $\hat{V}_{EP}$, is given by

$$\hat{V}_{EP} = \frac{4}{P^2}\hat{q}_{\mathcal{M}}(1-\hat{q}_{\mathcal{M}})\sum_{t=0}^{P-1}(r_{t+1} - \overline{r}_{t+1})^2,$$

where $\hat{q}_{\mathcal{M}} \equiv 0.5(1 + P^{-1}\sum_{t=0}^{P-1} sign(\hat{r}_{\mathcal{M},t+1}))$.

Table 6 shows the results for our sample of eight countries. All the metrics are computed considering forecast horizons h between 1- and 12-month ahead. The first market timing metric reported in Table 6 is the hit ratio, defined as the percentage of times a forecast model based on TVRA estimates correctly predicts the sign of stock returns. A hit ratio above 50% indicates that the model under consideration produces

Table 6. Market Timing Tests Based on Time-varying Risk Aversion-Based Forecasts

		Forecasting Horizon											
		1	2	3	4	5	6	7	8	9	10	11	12
France (CAC 40)	Hit ratio	0.75	0.74	0.76	0.72	0.73	0.72	0.77	0.77	0.79	0.78	0.78	0.75
	DA	6.68***	6.45***	6.89***	5.67***	5.91***	5.52***	6.88***	7.00***	7.53***	7.15***	7.06***	6.37***
	EP	5.55***	4.82***	5.11***	4.78***	4.34***	4.27***	5.62***	5.34***	5.06***	5.70***	5.53***	6.09***
Germany (DAX 30)	Hit ratio	0.80	0.77	0.74	0.73	0.73	0.73	0.69	0.69	0.73	0.78	0.78	0.80
	DA	7.02***	6.29***	5.60***	5.71***	6.02***	5.66***	4.81***	4.27***	4.20***	5.51***	5.65***	6.05***
	EP	7.00***	5.15***	3.06***	4.55***	3.64***	5.66***	5.72***	2.98***	2.78***	4.54***	4.32***	5.47***
UK (FTSE 100)	Hit ratio	0.65	0.68	0.68	0.66	0.65	0.63	0.72	0.73	0.77	0.81	0.83	0.80
	DA	3.01***	3.72***	3.59***	3.06***	2.89***	2.41***	5.11***	5.35***	6.35***	7.72***	8.09***	7.34***
	EP	-0.51	-0.55	-0.35	-1.36	-1.82	-1.23	-1.00	-1.07	-0.52	1.30*	4.02***	5.81***
Hong Kong (HSI)	Hit ratio	0.77	0.77	0.76	0.76	0.71	0.67	0.69	0.65	0.62	0.58	0.57	0.57
	DA	6.58***	6.53***	6.31***	6.07***	4.99***	3.92***	4.48***	3.53***	2.99***	1.83**	1.81**	1.74**
	EP	4.26***	2.31***	1.21	-0.30	-1.19	-1.47	-0.92	-0.42	0.12	1.71**	3.10***	5.16***
South Korea (KOSPI)	Hit ratio	0.69	0.75	0.70	0.69	0.72	0.71	0.76	0.77	0.75	0.75	0.74	0.72
	DA	3.93***	5.58***	4.30***	4.13***	4.95***	4.83***	5.85***	6.32***	5.84***	5.72***	5.46***	5.13***
	EP	0.79	2.17**	3.09***	3.52***	4.00***	4.57***	4.91***	5.16***	5.16***	4.60***	4.16***	3.29***
Japan (NIKKEI 225)	Hit ratio	0.67	0.71	0.74	0.78	0.86	0.87	0.84	0.84	0.84	0.82	0.79	0.77
	DA	4.81***	5.45***	6.24***	7.25***	9.08***	9.33***	8.58***	8.40***	8.56***	8.09***	7.11***	6.67***
	EP	5.87***	6.59***	7.15***	7.40***	7.65***	7.80***	7.66***	7.62***	7.41***	6.97***	5.99***	5.12***
Switzerland (SMI 20)	Hit ratio	0.85	0.88	0.84	0.84	0.81	0.81	0.82	0.79	0.82	0.88	0.90	0.88
	DA	9.18***	10.04***	8.89***	8.98***	8.12***	7.89***	8.14***	7.44***	8.17***	9.72***	10.15***	9.77***
	EP	7.43***	7.85***	7.37***	7.50***	6.36***	4.78***	5.69***	6.07***	7.25***	8.19***	8.59***	8.27***
US (S&P 500)	Hit ratio	0.78	0.80	0.82	0.83	0.79	0.81	0.77	0.82	0.84	0.82	0.83	0.81
	DA	10.30***	10.35***	10.72***	10.39***	8.46***	9.31***	7.53***	9.05***	9.87***	9.71***	10.08***	9.33***
	EP	9.38***	9.15***	9.82***	8.37***	7.21***	8.13***	6.78***	7.82***	8.65***	9.79***	9.96***	9.48***

Note: the table shows result of market timing tests. The hit ratio is the fraction of signs predicted correctly by the TVRA model, DA is the Direction Accuracy test of Pesaran and Timmermann (1992) and EP is the Excess Profitability test of Anatolyev and Gerko (2005). OOS forecasts are generated using a rolling 30-month window framework. *, ** and *** indicate significance at the 10%, 5% and 1% percent, respectively.

better sign signals than a forecast based on simply flipping a coin. In the table, this metric is above 50% across all countries and forecasting horizons, indicating that the TVRA model consistently provides useful information for forecasting the sign of international stock returns. In fact, the average hit ratio is around 60% overall. For example, in the case of Germany, this metric varies between 69% and 80% across forecast horizons. In the case of the US, the hit ratio ranges between 77% and 83%, which is quite remarkable. A similar pattern is found for all the remaining countries.

The second market timing test is the Direction Accuracy test, performed under a null hypothesis of no market timing ability, see the second row of each panel in Table 6, where we have marked with stars the cases of rejection of the null hypothesis of no directional accuracy, which is statistical evidence suggesting the existence of timing ability of the TVRA model. Our results show overwhelming evidence favoring the market timing ability associated to the use of the TVRA as prediction signal. The test rejects the null hypothesis for all countries and all the horizons considered at a 1% size in all cases.

Our third market timing metric is the Excess Predictability (EP) test in (17), for which results are shown in the third row of each panel in Table 6. Also in this case we have applied stars in correspondence to cases of rejection of the null hypothesis. In line with the results from the DA test, the EP test strongly supports the existence of market timing ability when a model based on TVRA is used for trading. The EP test rejects the null of no market timing ability for all the prediction horizons when applied to France, Germany, Japan, Switzerland, and the US. In the case of South Korea, we observe a similar pattern with the exception of $h = 1$, for which we cannot reject the null. On the other hand, less favorable evidence of market timing is found in the cases of Hong Kong and the UK where the test rejects the null hypothesis for a few horizons only. For example, in the case of the UK, we find evidence of market timing under for horizons $h = 10, 11$ and 12, while in the case of Hong Kong for $h = 1, 2, 10, 11$ and 12. All in all, the empirical evidence reported in this section supports the hypothesis that a model in which the TVRA metric is used as a single predictor of index stock returns does help to time the market. Such a market timing power derives from both the ability of the model to predict the direction of future index stock returns as well as on its power to outperform a benchmark according to the economic value of simple trading strategies.

5.2 Economic Value Assessment

In the previous section, we have shown that a forecasting model that uses the estimated TVRA as a single predictor can time the market. We now look for further evidence on the economic value of option-implied TVRA by investigating how profitable it may be to build a mean-variance portfolio strategy when predicted excess returns come from a forecasting model centered on TVRA. In particular, we consider the case of a mean-variance investor that allocates her wealth between a risk-free asset and a stock index under a h-month horizon. Thus, we compare an investment strategy derived from the predictive regression $r_{t‘+1} = \beta_0 + \beta_1 TVRA_t + \varepsilon_{t+1}$ to a simple benchmark that uses average returns as the predictor of excess returns.[20] Consider an investor who solves the problem

$$\max_{w_{t+1}} E_t\left[r^P_{t+1}\right] - \frac{1}{2} TVRA_t \cdot Var_t\left[r^P_{t+1}\right], \tag{18}$$

where $E_t\left[r^P_{t+1}\right]$ and $Var_t\left[r^P_{t+1}\right]$ are the expected value and the variance of the portfolio return, r_p, given by $r^P_{.t+1} = r^f_{t+1} + w_{t+1} r_{t+1}$, where r^f_{t+1} is the risk-free rate of return over the $[t, t+1]$ interval, and r_{t+1} is the excess return on the stock index. The solution to the optimization problem in (18) is a dynamically rebalanced portfolio with time-varying weights given by:

$$w^*_{t+1} = \frac{E_t\left[r^P_{t+1}\right]}{TVRA_t \cdot Var_t\left[r^P_{t+1}\right]}. \tag{19}$$

Assuming that the risk-free rate r^f_{t+1} is known in advance at the end of month t, the variance of the portfolio return is:

$$Var_t\left[r^P_{t+1}\right] = w^2_{t+1} Var_t\left[r_{t+1}\right]. \tag{20}$$

To implement the optimal dynamic mean-variance strategy, we need an estimate of the variance of the stock index excess return. Following Fleming et al. (2001), we estimate a simple GARCH(1,1) volatility model to compute a conditional return volatility, $Var^{garch}_t[r_{t+1}]$, that we plug in (20) and (19), respectively. After estimating the optimal portfolio weights, we compute three ex-post portfolio performance metrics to compare the investment strategy associated to TVRA and the benchmark investment strategy. Let $\left\{r^P_t\right\}^T_{t=t_1}$ be the time-series of ex-post portfolio returns, the Sharpe ratio (SR) is defined as $\widehat{SP}_p = \widehat{\mu}_p / \widehat{\sigma}_p$, where $\widehat{\mu}_p$ and $\widehat{\sigma}_p$ are the average and standard deviation of the portfolio returns, respectively, computed over the OOS period of length P. We also compute the certainty equivalent strategy return (CER) as $\widehat{CER}_p = \widehat{\mu}_p - (TVRA_t)^{-1}\widehat{\sigma}_p$. Of course, higher values of either SR or CER indicates better realized performance when compared to lower values.

Similar to West et al. (1993), after solving for the optimal portfolio, we compute the average realized utility

[20] A similar exercise is performed by Demirer et al. (2022). They document significant economic gains associated to a currency portfolio formed from long and short positions defined according to the sensitivity of individual currencies to a U.S. time-varying risk aversion estimate.

for an investor with initial wealth W, as

$$\bar{U_P} = \frac{W}{P} \sum_{t=0}^{P-1} \left(R_{t+1}^P - \frac{1}{2} \frac{TVRA_t}{(1+TVRA_t)} \frac{1}{P} \sum_{t=0}^{P-1} \left(R_{t+1}^p - \frac{1}{P} \sum_{t=0}^{P-1} R_{t+1}^p \right)^2 \right), \tag{21}$$

where R_{t+1}^P is equal to $(1 + r_{t+1}^P - c_{t+1})$ and represents the return on the optimal portfolio net of transaction costs, c_{t+1}. We assume that at the beginning of month $t+1$, the investor rebalances her portfolio from w_t to w_{t+1}. As in Çakmaklı and van Dijk (2016), transaction costs are a fixed proportion, c, of the wealth invested so that the overall cost of rebalancing between t and $t+1$ is given by $c_{t+1} = 2c|w_{t+1} - w_t|$.

To obtain a utility-based measure of economic value, we compare the investment strategy associated to TVRA ($\mathcal{M}$) and the benchmark investment strategy based on historical mean returns. In particular, to compare both strategies, we estimated the risk-less return that makes a risk-averse investor indifferent between the two strategies. We interpret this quantity, Δ, as the maximum performance fee that the investor would be willing to pay to switch from the investment strategy $\mathcal{M}$ to the benchmark historical average return strategy (HA). This implies finding the value of Δ that satisfies the equation:

$$\begin{aligned} &\frac{1}{P} \sum_{t=0}^{P-1} \left((R_{\mathcal{M},t+1}^P - \Delta) - \frac{1}{2} \frac{\gamma}{(1+\gamma)} \frac{1}{P} \sum_{t=0}^{P-1} \left((R_{\mathcal{M},t+1}^P - \Delta) - \frac{1}{P} \sum_{t=0}^{P-1} (R_{\mathcal{M},t+1}^P - \Delta) \right)^2 \right) = \\ &\qquad \frac{1}{P} \sum_{t=0}^{P-1} \left(R_{HA,t+1}^P - \frac{1}{2} \frac{\gamma}{(1+\gamma)} \frac{1}{P} \sum_{t=0}^{P-1} \left(R_{HA,t+1}^P - \frac{1}{P} \sum_{t=0}^{P-1} R_{HA,t+1}^P \right)^2 \right) \end{aligned} \tag{22}$$

If an investment strategy based on TVRA forecasts outperforms the benchmark investment strategy based on historical average returns, we expect $\Delta > 0$. A negative value of the performance parameter, $\Delta \leq 0$, would indicate instead that the benchmark strategy is the one producing higher utility levels for a mean-variance investor, as compared to the TVRA investment strategy. We consider three alternative levels of the fixed transaction costs, c, of 0%, 0.1%, and 0.3%, respectively.

Table 7 shows our economic value findings. We report our baseline findings for three investment horizons: $h = 1, 6, 12$.[21] For each country, we report the SR and CER of the two competing investing strategies: the one based on the estimated TVRA ($\mathcal{M}$), and the benchmark ($\mathcal{M}_{mean}$). In the last three columns, we report the performance fee, (Δ) expressed in terms of annualized basis points, obtained from equation (22).

The investment strategy based on estimated TVRA as a single predictor outperforms the benchmark for most countries. In seven out of eight countries (all but Germany), the TVRA strategy delivers higher re-

[21]In unreported results, we compute the metrics for the remaining investment horizons considered in the rest of the paper (2-11 months, excluding month 6), obtaining similar results that remain available upon request.

Table 7. Economic Value of an Investment Strategy Based on Estimated TVRA

Country (Index)	$SR_{\mathcal{M}}$	$SR_{\mathcal{M}_{mean}}$	$CER_{\mathcal{M}}$	$CER_{\mathcal{M}_{mean}}$	Δ^0	$\Delta^{0.1}$	$\Delta^{0.3}$
			$h = 1$ month				
France (CAC 40)	0.05	-0.21	9.06	8.89	-7	-14	-27
Germany (DAX 30)	0.13	0.13	12.92	13.73	-91	-99	-115
UK (FTSE 100)	0.05	-0.27	15.71	14.23	136	132	124
Hong Kong (HSI)	0.03	-0.04	2.77	2.21	66	71	82
South Korea (KOSPI)	0.16	-0.12	33.93	33.33	6	2	-8
Japan (NIKKEI 225)	0.13	-0.05	1.17	-1.94	321	316	305
Switzerland (SMI 20)	0.12	-0.20	3.00	0.84	217	215	211
US (S&P 500)	0.59	0.41	30.01	27.94	207	188	150
			$h = 6$ months				
France (CAC 40)	0.09	-0.20	10.12	9.66	21	16	4
Germany (DAX 30)	0.11	0.11	13.29	14.25	-106	-115	-135
UK (FTSE 100)	0.05	-0.29	16.24	14.64	147	145	141
Hong Kong (HSI)	-0.01	-0.24	2.62	1.34	139	144	155
South Korea (KOSPI)	0.17	-0.12	34.84	34.17	9	4	-5
Japan (NIKKEI 225)	0.01	-0.15	0.48	-2.74	331	326	316
Switzerland (SMI 20)	0.09	-0.24	3.16	0.97	220	217	210
US (S&P 500)	0.56	0.39	30.02	27.9	211	191	153
			$h = 12$ months				
France (CAC 40)	-0.01	-0.36	10.08	9.62	21	18	11
Germany (DAX 30)	0.01	-0.01	12.78	13.71	-103	-113	-134
UK (FTSE 100)	0.01	-0.31	16.69	15.12	144	142	136
Hong Kong (HSI)	0.01	-0.24	2.53	1.19	144	149	157
South Korea (KOSPI)	0.20	-0.10	36.39	35.47	29	24	15
Japan (NIKKEI 225)	-0.11	-0.22	0.01	-3.36	346	341	331
Switzerland (SMI 20)	0.04	-0.32	3.45	1.14	233	231	227
US (S&P 500)	0.55	0.37	30.34	28.18	215	196	158

Note: the table shows performance measures for a portfolio strategy based on a monthly excess return predictions based on estimated TVRA. $SR_{\mathcal{M}}(CER_{\mathcal{M}})$ is the Sharpe ratio (Certainty Equivalent) of the model based on the estimated TVRA and $SR_{\mathcal{M},mean}(CER_{\mathcal{M},mean})$ is the Sharpe ratio (Certainty Equivalent) of the model based on the historical mean. Δ^c corresponds to the performance fees (in annualized basis points) a mean-variance investor is willing to pay for switching between strategies considering fixed proportional transaction costs of c%. Both CER and Δ are estimated assuming $\gamma = 6$.

alized Sharpe ratios than the benchmark. In fact, the benchmark typically leads to negative ratios. For instance, across the eight markets investigated, SR_{HA} equals on average -0.08 while $SR_{\mathcal{M}}$ is 0.20. While the highest TVRA-driven Sharpe ratio is 0.59 in the case of the US followed by 0.16 for South Korea, only the US (at 0.41) and Germany (0.13) score positive Sharpe ratios under the benchmark. Of course, that a naive sample mean leads to an attractive Sharpe ratio for the US is well known from earlier literature, but this result does not seem to generally extend on a global scale.[22] We find similar evidence favoring the TVRA strategy when we base ourselves on the recursive realized CER which is again higher vs. the benchmark in seven out of eight countries. The exception is Germany, where we find that Sharpe ratios and CER measures are essentially the same across the two strategies. The highest CER differentials are recorded for Switzerland. When alternative investment horizons are considered, the evidence is qualitatively and quantitatively the same for both SR and CER estimates, although the values tend to decline. For instance, at $h = 12$ months, the average SR for the benchmark is -0.17 vs. +0.14 under a TVRA prediction model.

The evidence obtained from the estimated Δ is slightly weaker but still supports the inference that estimated TVRA is an economically valuable input to an investor. On average, we obtain that $\Delta > 0$, i.e., an investor is willing to pay to switch from the benchmark to the TVRA strategy in seven out of eight in the sample in the case with no transaction costs (Δ^0) and in five national markets after high transaction costs ($\Delta^{0.3}$), with the intermediate case of $\Delta^{0.1}$ falling in-between. Interestingly, the evidence is more favorable concerning the value added by TVRA at longer investment horizons ($h = 6$ and 12) vs. the shortest horizon ($h = 1$). For example, in Japan, an investor would be willing to pay 297 basis points to switch from the benchmark to the TVRA strategy, but this estimate grows to 331 bps as h grows. In the case of Switzerland, the estimated Δ is around 210 bps depending on the horizon and transaction costs considered. For the US and the UK, we also find significant gains from switching from the benchmark to the TVRA rule, as the estimated Δ are around $150 \sim 200$ bps and $120 \sim 140$ bps, respectively. In the cases of France and South Korea, we tend to find $\Delta > 0$, but the magnitudes of estimates are smaller, indicating a hardly economically significant effect associated to the TVRA-based strategy.[23]

[22] While (with the exception of Germany), all Sharpe ratios are significantly higher than the benchmark ones at all horizons using a test size of 5%, the differences are estimated much less accurately in the case of the CER.

[23] The least favorable evidence to attributing to a TVRA strategy economic value comes once more from Germany, for which the estimated Δ is around -100 bps.

6 Additional Results

6.1 Country-Level Regressions

So far, we have studied whether the estimated TVRA measure has predictive power to forecast stock returns. Our evidence, based on panel regression methods with country and time fixed effects, shows that it is indeed the case that TVRA leads with remarkable statistical reliability the variation in global excess stock returns by at least 12 months. The use of panel regressions in the earlier analysis implies however that the estimated effect is a sort of average effect across the countries in our sample, as also pointed out by Ang and Bekaert (2006); Hjalmarsson (2010); Rapach et al. (2013). In fact, it is also of separate interest to investigate the predictive power of the estimated TVRA function(s) for stock returns at the country level. We conduct this analysis in this sub-section.

Table 8 shows our estimation results. For each country in the sample, we report OLS estimates of stock return predictability regressions at different horizons (from 1 to 12) and the corresponding R^2. We include the same control variables used in the panel estimation in section (4) to make our inference more robust and avoid omitted regressor biases. Similar to Rapach et al. (2016), the *t*statistics are computed using a wild bootstrapped procedure that accounts for persistent regressors, heteroskedasticity, and any autocorrelation in residuals. We find that in all countries/indices but Hong Kong, the estimated TVRA has remarkable predictive power over the subsequent 12 months. The strongest effects are found in the case of the Germany, the UK, Hong-Kong, South Korea, and Switzerland, where the estimated TVRA coefficient is positive and highly significant in each of the 12 months analyzed. In the case of France, Japan and the US, the estimated strength of predictability is slightly weaker but still precisely estimated for the horizons considered.

All in all, the evidence obtained from country-level, classical 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), the results from country-level regressions are consistent with pooled estimates obtained in a panel framework.

6.2 The Role of the US VRP

Recent empirical evidence has cast doubts on the predictive power of the domestic, country-level VRP for future stock returns. Indeed, Londono (2015) shows that it is only US VRP the variable that is able to forecast future stock returns for a large set of countries. A priori, this puzzling result, is interpreted by the author as evidence that stock returns, in an international context, are mainly driven by a global factor, captured in

Table 8. Stock Return Predictability Regressions at the Country-level

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	$\hat{\beta}_{TVRA}$	3.52***	1.88***	1.38***	1.05***	0.91***	0.78***	0.69***	0.62***	0.58***	0.51***	0.47***	0.43***
	R^2	3.39	3.56	3.80	3.83	4.13	4.20	4.30	4.40	4.75	4.59	4.58	4.53
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
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

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

$$h^{-1}r_{t,t+h} = a(h) + b(h)TVRA_t + \gamma(\mathbf{h})'\mathbf{z}_t + u_{t,t+h} \quad h = 1, 2, ..., 12,$$

where $r_{t,t+h}$ is the stock index excess return at horizon of h months ahead, $TVRA_t$ is the time-varying risk aversion function estimated in section 2, and $\mathbf{z}_t$ 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 reported for parameter of interest, $\hat{\beta}_{TVRA}$. *, ** and *** indicate significance at the 10, 5 and 1 percent, respectively.

his setting, by the US VRP. Bollerslev et al. (2014) also support the existence of a global VRP able to forecast domestic stock returns in several countries. Finally, Miranda-Agrippino and Rey (2015) provide evidence of a global factor reflecting aggregate realized variance and the time-varying degree of market-wide risk aversion.

Considering this evidence, we perform two additional robustness check to our results: first, we re-run country-by-country regressions replacing the domestic measure of VRP by the US VRP, similar to Londono (2015); second, for non-US data, we include in the regressions both VRP variables (domestic and the US) at the same time. In unreported results (available upon request), we find that our results are robust to these two alternative specifications. We find that the estimated TVRA remains significant in each country in both cases, when the domestic VRP is replaced by the US VRP, and when both variables are included simultaneously. Moreover, consistent with the evidence in Londono (2015), we find that the domestic VRP tends to be absorbed by the US VRP in the predictive regressions.

7 Conclusions

We estimate a time-varying risk aversion function for a set of 8 countries (France, Germany, Hong Kong, Japan, South Korea, Switzerland, the UK, and the US) using index stock returns, equity index option prices, and macroeconomic data. Thereafter, we investigate whether this metric predicts index returns up to 12 months ahead both in-sample and out-of-sample. Finally, we asses the economic value of such finding by performing a set of market timing tests and evaluating the performance of a portfolio strategy that uses the estimated function as single predictor of stock returns. We find strong evidence of time variation in risk aversion across countries. Besides, the estimated function is counter-cyclical and 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, France, Japan, and Switzerland are the most risk averse countries in the sample, while the US, Hong Kong, and the UK are the least risk averse ones. Yet, also in the latter three countries, time variation in TVRA forecast subsequent stock index returns.

Using panel regressions, we find that the estimated risk aversion function predicts stock returns 12-months ahead. This result is robust to controlling for the predictive power of the VRP, of investor's sentiment, and of economic uncertainty. This evidence confirms that the estimated risk-aversion function contains additional information vs. the one embedded in this set of control variables. Consistent with prior literature, we find that VRP and economic uncertainty help 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. When we conduct the OOS forecasting evaluation proposed by Welch and Goyal (2007), we find strong statistical evidence that risk aversion predicts future stock returns out-of-sample as well. This evidence is particularly strong in countries like Germany, Japan, Hong Kong, and the UK.

Finally, we document that the estimated risk aversion function may generate economic value to investors. When used as an investment signal, the estimated function allows investors to time the market according to the Directional Accuracy test of Pesaran and Timmermann (1992) and the Excess Predictability test of Anatolyev and Gerko (2005). Moreover, we find that a portfolio which is built using the estimated risk aversion function as the main predictor of future stock returns outperforms a benchmark portfolio that uses the historical mean as the sole predictor (i.e., under the assumption of no predictability): we consistently find higher Sharpe ratios and certainty equivalent returns for the former portfolio when compared to the latter. In half of the countries in the sample, we find that an investor would be willing to pay a fee to switch from the benchmark portfolio to the one backed by the estimated risk aversion. This confirms that risk aversion not only varies over time but also that—by reflecting deep economic forces—it changes future investment opportunities in ways that are as empirically detectable as exploitable.

Several extensions would of course be possible, if not envisionable. First, also because equity premia do co-move across countries, it would be interesting to test whether the TVRA measures do cross-correlate across countries and, in particular, whether US risk aversion estimates do have predictive power for foreign ones. Second, in this paper we have proxied monthly realized variance as the sum of squared daily returns within that month, which is equivalent to assume that instantaneous, realized variances follows a random walk process. While this is a plausible assumption which has been used by some of the literature, it would be interesting to test the robustness of our results on in- and out-of-sample predictability to assuming instead that variance followed a stationary AR(1) process. Second, it would be interesting to derive the moments used to perform GMM estimation of the parameters, in particular those characterizing the TVRA function in (10), when the Heston's SV model explicitly contains in its description the continuous time analog of (10) along with the dynamics of the relevant factors. However, obtaining closed form expressions from the resulting non-affine model for the risk premium appears a daunting task and this would force us to complex and less practical estimation methods, especially in view of our prediction goals.

References

Alan, S., Attanasio, O., and Browning, M. (2009). Estimating euler equations with noisy data: two exact gmm estimators. *Journal of Applied Econometrics*, 24(2):309–324.

Anatolyev, S. and Gerko, A. (2005). A trading approach to testing for predictability. *Journal of Business & Economic Statistics*, 23(4):455–461.

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? *Review of Financial Studies*, 20(3):651–707.

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

Baker, M. and Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2):129–152.

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

Bakshi, G. and Madan, D. (2006). A theory of volatility spreads. *Management Science*, 52(12):1945–1956.

Bali, T. G., Cakici, N., and Chabi-Yo, F. (2011). A generalized measure of riskiness. *Management Science*, 57(8):1406–1423.

Bali, T. G. and Hovakimian, A. (2009). Volatility spreads and expected stock returns. *Management Science*, 55(11):1797–1812.

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 Grenadier, S. R. (2010). Stock and bond returns with moody investors. *Journal of Empirical Finance*, 17(5):867–894.

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. (2014). The vix, the variance premium and stock market volatility. *Journal of Econometrics*, 183(2):181–192.

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.

Blanchard, O., Cerutti, E., and Summers, L. (2015). Inflation and activity–two explorations and their monetary policy implications. Technical report, National Bureau of Economic Research.

Bliss, R. R. and Panigirtzoglou, N. (2004). Option-implied risk aversion estimates. *Journal of Finance*, 59(1):407–446.

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. *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.

Bouri, E., Gupta, R., Majumdar, A., and Subramaniam, S. (2021). Time-varying risk aversion and forecastability of the us term structure of interest rates. *Finance Research Letters*, 42:101924.

Brandt, M. W. and Wang, K. Q. (2003). Time-varying risk aversion and unexpected inflation. *Journal of Monetary Economics*, 50(7):1457–1498.

Britten-Jones, M. and Neuberger, A. (2000). Option prices, implied price processes, and stochastic volatility. *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.

Brunnermeier, M. K. and Nagel, S. (2008). Do wealth fluctuations generate time-varying risk aversion? micro-evidence on individuals. *American Economic Review*, 98(3):713–36.

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 Thompson, S. B. (2007). Predicting excess stock returns out of sample: Can anything beat the historical average? *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.

Cenesizoglu, T. and Timmermann, A. (2012). Do return prediction models add economic value? *Journal of Banking & Finance*, 36(11):2974–2987.

Çepni, O., Demirer, R., Gupta, R., and Pierdzioch, C. (2020). Time-varying risk aversion and the predictability of bond premia. *Finance Research Letters*, 34:101241.

Chiang, T. C. (2021). Spillovers of us market volatility and monetary policy uncertainty to global stock markets. *The North American Journal of Economics and Finance*, 58:101523.

Clark, T. E. and McCracken, M. W. (2001). Tests of equal forecast accuracy and encompassing for nested models. *Journal of Econometrics*, 105(1):85–110.

Cochrane, J. H. (2009). *Asset pricing: Revised edition*. Princeton University Press.

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.

Cuesdeanu, H. and Jackwerth, J. C. (2018). The pricing kernel puzzle: Survey and outlook. *Annals of Finance*, 14(3):289–329.

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

Dal Pra, G., Guidolin, M., Pedio, M., and Vasile, F. (2018). Regime shifts in excess stock return predictability: an out-of-sample portfolio analysis. *Journal of Portfolio Management*, 44(3):10–24.

Demirer, R., Yuksel, A., and Yuksel, A. (2022). Time-varying risk aversion and currency excess returns. *Research in International Business and Finance*, 59:101555.

Drechsler, I. (2013). Uncertainty, time-varying fear, and asset prices. *Journal of Finance*, 68(5):1843–1889.

Drechsler, I. and Yaron, A. (2010). What's vol got to do with it. *Review of Financial Studies*, 24(1):1–45.

Faccini, R., Konstantinidi, E., Skiadopoulos, G., and Sarantopoulou-Chiourea, S. (2018). A new predictor of us real economic activity: The s&p 500 option implied risk aversion. *Management Science*.

Fleming, J., Kirby, C., and Ostdiek, B. (2001). The economic value of volatility timing. *Journal of Finance*, 56(1):329–352.

Gai, P. and Vause, N. (2006). Measuring investors risk appetite. *International Journal of Central Banking*.

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.

Gordon, S. and St-Amour, P. (2000). A preference regime model of bull and bear markets. *American Economic Review*, 90(4):1019–1033.

Guiso, L., Sapienza, P., and Zingales, L. (2018). Time varying risk aversion. *Journal of Financial Economics*, 128(3):403–421.

Hansen, P. R. and Tong, C. (2022). Option pricing with time-varying volatility risk aversion. *arXiv preprint arXiv:2204.06943*.

Heston, S. L. (1993). A closed-form solution for options with stochastic volatility with applications to bond and currency options. *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. *Review of Financial Studies*, 28(3):791–837.

Jackwerth, J. C. (2000). Recovering risk aversion from option prices and realized returns. *Review of Financial Studies*, 13(2):433–451.

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

Kandel, S. and Stambaugh, R. F. (1996). On the predictability of stock returns: an asset-allocation perspective. *Journal of Finance*, 51(2):385–424.

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

Kosolapova, M., Hanke, M., and Weissensteiner, A. (2023). Estimating time-varying risk aversion from option prices and realized returns. *Quantitative Finance*, 23(1):1–17.

Kostakis, A., Panigirtzoglou, N., and Skiadopoulos, G. (2011). Market timing with option-implied distributions: A forward-looking approach. *Management Science*, 57(7):1231–1249.

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. *Review of Financial Studies*, 19(4):1499–1529.

Li, J. and Zinna, G. (2018). The variance risk premium: Components, term structures, and stock return predictability. *Journal of Business & Economic Statistics*, 36(3):411–425.

Liao, W. J. and Sung, H.-C. (2020). Implied risk aversion and pricing kernel in the ftse 100 index. *The North American Journal of Economics and Finance*, 54:100826.

Londono, J. M. (2015). The variance risk premium around the world. *Available at SSRN 2517020*.

Londono, J. M. and Xu, N. R. (2019). Variance risk premium components and international stock return predictability. *Available at SSRN 3366592*.

McCracken, M. W. (2007). Asymptotics for out of sample tests of granger causality. *Journal of Econometrics*, 140(2):719–752.

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

Miranda-Agrippino, S. and Rey, H. (2015). World asset markets and the global financial cycle.

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.

Paravisini, D., Rappoport, V., and Ravina, E. (2016). Risk aversion and wealth: Evidence from person-to-person lending portfolios. *Management Science*, 63(2):279–297.

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

Pesaran, M. H. and Timmermann, A. (1992). A simple nonparametric test of predictive performance. *Journal of Business & Economic Statistics*, 10(4):461–465.

Pflueger, C. and Rinaldi, G. (2022). Why does the fed move markets so much? a model of monetary policy and time-varying risk aversion. *Journal of Financial Economics*, 146(1):71–89.

Pyun, S. (2019). Variance risk in aggregate stock returns and time-varying return predictability. *Journal of Financial Economics*, 132(1):150–174.

Rapach, D. and Zhou, G. (2013). Forecasting stock returns. In *Handbook of Economic Forecasting*, volume 2, pages 328–383. Elsevier.

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? *Journal of Finance*, 68(4):1633–1662.

Rehman, M. U., Sensoy, A., Eraslan, V., Shahzad, S. J. H., and Vo, X. V. (2021). Sensitivity of us equity returns to economic policy uncertainty and investor sentiments. *The North American Journal of Economics and Finance*, 57:101392.

Rosenberg, J. V. and Engle, R. F. (2002). Empirical pricing kernels. *Journal of Financial Economics*, 64(3):341–372.

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.

Timmermann, A. (2018). Forecasting methods in finance. *Annual Review of Financial Economics*, 10:449–479.

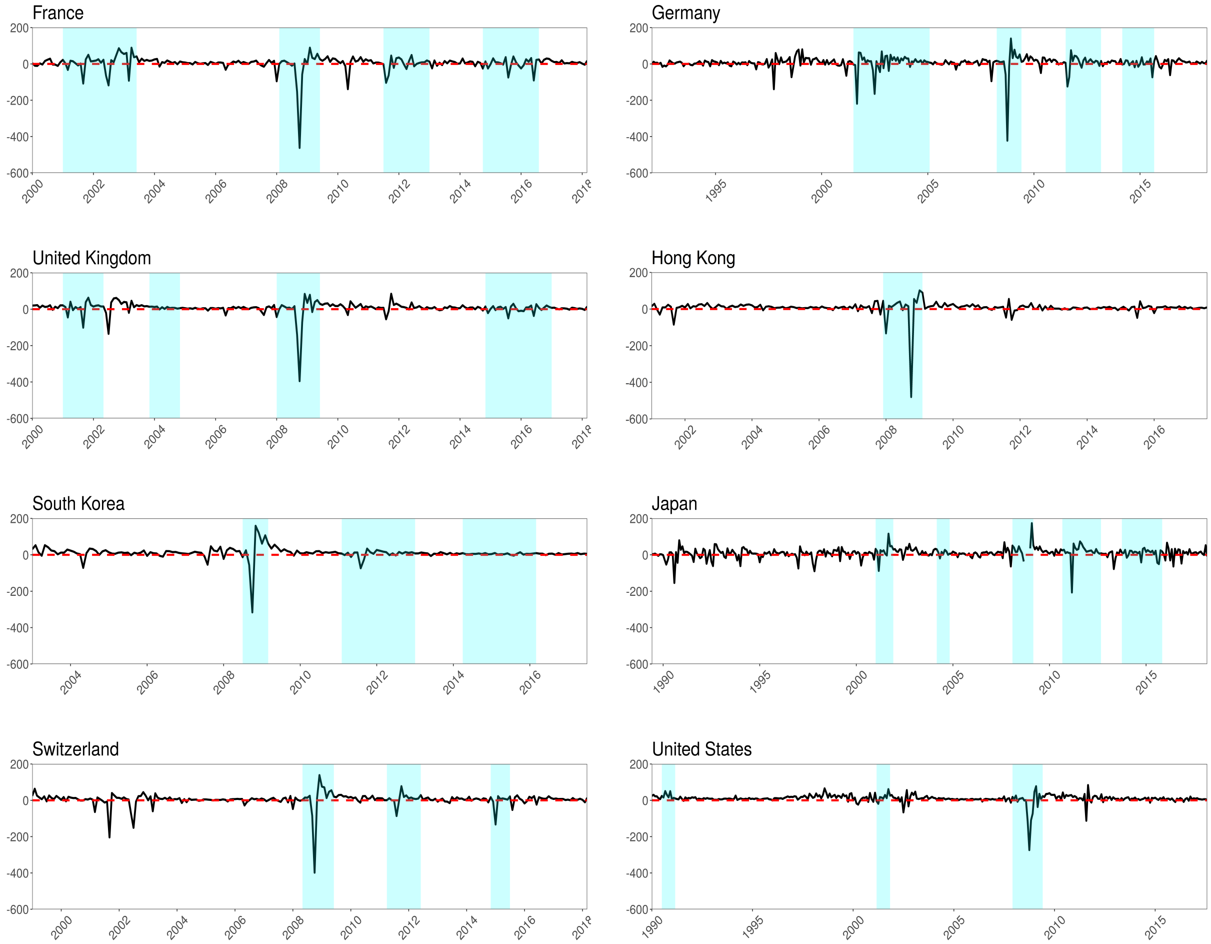
Wachter, J. A. and Warusawitharana, M. (2009). Predictable returns and asset allocation: Should a skeptical investor time the market? *Journal of Econometrics*, 148(2):162–178.

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

West, K. D., Edison, H. J., and Cho, D. (1993). A utility-based comparison of some models of exchange rate volatility. *Journal of International Economics*, 35(1-2):23–45.

Xu, Y., Wang, J., Chen, Z., and Liang, C. (2021). Economic policy uncertainty and stock market returns: New evidence. *The North American journal of economics and finance*, 58:101525.

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



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 (3) for details on data sources and realized volatility estimation.

A Variance Risk Premium Time Series by Country

B Descriptive Statistics of Stock Index Returns

	CAC 40	DAX 30	FTSE 100	HSI	KOSPI	NIKKEI 225	SMI 20	S&P 500
Mean	-0.14	0.23	-0.06	0.66	0.62	-0.09	0.01	0.21
SD	6.00	6.26	4.19	6.17	5.56	5.95	3.98	4.18
Skew.	-0.81	-1.03	-0.68	-0.86	-0.74	-0.47	-0.69	-0.79
Kurt.	5.15	6.25	4.23	5.37	5.85	4.20	3.81	4.77
Min.	-22.09	-29.61	-14.36	-25.49	-26.35	-24.75	-14.13	-18.96
5 %	-10.33	-10.37	-8.04	-9.33	-7.87	-10.78	-7.48	-7.31
25 %.	-3.05	-2.76	-2.3	-2.15	-2.23	-3.35	-2.07	-2.04
50 %	0.76	1.20	0.44	1.50	0.97	0.19	0.70	0.69
75 %	3.3	3.92	2.52	4.20	3.88	3.58	2.68	2.91
95 %	7.87	8.63	5.73	10.26	9.51	9.50	5.08	6.48
Max.	16.58	19.17	11.9	15.75	12.67	18.83	10.59	10.18

Note: the table reports descriptive statistics for monthly stock index returns in percentages. The countries (stock indices) considered are France (CAC 40), Germany (DAX 30), The United Kingdom (FTSE 100), Hong Kong (HSI), South Korea (KOSPI), Japan (NIKKEI 225), Switzerland (SMI 20), and the US (S&P 500).

C Data Sources

	Countries (Indices)							
Variables	France (CAC40)	Germany (DAX 30)	UK (FTSE 100)	Hong Kong (HSI)	Japan (NIKKEI 225)	Switzerland (SMI 20)	The 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	HK Monetary Authority	Bank of Japan	SNB - Swiss National Bank	Federal Reserve Economic Data	The Bank of Korea
Payroll Employment	OECD	Bundesagentur fur Arbeit, Germany	OECD	HK Monetary Authority	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	HK Monetary Authority	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	HK Monetary Authority	Bank of Japan	KOF - Swiss Economic Institute	Federal Reserve Economic Data	The Bank of Korea
Housing Starts	Ministere de l'Ecologie du Developpement et de l'Amenagement durables, France	OECD	CLG - Communities and Local Government, United Kingdom	HK Monetary Authority	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	HK Monetary Authority	Ministry of Internal Affairs and Communications, Japan"	SECO - State Secretariat for Economic Affairs, Switzerland	Federal Reserve Economic Data	KOSTAT - Statistics Korea
PE ratio	Bloomberg	Bloomberg	Bloomberg	Bloomberg	Bloomberg	Bloomberg	Bloomberg	Bloomberg

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

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			
Hong Kong (HSI)	2007-12-01	2009-02-01	South Korea (KOSPI)	2008-07-01	2009-03-01
				2011-02-01	2013-01-01
				2014-04-01	2016-11-01

Note: the table reports recession dates for countries in the sample. For the US, the information comes from NBER business cycle webpage, and for the remaining countries (but Hong Kong) from OECD recession indicators. For Hong Kong, we use quarterly GDP growth rate (from Hong Kong Monetary Authority webpage) to identify recession episodes.

D Macroeconomic Recession Dates