# The Global Determinants of International Equity Risk Premiums[*]

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### Abstract

We examine the commonality in international equity risk premiums by linking *empirical evidence* for the international stock return predictability of US downside and upside variance risk premiums (DVP and UVP, respectively) with *implications* from an international asset pricing framework, which features asymmetric global macroeconomic, financial market, and risk aversion shocks. We find that DVP and UVP predict international stock returns through different global equity risk premium determinants: bad and good macroeconomic uncertainties, respectively. Across countries, US investors demand lower macroeconomic risk compensation but higher financial market risk compensation for more-integrated countries.

**JEL Classification:** F36, G12, G13, G15.

**Keywords:** Downside variance risk premium, Upside variance risk premium, International stock markets, Asymmetric state variables, Stock return predictability.

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# 1. Introduction

Contributing to the extensive discussions on how global shocks transmit across international equity markets (see, for instance, Colacito, Croce, Gavazzoni, and Ready (2018)), we propose a new approach to examine which, and to what extent, common risk variables drive equity risk premiums across countries at short (within-one-year) horizons. The main intuition of our analysis is that international stock return predictability should be driven by fundamental determinants that are common to both the global predictors and the global equity risk premium. An asset pricing framework with the perspective of a US (global) investor should help motivate these common determinants and infer their relative importance in driving global equity risk compensations at various horizons. In this paper, we formalize this intuition by linking novel *empirical evidence* for the international stock return predictability of US downside and upside variance risk premiums with *implications* from a parsimonious no-arbitrage asset pricing framework featuring time-varying and asymmetric economic uncertainty, risk aversion, and financial uncertainty in the form of illiquidity.

We find that 70-80% of the dynamics of the global equity risk premium for horizons under seven months may be driven by US economic uncertainty, while US risk aversion and financial uncertainty may matter more for longer horizons. Both good and bad US economic uncertainties contribute positively to the global equity risk premium, with the latter becoming dominant after 4 months. The global equity risk premium exhibits countercyclical dynamics and a downward-sloping term structure particularly during downturns. Our approach also allows us to study cross-country variations in global risk compensations. We find that US investors demand a lower global economic risk compensation but a higher financial risk compensation for more globally integrated countries.

For our empirical evidence, we consider the US variance risk premium's downside and upside components (DVP and UVP, respectively) as our two main global predictors, aiming to maximally infer information about short-horizon global equity risk compensations in light of the recent evidence in Kilic and Shaliastovich (2019), Bollerslev, Marrone, Xu, and Zhou (2014), and Feunou, Jahan-Parvar, and Okou (2017). We calculate DVP and UVP as the difference between the risk-neutral and physical expectations of one-month-ahead stock return variance, conditional on whether the one-month-ahead stock price is below (bad states) or above (good states) the current stock price, respectively. We approximate the risk-neutral expectation of the downside (upside) stock return variance using puts (calls) on the S&P 500 index at different strikes and maturities, and we obtain the physical expectation of the downside (upside) stock return variation using the best forecast of the downside (upside) realized variance given a set of forecasting models. Our sample spans from April 1991 to December 2019. We find that DVP and UVP be-

have quite differently. The total VP and its downside component are highly correlated, significantly positive, and countercyclical with large positive spikes around key episodes of market stress and economic turmoil. In contrast, UVP is positive but smaller in magnitude, less persistent, and procyclical with occasional negative spikes, some of which coincide with major positive DVP spikes.

We then examine the predictive power of DVP and UVP for the excess returns of 22 countries' headline stock indexes expressed in US dollars. Considering both pooled and country-level predictive frameworks, we find evidence that decomposing the US VP into its asymmetric components yields gains in predicting international stock returns. In addition, the predictability patterns of DVP and UVP are considerably different along several dimensions. The international stock return predictability is mainly explained by UVP at very short horizons and by DVP at horizons between four and seven months. The predictive power of DVP follows a hump-shaped pattern peaking at mid four- to seven-month horizons, while that of UVP follows a decreasing pattern after peaking at the one-month horizon.

The second part of the paper formalizes the main intuition of our exercise using minimal structural assumptions, therefore allowing the data to speak for themselves. We first motivate potential economic determinants of both US VP(s) and international equity risk premiums in a conceptual framework. Given the empirical focus and the US investor perspective of this paper, we write down a flexible US log pricing kernel that is sensitive to changes in macroeconomic conditions, investor risk aversion, and stock market illiquidity. These reduced-form kernel state variables and shocks can be motivated from both the consumption-based and intermediary-based asset pricing literature linking equity and variance risk premiums. For instance, the interplay between macroeconomic uncertainty and investors' attitudes toward risk plays a prominent role in the variance premium literature (rare disaster models in, e.g., Gabaix (2012), long-run risk models in, e.g., Bollerslev, Tauchen, and Zhou (2009), models with habit formation and bad environment-good environment dynamics, as in Bekaert and Engstrom (2017), and models with time-varying fear in, e.g., Drechsler (2013)). Fan, Imerman, and Dai (2016) propose an intermediary-based explanation for the dynamics of the variance risk premium. We construct parsimonious state variable processes with VAR and composite heteroskedastic gamma shock assumptions in order to flexibly describe the tail behaviors of our key state variables. Finally, to model the transmission of global/US shocks to other countries, we allow for country cash flow growths to be exposed to common (US) state variables and shocks.

The model solution has two relevant implications for our research objective. First, both the dynamics of US VP (and its components) and the global compensation part of international equity risk premiums should be driven by the second moments of kernel shocks. Second, this commonality implies the various excess return predictability

channels. When confronted with the data, our model allows us to identify the relative importance of these common risk premium state variables in DVP and UVP and in international equity risk premiums at various horizons, which is the main contribution of the paper.

We first find that 62% of the DVP variability is explained by risk aversion and 30% by bad economic uncertainty. Under volatile economic conditions, DVP becomes more sensitive to high market illiquidity uncertainty. UVP, on the other hand, increases with the procyclical good economic uncertainty through the hedging demand of upside risk, as well as countercyclical state variables, such as risk aversion and illiquidity uncertainty, through the general hedging demand for variance risk. These two channels counteract, resulting in the relatively less persistent and smaller UVP than DVP.

We then identify the relative importance of common economic determinants in international equity risk premiums using the economic interpretations of the VP components and their international stock return predictive coefficients. We utilize the whole cross-section of country-level predictive coefficients. To avoid heavy parameterization, we use two integration measures to describe the cross-country differences in the predictive coefficients: economic integration, proxied by the ratio of total imports and exports to GDP, and financial integration, proxied by the ratio of total asset and liability holdings from one country to the rest of the world to GDP.

For our global-level inferences, which can be related to the panel-data predictive regression results, we calibrate a country with a median level of economic and financial integration. We find that global equity risk premium's sensitivities to the common risk premium determinants change over the horizon. Both good and bad US economic uncertainties contribute positively to the global equity risk premium, which is consistent with the domestic (US) implications from Segal, Shaliastovich, and Yaron (2015). Together, US economic uncertainties explain 70-80% of the global risk premium variability at horizons under seven months, with the bad uncertainty dominating after four months. Risk aversion and illiquidity uncertainty, on the other hand, have a stable and positive impact for all horizons, with one SD increase leading to a two to three annualized percent increase in the average country's equity risk premium. Consistently, a Jackknife exercise shows that DVP predicts international stock excess returns mostly through their common determinant, bad economic uncertainty, while the good economic uncertainty channel is potentially crucial for explaining the pattern of the international predictability of UVP.

Finally, we complement our global-level inference by examining whether global investors demand different global risk compensations for holding assets in countries with different integration levels, which relates to our country-level predictive regression results. We find that, for countries with higher integration (especially financial integration), global investors demand lower global macro risk compensation but higher global financial risk compensation. The former result is potentially consistent with the international

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risk sharing intuition given a lower cost of capital, greater firm and fundamental invest-ment opportunities, and higher potential growth (Bekaert and Harvey (2003); Carrieri, Errunza, and Hogan (2007)); the latter result is likely due to the increasing chance of higher systemic risk exposure that cannot be diversified away.

**Our research contributes to several strands of the literature:**

First, our exploration of the global determinants of international equity risk pre-miums contributes to the ongoing discussion of how global shocks matter and transmit across international equity markets (see, e.g., Colacito, Croce, Gavazzoni, and Ready (2018); Bonciani and Ricci (2020); Bekaert, Hoerova, and Xu (2020); Avdjiev, Gamba-corta, Goldberg, and Schiaffi (2020); Aldasoro, Avdjiev, Borio, and Disyatat (2020); Xu (2019)). Different from existing research, our framework exploits empirical evidence from international stock return predictability, which allows us to look at global risk compen-sations using cross-sectional information at various horizons.

Our research contributes to the literature on understanding and estimating the dy-namics of equity risk premiums, including using asset pricing models, as in Croce, Lettau, and Ludvigson (2015), Stathopoulos (2017), Martin (2017) and Bekaert, Engstrom, and Xu (forthcoming); surveys, as in Graham and Harvey (2005); and novel data sets such as dividend futures and dividend strips, as in Van Binsbergen, Brandt, and Koijen (2012) and Van Binsbergen, Hueskes, Koijen, and Vrugt (2013). Our model estimation strategy highlights two innovations. First, in an asset pricing framework, both US VP and inter-national equity risk premiums should be driven by common risk premium state variables. Empirically, we observe their covariance relationship (i.e., predictability results) and the dynamics of the VP components. By predetermining the loadings of the VP components on these premium state variables, the loadings of international equity premiums hence become the only unknowns in the estimation. Second, considering multiple predictors and multiple countries in a unified framework provides more information in the estimation.

Considering the US VP and its asymmetric components as our main global predic-tors also contributes to the literature on international stock return predictability. Broadly, we add to a branch of the literature that investigates the predictive power of US finan-cial variables for international stock returns (see Rapach, Strauss, and Zhou (2013) and papers cited therein). More specifically, we add to the literature documenting the robust predictability of the US VP for international stock returns (Londono (2015) and Boller-slev, Marrone, Xu, and Zhou (2014)). A more recent strand of the VP predictability literature finds that compensations for bearing stock return variations associated with good and bad states are potentially different and that acknowledging for asymmetry in the variance risk premium significantly increases its stock return predictability. This literature has focused only on the predictability for US stock returns (Kilic and Shalias-tovich (2019) and Feunou, Jahan-Parvar, and Okou (2017)). Given our goal to improve our understanding of global equity risk compensations through predictive coefficients, we

contribute to this strand of the literature by showing that decomposing the US variance risk premium into its downside and upside components also yields higher predictability for international stock returns.

Finally, while we are agnostic about the exact global transmission channels (e.g., central banks, firms, households) of risk premium state variables, our cross-country calibration suggests that US/global investors may demand more (less) financial market risk compensation (macroeconomic risk compensation) from countries with higher integration, shedding light on the non-trivial asset pricing implications of globalization (see, e.g., Kose, Prasad, Rogoff, and Wei (2009); Rapach, Strauss, and Zhou (2013); and Bekaert, Harvey, Kiguel, and Wang (2016)).

The remainder of the paper is organized as follows. Section 2 provides the empirical evidence for the dynamics and international stock return predictability of US downside and upside variance risk premiums. In Section 3, we propose a conceptual framework and discuss our core estimation strategy. Bringing the model solution to the empirical evidence, Section 4 presents the estimation results for common risk premium determinants, and Section 5 discusses the relative importance of these economic determinants in international equity risk premiums. Concluding remarks are included in Section 6.

## 2. Empirical Evidence

In this section, we explore the commonality in short-term international equity risk premiums by examining the predictive power of the US variance risk premium (VP) and its downside and upside components for international stock excess returns for horizons between one and twelve months. In the first part of the section, we construct and discuss the dynamic properties of the downside and upside components of the US VP; then, we examine their predictive power for international stock excess returns.

### 2.1. Definitions

We follow the notation in Bollerslev, Tauchen, and Zhou (2009) and define the total one-month-ahead VP as the difference between the risk-neutral ($Q$) and the physical ($P$) expectations of the total variance of one-month-ahead stock returns,

$$VP_{t;t+1} = V_t^Q(r_{t+1}) \quad V_t^P(r_{t+1}), \tag{1}$$

where $r_{t+1}$ denotes the log stock return between months $t$ and $t+1$. We decompose VP into its downside and upside components, which we label DVP and UVP, respectively. These components allow us to disentangle the compensations for bearing downside and upside variance risks. The general expression for this decomposition is as follows:

$$VP_{t;t+1} = \underbrace{V_t^Q(r_{t+1}1_{<0}) \quad V_t^P(r_{t+1}1_{<0})}_{DVP} + \underbrace{V_t^Q(r_{t+1}1_{>0}) \quad V_t^P(r_{t+1}1_{>0})}_{UVP}, \tag{2}$$

where $1_{<0}$ ($1_{>0}$) is a dummy equal to 1 when the one-month-ahead return is below (above) 0 (see Feunou, Jahan-Parvar, and Okou (2017); Kilic and Shaliastovich (2019); and Held, Kapraun, Omachel, and Thimme (2020)).

We estimate the risk-neutral and physical components of DVP and UVP separately. The risk-neutral components of DVP and UVP are extracted from option prices (see, for instance, Britten-Jones and Neuberger (2000); Andersen and Bondarenko (2009)) using the option-implied downside and upside variances, respectively, as follows:

$$iv_{t;t+1}^{D} = \left( \int_{0}^{S_t} \frac{2(1 + log(S_t/K)}{K^2} P(t+1, K) dK \right)^2, \tag{3}$$

$$iv_{t;t+1}^{U} = \left( \int_{S_t}^{1} \frac{2(1 - log(K/S_t)}{K^2} C(t+1, K) dK \right)^2,$$

where $S_t$ is the current stock index price and $P(K)$ ($C(K)$) is the price of a put (call) with strike $K$ and a one-month maturity. Intuitively, the option-implied downside (upside) variance is identified by put (call) options that pay off when the return realization is negative (positive). Next, we approximate the physical components of DVP and UVP using the expected values of one-month-ahead downside and upside realized variances, respectively. Intuitively, we separate the return variability due to intradaily negative and positive price movements, and the realized semivariances are obtained as follows:

$$rv_{t+1}^{D} = \sum_{=1}^{N} r^2 1_{r_\tau < 0}, \tag{4}$$

$$rv_{t+1}^{U} = \sum_{=1}^{N} r^2 1_{r_\tau > 0},$$

where $r$ represents the instantaneous return calculated using stock prices sampled at intradaily frequencies between months $t$ and $t + 1$ and $N$ is the total number of high-frequency return observations within the month. The physical expectations of downside and upside realized variances are obtained using linear projections, as follows:

$$E_t(rv_{t+1}^i) = \hat{\alpha}^i + \hat{}^i \mathbf{X_t^i}, \tag{5}$$

where $i = D$ or $U$ for downside and upside, respectively, and $\mathbf{X_t^i}$ is a chosen set of predictors observable at time $t$. We allow $\mathbf{X_t^i}$ to be different in predicting downside and upside realized variances. Therefore, DVP and UVP are obtained, respectively, as follows:

$$vp_{t;t+1}^{D} = iv_{t;t+1}^{D} - E_t(rv_{t+1}^{D}), \tag{6}$$

$$vp_{t;t+1}^{U} = iv_{t;t+1}^{U} - E_t(rv_{t+1}^{U}).$$

## 2.2. The dynamics of variance risk premiums

We use daily prices for options on the S&P 500 index at different strikes and maturities (source: OptionMetrics) to obtain the risk-neutral components of DVP and UVP,

and we use intradaily prices sampled every 15 minutes for this stock index (source: TICK-DATA) to obtain the realized semivariances. Our sample period runs between April 1991 and December 2019.

While the literature has examined various models for predicting the total realized variance (see Bekaert and Hoerova (2014) for a thorough discussion), there is limited research on predicting the downside and upside realized variances. Table 1 explores five forecast specifications of one-month-ahead realized semivariances using the regression framework in Equation (5). The specification in measure (1) assumes that realized semivariances follow a Martingale process (see also Kilic and Shaliastovich (2019)), while measures (2) to (5) consider various combinations of predictors including past realized variance and semivariances calculated at various horizons. Both the simple AR(1) and the heterogeneous autoregressive (HAR) framework using the past monthly ($rv^i_{t-1m;t}$), weekly ($rv^i_{t-5d;t}$), and daily ($rv^i_{t-1d;t}$) realized semivariances significantly improve the goodness of fit for both downside and upside realized variances, with respect to the Martingale specification.[1] In column (5), we include downside and upside option-implied variances, respectively. This last specification yields the best predictive performance for both downside and upside realized semivariances. Therefore, we use measure (5) to estimate the downside and upside expected physical variances.

With the risk-neutral and physical expected variance estimates, we obtain DVP and UVP as in Equation (6). The sum of the two VP components yields the total VP. In the remainder of the paper, we use the end-of-month estimates as our benchmark DVP and UVP measures.

We find that our benchmark monthly DVP and UVP measures differ in their unconditional and time-series properties. First, from Table 2, the option-implied downside variance is, on average, higher than the expected downside realized variance, yielding a positive DVP with an average of 15.97 squared percent The positive nature of DVP holds for all other measures considered and is consistent with the evidence in the existing literature. DVP is prone to large positive realizations, including the large spike during the 2007-2008 financial crisis, as shown in Figure 1. UVP is also, on average, significantly different from zero but is considerably smaller than the average DVP (1.27 versus 15.98, respectively). As shown in Figure 1, UVP displays negative spikes in a few episodes. For instance, UVP reached -35.48 squared percent during the Lehman Brothers aftermath, which is almost 11 standard deviations away from its historical average.

Second, we find that the total VP comoves closer to DVP than to UVP. Panel C of Table 2 shows that the correlation between VP and DVP using our chosen model is

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[1]This HAR framework for realized semivariances extends Corsi (2009), who focuses on forecasting the total realized variance. Feunou, Jahan-Parvar, and Okou (2017) also consider the HAR framework to approximate the expectations of downside and upside realized variances. However, they do not report the coefficients associated with the HAR components or the fit of the model, and they conclude that the results for the HAR specification are qualitatively similar to those for the Martingale specification.

0.97, while that between UVP and VP is 0.26. Moreover, our DVP and UVP measures are statistically uncorrelated.[2]

Third, DVP exhibits a negative correlation with the monthly US industrial production growth ($\rho = $ -0.29); in contrast, UVP is positively correlated with the growth rate ($\rho = 0.17$), suggesting weakly procyclical dynamics. Both correlations are statistically significant at the 1% confidence level.

Finally, UVP is more transitory than DVP. The AR(1) coefficient of our DVP measure is 0.80, whereas that of our UVP measure is only 0.22. These four empirical facts are robust across alternative measures. Taken together, our findings suggest that investors, in general, demand much higher compensations for downside shock exposures than for upside shock exposures, although both shocks lead to increases in total variance. On average, investors dislike risks emanating from both tails. However, compensations demanded for bearing downside and upside variance risks have different dynamics, in terms of their persistence and their relation with current economic conditions.

The properties of our VP measures are similar to those reported in the literature.[3] The dynamics of UVP vary slightly among the existing papers. In particular, the UVP measure in Kilic and Shaliastovich (2019) exhibits major negative spikes (given our definition of VP, as they define VP as the difference between the physical and the risk-neutral expectations) during episodes of financial turmoil. This behavior is likely due to the Martingale assumption when obtaining the physical expectation; that is, according to Bekaert and Hoerova (2014), realized variance is likely to be high during financial turmoil, which does not necessarily imply that the expectation of stock market variance continues to be this high in the near future.[4] However, as we discuss later in Section 2.3, the short-term predictability of UVP and DVP for international excess stock returns is robust to considering alternative VP measures, including the Martingale measure.

## 2.3. International stock return predictability

We now examine the international stock return predictability patterns of US DVP and UVP at the global level and at the country level. We take the perspective of a global investor whose asset values are denominated in US dollars. We consider US dollar excess returns of 22 countries' headline stock market indexes covering North America, Asia, and Europe. Log market returns are obtained from their total return indices (source:

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[2]Table A2 in Appendix A shows that both DVP and UVP are highly correlated across measures, with a correlation coefficient ranging from 0.74 to 0.99 for DVP and from 0.74 to 0.95 for UVP.

[3]For instance, Held, Kapraun, Omachel, and Thimme (2020) extend the calculation for the variance premium and its components to 8 international markets and their evidence is similar to ours for US VPs. In particular, they find that DVP is, on average, consistently positive for all markets and much larger in magnitude than UVP. UVP is, on average positive for the US, but turns negative for 4 countries in their sample.

[4]Figure A1 of Appendix A compares our benchmark VP measures with those obtained using the Martingale measure.

DataStream), and the risk free rate uses the zero-coupon yield of US Treasury bonds (source: FRED). As before, our sample runs from April 1991 to December 2019 (T = 345 months).

The main predictability regression is as follows:

$$\kappa^{-1} r_{i;t;t+\kappa} = a + a_{i;} + b^D v p^D_{t;t+1} + b^U v p^U_{t;t+1} + \epsilon_{i;t+\kappa},$$ (7)

where $t$ denotes the month; $r_{i;t;t+\kappa}$ denotes the $\kappa$-month-ahead log excess returns for country $i$. A useful null regression specification imposes the same predictive coefficients for DVP and UVP.

Table 3 compares the results of the null and the main predictability regressions at the 1-, 3-, 6-, and 12-month horizons; the full-horizon predictability patterns are shown in Figure 2. Our results for the null model are consistent with those in the literature (see, e.g., Londono (2015); and Bollerslev, Marrone, Xu, and Zhou (2014)). In particular, the hump-shaped predictability pattern of the total VP peaks at around the 6-month horizon.

Our main empirical result is that acknowledging for asymmetry in VP improves the predictability for international stock returns and, therefore, offers more joint information in understanding the latent behaviors of global equity risk premiums. The adjusted R-squareds of our main bivariate specification are larger than those of the null model for all within-one-year horizons considered. In addition, the predictability patterns of DVP and UVP are different. While DVP exhibits a hump-shaped predictability pattern similar to that of the total VP, UVP is only a significant predictor at very-short horizons. The variance decomposition (row "VARC%" in Table 3) confirms that the DVP contribution to predictability becomes dominant as the horizon increases, while the UVP contribution dominates mostly at horizons between one and three months. Our results thus suggest that decomposing US VP into its downside and upside components might introduce more flexibility in capturing mixed underlying dynamics of international equity risk premiums at different horizons.[5]

Next, we explore the predictability of DVP and UVP for stock returns at the country level. Figures 3 and 4 show the predictive coefficient estimates associated with DVP and UVP, respectively, in the following country-level regression setting:

$$\kappa^{-1} r_{i;t;t+\kappa} = a_{i;} + b^D_{i;} v p^D_{t;t+1} + b^U_{i;} v p^U_{t;t+1} + \epsilon_{i;t+\kappa}.$$ (8)

Consistent with the panel evidence, Figure 3 shows a similar hump-shaped predictability pattern with significant and positive predictive DVP coefficients for horizons around 6 months for almost all countries in our sample, with a few exceptions, such as Finland, the Netherlands, Ireland, Portugal, and Switzerland. Figure 4 shows that the predictive coefficients of UVP for most countries (except for Japan) exhibit a similar consistently

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[5]In unreported results, which are available upon request, we show that the predictability patterns using our sample period are robust to considering alternative VP measures, including Martingale measures, and to controlling for other predictors, including short-term interest rates, interest-rate differentials, and stock valuation ratios.

positive but decreasing pattern. Although the shape of the predictability patterns of DVP and UVP is by and large consistent across countries, the magnitude and significance of the estimates of the coefficients associated with DVP and UVP could vary across countries.

There are three main takeaways from this empirical section that are important to the conceptual framework that we introduce next. First, US DVP and UVP display different dynamics and are useful short-term predictors of international stock excess returns, which suggests distinct underlying determinants. Second, there are gains in acknowledging for asymmetric risk compensations in the international return predictability, which indicates the importance of asymmetric determinants. Finally, there is some degree of cross-country variation in the predictability patterns and significance of US DVP and UVP, which suggests that there is information in the cross section that can be exploited to understand the global risk premium and the drivers of the cross-country heterogeneity in global risk compensations.

# 3. Conceptual Framework

In this section, we propose a conceptual framework to understand the international stock return predictability of US VPs documented in Section 2. The main intuition is that the observed international stock return predictability should be driven by common economic determinants of US VPs and short-term international equity risk premiums (EPs). An asset pricing framework can help us motivate these common economic determinants and, when confronted with the data, infer their relative importance in driving global equity risk compensations. We first introduce the framework and its implications for VPs and EPs. Then, we explain our estimation strategy.

## 3.1. A No-Arbitrage Framework

Our conceptual framework consists of a characterization of the state evolution and a pricing kernel for a US/global representative agent. The US state evolution process is characterized by kernel state variables, second moment state variables, and a cash flow state variable (dividend growth). The dynamic state process, $Y_t$, follows a vector autoregressive nature, and the shocks, $\omega_t$, are mutually-independent centered gamma shocks that introduce heteroskedasticity and non-Gaussianity in an affine state variable system, as follows:

$$Y_{t+1} = \mu + AY_t + \Sigma \omega_{t+1}, \tag{9}$$

$$\omega_{t+1} \sim \Gamma(\Omega Y_t + e; 1) - (\Omega Y_t + e),$$

where $\mu$, $A$, $\Sigma$, $\Omega$ and $e$ are constant matrices, $\Gamma$ denotes a gamma distribution, and $\Omega Y_t + e$ denotes a vector of shape parameters which spans second (and higher-order)

moments of these shocks. The empirical assumption of asymmetric non-Gaussian shocks allows the framework to be relatively realistic and tractable.[6]

Next, we assume a general linear process of the log US real pricing kernel, as follows:

$$m_{t+1} = m_0 + \boldsymbol{m_1} Y_t + \boldsymbol{m_2} \Sigma \boldsymbol{!}_{t+1}, \tag{10}$$

where $\boldsymbol{m_1}$ and $\boldsymbol{m_2}$ denote the loadings on the lagged state variables and innovations, respectively. Given the no-arbitrage condition and the conditional asset pricing framework, the US price-dividend ratio can be solved in an approximate affine framework, and the log US market return can be expressed in the following quasi-linear process (see Appendix B for the proof):

$$r_{t+1} = \ln\left(\frac{P_{t+1} + D_{t+1}}{P_t}\right) \quad \xi_0 + \ _1 Y_t + \ _2 \Sigma \boldsymbol{!}_{t+1}. \tag{11}$$

We next assume that, for countries other than the US, there is a country-level dividend growth process that is sensitive to US macro and business conditions, $Y_t$, and shocks, $\boldsymbol{!}_{t+1}$. Thus, as shown in Appendix B, log stock returns for country $i$ can be derived as:

$$r^i_{t+1} = \ln\left(\frac{P^i_{t+1} + D^i_{t+1}}{P^i_t}\right) \quad \xi^i_0 + \ ^i_1 Y_t + \ ^i_2 \Sigma \boldsymbol{!}_{t+1} + \text{Idiosyncratic Parts.} \tag{12}$$

Constant matrices $\ _1$ ($\ ^i_1$) and $\ _2$ ($\ ^i_2$) represent the loadings of US (country $i$) log returns on the lagged US/global state variables and shocks, respectively.

The model-implied US variance risk premium has the following expression (see Appendix C for the proof):

$$V^Q_t(r_{t+1}) \quad V^P_t(r_{t+1}) = \left\{ (\ _2 \Sigma)^{\ 2} \quad \left[ (\mathbf{1} \quad \boldsymbol{m_2} \Sigma)^{\ 2} \quad \mathbf{1} \right] \right\} (\Omega Y_t + \boldsymbol{e}) \ ; \tag{13}$$

where " " denotes element-by-element matrix multiplication. Here are some economic insights. First, the dynamics of VP (and its components) should be driven by the shape parameters of kernel state variable shocks, as, for these shocks, the pricing kernel has non-zero loadings (that is, $m_2 \neq 0$). Second, for shocks with positive $m_2$ loadings, their shape parameters (as captured in $(\Omega Y_t + \boldsymbol{e})$) contribute positively to VP, given $\left[ \left( \frac{1}{1 \ m_2} \right)^2 \quad 1 \right] > 0$. Intuitively, for instance, in a standard habit formation model, the marginal utility loads positively on relative risk aversion, and, hence, VP in such a framework would increase with the expected variability in risk aversion; in Segal, Shaliastovich, and Yaron (2015)'s long-run risk model, the kernel has positive exposure to a bad macroeconomic shock, and, hence, VP could also increase with bad macroeconomic uncertainty. Note that it is not trivial to derive model-implied VP components that are consistent with the downside and upside definitions in the empirical section (negative and

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[6]There is an increasing interest in using non-Gaussian and/or composite shocks in asset pricing models to realistically capture the second and higher-order moments as well as tail behaviors of the underlying fundamental or non-fundamental state variables (see, e.g., Eraker and Shaliastovich (2008), Bekaert, Engstrom, and Xing (2009), Fulop, Li, and Yu (2015), Segal, Shaliastovich, and Yaron (2015), De Groot (2015), Colacito, Ghysels, Meng, and Siwasarit (2016), among others). Bekaert and Engstrom (2017) and Xu (2021) show that specifying economic fundamental innovations using gamma shocks is statistically and economically more realistic than using Gaussian shocks.

positive return realizations, respectively) because returns are endogenously determined, as shown in Equation (11). Therefore, our approach to determine the drivers of downside and upside VPs is entirely empirical, with minimum model assumptions (see Section 3.2).

Finally, the US equity risk premium is given by:

$$EP_{1;t} \quad E_t(r_{t+1}) \quad rf_t = f\ _2\Sigma + \ln\left[1 \quad (m_2 + \ _2)\Sigma\right] \quad \ln(1 \quad m_2\Sigma)g\left(\Omega Y_t + e\right), \tag{14}$$

which is determined by second moments of shocks that commonly drive the pricing kernel and asset returns. Similarly, these US second moments also determine the global compensation part of country $i$'s equity risk premium in our framework:

$$EP_{1;t}^i \quad E_t(r_{t+1}^i) \quad rf_t^i = f\ _2^i\Sigma + \ln[1 \quad (m_2 + \ _2^i)\Sigma] \tag{15}$$
$$\ln(1 \quad m_2\Sigma)(\Omega Y_t + e) + \text{Idiosyncratic Part.}$$

The Gaussian approximation of Equation (14) is $(m_2\Sigma \quad _2\Sigma)(\Omega Y_t + e)$, or $Cov_t(r_{t+1}, m_{t+1})$; similarly, for other countries, the global part of Equation (15) captures $Cov_t(r_{t+1}^i, m_{t+1})$. Appendix D provides more details.

In summary, our conceptual framework suggests two important implications for our research objective. First, both the dynamics of US VP and the global part of international equity risk premiums should be driven by the second moments of kernel shocks that enter asset returns, which we refer to as "common risk premium determinants" in the rest of the paper. Second, this commonality implies various stock return predictability channels, which together relate to the observed international predictive coefficients.

## 3.2. Estimation Strategy

We now discuss our estimation strategy to infer the composition and the dynamics of global equity risk premiums in light of the implications from the conceptual framework. There are two stages. We first estimate separate loadings of DVP and UVP on the common risk premium state variables by jointly matching moments of the empirical estimates of DVP and UVP in a GMM system.[7] We consider both constant and time-varying loadings.

The DVP and UVP candidates are denoted by $\widehat{vp_t^D}$ and $\widehat{vp_t^U}$, respectively, given the unknown loading parameter candidates, denoted by $W$:

$$\widehat{vp_t^D} = vp_0^D + \left(W_0^{D\prime} + W_1^{D\prime}z_t\right)\left(\Omega Y_t + e\right), \tag{16}$$
$$\widehat{vp_t^U} = vp_0^U + \left(W_0^{U\prime} + W_1^{U\prime}z_t\right)\left(\Omega Y_t + e\right),$$

---

[7]It may be quite natural to consider using simple OLS projections to obtain these separate loadings. However, OLS regressions allow for residuals and do not guarantee dynamic moment matching; in addition, OLS regressions suffer from co-linearity given that, by design, our risk premium state variables comove with each other (e.g., risk aversion loads on growth shocks; see details in Section 4 and Appendix E). Both concerns can be jointly resolved using a GMM framework.

where $\Omega Y_t + e$ denotes estimated shape parameters of the kernel shocks and $W_0^D$, $W_1^D$, $W_0^U$, and $W_1^U$ are all constant matrices. We use the squared real growth innovation as a proxy for $z_t$ to reflect the general observation that the effects of economic shocks on returns are typically intensified in an uncertain economic environment (for reasons such as learning, as in David and Veronesi (2013), or arbitragers, as in Hong, Kubik, and Fishman (2012)).

As for the equity premiums, from Equations (14) and (15), one-month-ahead country equity risk premiums have a global part that linearly spans the common risk premium state variables. Assuming that common state variables are stationary, the expectation of $\kappa$-month-ahead excess returns for country $i$, $EP^i_{,t}$, should linearly span these state variables. Hence, in the second stage, we consider the following general expression:

$$\widehat{EP}^i_{,t} = \left( V'_{,0} + V'_{,1} EI^i + V'_{,2} FI^i + V'_{,3} z_t \right) \left( \Omega Y_t + e \right) \tag{17}$$
$$+ \text{ Idiosyncratic Part,}$$

where we assume that the country-level loadings are characterized by both economic and financial integration levels, $EI^i$ and $FI^i$, respectively, and by current realized variance. $V_{,0}$, $V_{,1}$, $V_{,2}$ and $V_{,3}$ are all constant matrices and are common for all countries.

We use the average trade-to-GDP ratio (source: World Bank) to capture a country's economic integration (see, e.g., Alesina, Spolaore, and Wacziarg (2000)) and the average total holdings (asset and liability) from country $i$ to the rest of the world (source: IMF, The Coordinated Portfolio Investment Survey) to capture a country's financial integration (see, e.g., Schularick and Steger (2010)).[8] Table 4 presents the country-level integration proxies (in percents) and classifies countries with relatively high (H), medium/average (M), and low (L) integration for demonstration purposes. The two integration proxies are moderately correlated across countries ($\rho$=0.48).

Taken together, the model-implied $\kappa$-month predictive coefficients of DVP and UVP for country $i$'s equity risk premium are given by:

$$\widehat{b^{i;D}} \quad \frac{Cov(\widehat{vp_t^D}, \widehat{EP^i_{,t}})}{Var(\widehat{vp_t^D})} = \frac{(V^{i\prime} \Xi W^D)}{(W^{D\prime} \Xi W^D)}, \tag{18}$$
$$\widehat{b^{i;U}} \quad \frac{Cov(\widehat{vp_t^U}, \widehat{EP^i_{,t}})}{Var(\widehat{vp_t^U})} = \frac{(V^{i\prime} \Xi W^U)}{(W^{U\prime} \Xi W^U)},$$

where $V^i$ denotes matrix $\left[ V'_{,0} + V'_{,1} EI^i + V'_{,2} FI^i \quad V'_{,3} \right]^0$; $\Xi$ is the variane-covariance matrix of risk premium determinants and risk premium determinants each multiplied by $z_t$. $W^D$, which denotes matrix $\left[ W_0^{D\prime} \quad W_1^{D\prime} \right]^0$, and $W^U$, which denotes matrix $\left[ W_0^{U\prime} \quad W_1^{U\prime} \right]^0$, are estimated from the first stage (Equation (16)). We estimate unknowns in $f V_{,0}, V_{,1}, V_{,2}, V_{,3} g$ one horizon at a time (for twelve horizons). For each

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[8]The data are obtained from Tables 1 and 8 from the Coordinated Portfolio Investment Survey conducted by the International Monetary Fund. The first available year is 2001.

horizon $\kappa$, the estimation is conducted by minimizing the sum of squared standardized distances between model-implied and empirical country-level predictive coefficients from Section 2.

To implement this estimation strategy, in Section 4, we define and estimate plausible common risk premium determinants, $\boldsymbol{\Omega Y_t + e}$, or shape parameters of the kernel shocks. In Section 5, we discuss the estimation results for the composition and the dynamics of global equity risk premiums.

# 4. Common Risk Premium Determinants

We consider three kernel state variables: real economic growth, denoted by $\theta_t$; risk aversion, $q_t$; and stock market illiquidity, $illiq_t$. Their second moments should enter the dynamics of US and global risk premiums as common risk premium determinants. As discussed in the introduction, while the literature has examined more equity premium determinants, our research considers kernel state variables that have been used in both the consumption-based and the intermediary-asset-pricing branches of the literature to link equity and variance risk premiums. In this section, we first introduce the dynamic assumptions of the state variables. Then, we discuss the properties of their estimated time series.

## 4.1. The dynamics of state variables

We assume the disturbances of the three kernel state variables to be as follows (see Appendix E for explicit expressions):

$$
\begin{bmatrix}
\theta_{t+1} & E_t(\theta_{t+1}) \\
q_{t+1} & E_t(q_{t+1}) \\
illiq_{t+1} & E_t(illiq_{t+1})
\end{bmatrix} = \boldsymbol{\Sigma_m ! _{m;t+1}},
\tag{19}
$$

where $\boldsymbol{\Sigma_m}$ denotes the shock loading matrix and $\boldsymbol{!_{m;t+1}}$ denotes the orthogonal heteroskedastic shocks,

$$
\boldsymbol{\Sigma_m} = \begin{bmatrix}
\delta_{;\,p} & \delta_{;\,n} & 0 & 0 & 0 & 0 \\
\delta_{q;\,p} & \delta_{q;\,n} & \delta_{q;qh} & \delta_{q;ql} & 0 & 0 \\
\delta_{illiq;\,p} & \delta_{illiq;\,n} & \delta_{illiq;qh} & \delta_{illiq;ql} & \delta_{illiq;illiqh} & \delta_{illiq;illiql}
\end{bmatrix},
$$

$$
\boldsymbol{!_{m;t+1}} = \begin{bmatrix}
\omega_{p;t+1} & \omega_{n;t+1} & \omega_{qh;t+1} & \omega_{ql;t+1} & \omega_{illiqh;t+1} & \omega_{illiql;t+1}
\end{bmatrix}^{\theta}.
$$

We allow flexible tail behaviors of the state variables, given that their second (and higher-order) moments constitute the common risk premium determinants. Specifically, $\omega_{p;t+1}$ $\Gamma(\theta p_t, 1)$ $\theta p_t$ and $\omega_{n;t+1}$ $\Gamma(\theta n_t, 1)$ $\theta n_t$ denote the good and bad macro shocks with time-varying shape parameters $\theta p_t$ and $\theta n_t$, respectively, that characterize the right and left tail behaviors of the real economic growth. Similarly,

$\omega_{qh;t+1} \sim \Gamma(qh_t, 1)$ $qh_t$ and $\omega_{ql;t+1} \sim \Gamma(\overline{ql}, 1)$ $\overline{ql}$ denote the high and low risk aversion shocks, and $\omega_{illiqh;t+1} \sim \Gamma(illiqh_t, 1)$ $illiqh_t$ and $\omega_{illiql;t+1} \sim \Gamma(illiql_t, 1)$ $illiql_t$ denote the high and low illiquidity shocks. Shocks are mutually independent and follow centered gamma distributions with time-varying shape parameters, except that, for simplicity, we characterize the low risk aversion fluctuation as homoskedastic (i.e., $\overline{ql}$). This assumption is to capture the possibility that most of the heteroskedasticity in investor risk aversion is driven by high risk aversion events. Given the moment generating function of gamma shocks, the shape parameters govern the second and higher-order moments of these shocks.[9] We assume simple AR(1) processes for these shape parameters; that is, $\delta x \ 2 \begin{bmatrix} \theta p & \theta n & qh & illiqh & illiql \end{bmatrix}$,

$$x_{t+1} = \mu_x + \rho_x x_t + \sigma_x \omega_{x;t+1}. \tag{20}$$

Economically, this dynamic framework assumes non-zero correlations between level and second (or higher-order) moment shocks, which is consistent with empirical evidence. For instance, consistent with Adrian, Boyarchenko, and Giannone (2019) and Bekaert and Popov (2019), when growth spurts are observed this period (a large $\omega_{p;t}$ realization), we might expect a higher chance for future growth spurts (a higher $\theta p_t$ from the equation above given $\sigma_p > 0$). Also, consistent with Colacito, Ghysels, Meng, and Siwasarit (2016), time-varying growth skewness, which is effectively captured by the combination of $\theta p_t$ and $\theta n_t$, is a potentially important determinant of the equity risk premium. Moreover, it can be shown that the conditional variance of the relative risk aversion state variable (inverse surplus consumption ratio) in Campbell and Cochrane (1999)-type models comoves positively with the the relative risk aversion state variable, suggesting a potentially positive relationship between risk aversion level and volatility (see Xu (2021) for a detailed proof). Therefore, the use of gamma shocks is suitable for our research as it efficiently summarizes conditional moments with one state variable, which allows us to focus on comparing across the different categories of common risk premium determinants.

Finally, as illustrated in the loading matrix $\boldsymbol{\Sigma_m}$, we allow business cycle (growth) shocks to enter both risk aversion and stock market illiquidity dynamics. We also allow market illiquidity to change with investor risk aversion shocks that are orthogonal to business cycle shocks, given recent empirical evidence that stock market liquidity and risk aversion appear positively associated (see, e.g., ECB (2007)).

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[9]For instance, the conditional variance and (unscaled) skewness of the economic growth, $\delta_p \theta p_{t+1}$ $\delta_n \theta n_{t+1}$, can be derived in closed form as a function of two shape parameters; for instance, $Var_t(\theta_{t+1}) = \sigma_p^2 \theta p_t + \sigma_n^2 \theta n_t$, $Skew_t(\theta_{t+1}) = 2\sigma_p^3 \theta p_t \ 2\sigma_n^3 \theta n_t$.

## 4.2. Data and estimation

We follow the empirical macro literature (e.g., Jurado, Ludvigson, and Ng (2015)) and use the change in the log US industrial production as the empirical proxy for economic growth $\theta_t$. Our data runs from January 1947 to December 2019 and is obtained from FRED. We use Bates (2006)'s approximate MLE methodology to estimate non-Gaussian fundamental shocks ($\omega_{p;t}$, $\omega_{n;t}$) and uncertainty state variables ($\theta p_t$, $\theta n_t$).

We then filter the risk aversion state variable and shocks from the variable estimated in Bekaert, Engstrom, and Xu (forthcoming). Although measuring market-wide risk aversion is an ongoing debate, the Bekaert, Engstrom, and Xu (forthcoming) measure is potentially more suitable for our framework, given that it is filtered from a wide range of financial and risk variables while being consistent with equilibrium conditions and controlling for fundamental variable dynamics.[10] The longest available sample for risk aversion starts in June of 1986.

Finally, we follow Amihud (2002) to construct the stock market illiquidity measure ($illiq_t$) using asset returns and volume data of the largest 500 stocks each month from the CRSP NYSE/AMEX/NASDAQ universe, and then we filter our illiquidity state variables and shocks from January 1985 to December 2019.

## 4.3. Results

Table 5 shows standard summary statistics of the five time-varying risk premium determinants and Figure 5 shows their estimated dynamics during our sample period. Detailed parameter estimates and long-sample time series plots are deferred to Appendix E. We now discuss several key observations about the five common risk premium determinants. First, given that a lower shape parameter indicates a more skewed gamma distribution, the evidence from Table 5 implies that there is a higher chance of extreme values from the left tail of the real growth rate than from its right tail; moreover, $\theta p_t$ ($\theta n_t$) is procyclical (countercyclical) given the significant negative (positive) correlation with the NBER recession indicator. According to the first two plots of Figure 5, both good and bad uncertainty state variables are quite persistent. While $\theta p_t$ comoves mostly with the cyclical ups and downs, $\theta n_t$ captures excessively bad uncertainty events to industrial production, such as the impacts of Hurricane Katrina (September of 2005), the collapse of Lehman Brothers (October of 2008), and the US-China trade war (summer of 2018). The bad uncertainty contributes 67% (more during recessions) to the total conditional

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[10]In contrast, Campbell and Cochrane (1999)'s risk aversion would not be suitable for our research, as the measure is constructed as past quarterly consumption growth (Wachter (2006)), which is a fundamental variable. Miranda-Agrippino and Rey (2020) also provide a risk aversion measure, which is the residual of regressing their Global Financial Cycle series on current MSCI world realized return variance. Their measure is also not suitable for our research because it uses price series from all geographical areas, while we focus on developed markets and a US perspective.

variance of economic growth.

Second, the risk aversion state variable $qh_t$ captures the variability in the risk aversion shock that is cleansed from macroeconomic shocks. The estimated $qh_t$ process is strictly countercyclical and positively skewed, exhibiting moderate monthly persistence. The time series plot shows that risk aversion variability could also significantly spike in non-recession episodes such as 9/11 and several corporate scandals during the 2000s. To explain the total risk aversion variability, we find that macroeconomic shocks account for about 15% of this variability.

Third, Amihud (2002)'s illiquidity measure is typically found to be quite persistent; during our sample period, we document a persistent coefficient of 0.95. Table 5 shows that the high stock market illiquidity uncertainty, $illiqh_t$, is weakly countercyclical, while the expected liquidity shock fluctuation, $illiql_t$, is acyclical, suggesting that these two state variables may be capturing a financial cycle that is orthogonal to the business cycle. From Figure 5, $illiql_t$ appears more stable than $illiqh_t$, capturing an asymmetry that is consistent with Amihud (2019). Finally, we find that 73% of the total stock market illiquidity variability is explained by illiquidity uncertainties (mostly $illiqh_t$) and 26% by risk aversion, rendering a weak macroeconomic effect through stock market illiquidity state variables.

## 5. Economic Interpretations

In this section, we bring the empirical evidence and conceptual framework together to understand the sources of the commonality in international equity risk premiums. Section 5.1 provides more estimation details; Section 5.2 examines the model fit; and Section 5.3 presents the results.

### 5.1. Estimation

For the first stage estimation of the GMM (Section 3.2), we use the empirical estimates of the VP components from Section 2 to generate orthogonality conditions: mean, variance, scaled skewness, scaled kurtosis of DVP and UVP (8 moments), the covariance between DVP and UVP (1), and the fraction of the DVP in total VP (1). Each raw moment condition is then tensor-multiplied with a set of lagged instruments $\{1, \theta_{t-1}, q_{t-1}, illiq_{t-1}\}$. The GMM system has 40 moments and 22 unknowns and is estimated iteratively. Then, for each horizon, the second stage estimation uses the first-stage VP parameter estimates and 44 international predictive coefficients (22 $\widehat{b^{i;D}}$'s and 22 $\widehat{b^{i;U}}$'s) to obtain the optimal loadings (20 unknowns in $V$'s) of the common part of international equity risk premiums on the pre-determined premium state variables. We use a grid of 10,000 initial value combinations in each estimation.

## 5.2. Model fit

Table 6 presents the moment matching results and test specifications of the GMM system for the dynamics of the VP components with time-varying or constant loadings. The constant-loading model is rejected, according to the Hansen $J$ overidentification test statistic value and its poor moment matching. On the other hand, we fail to reject the null hypothesis that the extra moments in the time-varying loading model are valid; all moments are significantly close to their empirical counterparts. On the dynamic fit of DVP and UVP, Figure 6 shows that our model-implied DVP and UVP estimates from the time-varying loading model (solid lines) are highly correlated with their empirical counterparts (dashed lines) at a coefficient of 0.88 and 0.48, respectively. In contrast, the DVP and UVP estimates implied from the constant-loading model (dotted lines) show weaker correlations with empirical estimates at 0.74 and 0.16, respectively. In the remainder of the paper, we focus on the time-varying loading model for the VP components.

Table 7 illustrates the fit of international predictive coefficient estimates of DVP and UVP by evaluating the fit of model-implied mean, median, and standard deviation of the country predictive coefficients at each horizon. From Panel A, the model fits the level and the cross-country dispersion of the DVP predictive coefficients quite well. Most model moments are within the 1.96 standard deviations of the empirical counterparts. If we only consider horizons when most countries' DVP predictive coefficients are significant in the empirical evidence (i.e., horizon between two and seven months), all model moments are statistically close to their empirical counterparts. From Panel B, the model-implied level and cross-country dispersion of UVP predictive coefficients are statistically close to their empirical counterparts, except for the dispersion statistics at the 3- and 4-month horizons. In general, our evidence suggests that the integration measures, as conjectured in Equation (17), have the potential to explain the cross-country dispersion in the predictive coefficients. This evidence is, to the best of our knowledge, new to the literature.

Finally, we discuss two other observations from Table 7 that are consistent with the empirical evidence. First, both the mean and the median of country predictive coefficients for the 22 countries are statistically close to the panel-data estimates (in Table 3), and to each other, suggesting that there is no major skewness in the cross section of country predictive coefficients. Second, there is more cross-country heterogeneity in predictability at shorter horizons. If integration remains relatively constant for most countries in our sample, predictability likely means that common risk premium determinants that are more economically important should be those that relate more closely to the economic or financial integration channels. The fact that predictability heterogeneity is stronger at shorter horizons indicates that such common risk premium determinants are also more

dominant at shorter horizons. This observation further supports our use of cross-country predictability evidence to understand the dynamics and determinants of global risk premium.

## 5.3. Economic interpretations

We now discuss economic interpretations of (1) the dynamics of the VP components, (2) their stock return predictability in an "average" country, which speaks to our global- or panel-level interpretations, and (3) their stock return predictability in countries with low/high economic and financial integration levels, which speaks to our cross-country interpretations.

### 5.3.1. The dynamics of the VP components

Table 8 presents the estimation results of the parameters from Equation (16) and the variance contribution of each premium state variable (see rows "VARC%").[11] From this table, DVP loads strongly and positively on variations in risk aversion that are not explained by business cycle fluctuations. According to the variance decomposition results, $qh_t$ accounts for most of the explained dynamics of DVP—62.49%, of which, 10.29% is explained by the time-varying component of the coefficient. This evidence suggests that DVP increases with risk aversion more strongly when the current market and business cycle condition is volatile, given the significant and positive $w_{qh;1}^D$ estimate. The bad economic uncertainty, $\theta n_t$, captures about 30% of the explained DVP dynamics. Different from risk aversion, bad uncertainty may exhibit slightly lower explanatory power in the DVP dynamics when the current business condition is volatile. Finally, the state variable capturing the right-tail fluctuations in stock market illiquidity, $illiqh_t$, appears to contribute positively to the DVP dynamics only during volatile periods; the corresponding VARC of around 9 is economically sizable.

Table 9 provides the economic magnitudes of these VP loadings at various values of the current economic condition characterized by the realized variance of economic growth, $z_t$. Because $z_t$ is right skewed and is always greater than 0, we calibrate several useful scenarios when $z_t$ equals the mean, 90th, 95th, and 99th percentile of its distribution. We find that, under normal conditions ($z_t$ at mean), one standard deviation (SD) increase in risk aversion is associated with the largest increase in DVP (around 9 monthly percentage squared), while bad uncertainty shows the second largest increase (around 6); both observations are consistent with the evidence in Table 8. Under more extreme economic conditions, one SD high illiquidity uncertainty corresponds to an increase of 9.9 monthly

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[11]The variance contribution is calculated as $\frac{_x cov(x_t, \hat{y}_t)}{\hat{y}_t}$ 100%, where $x_t$ denotes an explanatory variable, $\beta_x$ the corresponding loading, and $\hat{y}_t$ the total explained dependent variable.

percentage squared in DVP, which is comparable in magnitude to the marginal impact of one SD risk aversion, 11.3.

Under normal conditions, good economic uncertainty, risk aversion, and fluctuations in stock market liquidity all contribute positively to the variability of UVP. Our evidence suggests that UVP increases with the *procyclical* good economic uncertainty through the hedging demand of upside volatility risk; in addition, UVP also increases with the *countercyclical* risk aversion and market illiquidity risk through the general risk compensation intuition (i.e., higher compensation demanded when risk aversion or financial market risk increases). These counteracting drivers explain the procyclical and relatively less persistent UVP dynamics, as documented in Section 2.2.

Interestingly, the positive relation between good uncertainty and UVP is quite sensitive to the current economic condition. During extremely volatile months when $z_t$ is high, good economic uncertainty contributes less positively to UVP, leading to sudden drops in the UVP level (such as the one in October 2008). This is formally captured by the negative $w^U_{p;1}$ coefficient estimate (Table 8) and the decreasing UVP loading on $\theta p_t$ as $z_t$ increases (Table 9). One possible explanation is that an economic fallout leads to less demand to hedge against future upside variance risk.

### 5.3.2. International stock return predictability: A Global View

While the dynamic fitting of the VP components improves by allowing for time-varying loadings, we find little evidence that $z_t$ plays an economically important role in determining international equity risk premiums at the horizons of interests — the $V_{;3}$ coefficient estimates in Equation (17) are economically small.[12] Hence, we discuss our results using the mean value of $z_t$, and relegate the results using $z_t$ equal to $min(z_t)$ or $max(z_t)$ to Appendix F.

Figure 7-(A) shows the model-implied changes in an average country's equity risk premium (EP, in annualized percent) given one SD increase in a common risk premium state variable. For horizons up to 7 months, where we center the attention, the three main common risk premium sources – US economic uncertainty, risk aversion, and illiquidity uncertainty – contribute positively to the average country's equity risk premium. Moreover, the sensitivities of global equity risk premiums to these premium state variables change with the horizon. Both good and bad economic uncertainties contribute positively to the global equity risk premium. Furthermore, we find that the positive ef-

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[12]Analytically, according to Equations (13) and (14), kernel and return sensitivities to shocks ($m_2$'s and $\xi_2$'s, respectively) determine both the VP and EP loadings. A linear approximation to the VP (EP) loading is $2(\,_2\Sigma)^2$ $m_2\Sigma(\,m_2\Sigma\quad_2\Sigma)$. Suppose kernel and return sensitivities double; it can be easily shown that the VP loadings would increase much more than that the EP loadings. Economically, while stock and volatility pricing may reflect similar risk factors (and hence VP exhibits predictability), VP is not the appropriate direct proxy for EP as the underlying asset is more non-linear (by design) in VP.

fect of bad economic uncertainty, $\theta n_t$, can vary across horizons and becomes dominant in contributing to the global equity risk premium at horizons equal or longer than 4 months.

In contrast, risk aversion and illiquidity uncertainty have stable and positive effects for all horizons; one SD risk aversion, $qh_t$, or high illiquidity uncertainty, $illiqh_t$, leads to between two and three annualized percent increases in the global equity risk premium. These results suggest that economic risk compensations may be more crucial at short horizons. To directly demonstrate this point, Figure 8 depicts the variance decomposition of the model-implied global equity risk compensation at various horizons (see solid lines denoted as "MM" for the global-level view for calibrations with median $EI$ and median $FI$), and shows that economic uncertainty explains about 70-80% at horizons under 7 months.

We next illustrate the relative importance of the premium state variables in explaining the predictive coefficients of the VP components. We use a Jackknife exercise. Specifically, we replace the equity premium loading on a particular premium state variable with 0 and recompute the implied predictive coefficient. As a result, the lower the implied coefficient is, the more important the state variable is in explaining the predictability.

Figure 7-(B) depicts the implied coefficients focusing on horizons with significant predictability in our empirical evidence. The top plot shows that the DVP predictive coefficient decreases the most after deleting the bad economic uncertainty channel, $\theta n_t$, or the risk aversion channel, $qh_t$; between the two, $\theta n_t$ dominates. While $qh_t$ dominates $\theta n_t$ in explaining the variability of DVP, we find that DVP predicts international stock excess returns mostly through the bad economic risk compensation channel. In addition, the bottom plot shows that the good economic uncertainty channel is potentially crucial for explaining the pattern and magnitude of the international predictability of UVP.

Observations from Figure 7-(B) are not immediately intuitive. The variance risk premium predictability literature typically uses an equilibrium framework with one particular risk premium state variable to rationalize its asset pricing channel (see Zhou (2018) for a summary). However, our contribution is to use a relatively flexible framework and horse race these channels such that they jointly explain the predictability patterns, among VP components and across countries.

As a validation exercise, Figure 9 depicts the model-implied global equity risk compensation demanded by the US/global investor at 3-, 6-, and 12-month horizons. The first observation is that the model-implied global risk compensations at various horizons are all generally countercyclical, which is consistent with the literature. Second, on average, the global risk compensation is smaller at longer horizons (see the dotted line), which suggests a downward-sloping term structure of common global risk compensation in international equity markets, adding to the recent discussions considering the US equity market only (see e.g. Boguth, Carlson, Fisher, and Simutin (2011), Van Binsbergen, Brandt, and Koijen (2012), Van Binsbergen, Hueskes, Koijen, and Vrugt (2013),

Croce, Lettau, and Ludvigson (2015)). Third, the short-term global risk compensation appears to be particularly higher than the long-term counterpart during high economic uncertainty periods; for instance, the good uncertainty spikes of 1998 and the bad uncertainty spikes of 2007-2008. This finding is consistent with Figure 7, where we show that economic uncertainties may be more important risk premium determinants at short horizons, while risk aversion and financial market uncertainty likely determine the whole term structure.

### 5.3.3. International stock return predictability: A Cross-Country View

We complement our average country analysis and calibrate the results considering country groups with low and high integration. Specifically, we consider four country groups with low/high economic and financial integration, where "low" ("high") uses the 33th (67th) value of the cross-country integration level (see Table 4).

Figure 10 demonstrates that US/global investors demand a lower global economic risk compensation but a higher global financial market risk compensation for countries with higher integration (especially financial integration). The former result is potentially consistent with the international risk sharing story where global investors demand a lower risk compensation given a lower cost of capital, greater firm and fundamental investment opportunities, and higher expected growth (Bekaert and Harvey (2003); Carrieri, Errunza, and Hogan (2007)); the latter result is potentially consistent with the increasing chance of higher global systemic risk exposure that cannot be diversified away. Moreover, the relative importance of market-wide risk aversion is also slightly higher for countries with higher integration. Note that, while the two integration measures are able to generate a realistic cross-section of predictive coefficients (see Table 7), these integration measures are also moderately correlated at 0.48, which suggests that distinguishing the effects of the two integration types is challenging.

Figure 11 conducts similar Jackknife exercises for these four country groups. Panel (A) shows that the high (low) integration country return predictability is mainly through the financial market risk aversion (economic uncertainty) channel, as the bar size drops more significantly after deleting this channel. This result is consistent with Figure 10. As similarly seen in the average country analysis, Panel (B) illustrates a significant role of good uncertainty in explaining the predictability of UVP, which is even more salient for low integration countries.

## 6. Conclusion

Understanding the commonality in international equity risk premiums and the transmission of global risks across international financial markets remains an open de-

bate in the literature. In this paper, we add to this debate by using a novel approach in which we link empirical evidence for the international stock return predictability of US downside and upside variance risk premiums with the implications of an asset pricing framework using data for 22 countries from 1991 to 2019.

We find that the international predictability patterns of DVP (positive and countercyclical) and UVP (smaller in magnitude and procyclical) are considerably different, with DVP being a robust mid-horizon (4-7 month) predictor and UVP a short-horizon (1-3 month) predictor. We link these results to the implications of a conceptual asset pricing framework that takes the perspective of a US/global investor and features heteroskedastic and asymmetric US macroeconomic, financial market (illiquidity), and risk aversion shocks. The main intuition from the model solution is that international stock return predictability should be determined by common economic determinants of the VP components and global equity risk compensations. We find that DVP and UVP predict international stock returns through different common risk premium determinants, mainly bad and good US macroeconomic uncertainties, respectively. At the country level, our results also suggest that US/global investors demand a lower global macroeconomic risk compensation but a higher global pure financial market risk compensation for countries with higher integration.

Our approach of linking international predictability evidence with an asset pricing framework allows us to use more information to infer the global nature of risk compensations across time, across horizons, and across countries. This methodology should naturally inspire several extensions of our work, including examining whether global risk premium determinants transmit through local-currency equity risk pricing or through exchange rate channels, involving other international finance puzzles similar to the work in Colacito and Croce (2010) and Colacito, Croce, Gavazzoni, and Ready (2018). Moreover, future work should integrate our findings to existing general equilibrium models with an international perspective.

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## Table 1: Expected downside and upside realized variances

This table shows the coefficients associated with the predictors of one-month-ahead (22 days) downside and upside realized variances, in panels A and B, respectively. The specification in column (1) assumes that realized variances follow a Martingale ($E(rv_{t+1}^i) = rv_t^i$, for $i = D, U$ (downside or upside)). For the specifications in columns (2) to (5), we estimate the following regression setting:

$$E_t(rv_{t+1m}^i) = \hat{\alpha}^i + \hat{\gamma}^{\mathbf{i}} \mathbf{X_t^i}.$$

We consider the following predictors, $\mathbf{X_t}$, at time $t$: the total realized variance calculated over the last month ($rv_{t\ 1m;t}$) and its downside an upside components ($rv_{t\ 1m;t}^i$); realized semivariances calculated using either the last five days ($rv_{t\ 5d;t}^i$) or the last day of the month ($rv_{t\ 1d;t}^i$); and the downside and upside components of the option-implied variance ($iv_{t;t+1m}^i$). All regressions are estimated using daily data. The sample runs from April 1991 to December 2019. Heteroskedasticity and autocorrelation consistent (HAC) standard deviations with 44 lags are reported in parentheses. ( , ) represent significance at the 1% (5%, 10%) confidence level. The adjusted $R^2$s are reported at the end of each panel.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| **Panel A. Downside realized variance** | | | | | |
| Constant | 0 | 4.17*** | 4.11*** | 3.88*** | 3.18*** |
| | - | (0.63) | (0.67) | (0.55) | (1.00) |
| $rv_{t\ 1m;t}$ | | | 0.43 | | |
| | | | (0.36) | | |
| $rv_{t\ 1m;t}^D$ | 1 | 0.62*** | 0.10 | 0.29** | 0.23*** |
| | | (0.07) | (0.21) | (0.13) | (0.08) |
| $rv_{t\ 5d;t}^D$ | | | | 0.29** | 0.27* |
| | | | | (0.13) | (0.15) |
| $rv_{t\ 1d;t}^D$ | | | | 0.06*** | 0.04* |
| | | | | (0.01) | (0.03) |
| $iv_{t;t+1m}^D$ | | | | | 0.08 |
| | | | | | (0.10) |
| Adj. $R^2$ | 0.23 | 0.378 | 0.378 | 0.428 | 0.429 |
| **Panel B. Upside realized variance** | | | | | |
| Constant | 0 | 3.73*** | 3.80*** | 3.39*** | 0.84 |
| | - | (0.64) | (0.64) | (0.59) | (0.73) |
| $rv_{t\ 1m;t}$ | | | -0.60 | | |
| | | | (0.40) | | |
| $rv_{t\ 1m;t}^U$ | 1 | 0.64*** | 0.61*** | 0.30** | 0.07 |
| | | (0.08) | (0.17) | (0.15) | (0.11) |
| $rv_{t\ 5d;t}^U$ | | | | 0.30** | 0.24 |
| | | | | (0.15) | (0.15) |
| $rv_{t\ 1d;t}^U$ | | | | 0.05*** | 0.03** |
| | | | | (0.01) | (0.01) |
| $iv_{t;t+1m}^U$ | | | | | 0.57*** |
| | | | | | (0.11) |
| Adj. $R^2$ | 0.29 | 0.414 | 0.433 | 0.461 | 0.499 |

Table 2: Summary statistics for variance premium components

This table reports time series averages of the monthly risk-neutral and physical expectations of the variances ($iv_{t;t+1}$ and $E_t(rv_{t;t+1})$, respectively) as well as the corresponding monthly variance premiums (VPs). The monthly time series are end-of-month estimates from Table 1. All measures are in units of monthly variance—i.e., in annual percentage squared divided by 12 (as commonly used in the literature; see, e.g., Bekaert and Hoerova (2014), Kilic and Shaliastovich (2019), among many others). For VP estimates, we also report standard deviations and minimum and maximum values. The sample runs from April 1991 to December 2019.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Panel A. DVP | | | | | |
| $Mean(iv_{t;t+1}^D)$ | 23.67 | 23.67 | 23.67 | 23.67 | 23.67 |
| $Mean(E_t(rv_{t;t+1}^D))$ | 10.87 | 7.04 | 7.08 | 7.05 | 7.69 |
| $Mean(vp_{t;t+1}^D)$ | 12.79 | 16.63 | 16.58 | 16.61 | 15.97 |
| $SD(vp_{t;t+1}^D)$ | 11.24 | 14.08 | 14.10 | 13.85 | 13.52 |
| $Min(vp_{t;t+1}^D)$ | -23.49 | 2.47 | 2.41 | 2.21 | 2.24 |
| $Max(vp_{t;t+1}^D)$ | 81.25 | 97.91 | 99.64 | 91.00 | 93.05 |
| Panel B. UVP | | | | | |
| $Mean(iv_{t;t+1}^U)$ | 11.03 | 11.03 | 11.03 | 11.03 | 11.03 |
| $Mean(E_t(rv_{t;t+1}^U))$ | 10.50 | 7.07 | 7.02 | 7.34 | 9.76 |
| $Mean(vp_{t;t+1}^U)$ | 0.53 | 3.96 | 4.01 | 3.69 | 1.26 |
| $SD(vp_{t;t+1}^U)$ | 9.76 | 6.19 | 6.15 | 6.30 | 3.28 |
| $Min(vp_{t;t+1}^U)$ | -138.25 | -59.87 | -64.41 | -62.93 | -35.48 |
| $Max(vp_{t;t+1}^U)$ | 23.27 | 31.07 | 22.70 | 26.17 | 9.56 |
| Panel C. Correlations within models | | | | | |
| $Correl(vp_{t;t+1}, vp_{t;t+1}^D)$ | 0.85 | 0.95 | 0.94 | 0.93 | 0.97 |
| $Correl(vp_{t;t+1}, vp_{t;t+1}^U)$ | 0.79 | 0.69 | 0.65 | 0.59 | 0.26 |
| $Correl(vp_{t;t+1}^U, vp_{t;t+1}^D)$ | 0.35 | 0.43 | 0.36 | 0.25 | 0.03 |

Table 3: International predictability of VP and its components

The table reports evidence for the predictability of the variance premium and its components for international stock returns at various horizons of interest (in units of months). Our main specification is the following:

$$\kappa^{-1} r_{i;t;t+\kappa} = a_{i;\kappa} + a_\kappa + b_{\kappa;D} vp^D_{t;t+1} + b_{\kappa;U} vp^U_{t;t+1} + \epsilon_{i;t+\kappa},$$

where $r_{i;t;t+\kappa}$ denotes the $\kappa$-month-ahead log excess returns for country $i$ and $vp^D_{t;t+1}$ and $vp^U_{t;t+1}$ denote DVP and UVP estimates, respectively. We compare our main specification with one in which the coefficients associated with DVP and UVP are homogeneous, which is equivalent to a regression for the predictability of the total VP:

$$\kappa^{-1} r_{i;t;t+\kappa} = a_{i;\kappa} + a_\kappa + b_\kappa (vp^D_{t;t+1} + vp^U_{t;t+1}) + \epsilon_{i;t+\kappa}.$$

In both specifications, the coefficients are estimated using ordinary least squares (OLS) where the coefficients associated with VP and its components are restricted to be homogeneous across countries. The VP estimated coefficients and their $h$-lag corrected Newey-West standard errors (in parentheses) are reported along with the adjusted $R^2$. "VARC" indicates the variance decomposition of the model. ($\ast\ast\ast$, $\ast\ast$, $\ast$) represent significance at the 1% (5%, 10%) confidence level.

| | $\kappa$=1 | | $\kappa$=3 | | $\kappa$=6 | | $\kappa$=12 | |
|---|---|---|---|---|---|---|---|---|
| $vp$ | 0.1187 | | 0.2645 | | 0.3127*** | | 0.1604** | |
| (SE) | (0.3365) | | (0.1775) | | (0.1088) | | (0.0718) | |
| $vp^D$ | | -0.0111 | | 0.2149 | | 0.2987*** | | 0.1785*** |
| (SE) | | (0.3370) | | (0.1756) | | (0.1085) | | (0.0692) |
| [VARC%] | | [0.0%] | | [43.1%] | | [83.8%] | | [98.0%] |
| $vp^U$ | | 2.0996** | | 1.0198* | | 0.5263* | | -0.116 |
| (SE) | | (0.8620) | | (0.5834) | | (0.2883) | | (0.2395) |
| [VARC%] | | [100.0%] | | [56.9%] | | [16.2%] | | [2.0%] |
| Adj. $R^2$ | 0.04% | **0.82%** | 0.66% | **0.96%** | 1.67% | **1.71%** | 0.85% | **0.99%** |

Table 4: Country-level economic and financial integration indicators

This table presents the country-level integration proxies: the average trade-to-GDP ratio (source: World Bank; 1989-2018) as the proxy for a country's economic integration, and the average total asset and liability holdings from country $i$ to the rest of the world (source: IMF, The Coordinated Portfolio Investment Survey; 2001-2018) as the proxy for a country's financial integration (Schularick and Steger (2010)). This table also provides a within-variable sort: low, [0th, 33th); middle, [33th,67th); high, [67th,100th].

|  | Trade-to-GDP | | Holdings-to-GDP | |
| --- | --- | --- | --- | --- |
|  | in % | L/M/H | in % | L/M/H |
| Australia | 39.5 | L | 106.9 | L |
| Austria | 86.9 | M | 171.8 | H |
| Belgium | 138.7 | H | 236.0 | H |
| Canada | 65.8 | L | 121.0 | M |
| Denmark | 85.0 | M | 178.4 | M |
| Finland | 69.1 | M | 211.8 | M |
| France | 52.0 | M | 189.1 | L |
| Germany | 64.7 | M | 148.1 | M |
| Hong Kong | 309.9 | H | 330.4 | H |
| Ireland | 159.4 | H | 1185.9 | H |
| Italy | 48.1 | L | 121.9 | L |
| Japan | 24.6 | L | 86.3 | L |
| Netherlands | 125.2 | H | 396.2 | H |
| New Zealand | 57.7 | L | 63.6 | M |
| Norway | 70.0 | M | 223.5 | M |
| Portugal | 66.8 | M | 141.0 | M |
| Singapore | 356.6 | H | 450.7 | H |
| Spain | 52.1 | L | 114.7 | L |
| Sweden | 77.0 | M | 190.8 | M |
| Switzerland | 99.4 | H | 302.8 | H |
| United Kingdom | 52.9 | H | 236.1 | L |
| United States | 24.7 | L | 93.7 | L |

Table 5: Summary statistics of risk premium state variables

This table provides summary statistics of our main five risk premium state variables introduced in Section 4: good and bad economic uncertainty ($\theta p_t$ and $\theta n_t$, respectively), expected risk aversion fluctuations ($qh_t$), and high and low stock market illiquidity uncertainty ($illiqh_t$ and $illiql_t$, respectively). The full sample estimation results and detailed dynamic processes are deferred to Appendix B.    ( , ) represent significance at the 1% (5%, 10%) confidence level. The summary statistics are calculated for a sample running from April 1991 to December 2019.

| | $\theta p_t$ | $\theta n_t$ | $qh_t$ | $illiqh_t$ | $illiql_t$ |
|---|---|---|---|---|---|
| | Panel A. Univariate statistics | | | | |
| Mean | 476.020 | 3.342 | 0.838 | 1.191 | 0.702 |
| SD | 15.176 | 7.798 | 1.107 | 1.376 | 0.046 |
| Skewness | 0.724 | 5.133 | 3.379 | 1.935 | 1.247 |
| | | | | | |
| | Panel B. Correlation matrix | | | | |
| $\theta p_t$ | 1 | | | | |
| $\theta n_t$ | -0.222*** | 1 | | | |
| $qh_t$ | -0.070 | 0.191*** | 1 | | |
| $illiqh_t$ | 0.159*** | 0.084 | 0.115** | 1 | |
| $illiql_t$ | 0.348*** | -0.035 | 0.116** | 0.058 | 1 |
| NBER | -0.182*** | 0.532*** | 0.205*** | 0.142*** | -0.077 |
| Cyclicality | Pro- | Counter- | Counter- | Counter- | A-cyclical |

Table 6: Model fit: VP component dynamics

This table presents the moment matching results of the GMM system used to estimate the loadings of DVP and UVP on the five risk premium state variables (see details in Section 3.2). Two GMM systems are estimated: one with time-varying loadings (22 unknowns) and one with constant loadings (12 unknowns). Both GMM systems have 40 moments and are estimated using iterative GMM.    indicates that the model estimate is within 1.645 SD of the empirical point estimate in the same row. Standard model specification statistics and empirical correlations are shown at the end of the table.

| | Moment | | Empirical | Boot. SE | Model | |
|---|---|---|---|---|---|---|
| | | | | | time-varying | constant |
| 1 | $vp^D$ | | 15.972 | (0.725) | 16.464*** | 10.05 |
| 2 | $vp^U$ | | 1.265 | (0.173) | 1.241*** | -0.202 |
| 3 | $(vp^D$ | $E(vp^D))^2$ | 182.198 | (33.504) | 180.071*** | 175.881*** |
| 4 | $(vp^U$ | $E(vp^U))^2$ | 10.755 | (4.230) | 10.701*** | 4.383*** |
| 5 | $(vp^D$ | $E(vp^D))^3/(SD(vp^D)^3)$ | 2.656 | (0.885) | 2.752*** | 2.867*** |
| 6 | $(vp^U$ | $E(vp^U))^3/(SD(vp^U)^3)$ | -5.001 | (3.959) | -4.146*** | 0.687*** |
| 7 | $(vp^D$ | $E(vp^D))^4/(SD(vp^D)^4)$ | 12.293 | (4.287) | 11.955*** | 12.821*** |
| 8 | $(vp^U$ | $E(vp^U))^4/(SD(vp^U)^4)$ | 53.202 | (45.926) | 48.432*** | 7.718 |
| 9 | $(vp^D$ | $E(vp^D))$   $(vp^U$   $E(vp^U))$ | 1.262 | (8.555) | -1.981*** | -3.18*** |
| 10 | $vp^D/(vp^D + vp^U)$ | | 0.927 | (0.010) | 0.924*** | 0.626 |
| | GMM J Statistics: | | | | 15.78 | 61.56 |
| | DF: | | | | 18 | 28 |
| | Hansen's Overidentification Test, p-value: | | | | 0.61 | 0.00 |
| | Dynamic correlation with empirical estimates, DVP: | | | | 0.88 | 0.74 |
| | Dynamic correlation with empirical estimates, UVP: | | | | 0.48 | 0.16 |

Table 7: Model fit: VP component predictive coefficients

This table provides the model fit results of the international stock return predictive coefficients of the VP components (see details in Section 3.2). To summarize the information, Panels A and B report the average, mean, and cross-country variation of the DVP and UVP predictive coefficients, respectively, and provide closeness tests with their empirical counterparts;    ( ; ) indicates that the model estimate is within the 1.645 (1.96;2.576) SD of the empirical point estimate in the same row. Rows in bold indicate horizons with significant predictability for most countries according to our empirical evidence.

| Panel A | Average DVP coeff. | | | Median DVP coeff. | | | Cross-country SD DVP coeff. | | |
|---|---|---|---|---|---|---|---|---|---|
| Horizon | Emp. | SE | Model | Emp. | SE | Model | Emp. | SE | Model |
| 1 | -0.011 | (0.052) | -0.059*** | -0.036 | (0.070) | -0.027*** | 0.245 | (0.027) | 0.148 |
| **2** | **0.188** | **(0.043)** | **0.142*** | **0.151** | **(0.048)** | **0.177*** | **0.202** | **(0.025)** | **0.147*** |
| **3** | **0.215** | **(0.036)** | **0.176*** | **0.188** | **(0.032)** | **0.205*** | **0.171** | **(0.023)** | **0.130**** |
| **4** | **0.226** | **(0.036)** | **0.186*** | **0.221** | **(0.026)** | **0.215*** | **0.169** | **(0.024)** | **0.134*** |
| **5** | **0.262** | **(0.036)** | **0.225*** | **0.262** | **(0.031)** | **0.26*** | **0.169** | **(0.025)** | **0.128*** |
| **6** | **0.299** | **(0.036)** | **0.253*** | **0.289** | **(0.030)** | **0.287*** | **0.168** | **(0.025)** | **0.131*** |
| **7** | **0.287** | **(0.035)** | **0.247*** | **0.265** | **(0.030)** | **0.284*** | **0.166** | **(0.027)** | **0.136*** |
| 8 | 0.235 | (0.034) | 0.202*** | 0.220 | (0.027) | 0.239*** | 0.161 | (0.028) | 0.134*** |
| 9 | 0.214 | (0.033) | 0.181*** | 0.214 | (0.023) | 0.217*** | 0.157 | (0.028) | 0.128*** |
| 10 | 0.189 | (0.033) | 0.164*** | 0.191 | (0.021) | 0.199*** | 0.155 | (0.028) | 0.125*** |
| 11 | 0.185 | (0.033) | 0.158*** | 0.184 | (0.022) | 0.195*** | 0.153 | (0.028) | 0.132*** |
| 12 | 0.179 | (0.032) | 0.157*** | 0.174 | (0.023) | 0.192*** | 0.149 | (0.027) | 0.127*** |

| Panel B | Average UVP coeff. | | | Median UVP coeff. | | | Cross-country SD UVP coeff. | | |
|---|---|---|---|---|---|---|---|---|---|
| Horizon | Emp. | SE | Model | Emp. | SE | Model | Emp. | SE | Model |
| **1** | **2.100** | **(0.241)** | **1.859*** | **1.999** | **(0.178)** | **1.807*** | **1.128** | **(0.203)** | **0.627*** |
| **2** | **0.922** | **(0.174)** | **0.782*** | **0.995** | **(0.150)** | **0.814*** | **0.814** | **(0.142)** | **0.450**** |
| **3** | **1.020** | **(0.117)** | **0.903*** | **1.272** | **(0.137)** | **0.953*** | **0.548** | **(0.101)** | **0.392**** |
| **4** | **1.227** | **(0.106)** | **1.096*** | **1.309** | **(0.126)** | **1.175*** | **0.497** | **(0.074)** | **0.268** |
| **5** | **0.891** | **(0.081)** | **0.816*** | **0.906** | **(0.120)** | **0.881*** | **0.380** | **(0.050)** | **0.217** |
| 6 | 0.526 | (0.063) | 0.482*** | 0.551 | (0.073) | 0.555*** | 0.293 | (0.046) | 0.224*** |
| 7 | 0.276 | (0.053) | 0.273*** | 0.299 | (0.083) | 0.329*** | 0.247 | (0.033) | 0.188*** |
| 8 | 0.237 | (0.053) | 0.217*** | 0.296 | (0.083) | 0.251*** | 0.250 | (0.031) | 0.158 |
| 9 | -0.009 | (0.045) | -0.004*** | -0.009 | (0.047) | 0.038*** | 0.209 | (0.032) | 0.126 |
| 10 | -0.069 | (0.047) | -0.074*** | -0.049 | (0.055) | -0.042*** | 0.219 | (0.036) | 0.100 |
| 11 | -0.125 | (0.048) | -0.127*** | -0.122 | (0.058) | -0.089*** | 0.225 | (0.036) | 0.109 |
| 12 | -0.116 | (0.047) | -0.115*** | -0.107 | (0.056) | -0.08*** | 0.220 | (0.036) | 0.114 |

Table 8: Loadings of VP components on risk premium state variables

This table presents the estimation results of the GMM framework and the relative importance of the risk premium state variables in driving the dynamics of VPs. Details are presented in Section 3.2. For each GMM iteration, the model-implied DVP and UVP ($\widehat{vp_t^D}$ and $\widehat{vp_t^U}$, respectively) can be expressed as:

$$\widehat{vp_t^D} = vp_0^D + w_{p;t}^D \widehat{\theta p}_t + w_{n;t}^D \widehat{\theta n}_t + w_{qh;t}^D \widehat{qh}_t + w_{illiqh;t}^D \widehat{illiqh}_t + w_{illiql;t}^D \widehat{illiql}_t,$$

$$\widehat{vp_t^U} = vp_0^U + w_{p;t}^U \widehat{\theta p}_t + w_{n;t}^U \widehat{\theta n}_t + w_{qh;t}^U \widehat{qh}_t + w_{illiqh;t}^U \widehat{illiqh}_t + w_{illiql;t}^U \widehat{illiql}_t,$$

where, for $x \in \{\theta p, \theta n, qh, illiqh, illiqlg\}$, $\widehat{x}$ indicates the estimated risk premium state variables (Section 4), and $w_{x;t}^D$ and $w_{x;t}^U$ indicate the corresponding time-varying coefficients:

$$w_{x;t}^D = w_{x;0}^D + w_{x;1}^D z_t,$$

$$w_{x;t}^U = w_{x;0}^U + w_{x;1}^U z_t,$$

and $z_t$ is the current squared innovation to real economic growth. Standard errors are shown in parentheses and variance decomposition results are shown in the third row ("VARC"). The variance contribution is calculated as $\frac{v\,cov(v_t;\widehat{y_t})}{\widehat{y_t}}$ 100%, where $v_t$ denotes an explanatory variable, $\beta_v$ the corresponding loading, and $\widehat{y_t}$ the total explained $y$ variable. ( , ) represent significance at the 1% (5%, 10%) confidence level.

| | | $\theta p_t$ | $\theta n_t$ | $qh_t$ | $illiqh_t$ | $illiql_t$ | Constant |
|---|---|---|---|---|---|---|---|
| DVP | $w_0^D$ | -0.041 | 0.885*** | 7.762*** | -0.35 | 83.505*** | -32.257 |
| | | (0.061) | (0.134) | (0.358) | (0.506) | (14.412) | (25.616) |
| | [VARC%] | [0.46%] | [33.27%] | [52.20%] | [-0.49%] | [9.34%] | |
| | $w_1^D$ | 14.143 | -522.083*** | 5323.575*** | 16282.641*** | -27746.517*** | |
| | | (11.003) | (5.474) | (70.288) | (269.496) | (7465.181) | |
| | [VARC%] | [2.64%] | [-8.97%] | [10.29%] | [8.98%] | [-7.72%] | |
| UVP | $w_0^U$ | 0.074** | 0.177*** | 1.19*** | 0.476*** | -26.99** | -15.935 |
| | | (0.036) | (0.039) | (0.145) | (0.122) | (13.106) | (11.539) |
| | [VARC%] | [5.82%] | [-4.04%] | [5.11%] | [6.62%] | [6.04%] | |
| | $w_1^U$ | -76.725*** | 41.821*** | -1.364 | 1306.134*** | 1068.634 | |
| | | (18.526) | (5.932) | (34.542) | (90.690) | (1273.898) | |
| | [VARC%] | [88.54%] | [-3.74%] | [0.01%] | [-2.54%] | [-1.82%] | |

Table 9: Economic magnitude of VP loadings

This table complements Table 8 and provides economic magnitude of the sensitivity of the VP components to each risk premium state variable at four different values of $z_t$, the proxy for the current economic condition (sample average, 90th, 95th, and 99th percentiles).

|  | $z_t$ values | $\theta p_t$ | $\theta n_t$ | $qh_t$ | $illiqh_t$ | $illiql_t$ |
|---|---|---|---|---|---|---|
| DVP | Mean($z_t$) | -0.6123 | 6.8424 | 8.6720 | -0.1713 | 3.8341 |
|  | 90th($z_t$) | -0.5989 | 6.5886 | 9.0393 | 1.2258 | 3.7543 |
|  | 95th($z_t$) | -0.5862 | 6.3463 | 9.3900 | 2.5593 | 3.6782 |
|  | 99th($z_t$) | -0.5158 | 5.0125 | 11.3204 | 9.9011 | 3.2588 |
| UVP | Mean($z_t$) | 1.1085 | 1.3868 | 1.3172 | 0.6803 | -1.2443 |
|  | 90th($z_t$) | 1.0359 | 1.4071 | 1.3171 | 0.7924 | -1.2412 |
|  | 95th($z_t$) | 0.9666 | 1.4265 | 1.3170 | 0.8994 | -1.2383 |
|  | 99th($z_t$) | 0.5851 | 1.5334 | 1.3165 | 1.4883 | -1.2221 |
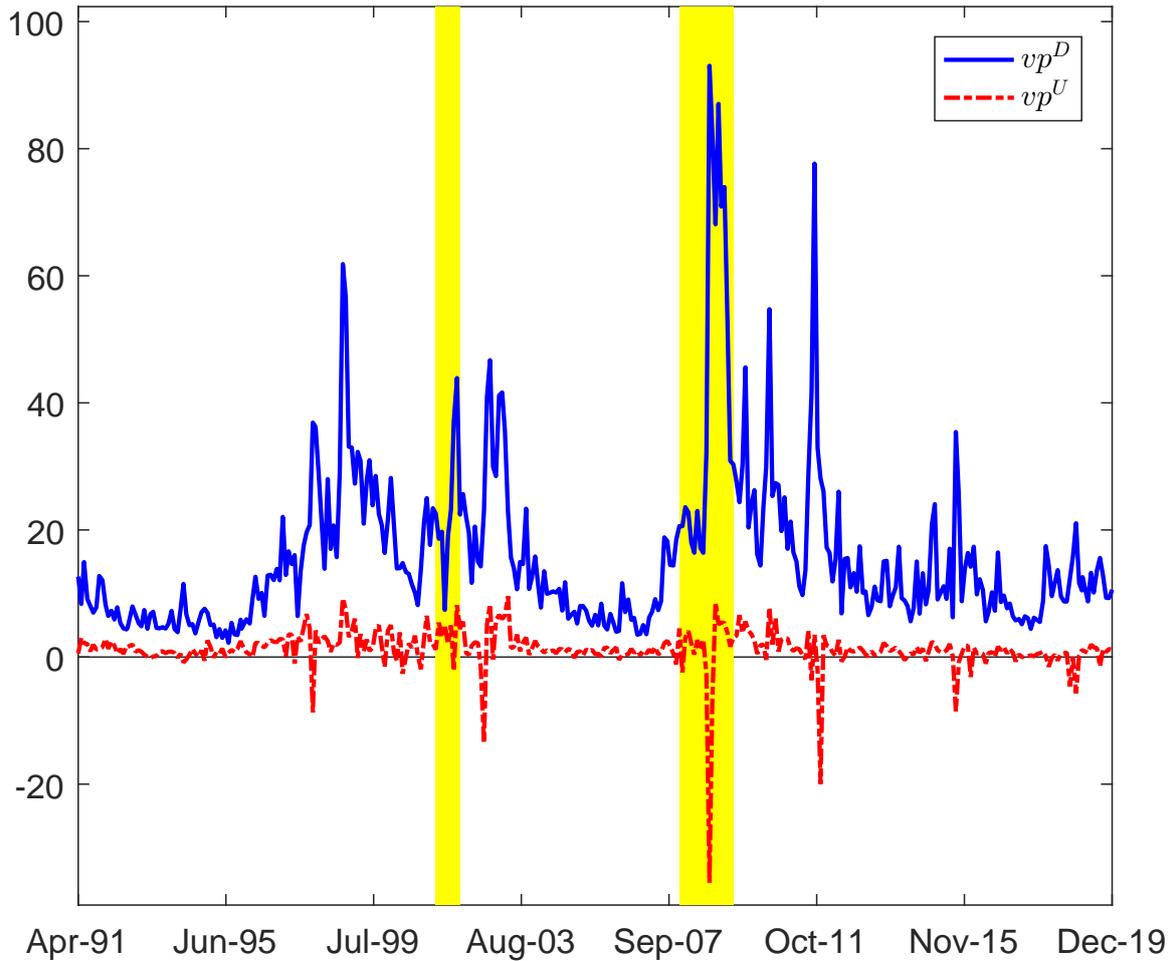
Figure 1: Downside and upside components of the variance risk premium

This figure shows the time series of the downside and upside variance premium components. The construction details of variance risk premiums are discussed in Section 2. The downside (upside) variance risk premium is calculated as the difference between the option-implied downside (upside) variance and the expected downside (upside) realized variance. We use the best forecasts of the downside and upside realized variances from Table 1 (specification (5)). Measures are in units of monthly percentages.
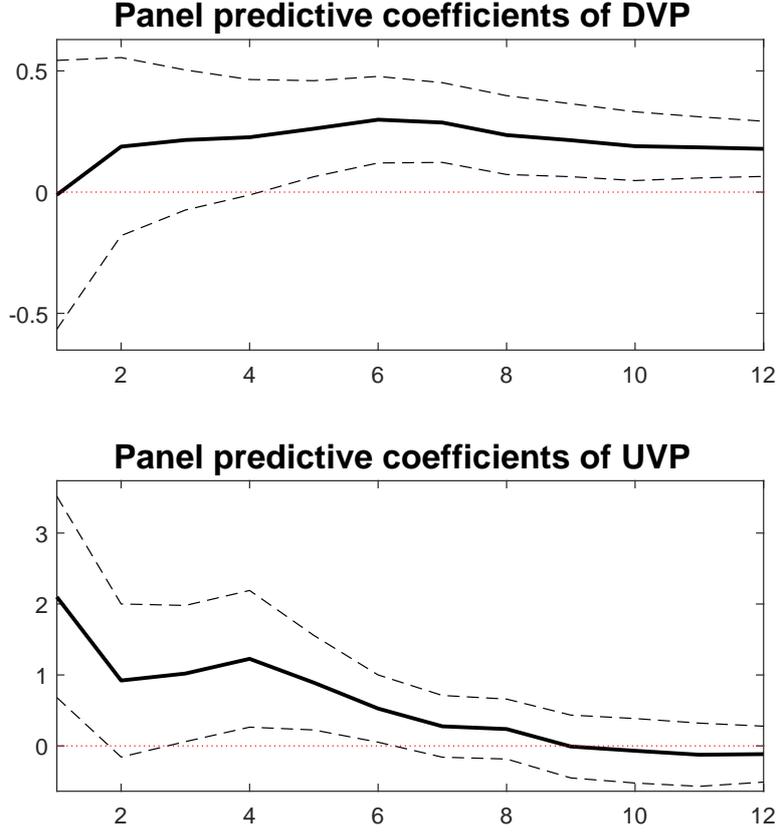
Figure 2: International stock return predictability of DVP and UVP

This figure shows the predictive coefficient estimates of the downside (DVP, top) and upside (UVP, bottom) variance premiums at horizons between 1 and 12 months for the main predictability regression setting:

$$\kappa^{-1} r_{i;t;t+\kappa} = a_{i;\kappa} + a_{\kappa} + b_{\kappa;d} vp^{D}_{t;t+1} + b_{\kappa;u} vp^{U}_{t;t+1} + \epsilon_{i;t;t+\kappa},$$

where $r_{i;t;t+\kappa}$ denotes the cumulative $\kappa$-month-ahead log excess returns for country $i$. The dashed lines depict 90% confidence intervals given Newey-West standard errors.
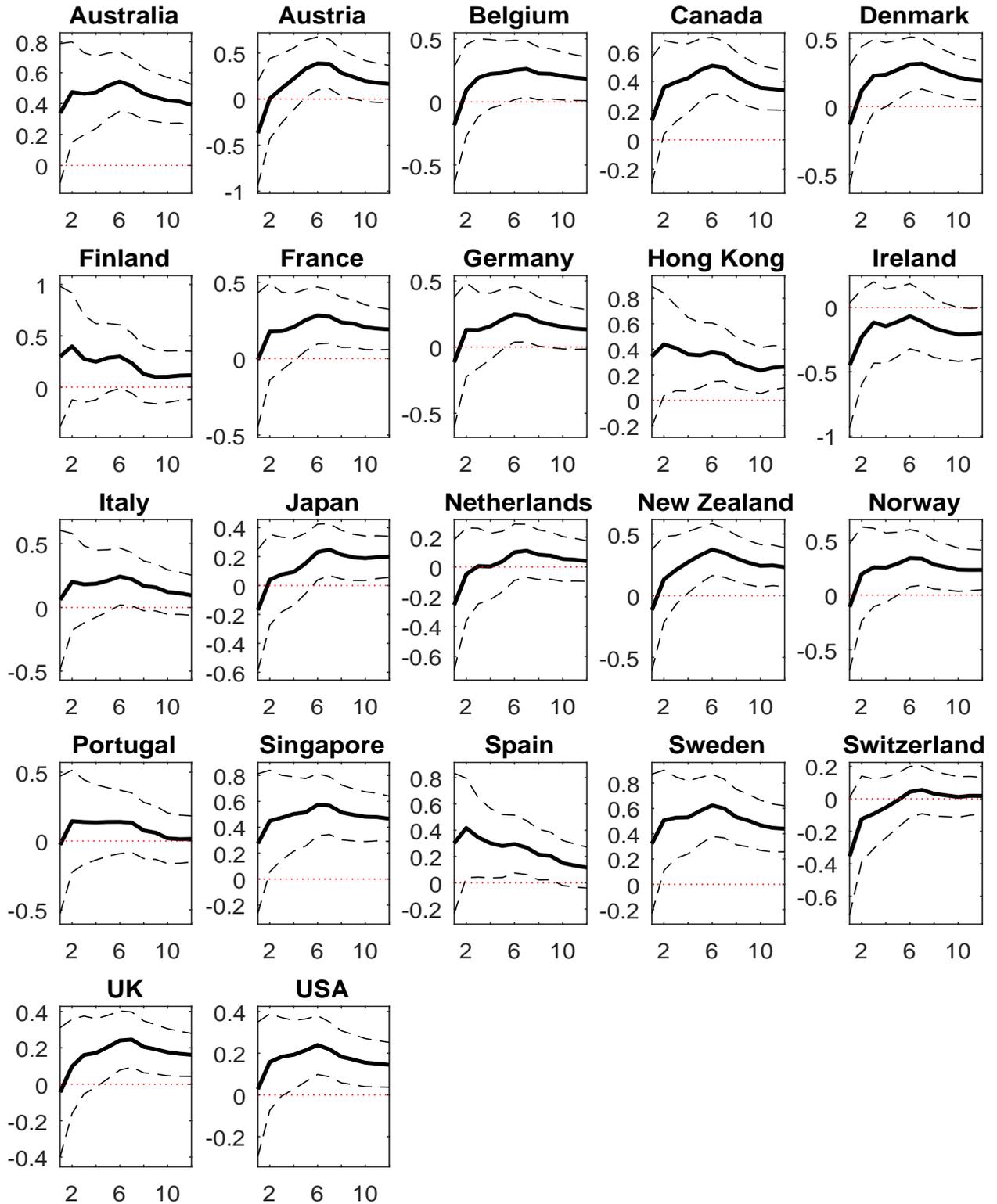
Figure 3: DVP coefficients

This figure shows the predictive coefficient estimates of the downside variance premium (the solid lines) and its 90% confidence interval given Newey-West standard errors (the dashed lines) at the country level. The regression setting is the following:

$$\kappa^{-1} r_{i;t;t+\kappa} = a_{i;\kappa} + b_{i;\kappa;d} vp^{D}_{t;t+1} + b_{i;\kappa;u} vp^{U}_{t;t+1} + \epsilon_{i;t;t+\kappa},$$

where $r_{i;t;t+\kappa}$ denotes the cumulative $\kappa$-month-ahead log excess returns for country $i$.

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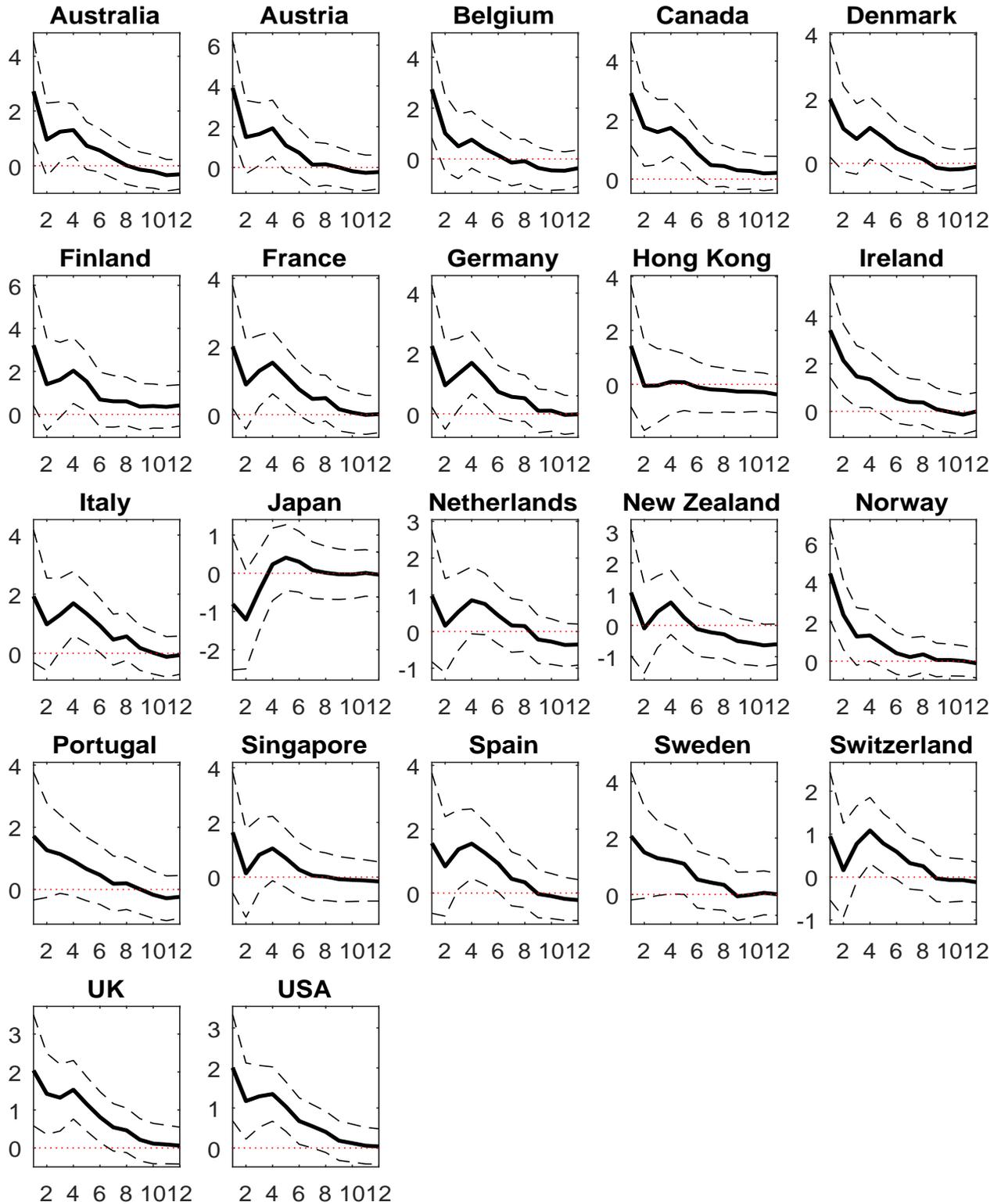
Figure 4: UVP coefficients

This figure shows the predictive coefficient estimates of the upside variance premium (the solid lines) and its 90% confidence interval given Newey-West standard errors (the dashed lines) at the country level. The regression setting is the following:

$$\kappa^{-1} r_{i;t;t+\kappa} = a_{i;\kappa} + b_{i;\kappa;d} vp^D_{t;t+1} + b_{i;\kappa;u} vp^U_{t;t+1} + \epsilon_{i;t;t+\kappa},$$

where $r_{i;t;t+\kappa}$ denotes the cumulative $\kappa$-month-ahead log excess returns for country $i$.
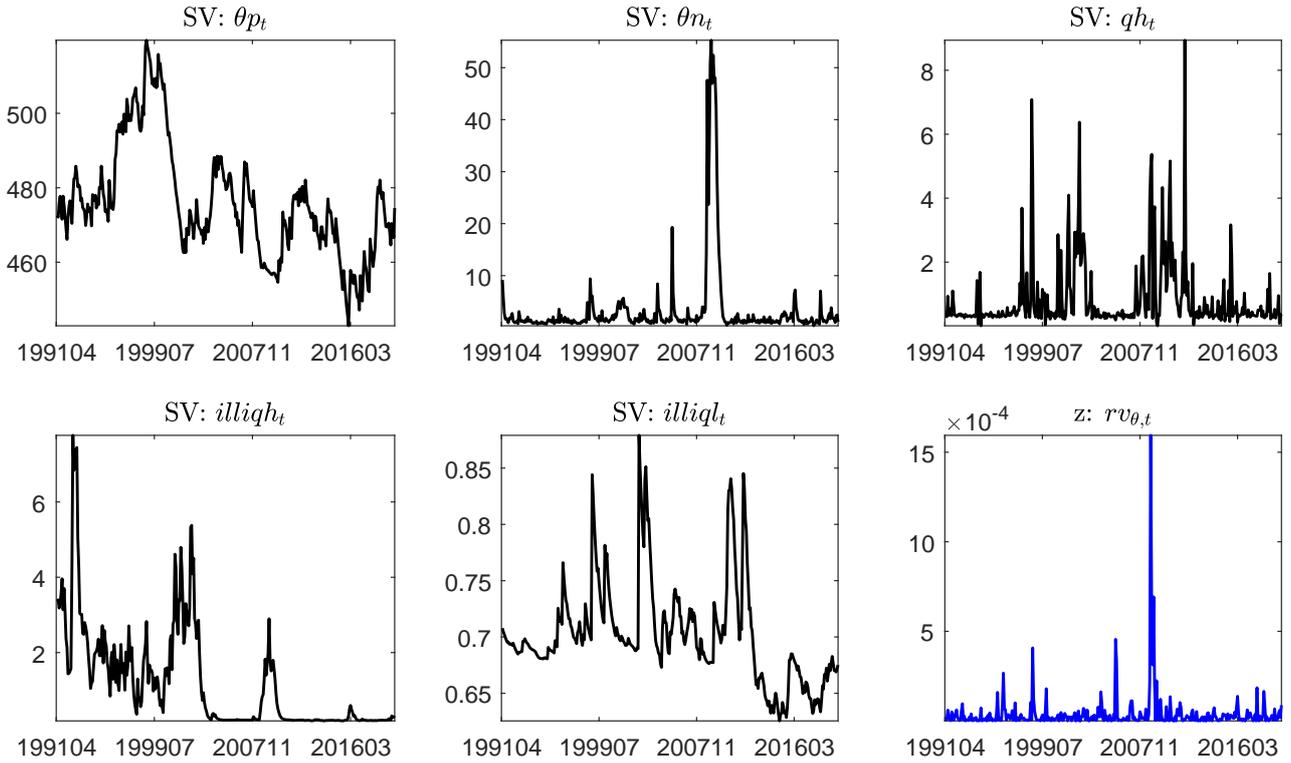
Figure 5: State variable dynamics

This figure shows the dynamics of the estimated risk premium state variables (good and bad economic uncertainty, $\theta p_t$ and $\theta n_t$, expected risk aversion fluctuations, $qh_t$, and high and low stock market illiquidity uncertainty, $illiqh_t$ and $illiql_t$) and the time-varying loading instrument (realized variance of economic growth, $z_t$) for the sample running between April 1991 and December 2019. The corresponding summary statistics are shown in Table 5. The full sample estimation results and detailed dynamic processes are deferred to Appendix B.
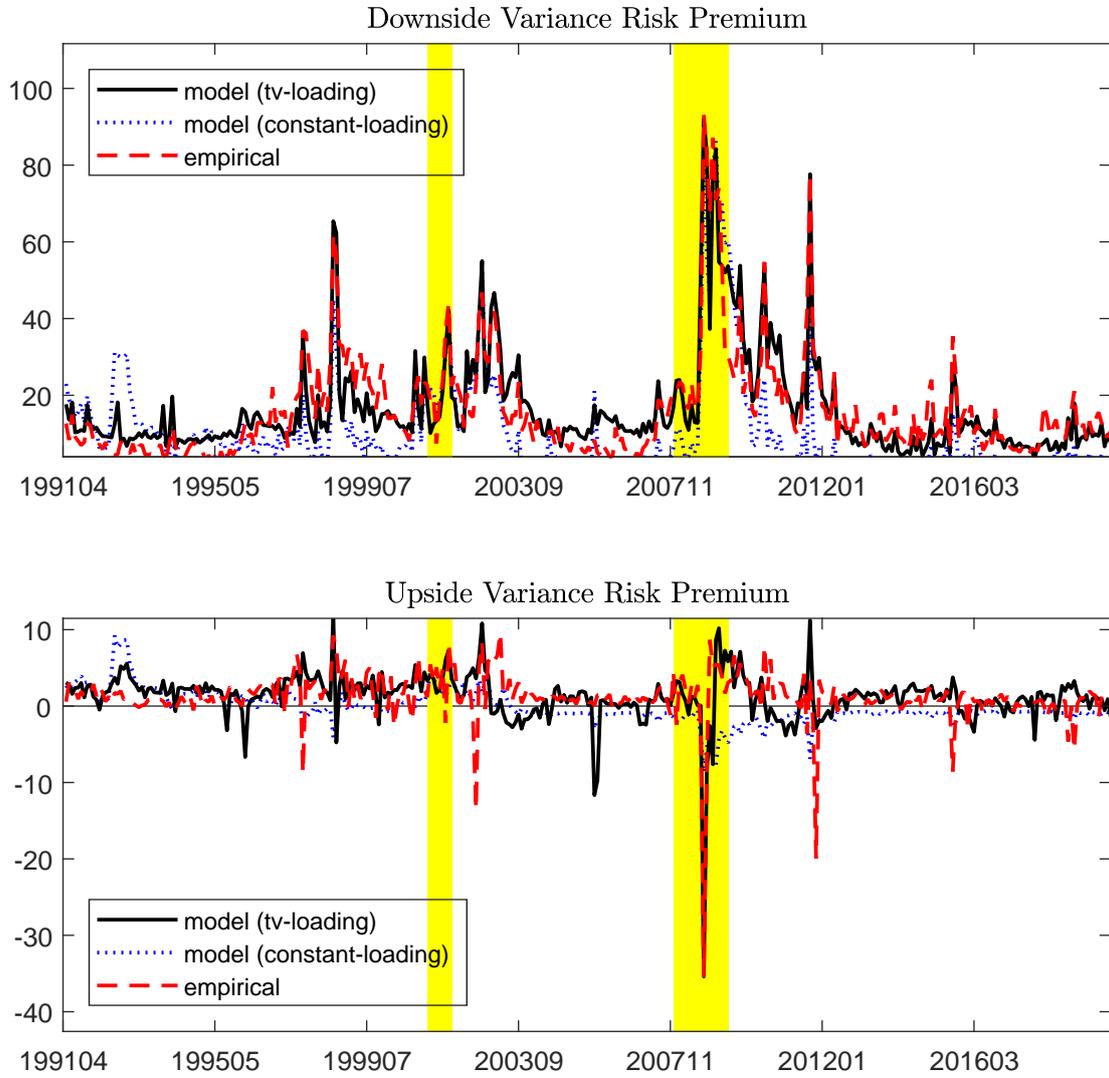
Figure 6: Dynamic fit

This figure shows the dynamics of empirical and model-implied DVP (top) and UVP (bottom) estimates. The empirical estimates, in dashed red lines, are obtained from Section 2. The model-implied estimates are obtained from Section 5 and we consider both constant (dotted blue lines) and time-varying (solid black lines) loadings. Other estimation details are shown in Table 6.

**(A). Changes in EP given 1SD increase in S.V.**

**(B). Predictive coefficients w/o a S.V.**
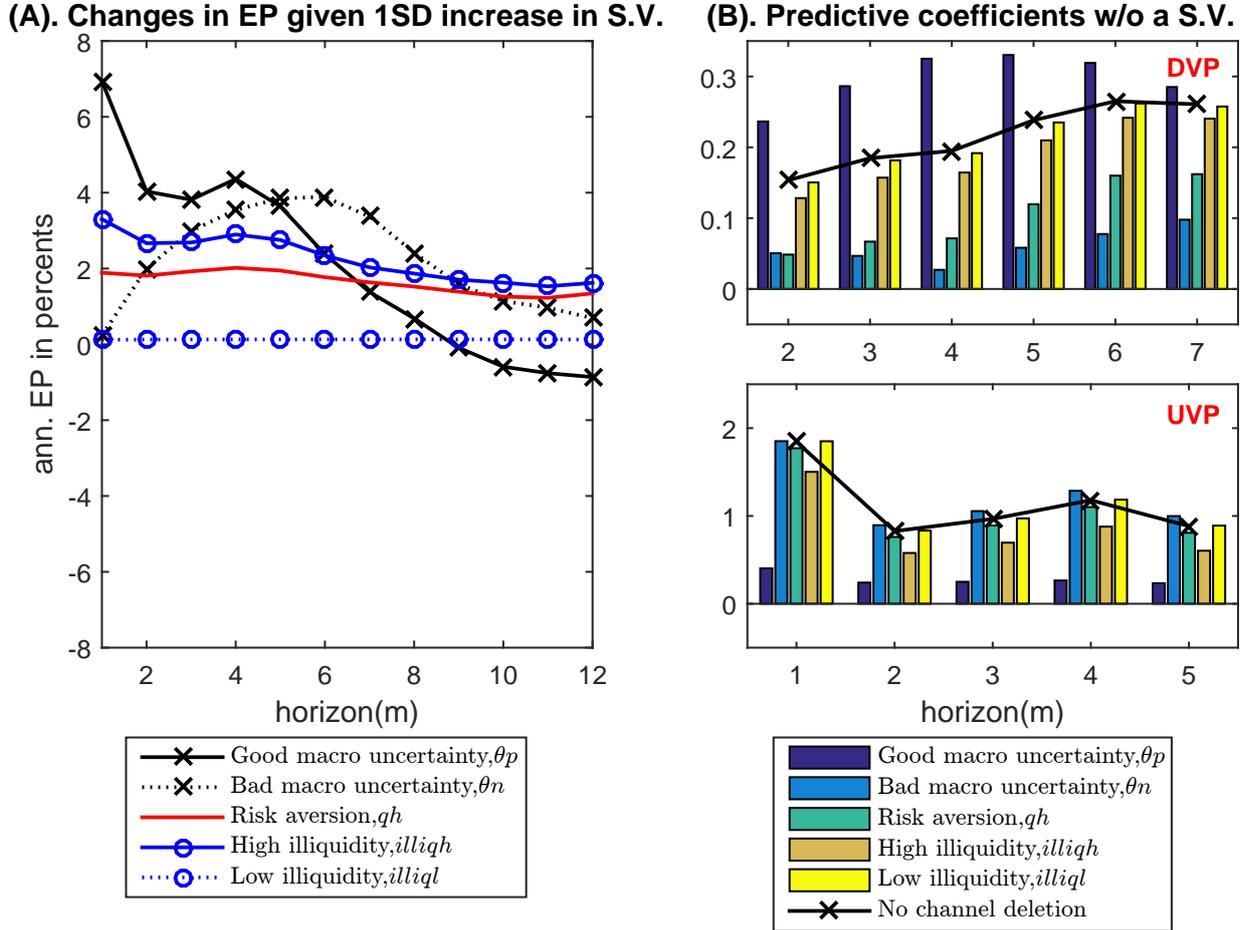
Figure 7: Economic interpretations of international equity risk premiums and stock return predictability: An average-country view

Panel (A) shows the model-implied changes in an average country's equity risk premium (EP) given one SD increase in a US/global risk premium state variable, where an average country is calibrated with median trade-to-GDP and holdings-to-GDP values and EP is expressed in annualized percents for all horizons. Panel (B) shows the implied predictive coefficients after deleting one risk premium state variable in the implied EP at a time; the lower the implied coefficient (the bar size) is, the more important the state variable is in explaining the predictability. This panel focuses on horizons with significant predictability according to the empirical evidence (less than seven months).
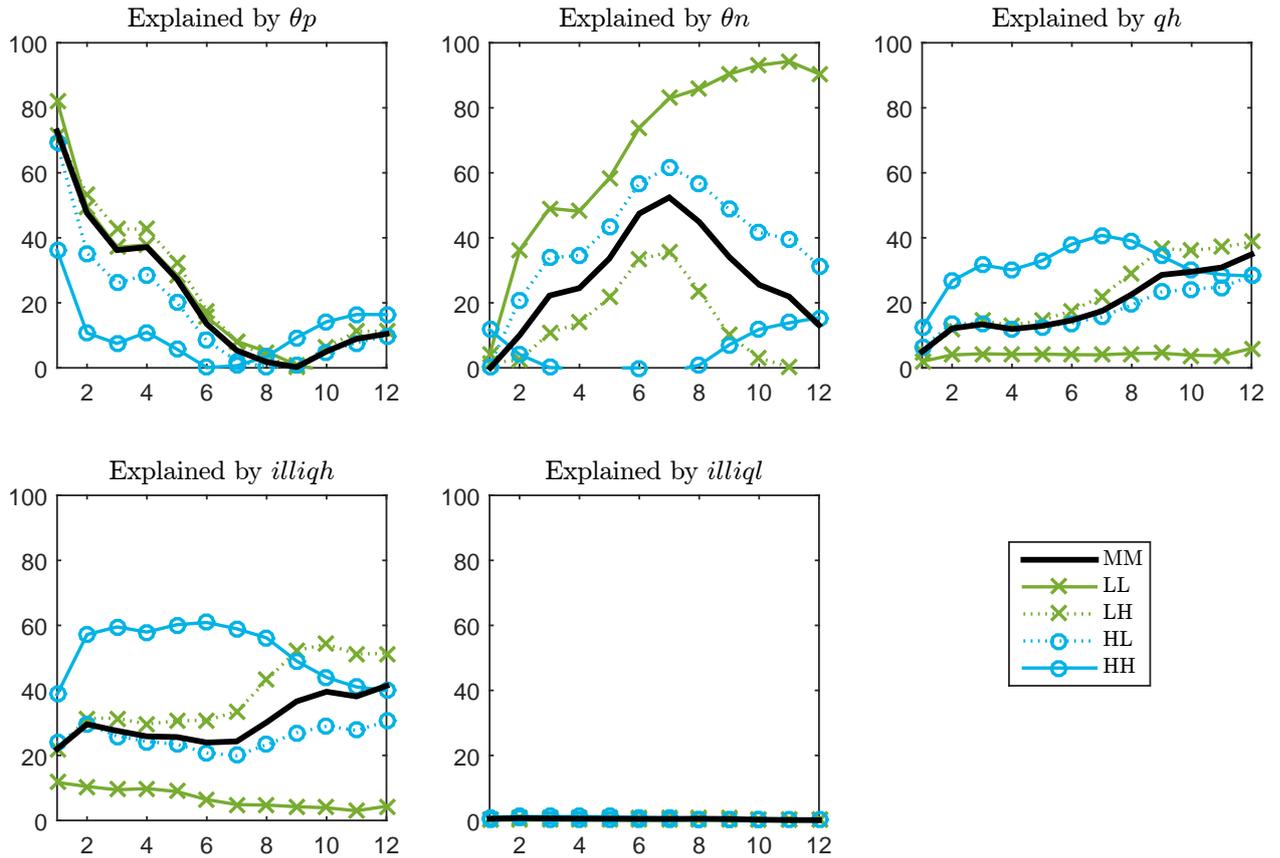
Figure 8: Variance decomposition

This figure shows the variance decomposition (in %) of the model-implied international equity risk premiums at various horizons. The solid black lines show variance decomposition results for an average country with median economic and financial integration, MM, to make inferences about global risk compensations. The other four lines show results for country groups with various low/high economic and financial integration (see Table 4).
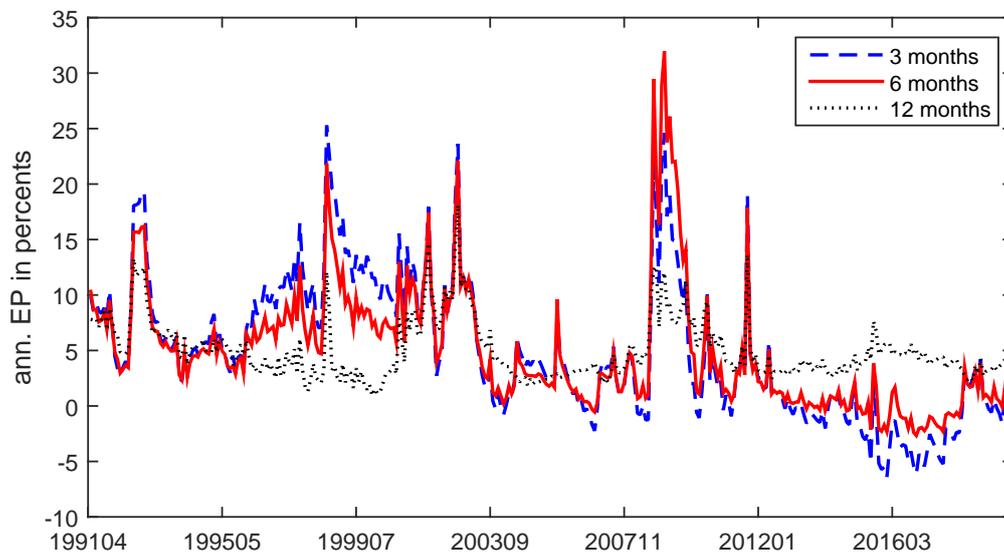
Figure 9: Time variation in model-implied equity risk premiums

This figure shows the time variation in model-implied equity risk premiums for an average country with median economic and financial integration at the 3-, 6-, and 12-month horizons. Equity risk premiums are expressed in annualized percents.
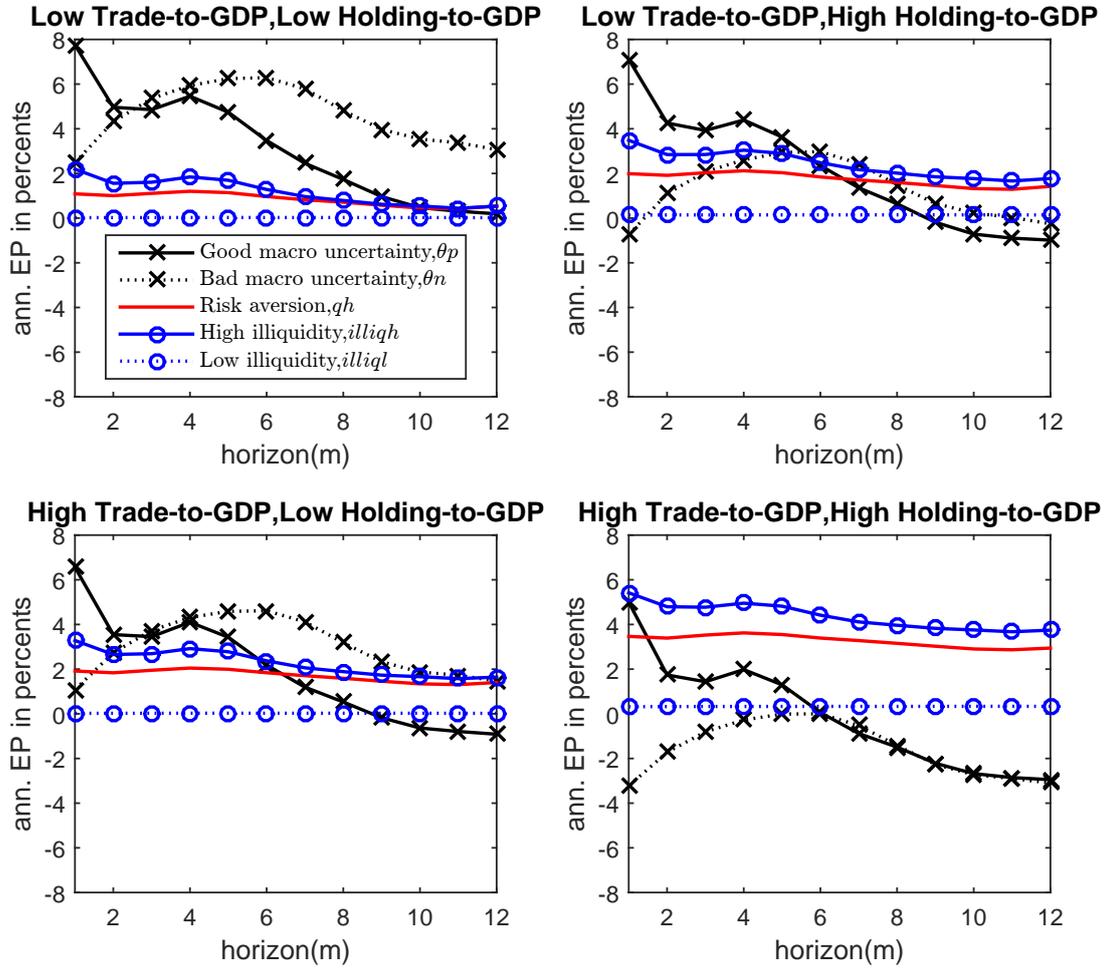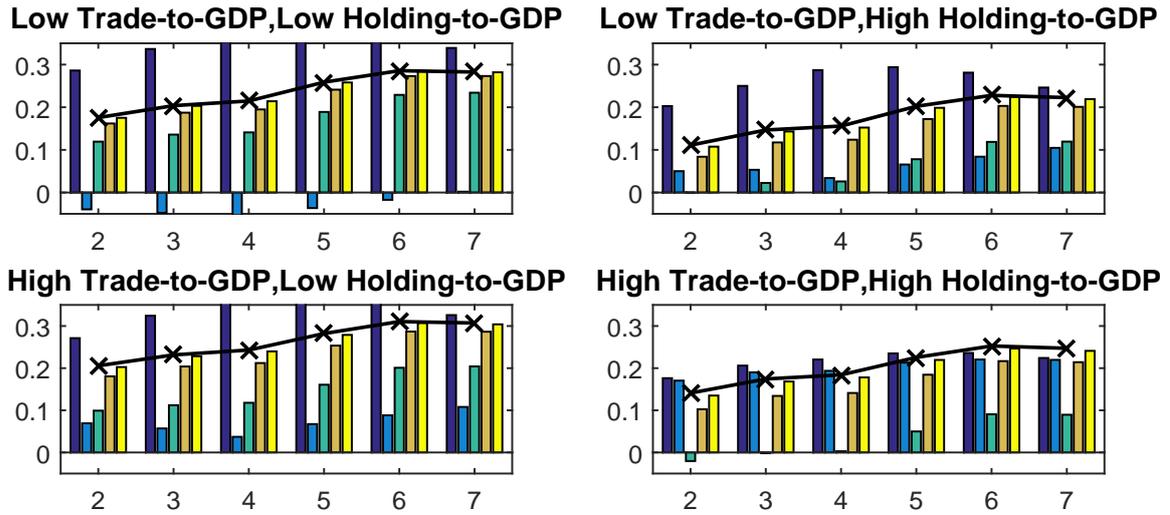
Figure 10: Economic interpretations of international equity risk premiums: A cross-country view

This figure complements Figure 7-(A) with a cross-country view, showing the marginal changes in four country-type equity risk premiums given one SD increase in a common premium state variable. The results are calibrated using low/high economic and financial integration, with low (high) using the 33th (67th) percentile value of the 22 countries. See other details in Figure 7.

(A) DVP predictive coefficients without a state variable

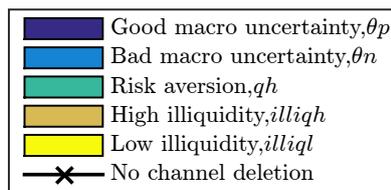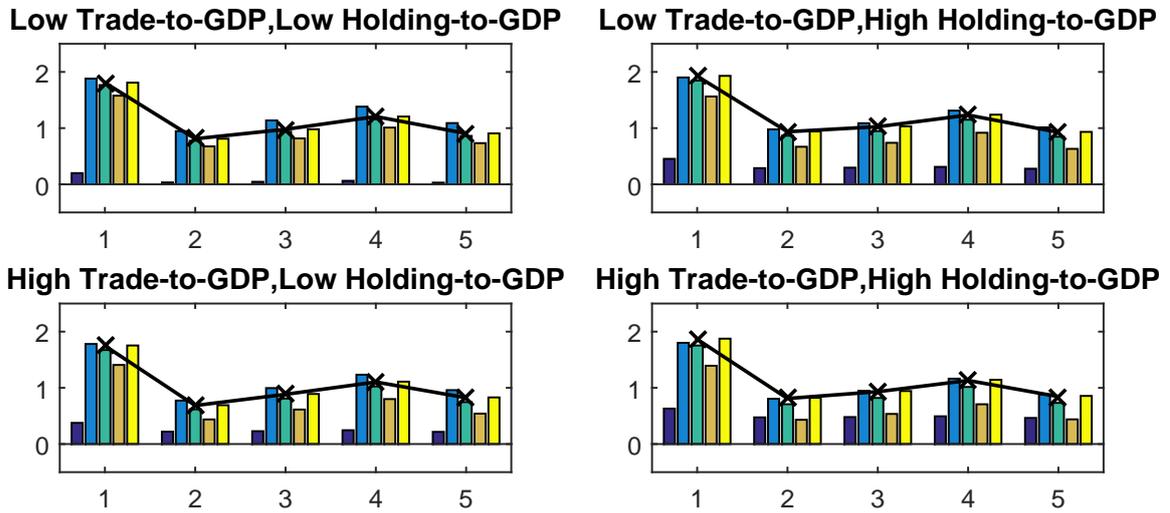(B) UVP predictive coefficients without a state variable

Figure 11: Economic interpretations of international stock return predictability: A cross-country view

This figure complements Figure 7-(B) with a cross-country view, showing the implied predictive coefficients for four country types after deleting one premium state variable in the implied EP at a time. The lower the implied coefficient (bar) is, the more important the state variable is in explaining the predictability. The results are calibrated using low/high economic and financial integration, with low (high) using the 33th (67th) percentile value of the 22 countries. See other details in Figure 7.

# APPENDICES

## A. Additional tables and figures for Section 2

Table A1: Expected realized variance

This table shows the coefficients associated with the predictors of one-month-ahead (22 days) total realized variance. The specifications are similar to those for realized semivariances in Table 1. The specification in column (1) assumes that realized variance follow a Martingale ($E_t(rv_{t+1m}) = rv_t$). For the specifications in columns (2) to (5), we estimate the following regression setting: $E_t(rv_{t+1}) = \hat{\alpha} + \hat{\gamma}\mathbf{X_t}$. We consider the following predictors in matrix $\mathbf{X}$: the total realized variance calculated over the last month ($rv_{t\ 1m;t}$); realized variance calculated using either the last five days ($rv_{t\ 5d;t}$) or the last day of the month ($rv_{t\ 1d;t}$); and the option-implied variance ($iv_{t;t+1m}$). We report, in parentheses, heteroskedasticity and autocorrelation consistent (HAC) standard deviations with 44 lags. ( , ) represent significance at the 1% (5%, 10%) confidence level. The adjusted $R^2$s are reported at the end of the table.

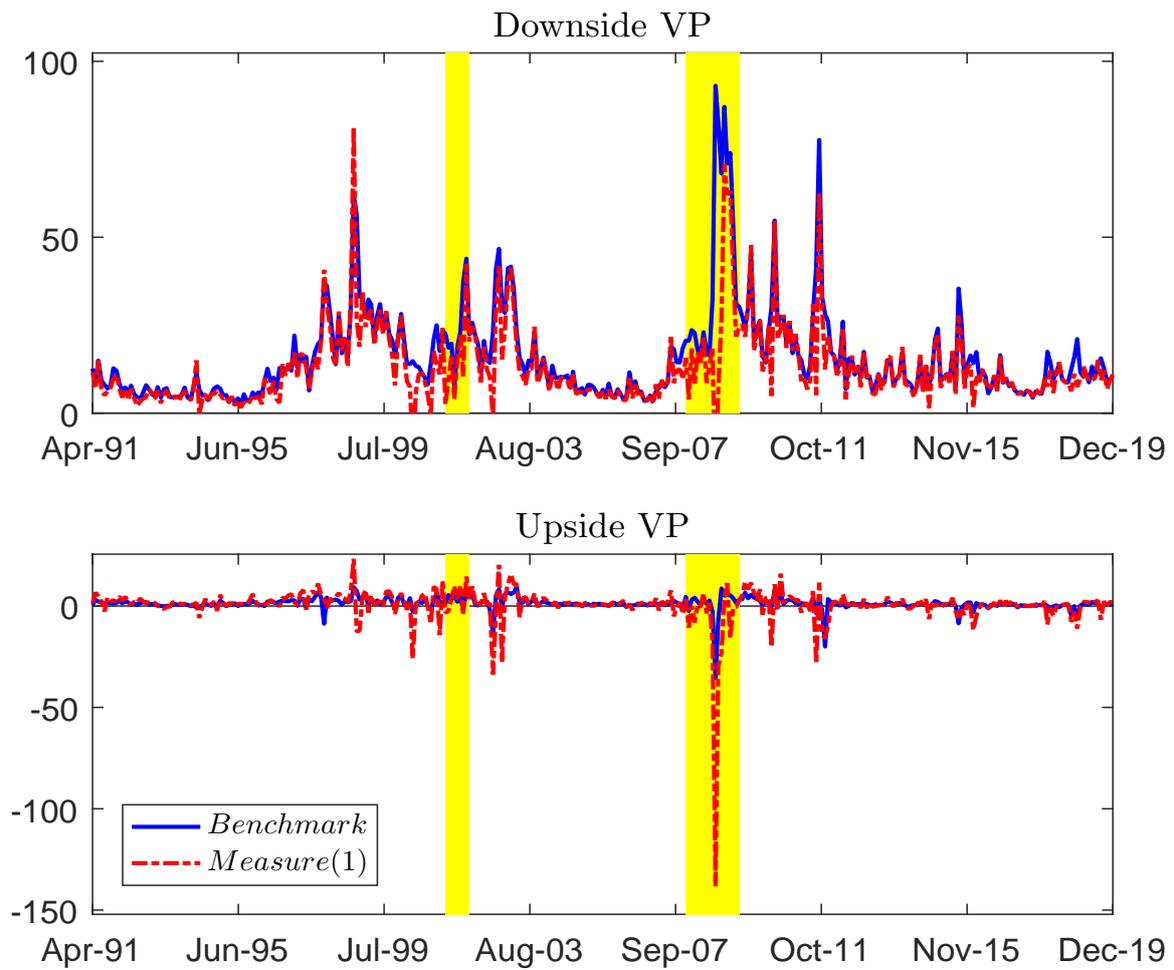|  | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Constant | 0 | 7.72*** | 7.72*** | 6.96*** | 4.15*** |
|  | - | (1.28) | (1.28) | (1.10) | (1.56) |
| $rv_{t\ 1m;t}$ | 1 | 0.64*** | 0.64*** | 0.27*** | 0.12 |
|  | - | (0.08) | (0.08) | (0.10) | (0.09) |
| $rv_{t\ 5d;t}$ |  |  |  | 0.32** | 0.29* |
|  |  |  |  | (0.16) | (0.17) |
| $rv_{t\ 1d;t}$ |  |  |  | 0.09*** | 0.06** |
|  |  |  |  | (0.02) | (0.02) |
| $iv_{t;t+1m}$ |  |  |  |  | 0.21* |
|  |  |  |  |  | (0.12) |
| Adj. $R^2$ | 0.27 | 0.406 | 0.406 | 0.466 | 0.474 |

Figure A1: Alternative measures of the VP and its components

The dashed lines denote the Martingale measure, or measure (1) in Tables 1 and 2. The solid lines denote the benchmark VP measures used in the main empirical results (Table 1 and Figure 1). The shaded regions indicate NBER recessions.

## Table A2: Correlations

This table reports correlations among the monthly US downside and upside variance premiums across various measures. Models are reported in Table 1. Panel A (Panel B) reports correlations of DVP (UVP) estimates across measures. The sample runs from April 1991 to December 2019.

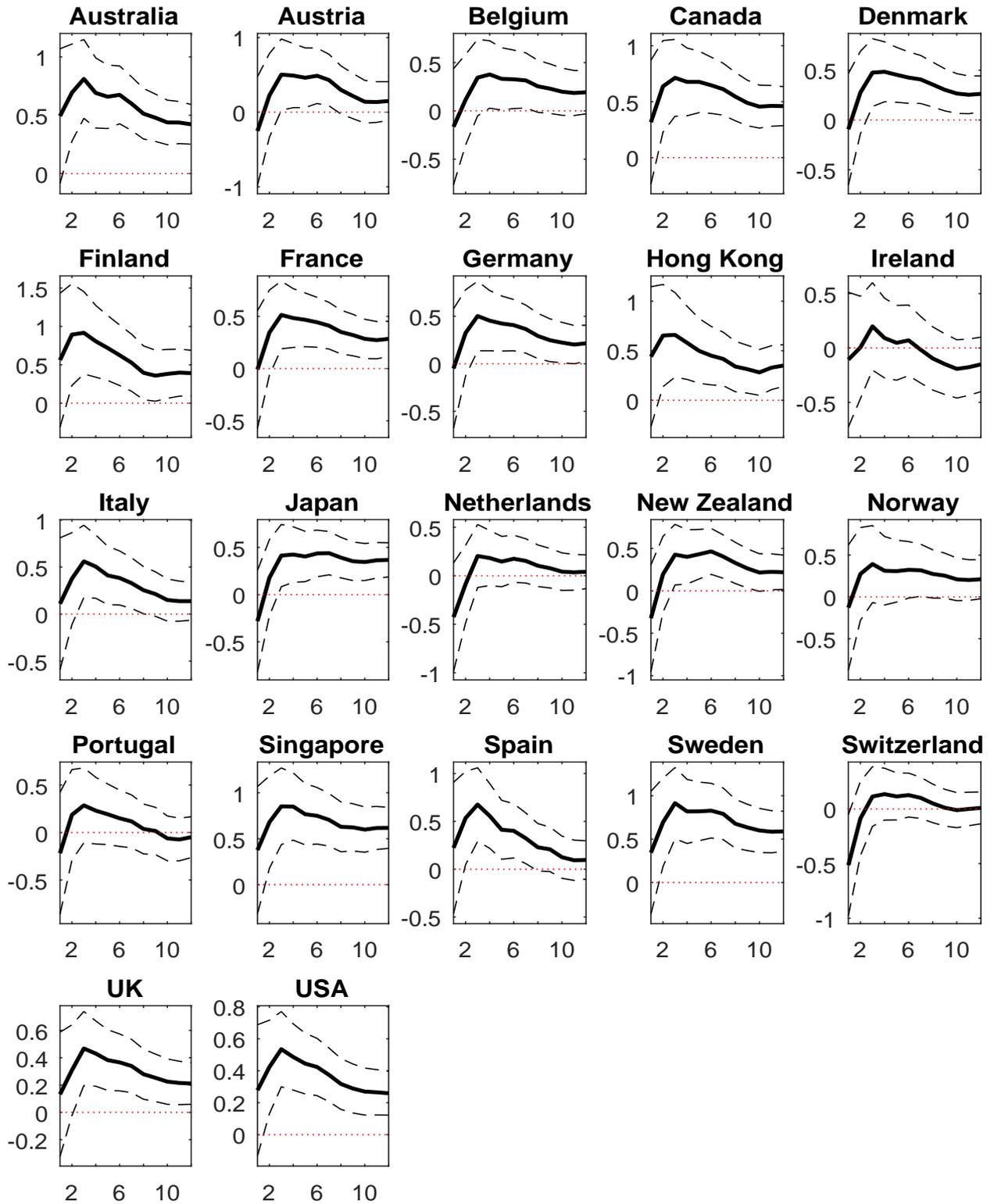| | (1) | (2) | (3) | (4) | (5) | | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| A. Correlations across models; DVP | | | | | | B. Correlations across models; UVP | | | | | |
| (1) | 1 | | | | | (1) | 1 | | | | |
| (2) | 0.87 | 1 | | | | (2) | 0.80 | 1 | | | |
| (3) | 0.87 | 0.99 | 1 | | | (3) | 0.77 | 0.94 | 1.00 | | |
| (4) | 0.77 | 0.97 | 0.97 | 1 | | (4) | 0.77 | 0.90 | 0.88 | 1 | |
| (5) | 0.74 | 0.97 | 0.96 | 0.99 | 1 | (5) | 0.77 | 0.74 | 0.75 | 0.95 | 1 |

Figure A2: DVP predictive coefficients, alternative VP measure

This figure shows the predictive coefficient estimates of DVP from the country-level predictive regression specification in Equation (7), where predictors DVP and UVP use Measure (1), the Martingale measure (see Table 2). The dashed lines correspond to the 90% confidence intervals for the given Newey-West standard errors. The model specification is introduced in Section 2.3.
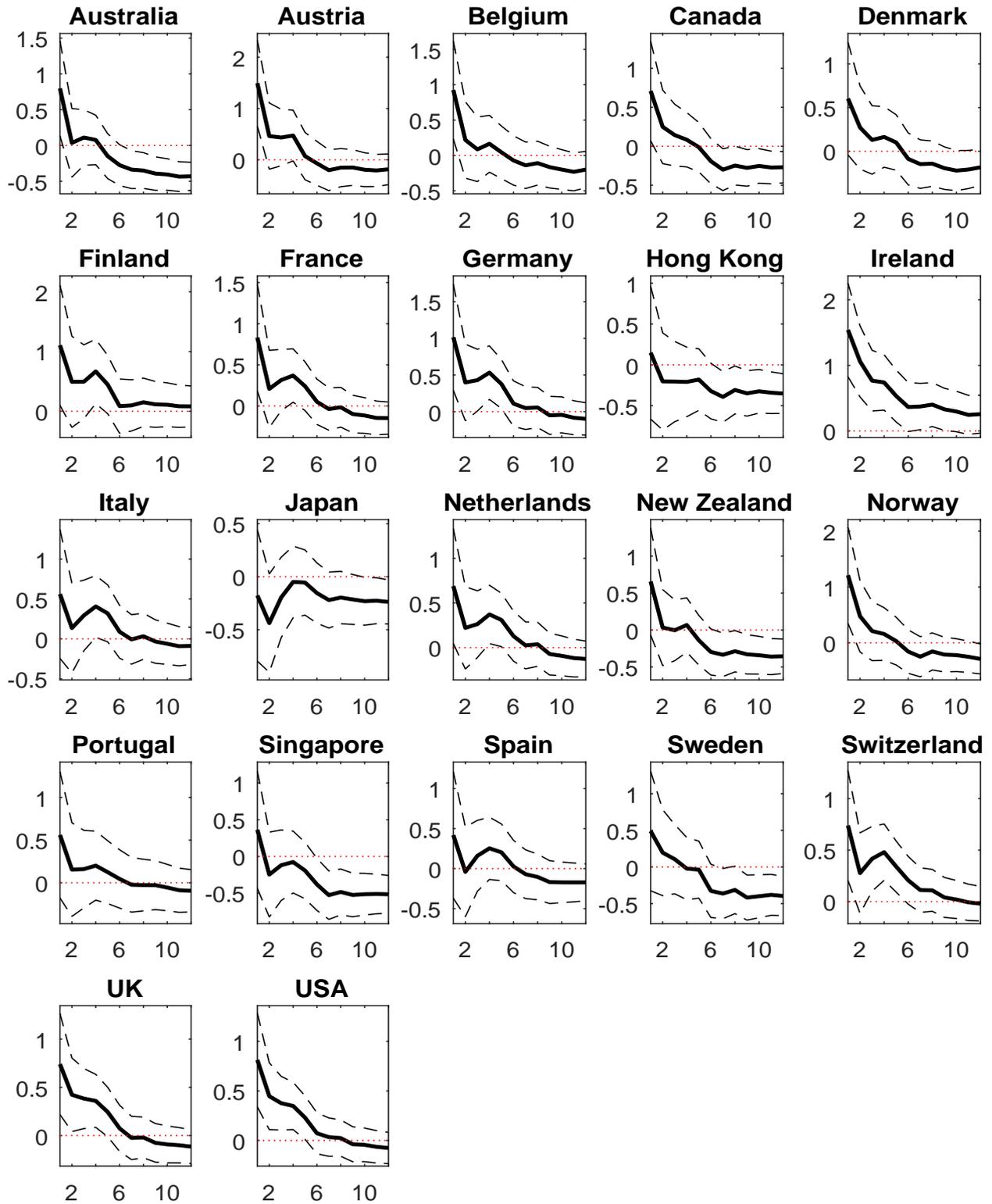
Figure A3: UVP predictive coefficients, alternative VP measure

This figure shows the predictive coefficient estimates of UVP from the country-level predictive regression specification in Equation (7), where predictors DVP and UVP use Measure (1), the Martingale measure (see Table 2). The dashed lines correspond to the 90% confidence intervals for the given Newey-West standard errors. The model specification is introduced in Section 2.3.
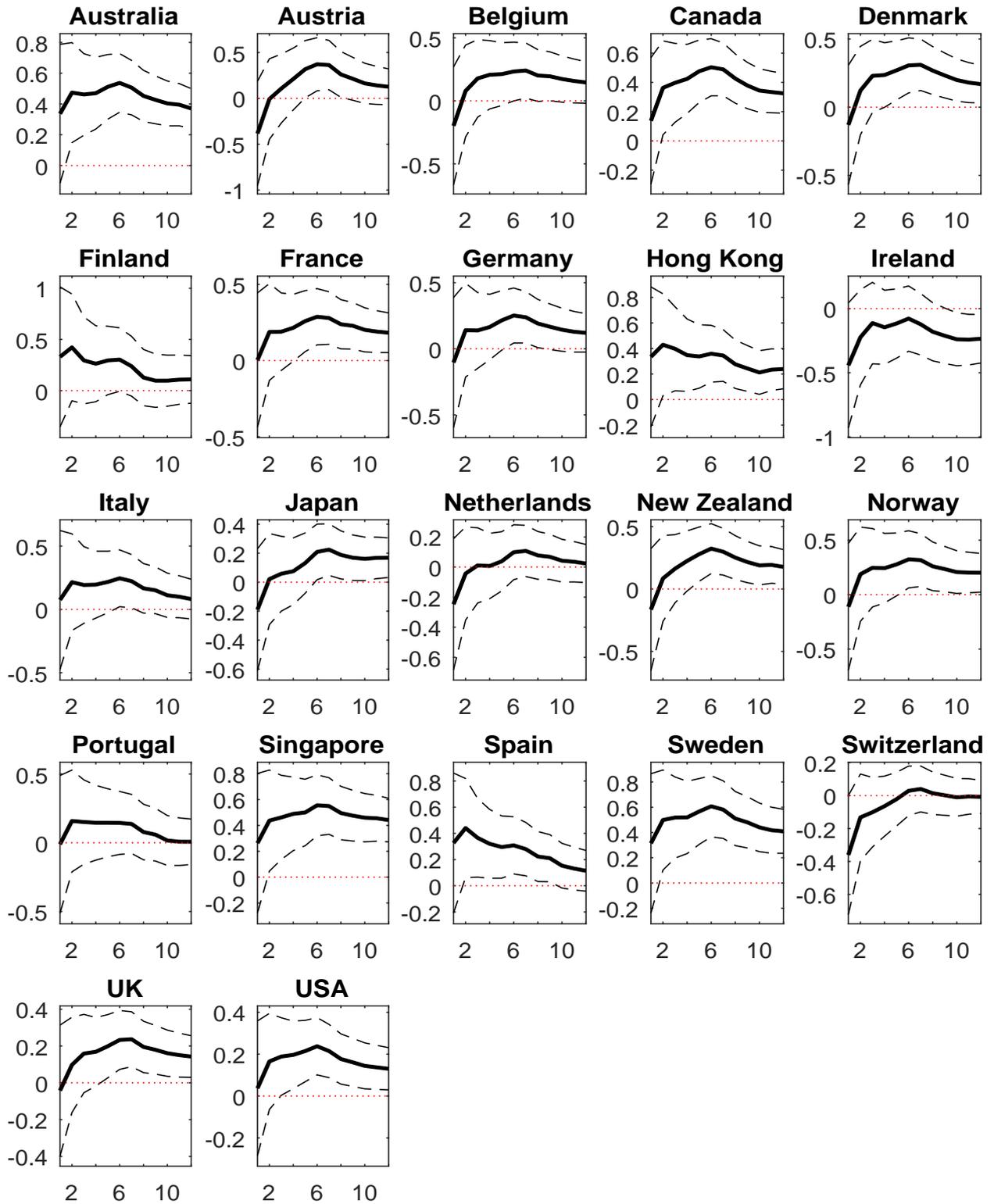
Figure A4: DVP predictive coefficients, model with control predictors

This figure shows the predictive coefficient estimates of DVP from the country-level predictive regression in an extended version of the setting in Equation (8) with control variables (US bill, earnings yield). The dashed lines correspond to the 90% confidence intervals for the given Newey-West standard errors. The model specification is introduced in Section 2.3.
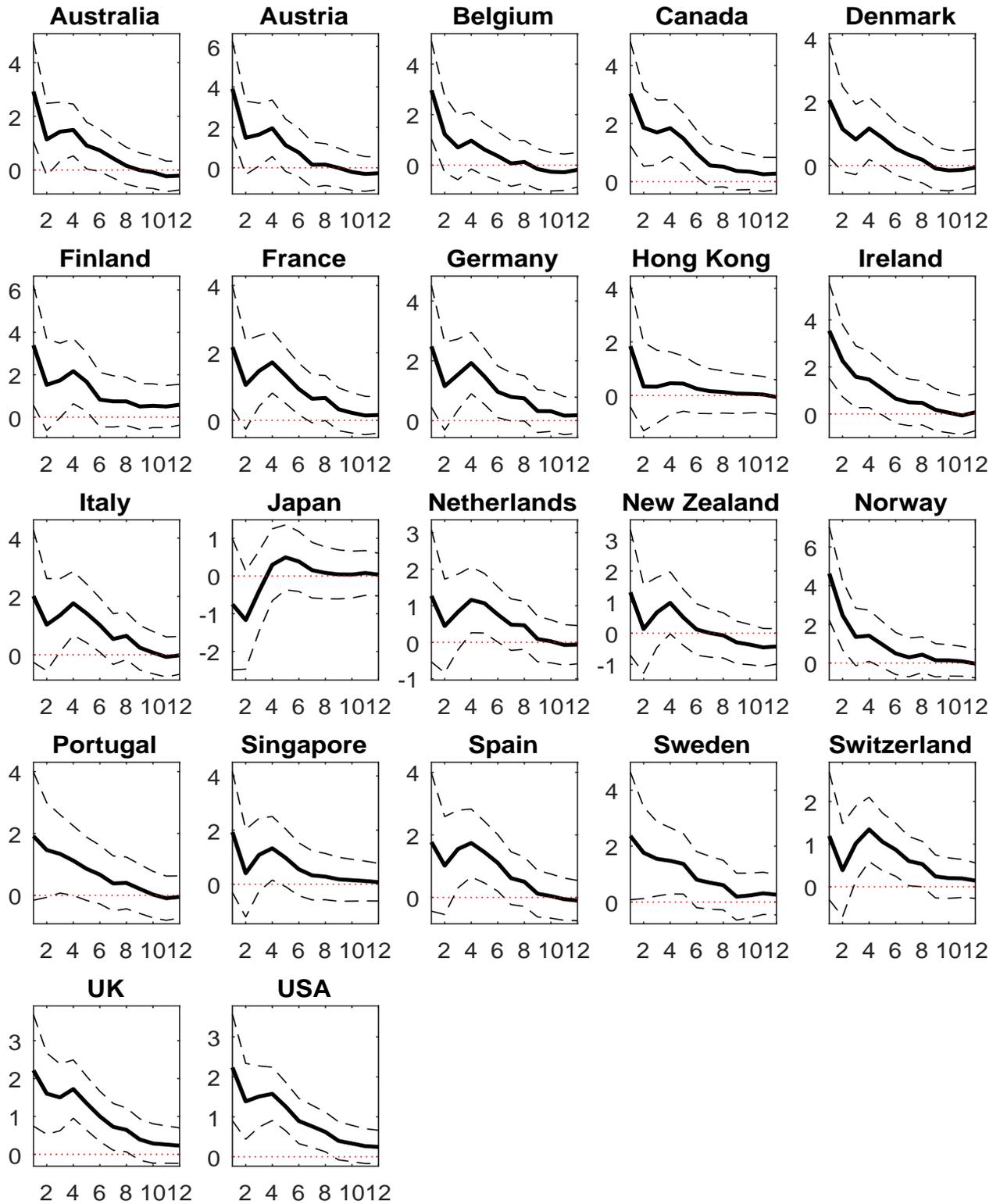
Figure A5: UVP predictive coefficients, model with control predictors

This figure shows the predictive coefficient estimates of UVP from the country-level predictive regression in an extended version of the setting in Equation (8) with control variables (US bill, earnings yield). The dashed lines correspond to the 90% confidence intervals for the given Newey-West standard errors. The model specification is introduced in Section 2.3.

# B. Solution for the price-dividend ratio and log stock returns

Rewrite the dividend growth process and the pricing kernel in a matrix representation, $\Delta d_{t+1} = d_0 + \boldsymbol{d_1} \boldsymbol{Y}_t + \boldsymbol{d_2} \boldsymbol{\Sigma \varepsilon}_{t+1}$ and $m_{t+1} = m_0 + \boldsymbol{m_1} \boldsymbol{Y}_t + \boldsymbol{m_2} \boldsymbol{\Sigma \varepsilon}_{t+1}$, where $\boldsymbol{Y}_t$ and $\boldsymbol{\varepsilon}_t$ are the state variable vector and the independent shock vector, respectively. Given the assumptions in Section 3, the US price-dividend ratio can be rewritten as,

$$PD_t = E_t\left[M_{t+1}\left(\frac{P_{t+1}+D_{t+1}}{D_t}\right)\right] = \sum_{n=1}^{\infty} E_t\left[\exp\left(\sum_{j=1}^{n} m_{t+j} + \Delta d_{t+j}\right)\right],$$

where $m_{t+j}$ indicates the future log US pricing kernel at month $j$ and $\Delta d_{t+j}$ the $j$-th month log dividend growth rates. Let $F_t^n$ denote the $n$-th term in the summation, $F_t^n = E_t\left[\exp\left(\sum_{j=1}^{n} m_{t+j} + \Delta d_{t+j}\right)\right]$, and hence $F_t^n D_t$ means the price of zero-coupon equity that matures in $n$ periods. The $PD_t$ can be rewritten as $\sum_{n=1}^{\infty} F_t^n$.

We first prove that, $\forall n \geq 1$, $F_t^n$ is an exactly exponential affine function of the state variables using induction. When $n = 1$, $F_t^1 = E_t\left[\exp\left(m_{t+1} + \Delta d_{t+1}\right)\right] = E_t\left\{\exp\left[(m_0 + d_0) + (\boldsymbol{m_1} + \boldsymbol{d_1})\boldsymbol{Y}_t + (\boldsymbol{m_2} + \boldsymbol{d_2})\boldsymbol{\Sigma \varepsilon}_{t+1}\right]\right\} = \exp\left(e_0^1 + \boldsymbol{e_1^1} \boldsymbol{Y}_t\right)$, where $e_0^1$ and $\boldsymbol{e_1^1}$ are implicitly defined. Suppose that the $(n-1)$-th term $F_t^{n-1} = \exp\left(e_0^{n-1} + \boldsymbol{e_1^{n-1}} \boldsymbol{Y}_t\right)$, then

$$F_t^n = E_t\left[\exp\left(\sum_{j=1}^{n} m_{t+j} + \Delta d_{t+j}\right)\right]$$

$$= E_t\left\{\exp(m_{t+1} + \Delta d_{t+1}) \underbrace{E_{t+1}\left[\exp\left(\sum_{j=1}^{n-1} m_{t+j+1} + \Delta d_{t+j+1}\right)\right]}_{F_{t+1}^{n-1}}\right\}$$

$$= E_t\left[\exp(m_{t+1} + \Delta d_{t+1}) \exp\left(e_0^{n-1} + \boldsymbol{e_1^{n-1}} \boldsymbol{Y}_{t+1}\right)\right] = \exp\left(e_0^n + \boldsymbol{e_1^n} \boldsymbol{Y}_t\right),$$

where $e_0^n$ and $\boldsymbol{e_1^n}$ are implicitly defined. Hence, the price-dividend ratio can be solved as $PD_t = \sum_{n=1}^{\infty} F_t^n = \sum_{n=1}^{\infty} \exp\left(e_0^n + \boldsymbol{e_1^n} \boldsymbol{Y}_t\right)$. The log return can be solved and approximated as,

$$r_{t+1} = \ln\left(\frac{P_{t+1}+D_{t+1}}{P_t}\right) = \Delta d_{t+1} + \ln\left[\frac{1 + \sum_{n=1}^{\infty} \exp\left(e_0^n + \boldsymbol{e_1^n} \boldsymbol{Y}_{t+1}\right)}{\sum_{n=1}^{\infty} \exp\left(e_0^n + \boldsymbol{e_1^n} \boldsymbol{Y}_t\right)}\right]$$

$$\Delta d_{t+1} + \text{const.} + \frac{\sum_{n=1}^{\infty} \exp\left(e_0^n + \boldsymbol{e_1^n} \bar{\boldsymbol{Y}}\right)\boldsymbol{e_1^n}}{\frac{1+\sum_{n=1}^{\infty}\exp\left(e_0^n + \boldsymbol{e_1^n} \bar{\boldsymbol{Y}}\right)}{\sum_{n=1}^{\infty}\exp\left(e_0^n + \boldsymbol{e_1^n} \bar{\boldsymbol{Y}}\right)}} \boldsymbol{Y}_{t+1} \quad \frac{\sum_{n=1}^{\infty} \exp\left(e_0^n + \boldsymbol{e_1^n} \bar{\boldsymbol{Y}}\right)\boldsymbol{e_1^n}}{\sum_{n=1}^{\infty}\exp\left(e_0^n + \boldsymbol{e_1^n} \bar{\boldsymbol{Y}}\right)} \boldsymbol{Y}_t$$

$$= \xi_0 + \xi_1 \boldsymbol{Y}_t + \xi_2 \boldsymbol{\Sigma \varepsilon}_{t+1}.$$

Similarly, as the model takes the perspective of a US investor, the price-dividend ratio of country $i$ is modeled as $PD_t^i = E_t\left[M_{t+1}\left(\frac{P_{t+1}^i+D_{t+1}^i}{D_t^i}\right)\right] = \sum_{n=1}^{\infty} E_t\left[\exp\left(\sum_{j=1}^{n} m_{t+j} + \Delta d_{t+j}^i\right)\right]$. Suppose the country $i$ log dividend growth is $\Delta d_{t+1}^i = d_0^i + \left(\boldsymbol{d_1^i} \boldsymbol{Y}_t + \boldsymbol{d_2^i} \boldsymbol{\Sigma \varepsilon}_{t+1}\right) + \mu_t^i + u_{d;t+1}^i$, where $\boldsymbol{d_1^i}$ ($\boldsymbol{d_2^i}$) indicates the loadings of country $i$'s dividend growth on the US lagged state variable levels (state variable shocks), and $\mu_t^i$ and $u_{d;t+1}^i$ indicate the additional country-specific dividend growth mean and shock processes that are orthogonal to the US shocks, respectively. Using the same induction procedure, it can be easily shown that,

$$PD_t^i = \sum_{n=1}^{\infty} F_t^n = \sum_{n=1}^{\infty} \exp\left(e_0^{i;n} + \boldsymbol{e_1^{i;n}} \boldsymbol{Y}_t + \text{Idiosyncratic Parts}\right),$$

$$r^i_{t+1} = \ln\left(\frac{P^i_{t+1} + D^i_{t+1}}{P^i_t}\right) = \xi^i_0 + {}_1 Y_t + {}_2 \Sigma ! _{t+1} + \text{Idiosyncratic Parts.}$$

# C. Solution for the variance risk premium

The proof is similar to that in Bekaert, Engstrom, and Xu (forthcoming). First, the US one-period physical conditional return variance can be easily obtained, given that $! _{t+1} \quad \Gamma(\Omega Y_t + e; 1) - (\Omega Y_t + e)$, as:

$$VAR_t(r_{t+1}) = ( {}_2 \Sigma)^{2} (\Omega Y_t + e),$$

where " " indicates element-by-element matrix multiplication.

Second, the US one-period risk-neutral conditional return variance can be obtained using the moment generating function (MGF) of gamma-distributed shocks. We start from the MGF under the risk-neutral measure:

$$
\begin{aligned}
mgf^Q_t(r_{t+1}; \nu) &= \frac{E_t\left[\exp\left(m_{t+1} + \nu r_{t+1}\right)\right]}{E_t\left[\exp\left(m_{t+1}\right)\right]} \\
&= \exp\{E_t(m_{t+1}) + \nu E_t(r_{t+1}) + [ \ (m_2 + \ _2)\Sigma \ \ln(1 \ (m_2 + \ _2)\Sigma)](\Omega Y_t + e)\} \\
&/ \ \exp\{E_t(m_{t+1}) + [ \ m_2 \Sigma \ \ln(1 \ m_2 \Sigma)](\Omega Y_t + e)\} \\
&= \exp\{\nu E_t(r_{t+1}) + [ \ \ _2\Sigma + [ \ \ln(1 \ (m_2 + \ _2)\Sigma) + \ln(1 \ m_2\Sigma)]](\Omega Y_t + e)\}.
\end{aligned}
$$

The first-order moment is the first-order derivative at $\nu = 0$:

$$
\frac{\partial mgf^Q_t(r_{t+1}; \nu)}{\partial \nu} = mgf^Q_t(r_{t+1}; \nu) \ \left\{E_t(r_{t+1}) + \left[(m_2 + \ _2)\Sigma \ \ _2\Sigma \ (1 \ (m_2 + \ _2)\Sigma)^{1}\right](\Omega Y_t + e)\right\}
$$

$$
\begin{aligned}
E^Q_t(r_{t+1}) &= \frac{\partial mgf^Q_t(r_{t+1}; \nu)}{\partial \nu}\Big|_{=0} \\
&= E_t(r_{t+1}) + \left[m_2\Sigma \ \ _2\Sigma \ (1 \ m_2\Sigma)^{1}\right](\Omega Y_t + e).
\end{aligned}
$$

The second-order moment can be derived as follows:

$$
\begin{aligned}
\frac{\partial^2 mgf^Q_t(r_{t+1}; \nu)}{\partial \nu^2} &= mgf^Q_t(r_{t+1}; \nu) \ \left\{E_t(r_{t+1}) + \left[(m_2 + \ _2)\Sigma \ \ _2\Sigma \ (1 \ (m_2 + \ _2)\Sigma)^{1}\right](\Omega Y_t + e)\right\}^2 \\
&\quad + mgf^Q_t(r_{t+1}; \nu) \ \left\{\left[(m_2 + \ _2)\Sigma \ ( \ _2\Sigma)^{2} \ (1 \ (m_2 + \ _2)\Sigma) \ ( \ _2\Sigma)^{2}\right] \ (1 \ (m_2 + \ _2)\Sigma)\right.
\end{aligned}
$$

$$
\begin{aligned}
E^Q_t(r^2_{t+1}) &= \frac{\partial^2 mgf^Q_t(r_{t+1}; \nu)}{\partial \nu^2}\Big|_{=0} \\
&= \left(E^Q_t(r_{t+1})\right)^2 + \left[( \ _2\Sigma)^{2} \ (1 \ m_2\Sigma)^{2}\right](\Omega Y_t + e).
\end{aligned}
$$

As a result, the one-period risk-neutral conditional variance is

$$
\begin{aligned}
VAR^Q_t(\widetilde{r}^i_{t+1}) &= E^Q_t\left((\widetilde{r}^i_{t+1})^2\right) \ \left(E^Q_t(\widetilde{r}^i_{t+1})\right)^2 \\
&= \left[( \ _2\Sigma)^{2} \ (1 \ m_2\Sigma)^{2}\right](\Omega Y_t + e).
\end{aligned}
$$

The US variance risk premium is, as displayed in Equation (13), given by:

$$VAR^Q_t(\widetilde{r}^i_{t+1}) \quad VAR_t(\widetilde{r}^i_{t+1}) = \left\{( \ _2\Sigma)^{2} \ \left[(1 \ m_2\Sigma)^{2} \ 1\right]\right\}(\Omega Y_t + e).$$

# D. Solution for the equity risk premiums

The risk free rate is derived as,

$$
\begin{aligned}
rf_t &= \ln\{E_t[\exp(m_{t+1})]\} \\
&= \ln\{E_t(m_{t+1}) + [-m_2\Sigma - \ln(1 - m_2\Sigma)](\Omega Y_t + e)\}.
\end{aligned}
$$

We then impose the no-arbitrage condition, $1 = E_t[\exp(m_{t+1} + r_{t+1})]$, and obtain the expected excess returns. By expanding the law of one price (LOOP) equation, we obtain:

$$
\begin{aligned}
1 &= E_t[\exp(m_{t+1} + r_{t+1})] \\
&= \exp\{E_t(m_{t+1}) + E_t(r_{t+1}) + [-(m_2 + \kappa_2)\Sigma - \ln(1 - (m_2 + \kappa_2)\Sigma)](\Omega Y_t + e)\},
\end{aligned}
$$

where $m_2$, $\kappa_2$, $\Sigma$ and $e$ are constant matrices defined above. Given the risk free rate derived above, the US equity risk premium is, as displayed in Equation (14), given by:

$$
E_t(r_{t+1}) - rf_t = [-\kappa_2\Sigma + \ln[1 - (m_2 + \kappa_2)\Sigma] - \ln(1 - m_2\Sigma)](\Omega Y_t + e).
$$

Similarly, the international equity risk premium is, as displayed in Equation (15), given by:

$$
E_t(r_{t+1}^i) - rf_t = \underbrace{\{-\kappa_2^i\Sigma + \ln[1 - (m_2 + \kappa_2^i)\Sigma] - \ln(1 - m_2\Sigma)\}(\Omega Y_t + e)}_{\text{The Global Compensation Part}}
$$
$$
+ \quad \text{Idiosyncratic Parts.}
$$

The total country equity risk premiums can also be driven by a pure local risk compensation component, which however is not the focus of the paper and in theory should be un-predictable by common/US predictors, and hence is abbreviated above without loss of generality.

# E. Individual US state variable processes and estimation results

In this appendix, we complement Section 4 by providing the exact dynamic processes of individual state variables and their detailed estimation results:

$$
\Sigma_m \mathcal{I}_{m;t+1} = \begin{bmatrix} \theta_{t+1} - E_t(\theta_{t+1}) \\ q_{t+1} - E_t(q_{t+1}) \\ illiq_{t+1} - E_t(illiq_{t+1}) \end{bmatrix}, \tag{E1}
$$

where $\theta_{t+1}$ denotes the economic growth, $q_{t+1}$ risk aversion, and $illiq_{t+1}$ stock market illiquidity. Our state variable system is estimated and assumed realistic at the monthly frequency.

## E.1. Dynamic processes

The economic growth state variable is assumed to follow a reduced-form dynamic process that captures time-varying expected growth and asymmetric/skewed and heteroskedastic shocks to be potentially consistent with recent work (see, e.g., Adrian, Boyarchenko, and Giannone (2019)):

$$
\theta_{t+1} = \bar{\theta} + \rho_{\theta;\theta}(\theta_t - \bar{\theta}) + \rho_{\theta;p}(\theta p_t - \overline{\theta p}) + \rho_{\theta;n}(\theta n_t - \overline{\theta n}) + \delta_{\theta;p}\omega_{p;t+1} - \delta_{\theta;n}\omega_{n;t+1}, \tag{E2}
$$

where the conditional mean is subject to an AR(1) term capturing persistence as well as changes in expected good and bad economic uncertainties capturing the GARCH-in-mean intuition. As in Bekaert, Engstrom, and Xu (forthcoming), the disturbance of the log economic growth is decomposed into two

independent centered gamma shocks:

$$\omega_{p;t+1} = \Gamma(\theta p_t, 1) - \theta p_t,$$
$$\omega_{n;t+1} = \Gamma(\theta n_t, 1) - \theta n_t,$$

where $\omega_{p;t+1}$ ($\omega_{n;t+1}$) governs the right-tail (left-tail) dynamics of the growth distribution with shape parameter $\theta p_t$ ($\theta n_t$) determining the conditional higher moments of the growth disturbance shock. For example, given the moment generating function (MGF) of independent gamma shocks, the conditional variance of $\theta_{t+1}$ is $\delta^2_{;p}\theta p_t + \delta^2_{;n}\theta n_t$ and the conditional unscaled skewness is $2\delta^3_{;p}\theta p_t - 2\delta^3_{;n}\theta n_t$. Increases in $\theta p_t$ ($\theta n_t$) imply higher (lower) conditional skewness while increasing conditional variance, and hence $\theta p_t$ ($\theta n_t$) can be interpreted as the "good" ("bad") uncertainty state variable. This disturbance structure is one of the non-Gaussian shock assumptions that the literature has explored to realistically model macro or financial state variable processes (see, e.g., Eraker and Shaliastovich (2008), Bekaert, Engstrom, and Xing (2009), Fulop, Li, and Yu (2015), Segal, Shaliastovich, and Yaron (2015), De Groot (2015), Bekaert and Engstrom (2017), Xu (2021)). The dynamics of the good and bad economic uncertainty state variables follow AR(1) processes:

$$\theta p_{t+1} = \overline{\theta p} + \rho_{;p}(\theta p_t - \overline{\theta p}) + \sigma_{;p}\omega_{p;t+1}, \tag{E3}$$
$$\theta n_{t+1} = \overline{\theta n} + \rho_{;n}(\theta n_t - \overline{\theta n}) + \sigma_{;n}\omega_{n;t+1}. \tag{E4}$$

Define a macroeconomic state variable vector, $\boldsymbol{Y}_{mac;t} \equiv [\theta_t \quad \theta p_t \quad \theta n_t]^{\prime}$, and its unconditional mean $\overline{\boldsymbol{Y}_{mac}} \equiv [\overline{\theta} \quad \overline{\theta p} \quad \overline{\theta n}]^{\prime}$.

The risk aversion state variable, $q_t$, evolves over time with a state-dependent conditional mean and a disturbance that is exposed to economic fundamental shocks. The residual is then separated into two independent gamma shocks, $\omega_{qh;t+1}$ and $\omega_{ql;t+1}$, potentially capturing distinct behaviors of the right-tail (high risk aversion) and left-tail (low risk aversion) preference shocks:

$$q_{t+1} = \overline{q} + \rho_{q;q}(q_t - \overline{q}) + \rho_{q;qh}(qh_t - \overline{qh}) + _{q;mac}(\boldsymbol{Y}_{mac;t} - \overline{\boldsymbol{Y}_{mac}})$$
$$+ \delta_{q;\,p}\omega_{p;t+1} + \delta_{q;\,n}\omega_{n;t+1} + \delta_{q;qh}\omega_{qh;t+1} - \delta_{q;ql}\omega_{ql;t+1},$$
$$\omega_{qh;t+1} = \Gamma(qh_t, 1) - qh_t,$$
$$\omega_{ql;t+1} = \Gamma(\overline{ql}, 1) - \overline{ql},$$
$$qh_{t+1} = \overline{qh} + \rho_{qh}(qh_t - \overline{qh}) + \sigma_{qh}\omega_{qh;t+1}. \tag{E5}$$

The conditional mean of risk aversion evolves with the macro variables (both level and volatility), an AR(1) term, and a high risk aversion state variable $qh_t$ that captures the fluctuation of the right-tail risk aversion shock. Given that risk aversion heteroskedasticity is likely driven by its right-tail movements when risk aversion is high, we shut down heteroskedasticity coming from the left-tail movements when risk aversion is low to keep the model relatively simple. Note that our risk aversion dynamics are different from those in the literature. First, Bekaert et al. (forthcoming) also assume a pure risk aversion shock that is orthogonal to consumption (fundamental) shocks; they assume its shape parameter same as risk aversion, whereas we elicit a new state variable $qh_t$ that does not equal to $q_t$ (but should very likely positively correlate with $q_t$ empirically, as we do find later). Second, the most acknowledged time-varying risk aversion model is Campbell and Cochrane (1999) which assumes that risk aversion is purely driven by changes in real fundamentals. Finally, define $\boldsymbol{Y}_{q;t} = [q_t \quad qh_t]^{\prime}$, and $\overline{\boldsymbol{Y}_q} = [\overline{q} \quad \overline{qh}]^{\prime}$.

The stock market illiquidity process, $illiq_t$, is isomorphic:

$$illiq_{t+1} = \overline{illiq} + \rho_{illiq;illiq}(illiq_t - \overline{illiq}) + \rho_{illiq;illiqh}(illiqh_t - \overline{illiqh}) + \rho_{illiq;illiql}(illiql_t - \overline{illiql})$$
$$+ _{illiq;mac}(\boldsymbol{Y}_{mac;t} - \overline{\boldsymbol{Y}_{mac}}) + _{illiq;q}(\boldsymbol{Y}_{q;t} - \overline{\boldsymbol{Y}_q})$$
$$+ \delta_{illiq;\,p}\omega_{p;t+1} + \delta_{illiq;\,n}\omega_{n;t+1} + \delta_{illiq;qh}\omega_{qh;t+1} + \delta_{illiq;ql}\omega_{ql;t+1} + \delta_{illiq;illiqh}\omega_{illiqh;t+1} - \delta_{illiq;illiql}\omega_{illiql;t+1},$$
$$\omega_{illiqh;t+1} = \Gamma(illiqh_t, 1) - illiqh_t,$$
$$\omega_{illiql;t+1} = \Gamma(illiql_t, 1) - illiql_t,$$
$$illiqh_{t+1} = \overline{illiqh} + \rho_{illiqh}(illiqh_t - \overline{illiqh}) + \sigma_{illiqh}\omega_{illiqh;t+1},$$
$$illiql_{t+1} = \overline{illiql} + \rho_{illiql}(illiql_t - \overline{illiql}) + \sigma_{illiql}\omega_{illiql;t+1}, \tag{E6}$$

where $illiqh_t$ ($illiql_t$) captures the right-tail (left-tail) of the pure illiquidity disturbance that is cleansed

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from risk aversion and macro shocks.

## E.2. Estimation results

The estimation of the three state variable systems is conducted sequentially given the overlaying shocks. First, the economic growth and uncertainty state variables are estimated using a monthly sample from 1947/02 to 2019/12 and the Approximate Maximum Likelihood (AML) methodology in Bates (2006). Then, the risk aversion measure uses the $q_t$ series from Bekaert et al. (forthcoming), from 1986/06 to 2019/12, and is first projected on known macro variables; the disturbance is estimated using Bates (2006)'s. Finally, the stock market illiquidity measure is constructed using Amihud (2002)'s methodology, from 1985/01 to 2019/12, and is first projected on known variables; the disturbance is also estimated using Bates (2006)'s. (Below: $(, ,)$: 1% (5%, 10%) test)

| A. Estimation Results of $\theta_t, \theta p_t, \theta n_t$ | | | | | | |
|---|---|---|---|---|---|
| $\theta_t$: | $\overline{\theta}$ | $\rho_{\theta;\theta}$ | $\rho_{\theta;p}$ | $\rho_{\theta;n}$ | $\delta_{\theta;p}$ | $\delta_{\theta;n}$ |
| Coeff. | 0.0023*** | 0.3799*** | 4.02E-05 | -0.0001 | 0.0001*** | 0.0028*** |
| SE | (0.0003) | (0.0313) | (0.0002) | (0.0012) | (2.81E-5) | (0.0003) |
| $\theta p_t$: | $\overline{\theta p}$ | $\rho_p$ | $\delta_p$ | | | |
| Coeff. | 500 (fix) | 0.9979*** | 0.3739*** | | | |
| SE | | (0.0171) | (0.0173) | | | |
| $\theta n_t$: | $\overline{\theta n}$ | $\rho_n$ | $\delta_p$ | | | |
| Coeff. | 10.3362*** | 0.9525*** | 2.2996*** | | | |
| SE | (2.0747) | (0.0096) | (0.1907) | | | |
| B. Estimation Results of $q_t, qh_t$ | | | | | | |
| $q_t$: | $\overline{q}$ | $\rho_{q;q}$ | $\rho_{q;qh}$ | $\rho_{q;\theta}$ | $\rho_{q;p}$ | $\rho_{q;n}$ |
| Coeff. | 0.3266*** | 0.7124*** | -0.0006 | -3.1851*** | 0.0008** | 0.0011 |
| SE | (0.0102) | (0.0355) | (0.0004) | (0.9238) | (0.0003) | (0.0009) |
| | $\delta_{q;p}$ | $\delta_{q;n}$ | $\delta_{q;qh}$ | $\delta_{q;ql}$ | $\overline{ql}$ | |
| Coeff. | 0.0004 | 0.0185*** | 1.0767*** | 0.0906*** | 786.6892*** | |
| SE | (0.0003) | (0.0034) | (0.0645) | (0.0001) | (102.74) | |
| $qh_t$: | $\overline{qh}$ | $\rho_{qh}$ | $\delta_{qh}$ | | | |
| Coeff. | 0.872*** | 0.5677*** | 1.0767*** | | | |
| SE | (0.0670) | (0.0307) | (0.0645) | | | |
| C. Estimation Results of $illiq_t, illiqh_t, illiql_t$ | | | | | | |
| $illiq_t$: | $\overline{illiq}$ | $\rho_{illiq;illiq}$ | $\rho_{illiq;illiqh}$ | $\rho_{illiq;illiql}$ | | |
| Coeff. | 8.9526*** | 0.9521*** | 0.0001 | -0.0005 | | |
| SE | (0.1311) | (0.0147) | (0.0046) | (0.0044) | | |
| | $\rho_{illiq;\theta}$ | $\rho_{illiq;p}$ | $\rho_{illiq;n}$ | $\rho_{illiq;q}$ | $\rho_{illiq;qh}$ | |
| Coeff. | -15.2507 | 0.0186* | 0.0145 | -4.622* | 1.5002*** | |
| SE | (27.2003) | (0.0113) | (0.0317) | (2.5668) | (0.4929) | |
| | $\delta_{illiq;p}$ | $\delta_{illiq;n}$ | $\delta_{illiq;qh}$ | $\delta_{illiq;ql}$ | $\delta_{illiq;illiqh}$ | $\delta_{illiq;illiql}$ |
| Coeff. | 0.0054 | 0.0345 | -1.2834** | -0.004 | 2.0855*** | 0.7175*** |
| SE | (0.0077) | (0.0988) | (0.5396) | (0.0052) | (0.0351) | (0.0323) |
| $illiqh_t$: | $\overline{illiqh}$ | $\rho_{illiqh}$ | $\delta_{illiqh}$ | | | |
| Coeff. | 1.1458*** | 0.9244*** | 0.4687*** | | | |
| SE | (0.0481) | (0.0413) | (0.0103) | | | |
| $illiql_t$: | $\overline{illiql}$ | $\rho_{illiql}$ | $\delta_{illiql}$ | | | |
| Coeff. | 0.699*** | 0.8651*** | 0.0219*** | | | |
| SE | (0.0347) | (0.0900) | (0.0025) | | | |

We next compare the closeness between average conditional moments (mean, variance) and empirical unconditional moments of $\theta_{t+1}$, $q_{t+1}$, and $illiq_{t+1}$. Bold values indicate that the average conditional moments are statistically close to the data. Moment matching is expected given the highly specified model assumptions; given that our paper is not about selecting the most efficient dynamic process but obtaining realistic estimates of state variables, we do not expand the model comparison exercise and

follow existing evidence and frameworks in the literature.

| | $\theta_{t+1}$ | | $q_{t+1}$ | | $illiq_{t+1}$ | |
|---|---|---|---|---|---|---|
| | Data | Model | Data | Model | Data | Model |
| Mean | 0.0023*** | **0.0025** | 0.3023*** | **0.3049** | 8.9468*** | **8.9570** |
| | (0.0003) | | (0.0084) | | (0.0084) | |
| Variance | 7.33E-05*** | **6.11E-05** | 0.0091*** | **0.0094** | 6.632*** | **7.4434** |
| | (7.73E-06) | | (0.0018) | | (1.1573) | |

Figures below depict the dynamics of state variables in the macro, risk aversion, and stock market illiquidity systems, respectively: (1) From top to bottom: Economic growth (gray) and its conditional mean (red); good macro uncertainty state variable $\theta p_t$; bad macro uncertainty state variable $\theta n_t$; total conditional volatility.
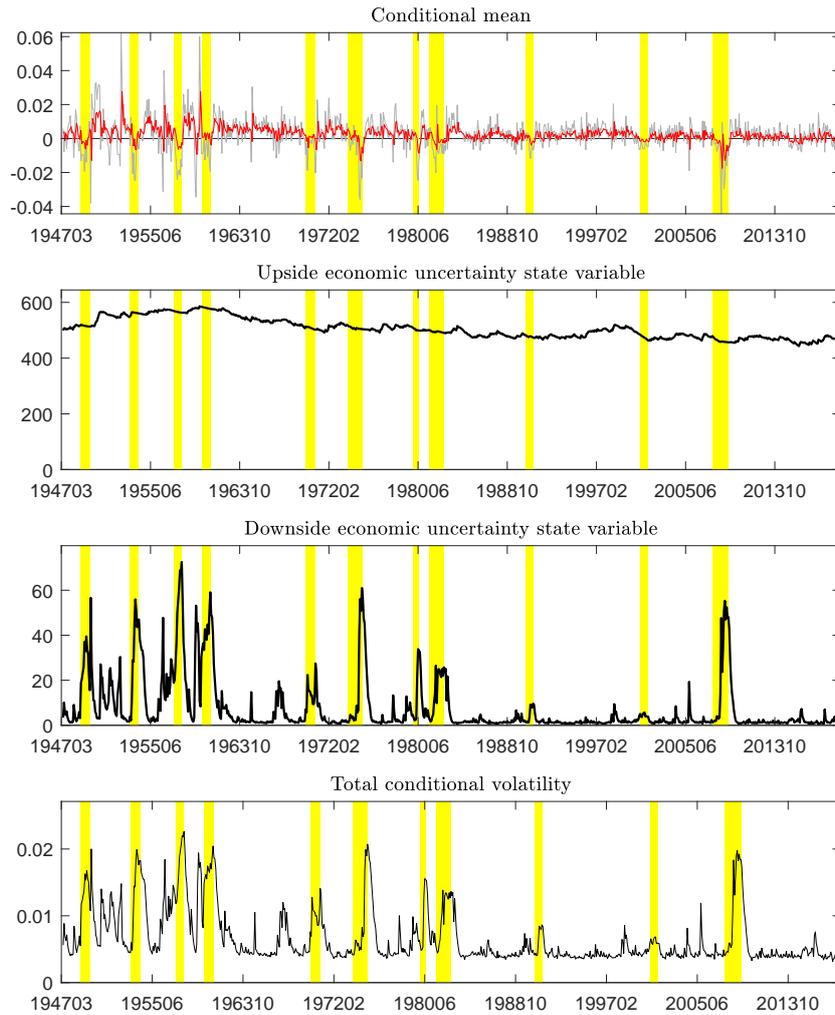


(2) From top to bottom: Risk aversion state variable $q_t$ from Bekaert et al. (forthcoming) (gray) and its conditional mean (red); high risk aversion state variable $qh_t$; total conditional volatility.

Conditional mean

High risk aversion state variable

Total conditional volatility
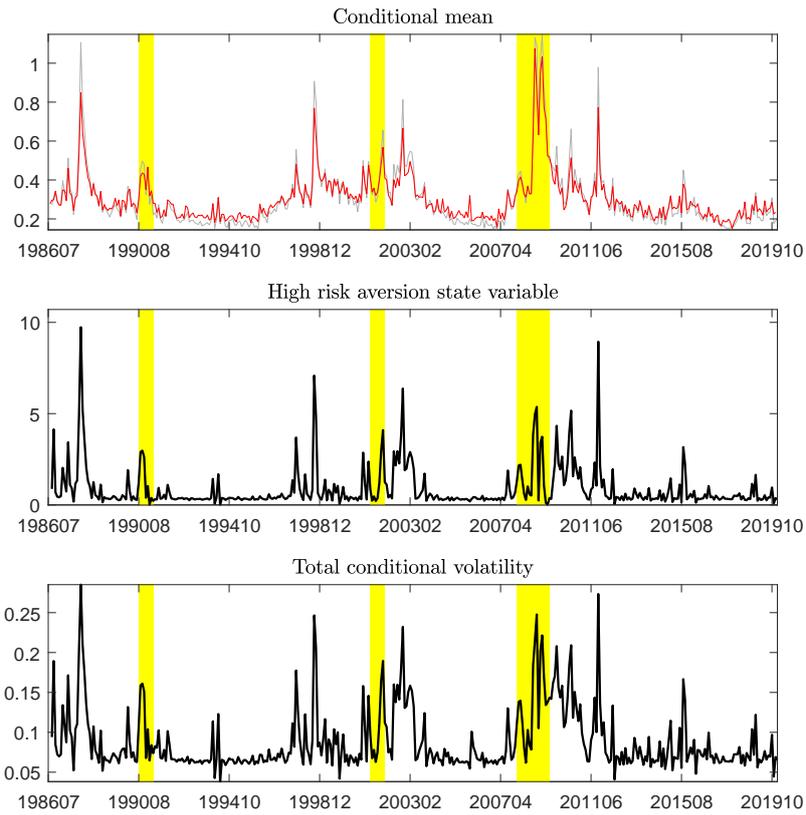
(3) From top to bottom: Stock market illiquidity measure using Amihud (2002)'s method (gray) and its conditional mean (red); high market illiquidity state variable $illiqh_t$; low market illiquidity state variable $illiql_t$; total conditional volatility.



Conditional mean

High illiquidity state variable

Low illiquidity state variable

Total conditional volatility
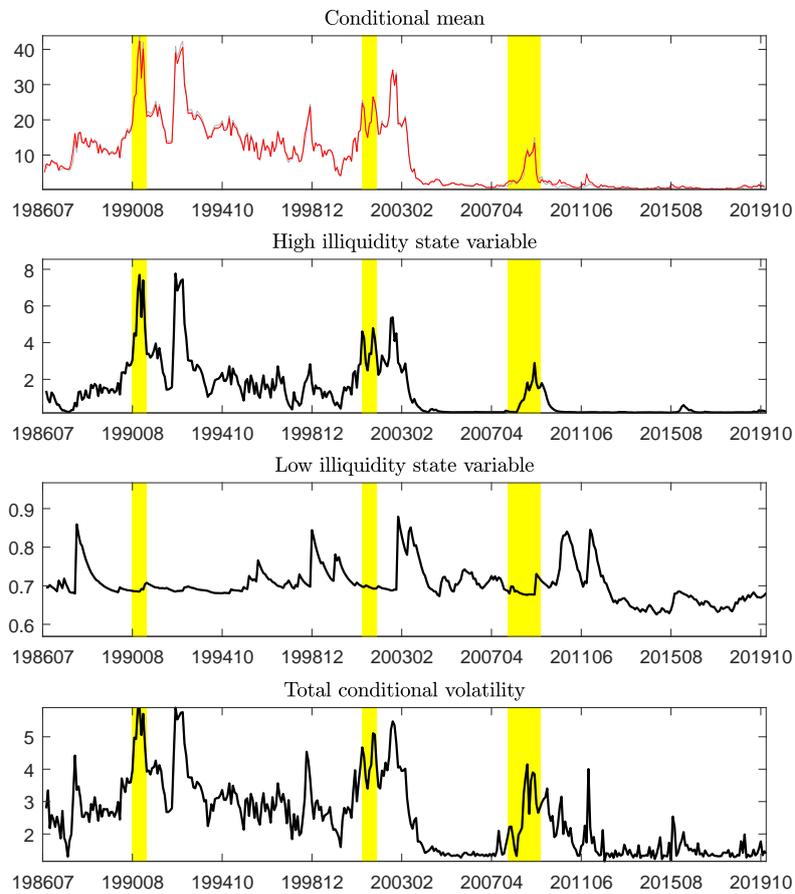
# F. The role of $z_t$ in the global equity risk premium loadings on common risk premium determinants

This plot complements Figure 7-(A) using $z_t=min(z_t)$ and $z_t=max(z_t)$. The message is that $z_t$ seems to matter insignificantly in the EP loadings.