A Consumption-Based Identification of Global Economic Uncertainty

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Abstract

This paper identifies a global uncertainty factor by estimating an international asset pricing model featuring macroeconomic uncertainty with long-run risk factors. The global factor captures the time-varying fluctuations of common stochastic volatilities of consumption and dividend growths for countries, and reflects uncertainty in that it generates the highest volatility of volatility in transition period. The model quantitatively explains key asset pricing moments, and the estimated factor sharply increases during major international adverse events. Shocks to our global economic uncertainty factor significantly account for the likelihood of key economic and financial events, and outperforms existing measures of economic and financial uncertainties.

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1 Introduction

One of the trends in financial markets over the last decade is significant increases in the amount and depth of interactions among market participants from different countries. Financial innovations, advances in information technology and regulations are responsible for this phenomenon. Integration of financial markets implies that investors’ discount factors can depend on both global shocks as well as country-specific shocks, and the market prices of financial assets can reflect risk and uncertainty associated with common and idiosyncratic fluctuations of key macroeconomic variables such as consumption and earnings of international economies. To properly identify factors that generate uncertainty, it is therefore desirable to consider market participants’ preferences regarding risk and uncertainty in conjunction with statistical models that capture both risk and uncertainty.

In this light, we estimate an international asset pricing model in a long-run risk framework by Bansal and Yaron (2004) and Hansen et al. (2008) to incorporate a global economic uncertainty factor as well as country-specific uncertainty factors. The global uncertainty factor captures the time-varying fluctuations of common stochastic volatilities of both consumption and dividend growths from different countries, and it is identified as a latent factor that evolves over time between two asymptotic regimes of the macroeconomic volatilities with smooth transitions. Kim et al. (2010) and Kim and Park (2018) propose as a stochastic volatility model, a sinusoidal function such as a logistic function for smooth transition. The main rationale for this suggestion is that these nonlinear transitions in volatility imply that volatility of volatility, an increasingly popular measure of uncertainty, becomes higher in transition. Importantly enough, the choice of a logistic volatility setup suggests that uncertainty can be high in the middle of good and bad economic states, which is intuitively appealing and makes uncertainty distinct from conventional risks. Further, this setup enables researchers to extract common and idiosyncratic factors that generate volatility of fundamental variables. In conjunction with recursive preferences such as that of Epstein and Zin (1989) and Weil (1989), where the preference about the speed of uncertainty resolution matters, this volatility setup has potentials to properly extract uncertainty-generating factors. Given the unobservable nature of risk and uncertainty, we believe that this econometric method can shed light on the measurement of global economic uncertainty. We tackle this question by developing a Bayesian econometric procedure to estimate international asset pricing models with both common and idiosyncratic latent factors. Using the data
from Australia, Canada, the United Kingdom, and the United States between 1970 and 2012, we estimate the model. The estimated factor sharply increases during major international adverse events. Its trend steadily decreased until early 1990s, then shoot up since 1995, consistent with the trends of international market integration. Our global economic uncertainty factor significantly helps to explain global equity premia.

The main findings are highlighted as follows. First, the estimated global uncertainty factor extracted out of consumption and dividend growth rates is persistent and consistent with major economic and political events or shocks that have been occurring around the world. Our consumption-based economic uncertainty measure is positively correlated to popular measures of economic risk and uncertainty, such as the VIX, National Financial Conditions Index (NFCI), and Global Economic and Political Uncertainty (GEPU) Index. Values of correlations range between 0.2 and 0.35, hinting at the possibility of different roles in accounting for shocks to economic and political uncertainty. It turns out that shocks to our uncertainty measure significantly affect key adverse economic events and recessions. However, other aforementioned uncertainty measures are insignificant in explaining these events. This is surprising, because our global uncertainty measure only uses the two macroeconomic variables, together with the stock market index and the short-term interest rate. We suspect that a proper theoretical structure helps identify economic uncertainty factors.

Second, the estimated preference parameters for the Epstein-Zin-Weil utility function are reasonable and help solve several asset pricing puzzles such as the equity premium puzzle, the risk-free rate puzzle, and the volatility puzzle. Our estimation states that the relative risk aversion is significantly estimated around 1.7, a significantly lower value compared to existing studies, and it is close to the values often used in related studies. Regarding the elasticity of intertemporal substitution, our estimate is around 7.3 with a \( t \)-statistics of 1.4. While it is not significant, this is consistent with the existing empirical studies that report a weak identification issue for this preference parameter. Using the estimated parameters, we simulate the model to compare the key moments of asset prices and macroeconomic variables. Our model can quantitatively generate the first and second moments of the stock market returns, the short-term interest rates, consumption growth, and dividend growth for all four countries. We find that the role of global economic uncertainty is nontrivial.

The remainder of the paper begins with a brief literature review. Then we spell out our economic model in section 3. We develop our econometric procedure to estimate the model in section 4. Section 5 explains and discusses our empirical findings. Then we conclude.
2 Literature Review

Our paper connects several strands of the literature. First, the paper studies international asset prices. A key feature of the international asset pricing in the literature is that excess returns are priced by the covariance with a common global market factor when international equity markets are integrated. The early empirical studies provide the unconditional tests of the world capital asset pricing model (CAPM). Results supportive of the model are found in Solnik (1974b), Stehle (1977), Jorion and Schwartz (1986), and Mittoo (1992). However, the rejections for the simple standard world CAPM model in a conditional setting with time-varying expected returns, variances, and covariances are found in Mark (1988), Giovannini and Jorion (1989), McCurdy and Morgan (1992), and Harvey (1991), showing that local risk is important. Related, Bekaert et al. (2009) consider various models and show that the performance of the models considered improves by adding a local factor. Therefore, it matters to construct an international asset pricing model with both global and local risk factors. Recently, consumption-based models with exotic preferences shed light on the time-varying risk and uncertainty preferences in understanding the prices of international assets. Colacito and Croce (2011) proposed an equilibrium model that combines cross-country correlated long run risk, extending Bansal and Yaron (2004) to explain a wide range of international finance puzzle. Bansal and Shaliastovich (2013) also used a two-country model, focusing on the term premium in bond market and the premium in currency market. Our model shares the spirit of these long-run risk model, yet the main focus of our paper is to identify global and country-specific uncertainty factors.

In the context of consumption-based asset pricing models, the model is typically calibrated or estimated using traditional methods (e.g., Hansen and Singleton (1982a), Hansen and Singleton (1983), and Hansen and Singleton (1996)). The Generalized Method of Moment (GMM) approach proposed by Hansen (1982) is commonly used for variety of economic models. The first empirical application of GMM was Hansen and Singleton (1982a)’s investigation of the consumption-based asset pricing model. A system GMM estimator robust to various specification issues is developed in Hansen and Singleton (1996) and Hansen

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4 Karolyi and Stulz (2003) and Lewis (2011) provide extensive surveys for global asset pricing. In early work, Solnik (1974a) and Grauer et al. (1976) described a world capital asset pricing model in the Sharpe-Littner type CAPM framework. Stulz (1981) developed an intertemporal model of international asset pricing, which allows differences in consumption opportunity sets across countries and it is shown that the excess returns are determined by a common global source of risk under purchasing power parity.
et al. (1996) suggest the so-called continuous updating GMM estimation, which has some advantages in terms of reliable inference. According to the conventional first-order asymptotic theory, choice of normalization for the moment restriction based on the linearized Euler equation and the choice of the method such as TSLS and limited-information maximum likelihood (LIML) should be negligible in large sample. However as discussed by Neely et al. (2001), Campbell (2003) and Yogo (2004), this issue matters greatly in practice due to weak instruments. Related, the preference parameters can be estimated by GMM through the nonlinear Euler equation, yet Epstein and Zin (1991) note that the GMM approach using nonlinear Euler equation in estimating the preference parameters has difficulty since it requires knowledge of returns on the wealth portfolio. For nonlinear problems, an alternative statistical method is suggested by Chernozhukov and Hong (2003). Chernozhukov and Hong (2003) develops a class of estimators called Laplace type estimator or quasi-Bayesian estimators, which are defined similarly to Bayesian estimators but use general statistical criterion function instead of the parametric likelihood function. We contribute to the literature by offering a novel hybrid approach to estimate international models with both observable and latent factors.

Finally our paper contributes to econometric studies regarding the measurement of uncertainty. An overview of the literature on economic uncertainty and its effects is provided by Bloom (2014). Many theoretical studies show that how uncertainty potentially affects economic variables such as investment, hiring, consumption, trade, financing cost, output and asset prices. The theoretical literature such as Bernanke (1983) and Cooper and Haltiwanger (2006) focus on real-options effects which act to make firms more cautious about hiring and investing, and consumers more cautious about buying durable goods if agents are subject to fixed costs or partial irreversibilities. Another channel for uncertainty to impact growth is from consumers’ desire for precautionary saving, which itself reduces consumption expenditure (precautionary saving effect). For example, Guerrón-Quintana et al. (2011) emphasize this channel, demonstrating that increase in uncertainty can damp growth in smaller open emerging economies. The risk premium effect, which uncertainty can reduce growth, is through increasing risk premia. A related mechanism to risk premia is that uncertainty increases the cost of debt finance. Therefore, increase in uncertainty can depress economic activities if financial constraints tighten in response to higher uncertainty, as emphasized in Christiano et al. (2010).

One of the proxies of uncertainty is the implied or realized volatility of stock market,
bond market, and exchange rates. Jeong et al. (2015), Chang et al. (2016) and other papers show that return volatility captures uncertainty, the return premiums reflect the link. As mentioned by Bekaert et al. (2013), the fluctuations in the VIX appear to heavily reflect movements in uncertainty. Jurado et al. (2015) also note that stock market volatility can change over time even if there is no change in uncertainty about economic fundamentals. As noted by Bloom (2014), other financial prices, such as exchange rates and bond yields, are also similarly more volatile in recessions.

Another proxy of uncertainty is disagreement amongst professional forecasters (Bachmann et al. (2013)) and the frequency of newspaper articles about economic uncertainty. Baker et al. (2016) develop an indices of economic policy uncertainty (EPU) that draws on the frequency of newspaper references to policy uncertainty and other indicators. Baker et al. (2016) indicate that EPU index offers a good proxy for movements in policy-related economic uncertainty over time. They find that negative effects of EPU on firm-level investment and hiring and that innovations in EPU foreshadow sizable declines in GDP and employment in the VAR framework. Building on Baker et al. (2016), Davis (2016) construct a monthly index of Global Economic Policy Uncertainty, which is a GDP-weighted average of national EPU indices for 16 countries that account for two-thirds of global output. An eclectic mix of other indicators of macro uncertainty is provided by Jurado et al. (2015) and Nakamura et al. (2017). Jurado et al. (2015) provide econometric estimates of time-varying macroeconomic uncertainty and relates them to macroeconomic activity. In Jurado et al. (2015), macroeconomic uncertainty is constructed by aggregating individual uncertainty at each date using aggregation weights where individual uncertainty is defined by the conditional volatility of the purely unforecastable component of the future value of the series. Nakamura et al. (2017) provide the estimates of the importance of growth-rate shocks and uncertainty shocks for developed countries, using consumption data from 16 OECD countries. Several papers examine the proxies or indicators of uncertainty related to the cross-sectional forecast dispersion of firm characteristics (e.g., Campbell et al. (2001), Kim (2013) and Kim et al. (2018)).

3 Asset Pricing with Global Uncertainty

This section describes the economic model to be estimated and analyzed.
3.1 Preferences

We consider a simple endowment economy in which the representative agent in each country \( i \) has an Epstein-Zin-Weil recursive preference. The consumer in country \( i \) has the following preferences:

\[
U_{i,t} = [(1 - \delta)C_{i,t}^{(1-\gamma)} + \delta(E_tU_{i,t+1}^{1-\gamma})^{1/\theta}]^{\theta/\gamma}
\]  

(1)

where \( 0 < \delta < 1 \) is the time discount factor, \( \gamma \geq 0 \) is the coefficient of risk aversion, and \( \psi \geq 0 \) is the elasticity of intertemporal (EIS), \( \theta \equiv \frac{1-\gamma}{1-\psi} \). Agents from different countries have the same risk aversion and the EIS parameters. Then, the logarithm of the real stochastic discount factor implied by these preferences is given by

\[
m_{i,t+1} = \theta \log \delta - \frac{\theta}{\psi} \Delta c_{i,t+1} + (\theta - 1)r_{c,t+1},
\]

(2)

where \( \Delta c_{t+1} = \log(C_{t+1}/C_t) \) is the log growth rate of the aggregate consumption and \( r_{c,t+1} \) is the log return on the asset, which delivers the aggregate consumption as its dividends, at each time period.\(^5\)

\[
E_t(\exp(m_{i,t+1} + r_{t+1}^i)) = 1,
\]

(3)

To complete the model, the following sub-section spells out stochastic processes for consumption and dividend growth rates for each country. In so doing, global and country-specific risk and uncertainty factors are described as well.

\(^{5}\)Denoting the value of a consumption claim by \( P_c \), \( \exp(r_{c,t+1}) \) is defined as \( \frac{P_{c,t+1} + C_{t+1}}{P_{c,t}} \). In addition, if we denote the household wealth by \( A \), the periodic budget constraint is recursively written as \( A_{t+1} = (A_t - C_t) \exp(r_{c,t+1}) \).
3.2 Factor Structure of Consumption and Dividend Growth Rates

Denoting the consumption growth rates and dividend growth rates for country \(i\) by \(g_{c,t+1}^i\) and \(g_{d,t+1}^i\) respectively,

\[
g_{j,t+1}^i = \mu_{j}^i + \nu_{j,t}^i + \sqrt{f_{j}^i (x_{j,t}^i)} e_{j,t+1}^i
\]  
(4)

\[
\nu_{j,t+1}^i = \rho_{j}^i \nu_{j,t}^i + \psi_{j}^i \sqrt{f_{j}^i (x_{j,t}^i)} \eta_{j,t+1}^i
\]  
(5)

\[
x_{c,t}^i = \lambda_{c}^i (x_{c,t}^i) + e_{c,t}^i
\]  
(6)

\[
x_{d,t}^i = \lambda_{d}^i (x_{d,t}^i) + e_{d,t}^i
\]  
(7)

\[
w_{t}^q^i = \rho_{w}^i w_{t-1}^q + u_{t}^q
\]  
(8)

\[
\tilde{w}_{t}^i = \rho_{\tilde{w}}^i \tilde{w}_{t-1}^i + \tilde{u}_{t}^i
\]  
(9)

Equations (4) states that \(g_{c,t+1}^i\) and \(g_{d,t+1}^i\) have the conditional mean component, denoted by \(\mu^i + \nu^i\) and a time-varying volatility component driven by scalar processes \(x_{c,t}^i\) and \(x_{d,t}^i\) respectively. The conditional expectation of consumption growth consists of the time-varying component, and shocks to this component affects future consumption, and the conditional expectation of the dividend growth consists of the time-varying component as well. If this shock is highly persistent, or the values of \(\rho_{j}^i\) are very close to 1, it can have a long run effect, as shown in equation (5). Equations (6) and (7) define the latent volatility factors, \(x_{j,t}^i\) for \(j = c, d\), which consist of three components. The common global macroeconomic volatility factor \(w_{t}^q\) captures the common volatility factor of both consumption and dividend growth rates across all countries, \(\tilde{w}_{t}^i\) denotes the country-specific macroeconomic volatility factors, and the last term refers to the idiosyncratic factor, \(e_{j,t}^i\). The stochastic volatilities of consumption and dividend growth rates are assumed to be the logistic transformations of latent factors, \(x_{j,t}^i\) for \(j = c, d\).

\[
f(x_{j,t}^i) = \frac{\alpha_{j}^i}{1 + \exp[-(x_{j,t}^i - \kappa_{j}^i)]} \quad \text{with} \quad \alpha_{j}^i > 0, \ \beta_{j}^i > 0 \ \text{for} \ \ j = c, d
\]  
(10)

\[
\begin{pmatrix}
    e_{c,t}^i \\
    e_{d,t}^i
\end{pmatrix}
\sim iidN(0, \Sigma^i), \quad \Sigma^i = \begin{pmatrix}
    1 & \rho^i \\
    \rho^i & 1
\end{pmatrix}
\]
The logistic function has several desirable properties to be used in the volatility model. In particular, it may be interpreted as representing the volatility levels into two asymptotic regimes, i.e., high and low volatility regimes, with a smooth transition between them. The parameters $\alpha$ and $\alpha + \beta$ dictate the low and high volatility regimes, respectively and parameters specify the transition between the two regimes, i.e., the reflection point ($\kappa$) and the speed of the transition ($\lambda$), respectively. Thus, despite the parsimony, the model is flexible and encompasses many existing volatility models. Further, as shown by Kim et al. (2010) and Kim and Park (2018), the logistic stochastic volatility model or other volatility setups using sinusoidal functions has an implication for the volatility of volatility, a popular proxy to measure uncertainty. To illustrate this, assume temporarily that the variable responsible to generate stochastic volatility, $x$ in equation (10) follows an Ito process. Then, by Ito’s lemma, it is straightforward to compute the volatility of the conditional macroeconomic variance $f(x)$ as the differential of $f(x)$, denoted as $f'(x)$

$$\sqrt{\text{var}(f(x))} = \frac{(f(x) - \alpha)(\alpha + \beta - f(x))}{\beta},$$  

(11)

where $f(x) \in (\alpha, \alpha + \beta)$ holds. Equation (11) states that the volatility of volatility is the highest in the middle of the range in the variance $f(x)$ and becomes small as the variance converges to its infimum or supremum. That is, uncertainty is highest when the risk is in the middle and can move to either high or low level in a future. In addition, from equations (6) and (7), $\lambda_c$ and $\lambda_d$ affect the speed of transitions in that a high value of $\lambda_j$, for $j = c, d$ makes transition fast and abrupt so that the volatility function is closer to a regime-switching model, whereas a low value of $\lambda_j$ implies gradual transitions. Therefore, our stochastic volatility model can capture uncertainty effects in addition to the conventional risk channels.
3.3 Asset Prices

This section describes the asset pricing implications of our economic model. The log-linearized return on consumption claim is given by

\[ r_{c,t+1} = k_0 + k_1 z_{t+1} - z_t + g_{t+1}, \]

where \( z_t \equiv \log(P^c_t/C_t) \) is the log price-to-consumption ratio. Parameters \( k_0 \) and \( k_1 \) are approximating constants which are based on the endogenous average price-to-consumption ratio in the economy. The approximation solution for the log price-consumption ratio is linear in states,

\[ z_t = A_0 + A_{\nu c} \nu_{ct} + A_{sc} f_{ct}. \]

The product term \( A_{sc} f_{ct} \) in \( z \) depicts effects from macroeconomic volatility. Kim et al. (2010) offer the validity of the approximate solutions by comparing with numerical solutions. The equilibrium loadings are as derived as

\[ A_0 = \frac{\theta \ln \delta + (1 - \gamma) \mu_c + \theta k_0 + 0.5(\theta k_1 A_{sc})^2(\xi_2^2 - \xi_1^2 f_{c,0}^2)}{\theta(1 - k_1)} \]

\[ A_{\nu c} = \frac{(1 - \gamma)}{\theta(1 - k_1 \rho_c)} = \frac{1 - 1/\psi}{(1 - k_1 \rho_c)} \]

\[ A_{sc} = (1 - k_1) + \sqrt{(k_1 - 1)^2 - 2k_1^2 \Upsilon((1 - \gamma)^2 + (\theta k_1 A_{\nu c} \varphi_c)^2)} \]

where \( \Upsilon = \xi_1(\xi_1 f_{c,0} + \xi_2), \xi_1 = \frac{\lambda_c}{\beta_c}(2\alpha_c + \beta_c - 2f_{c,0}), \xi_2 = \frac{\lambda_c}{\beta_c}(f_{c,0}^2 - \alpha_c(\alpha_c + \beta_c)) \) with \( f_{c,0} = f_c(x_{c,0}) \). \( A_{\nu c} > 0 \) and \( A_{sc} < 0 \) under the condition, \( \gamma > 1 \) and \( \psi > 1 \). This implies that an agent prefers higher expected further growth, but do not like a increase in macroeconomic volatility. In addition to the conventional channel of volatility \( (f_c(\lambda_c w_c)) \) in which a higher value of \( (\lambda_c w_c) \) means higher uncertainty, we observe from \( A_{sc} \) that the absolute value of \( A_{sc} \) increases via decreases in \( \Upsilon \), when there exists a slower transition. When uncertainty unfolds in a sluggish fashion and is in transit, an agent fears the possibility of being at the high volatility regime in the near future. A low to medium level of macroeconomic volatility does not necessarily mean that economic agents perceive the state of the economy as being safe.

\[ m_{t+1} - E_t m_{t+1} = -D_{\varepsilon c} \sqrt{f_{et} \varepsilon_{c,t+1}} - D_{\eta c} \sqrt{f_{et} \eta_{c,t+1}} - D_u(t) u_{t+1}, \]
\[ D_{\varepsilon c} = \gamma \]  
\[ D_{\eta c} = (\gamma - \frac{1}{\psi}) \frac{k_1 \phi_c}{1 - k_1 \rho_c} \]  
\[ D_u(t) = (1 - \theta) k_1 A_{sc}(\xi_1 f_{ct} + \xi_2) \]

where \( D_{\varepsilon c}, D_{\eta c} \) are positive but \( D_u(t) \) is negative.\(^6\)

Parameters \( D_{\varepsilon c}, D_{\eta c} \) and \( D_u(t) \) are the market price of risks for each source of risk, \( \varepsilon_{t+1}, \eta_{t+1} \), and \( u_{t+1} \) respectively. From equations (17) to (19), positive innovations in both short-term and long-term consumption growth lead to lower discount rates for the future, while higher volatility innovations refer to higher discounts for the future. The conditional variance of the stochastic discount factor, then, is as follows:

\[ Var_t(m_{t+1}) = D_{\varepsilon c}^2 f_{ct} + D_{\eta c}^2 f_{ct} + D_u(t)^2 \]  

4 Identification of Economic Uncertainties

This section explains the econometric method. Our economic model consists of the set of Euler equations and the specifications of economic variables. Thus, the statistical procedure mainly deals with two part, the estimation of the preference function and of stochastic volatility function with latent factors. Our setup contains latent factors inside the Euler equation. Chernozhukov and Hong (2003) and Gallant et al. (2014) show that drawing samples of parameters from a conditional posterior distribution made out of the moment condition is asymptotically equivalent to obtaining a sample from the asymptotic distribution of the GMM estimator under mild conditions. In this light, we incorporate a Bayesian approach called Markov Chain Monte Carlo (MCMC) methods into the GMM framework.

4.1 A Bayesian Algorithm for Stochastic Volatilities

In this part, we propose an econometric procedure to estimate the global uncertainty process and unknown parameters in our model. To this end, we rewrite (4) as

\[ y_{j,t+1} = \sqrt{f_j(x^j_{j,t})e^j_{j,t+1}}, \]

\(^6\)See Kim et al. (2010) for the derivation of the loadings.
where \( y^i_{j,t+1} = g^i_{j,t+1} - \mu^i_j - \nu^i_{j,t} \) for \( j = c, d \) and \( i = 1, \ldots, N \). It is noted that \( y^i_{j,t+1} \) is a martingale difference sequence. We subtract the conditional mean component of from \( g^i_{j,t+1} \) to obtain the estimated \( y^i_{j,t+1} \). For this step, we extend and apply the Hodrick-Prescott (HP) filter by optimally selecting a value of the smoothing parameter for the HP filter that makes the autocorrelation of \( y^i_{j,t+1} \) as close as possible to be zero, constraining \( y^i_{j,t+1} \) to be a martingale difference sequence. The Table in Figure 3 shows the values of the smoothing parameter for the HP filter to estimate the time-varying conditional mean component of the consumption and dividend growth rates for each country. With the estimates of \( y^i_{j,t+1} \) for \( j = c, d \) and \( i = 1, \ldots, N \), the logistic stochastic volatility model in equations (4) to (8) is taken into account. It is computationally costly and challenging to estimate the stochastic volatility (SV) models, since the SV models do not have closed form likelihood functions due to their latent structure of the conditional variance. Therefore, we can not directly apply a maximum likelihood estimation. To extract the latent variables such as global uncertainty and country-specific factors and estimate unknown parameters, we use a Bayesian approach by implementing a Markov chain Monte Carlo (MCMC) method. To fix the idea of the MCMC, let \( T \) and \( N \) be the sample size and the number of countries respectively, and define the observed samples, \( Y = (Y^1, \ldots, Y^N)' \) with \( Y^i = (y^1_i, \ldots, y^T_i) \) and \( y^i_t = (y^i_{c,t}, y^i_{d,t})' \) for \( i = 1, \ldots, N \) and \( t = 1, \ldots, T \), and we define \( L = (X, W, W^g) \) as the vector of the latent factors, with \( X = (X^1, \ldots, X^N)' \), \( X^i = (x^1_i, \ldots, x^T_i) \), \( x^i_t = (x^i_{c,t}, x^i_{d,t})' \), \( W = (\tilde{W}^1, \ldots, \tilde{W}^N)' \), \( \tilde{W}^i = (\tilde{w}^1_i, \ldots, \tilde{w}^T_i)' \), and \( W^g = (w^q_1, \ldots, w^q_T) \). In addition, we define the unknown parameters in our model, \( \Psi = (\Theta, \rho, \lambda, \chi, \sigma, \rho^q_w, \rho^q_{\tilde{w}}) \) with the stochastic volatility parameters, \( \Theta = (\Theta^1, \ldots, \Theta^N) \), \( \Theta^i = (\Theta^i_c, \Theta^i_d) \), \( \Theta^i_j = (\alpha^i_j, \beta^i_j, \kappa^i_j) \) for \( j = c, d \), \( \rho = (\rho^1, \ldots, \rho^N) \), \( \lambda = (\lambda^1, \ldots, \lambda^N) \), \( \lambda^i = (\lambda^i_c, \lambda^i_d) \), \( \lambda = (\chi^1, \ldots, \chi^N) \) and \( \sigma = (\sigma^1, \ldots, \sigma^N) \), \( \sigma^i = (\sigma^i_c, \sigma^i_d)' \) and

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Footnotes:

1. The HP filter has become a standard method for removing trend movements in the business cycle literature, and Hodrick and Prescott (1997) suggests 1600 as a value of the smoothing parameter for quarterly data. However, this method is not optimal for our purpose, and we use the extremum criterion to choose the optimal smoothing parameter value.

2. Several estimation methods have been proposed in the literature including quasi-maximum likelihood method (QML) (Harvey et al. (1994)), the simulated maximum likelihood method (Danielsson (1994), Durbin and Koopman (1997), and Sandmann and Koopman (1998)), the generalized method of moments (Melino and Turnbull (1990)), and the efficient method of moments (Gallant and Tauchen (1996) and Andersen and Sørensen (1996)). In addition to these methods, the Bayesian Markov chain Monte Carlo (MCMC) method has been used to estimate the SV models (see Jacquier et al. (1994), Jacquier et al. (2004); Kim et al. (1998), Chib et al. (2002)). Compared with other estimation methods, the Bayesian method is explicitly suitable and has been proven to perform well and provide relatively accurate results (e.g., Jacquier et al. (1994) and Andersen et al. (1999)). Moreover, Andersen et al. (1999) demonstrates that MCMC is one of the most efficient method.
\(\rho_\omega = (\rho_\omega^1, \ldots, \rho_\omega^N)\). We define \(D_t = (D_t^1, \ldots, D_t^N)\) with \(D_t^i = diag(\sqrt{J_t^i(x_{c,1}^i)}, \sqrt{J_t^i(x_{d,1}^i)})\). We construct the joint posterior distribution of the latent variables and the unknown parameters given the data in terms of the prior distribution \(p(\Psi)\) and the likelihood function as follows:

\[
p(L, \Psi|Y) \propto p(L, Y|\Psi)p(\Psi)
\]

\[
\propto \prod_{t=1}^T \prod_{i=1}^N p(y_t|x_t, \Psi)p(x_{c,t}|x_t, \Psi)p(x_{d,t}|x_t, \Psi)p(w_t|w_{t-1}, \Psi, \rho_\omega),
\]

\[
y_t^n_i|x_t^n_i, \Psi \sim N(0, D_t^i\Sigma^i_t D_t^i)
\]

\[
x_{j,t}^i|w_{t}^i, \Psi \sim N(\lambda_j^i(w_{t}^i + \chi_i^i w_{t}^q), (\sigma_j^i)^2)
\]

\[
\tilde{w}_{t}^i|\tilde{w}_{t-1}^i, \Psi \sim N(\rho_\omega^0 \tilde{w}_{t-1}^i, 1)
\]

\[
w_{t}^q|w_{t-1}^q, \Psi \sim N(\rho_\omega^q w_{t-1}^q, 1),\]

where \(p(y_t|x_t, \Psi) = p(y_t^n_i|x_t^n_i, \Psi)\), \(p(x_{c,t}|x_t, \Psi) = p(x_{c,t}^i|x_t^n_i, \Psi)\), \(p(x_{d,t}|x_t, \Psi) = p(x_{d,t}^i|x_t^n_i, \Psi)\), \(p(w_t|w_{t-1}, \Psi, \rho_\omega) = p(\tilde{w}_{t}^i|\tilde{w}_{t-1}^i, \Psi)p(w_{t}^q|w_{t-1}^q, \Psi)\), and \(p(\Psi) = p(\Psi)\). Regarding the prior distribution of \(\Psi\), we follow the literature, namely, all variables of \(\Psi\) are assumed to be independent and we employ a convenient conjugate and proper priors for the following parameters.\(^9\)

\(p(\alpha_j^i) \sim G(\alpha_j^i(1), \alpha_j^i(2))\), \(p(\beta_j^i) \sim G(\beta_j^i(1), \beta_j^i(2))\), \(p(\kappa_j^i) \sim N(\kappa_j^i(1), \kappa_j^i(2))\), \(p(\rho^i) \sim N(\rho_i, \sigma_i^2)\). \(I_{\{\lambda_j^i < \chi_i^i\}}\), \(p(\lambda_j^i) \sim N(\lambda_j^i(1), \lambda_j^i(2))I_{\{\lambda_j^i < \chi_i^i\}}\), \(\chi_i^i \sim N(\mu_i, \sigma_i^2)\), \(1_{\{\kappa_j^i < \chi_i^i\}}\), \(p(\sigma_j^i)^2 \sim IG(\nu_i^j, \nu_i^j)\). Let \(\rho_\omega^0 = (2(\rho_\omega^0)^* - 1)\), then the prior \((\rho_\omega^0)^*\) assumes to be the beta distribution, \(p((\rho_w^0)^*) \sim B(\rho_\mu, \rho_\mu^2)\). Similarly, define \(\rho_\omega^1 = (2(\rho_\omega^1)^* - 1)\), then we assume that \(p((\rho_w^0)^*) \sim B(\rho_\mu, \rho_\mu^2)\).

Following the conventional MCMC procedure, we sample \((L, \Psi)\) from the joint posterior distribution \(p(L, \Psi|Y)\) in (21). Monte Carlo simulation on \(p(L, \Psi|Y)\) using samples drawn from a Markov chain with invariant distribution \(p(L, \Psi|Y)\) is generally referred to as the MCMC method. Thus, the MCMC algorithm repeatedly samples from the posterior distributions to generate a Markov chain over \((L, \Psi)\), until convergence to the posterior distribution, \(p(L, \Psi|Y)\). In particular, we use the Gibbs sampler and the Metropolis-Hastings (MH) algorithm within the Gibbs sampler.\(^10\) To this intent, we derive the full conditional

---

\(^9\)The symbol \(N(a, b)\) denotes a normal distribution with mean \(a\) and variance \(b\). \(G\) and \(IG\) represent the gamma distribution and inverse gamma distribution, respectively and \(B\) indicates the beta distribution.

\(^10\)The Gibbs sampler is proposed in Geman and Geman (1987), Tanner and Wong (1987), Gelfand et al. (1990), Geweke (1996), and Geweke (1997). This method helps generate iterative samples from all the full conditional distributions. The Gibbs sampler reduces the problem of drawing samples from any multivariate distribution to that of drawing samples successively from multiple univariate distribution. Metropolis-
posteriors for the latent variables and unknown parameters. For notational ease, \( W^g_{-t} \) denotes \( W^g \) without \( w^g_t \). First, the full conditional density of the global latent factor, \( w^g_t \) is given by

\[
p(w^g_t | X, W^g_{-t}, \tilde{W}, Y, \Psi) \\
\propto \prod_{i=1}^{N} p(x^i_{c,t} | w^g_t, \tilde{w}^i_t, \Psi)p(x^i_{d,t} | w^g_t, \tilde{w}^i_t, \Psi)p(w^g_{t-1} | w^g_t, \Psi)p(w^g_{t+1} | w^g_t, \Psi) \\
\sim N(BA^{-1}, A^{-1})
\]

where \( A = \sum_{i} \left\{ \frac{(\lambda^{g,i}_{c})^2}{(\sigma^i_c)^2} + \frac{(\lambda^{g,i}_{d})^2}{(\sigma^i_d)^2} \right\} + (\rho^g_w)^2 + 1 \)

\[
B = \rho^g_w (w^g_{t-1} + w^g_{t+1}) + \sum_{i} \left\{ \frac{\lambda^{g,i}_{c}(x^i_{c,t} - \lambda^{g,i}_{c}w^g_t)}{(\sigma^i_c)^2} + \frac{\lambda^{g,i}_{d}(x^i_{d,t} - \lambda^{g,i}_{d}w^g_t)}{(\sigma^i_d)^2} \right\} \tag{22}
\]

The full conditional distribution of the country-specific latent factor for each country, \( \tilde{w}^i_t \) for \( i = 1, \ldots, N \) is given by

\[
p(\tilde{w}^i_t | X, \tilde{W}^i_{-t}, W^g, Y, \Psi) \\
\propto p(x^i_{c,t} | \tilde{w}^i_t, \Psi)p(x^i_{d,t} | \tilde{w}^i_t, \Psi)p(\tilde{w}^i_{t-1} | \tilde{w}^i_t, \Psi)p(\tilde{w}^i_{t+1} | \tilde{w}^i_t, \Psi) \\
\sim N(DC^{-1}, C^{-1})
\]

where \( C = \left\{ \frac{(\lambda^{i}_{c})^2}{(\sigma^i_c)^2} + \frac{(\lambda^{i}_{d})^2}{(\sigma^i_d)^2} \right\} + (\rho^i_w)^2 + 1 \)

\[
D = \rho^i_w (\tilde{w}^i_{t-1} + \tilde{w}^i_{t+1}) + \left\{ \frac{\lambda^{i}_{c}(x^i_{c,t} - \lambda^{g,i}_{c}w^g_t)}{(\sigma^i_c)^2} + \frac{\lambda^{i}_{d}(x^i_{d,t} - \lambda^{g,i}_{d}w^g_t)}{(\sigma^i_d)^2} \right\} \tag{23}
\]

Now, we can draw samples directly from (22) and (23). Next, the full conditional distribu-

Hastings (MH) algorithm is additionally used within the Gibbs sampler to construct a Markov chain. Chib and Greenberg (1995) provided a detailed account of the MH algorithm. However, the MH algorithm requires specifying candidate-generating distribution. For the choice of candidate-generating distributions, we follow the suggestion by Geweke and Tanizaki (2001). For the candidate density of the latent variables, we take the distributions obtained from the transition equation of our model. On the other hand, we take the proposal density as the prior distributions for the unknown parameters.
tion of the latent factors, \(x_{j,t}^i\) for \(j = c, d\) and \(i = 1, \ldots, N\) is written as

\[
p(x_{j,t}^i | \tilde{X}_{c,t}^i, W^g, \tilde{W}, Y, \Psi) \propto p(y_t^i | x_t^i, \Psi) p(x_{j,t}^i | \tilde{w}_t^i, w_t^q, \Psi)
\]

\[
\propto \text{det}(D_i^{\Sigma_i} D_i^T)^{-\frac{1}{2}} e^{xp(-\frac{(y_t^i - \tilde{D}_i^{\Sigma_i} D_i^T)(y_t^i)}{2} - \frac{(x_{j,t}^i - \chi_{j,t}^i(w_t^q + \chi_t^i w_t^q))^2}{2\sigma_j^2})}
\]

Instead of sampling from the conditional posterior distribution in (24), the MH algorithm is applied using \(p(x_{j,t}^i | \tilde{w}_t^i, w_t^q, \Psi)\) as a proposal density. The full conditional distribution of \(p_{w}^q\) is given by

\[
p(p_{w}^q | X, W^g, \tilde{W}, Y, \Psi_{-p_{w}^q}) \propto \prod_{t=1}^{T} p(w_t^q | w_{t-1}^q, \Psi)p(p_{w}^q)
\]

\[
\propto N(FE^{-1}, E^{-1})p(p_{w}^q),
\]

where \(E = \sum_{t=2}^{T}(w_{t-1}^q)^2\), and \(F = \sum_{t=2}^{T} w_t^q w_{t-1}^q\). For the same reason of sampling issues, we use the MH algorithm using \(N(FE^{-1}, E^{-1})\) as the candidate-generating density. For \(p_{w}^q\) for \(i = 1, \ldots, N\), the full conditional posterior is given by

\[
p(p_{w}^q | X, W^g, \tilde{W}, Y, \Psi_{-p_{w}^q}) \propto \prod_{t=1}^{T} p(\tilde{w}_t^i | \tilde{w}_{t-1}^i, \Psi)p(p_{w}^q)
\]

\[
\propto N(HG^{-1}, G^{-1})p(p_{w}^q),
\]

where \(G = (\sum_{t=2}^{T}(\tilde{w}_{t-1}^i)^2)\), and \(H = (\sum_{t=2}^{T} \tilde{w}_t^i \tilde{w}_{t-1}^i)\) and the MH algorithm is applied using \(N(HG^{-1}, G^{-1})\) as a proposal density. The full conditional density of \(\chi_i^t\) for \(i = 1, \ldots, N\) is given by

\[
p(\chi_i^t | X, W^g, \tilde{W}, Y, \Psi_{-\chi_i}) \propto \prod_{t=1}^{T} p(x_{c,t}^i | \tilde{w}_t^i, w_t^q, \Psi)p(x_{d,t}^i | \tilde{w}_t^i, w_t^q, \Psi)p(\chi_i^t)
\]

\[
\propto N(JI^{-1}, I^{-1})I_{\{0 < \chi_i\}}
\]

where

\[
J = \sum_{t=1}^{T}(\frac{\lambda_t^c w_t^q}{\sigma_c^2})^2 + \frac{\sum_{t=1}^{T}(\lambda_t^d w_t^q)^2}{\sigma_d^2} + \frac{1}{\sigma_{\chi_t}^2}
\]

\[
I = \sum_{t=1}^{T}(\frac{\lambda_t^c w_t^q}{\sigma_c^2})^2 + \frac{\sum_{t=1}^{T}(\lambda_t^d w_t^q)^2}{\sigma_d^2}
\]

\[
\frac{\sum_{t=1}^{T}(\lambda_t^c w_t^q)(x_{c,t}^i - \lambda_t^c \tilde{w}_t^i)}{\sigma_c^2} + \frac{\sum_{t=1}^{T}(\lambda_t^d w_t^q)(x_{d,t}^i - \lambda_t^d \tilde{w}_t^i)}{\sigma_d^2} + \frac{\pi(\chi_i^t)}{\sigma_{\chi_t}^2}.
Denote \( w_i^t = (\bar{w}_i^t + \chi^i w_i^0) \) and the full conditional posterior of \( \lambda_j^i \) and \( (\sigma_j^i)^2 \) for \( j = c, d \) and \( i = 1, \ldots, N \) are given by

\[
p(\lambda_j^i | X, W^g, \tilde{W}, Y, \Psi_{-\lambda_j^i}) \propto \prod_{t=1}^{T} p(x_{j,t}^i | w_i^t, \Psi) p(\lambda_j^i)
\]

\[
\propto N(LK^{-1}, K^{-1})I_{\{0<\lambda_j^i\}}
\]

where \( K = \sum_{t=1}^{T} (w_i^t)^2 / (\sigma_j^i)^2 \), \( L = \sum_{t=1}^{T} (x_{j,t}^i)^2 w_i^t / (\sigma_j^i)^2 \),

\[
p((\sigma_j^i)^2 | X, W^g, \tilde{W}, Y, \Psi_{-\sigma_j^i}) \propto \prod_{t=1}^{T} p(y_i^t | x_{i,t}^i, \Psi) p((\sigma_j^i)^2)
\]

\[
\propto IG(T/2 + \nu_{ij}, 1/2) \sum_{t=1}^{T} (x_{j,t}^i - \lambda_j^i (\bar{w}_i^t + \gamma^i w_i^0))^2 + \nu_{ij}^2)
\]

We can draw samples using (27)~(29). The full conditional distributions of \( \alpha_j^i, \beta_j^i \) and \( \kappa_j^i \) for \( j = c, d \) and \( i = 1, \ldots, N \) are given by

\[
p(\alpha_j^i | X, W^g, \tilde{W}, Y, \Psi_{-\alpha_j^i}) \propto \prod_{t=1}^{T} p(y_i^t | x_{i,t}^i, \Psi) p(\alpha_j^i)
\]

\[
= \prod_{t=1}^{T} \frac{1}{\sqrt{2\pi}} \det(D_i^t \Sigma^i D_i^t) \frac{1}{2} \exp\left(-\frac{(y_i^t - (D_i^t \Sigma^i D_i^t)^{-1}y_i^t)^2}{2}\right) p(\alpha_j^i)
\]

(30)

\[
p(\beta_j^i | X, W^g, \tilde{W}, Y, \Psi_{-\beta_j^i}) \propto \prod_{t=1}^{T} p(y_i^t | x_{i,t}^i, \Psi) p(\beta_j^i)
\]

(31)

\[
p(\kappa_j^i | X, W^g, \tilde{W}, Y, \Psi_{-\kappa_j^i}) \propto \prod_{t=1}^{T} p(y_i^t | x_{i,t}^i, \Psi) p(\kappa_j^i)
\]

(32)

Similarly, the conditional posterior of \( \rho^i \) for \( i = 1, \ldots, N \) is

\[
p(\rho^i | X, W^g, \tilde{W}, Y, \Psi_{-\rho^i}) \propto \prod_{t=1}^{T} p(y_i^t | x_{i,t}^i, \Psi) p(\rho^i)
\]

(33)
For the sampling of the full conditional density (30)\textendash(33), we apply the MH algorithm using their prior distributions as the candidate-generating density. In sum, the Gibbs sampler is employed to generate a Markov chain whose stationary distribution is the joint posterior distribution (21), and it works as follows in the first step. Given the initialization \((\Psi^0, L^0)\), we draw from each of the full conditional distributions derived above for \(j = c, d, i = 1, ..., N\) and \(t = 1, ..., T\):

1. Sample \(x_{j,t}^i\) from \(p(x_{j,t}^i|X_{-j,t}^i, W^g, \tilde{W}, Y, \Psi)\)
2. Sample \(w_t^g\) from \(p(w_t^g|X, W_{-t}^g, \tilde{W}, Y, \Psi)\)
3. Sample \(\tilde{w}_t^i\) from \(p(\tilde{w}_t^i|X, W^g, \tilde{W}_t^i, Y, \Psi)\)
4. Sample \(\rho_{0i}^g\) from \(p(\rho_{0i}^g|X, W^g, \tilde{W}, Y, \Psi_{-\rho_{0i}^g})\)
5. Sample \(\rho_{0i}^d\) from \(p(\rho_{0i}^d|X, W^g, \tilde{W}, Y, \Psi_{-\rho_{0i}^d})\)
6. Sample \(\alpha_j^i\) from \(p(\alpha_j^i|X, W^g, \tilde{W}, Y, \Psi_{-\alpha_j^i})\)
7. Sample \(\beta_j^i\) from \(p(\beta_j^i|X, W^g, \tilde{W}, Y, \Psi_{-\beta_j^i})\)
8. Sample \(\kappa_j^i\) from \(p(\kappa_j^i|X, W^g, \tilde{W}, Y, \Psi_{-\kappa_j^i})\)
9. Sample \(\chi_i^j\) from \(p(\chi_i^j|X, W^g, \tilde{W}, Y, \Psi_{-\chi_i^j})\)
10. Sample \(\lambda_j^i\) from \(p(\lambda_j^i|X, W^g, \tilde{W}, Y, \Psi_{-\lambda_j^i})\)
11. Sample \(\rho^i\) from \(p(\rho^i|X, W^g, \tilde{W}, Y, \Psi_{-\rho^i})\)
12. Sample \((\sigma_j^i)^2\) from \(p((\sigma_j^i)^2|X, W^g, \tilde{W}, Y, \Psi_{-\sigma_j^i})\). Then, go to 1.

The procedure is iterated for a large number of times until convergence. To ensure that the sample is drawn from the stationary distribution, all the results for all the parameters reported in this paper are based on samples which have passed the convergence diagnostic proposed by Geweke (1992).

4.2 GMM within Gibbs Sampling

To evaluate the empirical plausibility of an asset pricing model, Hansen and Singleton (1982b) used the GMM. This approach provides a convenient way to impose the model restrictions on asset payoffs and uses only the moment conditions derived from the Euler equation without additional assumptions on the probability distribution. However, the moment condition based on the Euler equation of our asset pricing model depends on the parameters and latent variables of the stochastic volatilities. Namely, the values of parameters and latent factors determine the identification of the preference parameters in the GMM estimation. Therefore, we extend a Bayesian MCMC method combining with...
the GMM criterion to exploit our asset pricing Euler equations. To fix this idea, let $L$ a number of available observations ($N \times T$) and the GMM object function is defined as

$$J_L = \left( \frac{1}{L} \sum_{t=1}^{L} \Omega_t(\omega) \right) W_L(\omega) \left( \frac{1}{L} \sum_{t=1}^{L} \Omega_t(\omega) \right)$$

(34)

where $\Omega_t(\omega)$ is a moment condition based on the Euler equation and $\omega = (\gamma, \psi)$ is a vector of preference parameters, and $W_L$ is a weighting function. The object function is to be minimized for GMM estimation. Now, we outline the procedure for the Bayesian MCMC method combining with the GMM estimation. Using the MCMC procedure developed in previous section, we have a sample of the volatilities. At each iteration, we construct the object function (34), and find the parameter estimates using GMM estimation. Then we save preference parameters estimates. In this step, it is worth noting that we only collect the sample draws of the parameters and latent factors in stochastic volatilities and the preference parameters when we can obtain the sample of the preference parameters in the GMM criterion. If the preference parameters cannot be identified given observable data and latent factors and parameters in stochastic volatilities, we set the values of the parameter and latent variables at the previous iteration. This procedure can be interpreted as naturally imposing the restrictions to identify the preference parameters in the model.

5 Quantitative Analysis

Based on the econometric method developed in the previous section, we estimate and simulate the model and explain our empirical findings.

5.1 Data

To estimate global economic uncertainties, we use the data for Australia, Canada, the United Kingdom, and the United States between January 1970 and December 2012. For the aggregate consumption, we use the quarterly real consumption of nondurables plus services for the UK and the USA and quarterly real consumption expenditure for Australia and Canada. The consumption data for Australia, Canada and the USA are obtained from the Federal Reserve Bank of St. Louis, and the consumption data for the UK is from Datastream. For the aggregate dividend data, we first obtain the dividend yield, which is calculated as $DY(t) = [RI(t)/RI(t-1)]/[PI(t)/PI(t-1)] - 1$ where $PI$ is MSCI Price
Index and RI is MSCI Total Return Index for each country, which are from Datastream. From this, the dividend for each month is calculated by $D(t) = DY(t) \times PI(t)$. The dividend for a quarter is the sum of the dividends for the three months comprising the quarter. Thus, the real dividend for a quarter is $RD(t) = D(t)/CPI(t)$ where $CPI(t)$ is the quarterly consumer price index which is from the Federal Reserve Bank of St. Louis. All consumption and dividend are seasonally adjusted and expressed as per capita\textsuperscript{11}.

To obtain the real market return $r_s$, we use the MSCI Price index and CPI from 1970 to 2012\textsuperscript{12}. For the real risk-free rates $(r_f)$, 3-month Treasury Bill(TB) rates for the UK and USA are used and the government bond rates and the government securities T-Bill rates are employed for Australia and Canada respectively. All interest rates come from webpages of the Federal Reserve Bank of St. Louis. CPI also used for real rates. Then, the real excess market return is defined by $r_s - r_f$. Table 1 displays summary statistics of the data described above. All four countries have comparable numbers for consumption and dividend growths, the short-term interest rates, and the market equity returns, and summary statistics are consistent with the related literature such as Campbell (2003).

### 5.2 Estimation Results

Table 2 reports the estimated parameters with standard errors.\textsuperscript{13} All the country-specific parameters in the upper panel determine the consumption and dividend growth rates for each country, in particular the stochastic volatility functions up to the latent uncertainty-generating factors. The lower panel reports the preference parameters ($\gamma$ and $\psi$) and the persistence of the global uncertainty factor ($\rho_g^u$).

While our paper focuses on the estimating uncertainty factors relative to a macroeconomic asset pricing model, the estimates of the model shed light on the identification of several deep parameters. Because these parameters are frequently used in macroeconomic and macro-finance papers, estimating models with recursive preferences is a critical research

\textsuperscript{11}The annual population data is only available. Therefore, the quarterly values are interpolated by assuming a constant growth rate for each year.

\textsuperscript{12}The real market returns $(r_s)$ is calculated as follow.

$$r_s = \log\left(\frac{MSPI_t + D_t}{CPI_t}\right) - \log\left(\frac{MSPI_{t-1} + D_{t-1}}{CPI_{t-1}}\right)$$

where $D$ and $MSPI$ indicate the dividend and MSCI Price index respectively.

\textsuperscript{13}All of the estimated parameters have the absolute values of Geweke (1992)'s convergence diagnostic less than 2. Thus together with standard errors, our estimation results are reliable and significant. Convergence diagnostics and the MCMC sample paths are available upon request.
Figure 1: Conditional Variance of Consumption Growths as a Function of Uncertainty

This figure displays the volatility function of consumption growth implied by the logistic volatility model using the estimated parameters. The conditional volatility function is denoted as $f(x)$. The horizontal axis represents the values of the volatility latent factor, $x$, and the thick solid line represents the USA, the thin solid line refers to the UK, the dotted line is for Canada, and the dashed line refers to Australia.

agenda. First, the long-run risk persistence parameters ($\rho_v^c$ and $\rho_v^d$) are highly persistent, estimated around 0.99, consistent with the prior studies. In addition, all other persistence parameters for uncertainty factors are persistent as well, estimated around 0.97. Thus, the first and second moments of the macroeconomic variables are slow-moving and subject to long-term fluctuations. In this case, preferences in favor of uncertainty resolution can produce a large risk premium, as discussed earlier. Indeed, our risk aversion parameter ($\gamma$) is significantly estimated around 1.73. This is a reasonable and sensible value. Regarding the EIS parameter, it is estimated around 7.37 with a $t$-statistics of 1.47. The weak identification problem of the EIS parameter is well known. Previous literature report a wide range of estimates from a value close to 0 to a very large number around 25.\textsuperscript{14} While we add little in this aspect, we verify how different combinations of preference parameters affect the performance of the model, we simulate it with different sets of parameters and compare the results, quantitatively.

The estimated RRA is greater than the reciprocal of the EIS, implying that the early resolution of uncertainty is preferred. Thus, our model is going to produce a large premium for taking slowly-moving uncertainty risks, which is further amplified as the volatility of

\textsuperscript{14}Regarding the estimation of the EIS parameter, readers are referred to Yogo (2004), Kim et al. (2010), Brown and Kim (2013), Chen et al. (2013), and Jeong et al. (2015).
This figure displays the volatility of volatility function implied by the logistic volatility function using the estimated parameters. The volatility of the conditional variance of consumption growth is derived as the differential of \( f_c(x) \) in (11), and it is denoted as \( f'(x) \). The horizontal axis represents the values of the volatility latent factor, \( x \). Thick solid line represents the USA, the thin solid line refers to the UK, the dotted line is for Canada, and the dashed line refers to Australia.

Volatility is going to become larger during transition periods. Figure 1 draws the estimated volatility function, and Figure 2 displays the implied volatility of volatility function. The result shows that not only the levels of macroeconomic volatility regimes differ substantially across countries, but also the speed of transitions vary substantially. In case of the US economy, the consumption volatility function is much lower than those of other countries, hence one can infer that the degree of the equity premium puzzle and the risk-free puzzle is more severe. However, Figure 2 suggests that the macroeconomic uncertainty evolves slowly and peaks around a small value. Other countries, especially Australia and Canada have much steeper and pronounced transitions from the low to the high asymptotes. Thus, for these countries, a two-regime model can be a good approximation, and the UK is in the middle of the pack. In terms of the parameters, \( \alpha \), \( \beta \) set the height of differences in volatility regimes, and \( \lambda \) parameters are responsible for the speed of uncertainty in transitions more directly.

Our paper investigates whether such shared uncertainties exist across countries, and if so, how capable this can be in producing globally uncertain events and the resultant premiums in financial markets. The estimation results are reminiscent of hurricane season. A weak hurricane, such as a low-numbered category hurricane, often results in much more...
and prolonged damages to affected regions due to heavy and never-ending rainfalls and other related subsequent disasters. Slow-moving, small but increasing uncertainty can produce equally large risk premiums as the one with large and more abrupt changes.

5.3 Does Global Uncertainty Matter?

Tables 3 reports the simulation results with the corresponding data. For simulation procedure, we use the method from Bansal and Yaron (2004) and Kim et al. (2010) that numerically solves the model. Panel A of Table 3 shows the mean and the standard deviation of consumption and dividend growth rates, and Panel B refers to the same statistical moments for the risk-free rate and the stock market returns. It is clear that the model successfully generates the stylized facts of the four countries studied. To investigate how preference parameters affect the simulation results, we check various specifications with the risk aversion parameters ranging between 1.2 and 5 as well as the elasticity of intertemporal substitution between 1.5 and 25, and we find that the results are as expected. We report all the results in our online appendix.

One of the advantages of our approach is the explicit estimation of both common and idiosyncratic risk and uncertainty factors, together with model parameters. Figure 3 to Figure 6 depict the time-series of filtered risk and uncertainty factors. Figure 3 displays the estimated long-run risk factors of consumption and dividend growths for each country. Unlike Bansal et al. (2008), we estimate the long-run risk factors exploiting the statistical fact that the growth processes netting out the long-run risk factors should follow martingale difference equations. The optimally selected HP penalty values are reported in the figure. The estimated long-run risk factors have weak positive correlations between consumption and dividend growths for Australia and Canada, and a strong positive correlation for the UK, and a counterfactually negative correlation in case of the US economy. Thus, the persistence of the risk factor is confirmed, but weak and possibly reversed are the degrees of co-movement to generate enough covariance between the stochastic discount factor and the equity returns. Across the countries, the extent to which the long-run risk factors fluctuate in tandem appear rather weak as well.

Our main channel of slow-moving risk/uncertainty lies in the globally common factor that simultaneously affect consumption and dividend growths for all the countries. Figure 4 plots the historical sample path of this global uncertainty common factor, $w_9$ on top of
Figure 3: Estimated Long-Run Risk Factors: $\hat{\nu}_{c,t}$ and $\hat{\nu}_{d,t}$

This figure shows the estimated long-run risk factors of consumption and dividend growths ($\Delta c, \Delta d$) together for each country. The solid line refers to consumption, and the dotted line represents the dividend growth rate. To estimate those, we use the Hodrick-Prescott method, exploiting the fact that consumption and dividend growth processes become martingale difference sequence, once netting out the conditional mean components ($\nu$). In the below, we report the value endogenously chosen. We also report the sample correlations between $\nu_c$ and $\nu_d$ in the below.

<table>
<thead>
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<th>US</th>
<th>UK</th>
<th>AUS</th>
<th>CAN</th>
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<td>129600</td>
<td>107600</td>
</tr>
<tr>
<td>HP penalty for $\Delta d$</td>
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<td>129600</td>
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<td>129600</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Correlations between $\nu_{c,t}$ and $\nu_{d,t}$</th>
<th>US</th>
<th>UK</th>
<th>AUS</th>
<th>CAN</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Corr}(\hat{\nu}<em>{c,t}, \hat{\nu}</em>{d,t})$</td>
<td>-0.3282</td>
<td>0.6449</td>
<td>0.0917</td>
<td>0.0034</td>
</tr>
</tbody>
</table>
Figure 4: Global Economic Uncertainty

This figure plots the estimated time-series of the global economic uncertainty factor together with globally adverse economic and political events. The solid line shows the estimated global uncertainty common factor, $w^g_t$, and the shaded areas denote major events including the global recession and global financial crisis period defined in Tables 4 and 5.

The shaded areas denoting major events including the global recession and global financial crisis period, which are recorded in Tables 4 and 5. First, the extracted global uncertainty generating factor stays relatively high during the 1973 oil crisis and 1973-1974 stock market crash, which contributed to the recession of U.S. and United Kingdom. And also the global uncertainty factor reaches its local peak during the 1979 oil shock, and 1987 Black Monday. During the early 1980s recession and early 2000s recession period including dot-com bubble, and the September 11 attacks of 2001, the global volatility factor also stays high. The trend of the estimated global uncertainty common factor steadily decreased until early 1990s, then shoot up since 1995. For instance, the 1994-1995 peso crisis period is well matched with local peaks of the global uncertainty common factor and during the 1997-1998 Asian financial crisis it increases sharply. In addition, the high estimated global common volatility factor is well matched the period of the 2007-2009 global financial crisis.

Figure 5 plots the uncertainty-generating factor that is specific to each country. That is, it is the common volatility factor to consumption and dividend growths, yet idiosyncratic.

In particular, Table 4 lists major economic events between 1970 and 2012, and Table 5 refers to economic recessions of the four countries respectively. Several existing studies were referenced and compared to appropriately select economic events and the correct period.
Figure 5: Country-Specific Uncertainty Generating Process

This figure plots the estimated time-series of the estimated country-specific macroeconomic volatility factor ($\tilde{w}_t$) of the stochastic volatility model for all countries, Australia, Canada, UK and USA, and the factor structure is defined in equations (6), (7) and (9).
Figure 6: Estimated Volatility Factors for Each Country

The figure displays the estimated volatility factors for each country for comparison. The thick line represents the estimated the common global macroeconomic volatility factor \( w^g_t \), defined in (6), (7) and (8). Note that \( \chi^i w^g_t + \tilde{w}^i_t = w^i_t \), then the line indicates the estimated \( w^i_t \) for each country. The dotted line and the dashed line show the estimated latent volatility factors of the consumption and dividend growth rates for each country \( x^i_{ct} \) and \( x^i_{dt} \) given in (6) and (7) respectively.
in terms of countries. All countries have heterogeneous peaks in their time series, and the
countries differ in timings of the rise and fall of the country-specific macroeconomic uncer-
tainty. Figure 6 displays all the estimated volatility factors for each country to highlight
the fact that there exist both common and idiosyncratic fluctuations in consumption and
dividend growth rates for each country.

Projecting macro volatilities onto those purely coming from the global uncertainty factor,
Table 6 Panel A reports the results for consumption volatility, Table 6 Panel B refers to
the result for dividend volatility. In case of the consumption volatility, the adjusted $R^2$
values are quite high Australia and the UK, followed by Canada and the USA. Thus, the US
consumption volatility appears more influenced by the country-specific factor. On the other
hand, for the dividend volatility, the opposite is true. The global uncertainty factor affects
the US economy the most, followed by the UK and Canada. Australian stock market is more
idiosyncratic in this regard. However, in sum, our global uncertainty factor plays significant
roles in explaining the volatilities of both consumption and dividend growth for all the
countries and the statistical moments of the key asset prices. Finally, an important condition
for a good measure of risk and uncertainty would be that the measures should be closely
associated with actual economic, financial, and political events. In particular, it is desirable
if changes to risk and uncertainty measures have high and significant correlations with a
broad range of economic, financial, and political events. Previously, Figure 4 shows some
potential in this regard, but analytical investigation is useful. Related, several measures
of economic and political uncertainty become available recently, and we can compare our
global uncertainty factor ($w_g$) with some of the well-known measures.

Among others, the most popular measure is the Chicago Board Options Exchange
Volatility Index (VIX) that computes the implied volatility of S&P 500 index options,
and closely related VXO measure refers to the CBOE S&P 100 Volatility Index. Another
frequently used measure is the Global Economic Policy Uncertainty (GEPU) Index by Davis
(2016).

Regarding an uncertainty index emphasizing the role of financial condition is the Federal
Reserve Bank of Chicago’s National Financial Conditions Index (NFCI) downloaded from
the Federal Reserve Bank of St. Louis. Figure 7 plots the historical paths of the above
variables together with the global uncertainty factor $w_g$ over the available time periods for
each measure. They are positively correlated, even from casual observation, and Table 7
confirms that our global uncertainty factor is significantly and positively correlated to the
Figure 7: Alternative Uncertainty Measures versus Global Economic Uncertainty Factor, $u^g_t$

This figure compares the global economic uncertainty factor with other uncertainty measures. The solid line in the left figure of the top panel depicts the VIX. The solid line in the right figure of the top panel indicates the VXO. The solid line in the left figure of the bottom panel shows the GEPU Index. The solid line in the right figure of the bottom panel indicates the NFCI. The dotted line in the figures represents the estimated global economic uncertainty factor ($u^g_t$).

alternative uncertainty measures. Correlation values are between 0.2 and 0.335, suggesting that each measures have significant degree of idiosyncratic variations.

If there exist changes in the value of these uncertainty measures, does it increase the likelihood of major global economic events? Previously, Tables 4 and 5 define these events, and we run several regressions with a limited-dependent variable onto changes in the economic and political uncertainty proxies. Table 8 reports the results when global economic and political events do not include economic recessions, and Table 9 include economic recessions as well.

Empirical results are quite striking. Shocks to our global uncertainty factor significantly increase the probability of such global events by 15 to 20 percent, based on the linear probability models, and both the probit and logit results show equally significant results with the values of $R^2$ up to 8.4 percents. All other uncertainty measures, however, show
insignificant results in explaining the marginal effect on the likelihood of major economic events around the globe. The uncertainty measures have shown good performances in measuring the degree of fear or deteriorating economic and financial conditions. On the other hand, our uncertainty measure is extracted from an economic model that reflects the essential feature of economic uncertainty. Theoretical structure imposed in the model may help and improve the performance in capturing the out-of-sample events in the cross-sectional sense. We believe that our econometric approach and the resulting uncertainty measure can be highly useful in understanding the nature of economic uncertainty and related consequences.

6 Conclusion

This paper proposes a new method to measure global economic uncertainty, using a consumption-based asset pricing model. Conventional statistical approaches focus on how to select useful signals from many related variables so that an index can be formed. We follow the spirit of extracting common factors from multiple variables, yet we emphasize the role of economic models to disentangle uncertainty-generating factors from other risks and related preferences. The estimated global uncertainty factor outperforms other uncertainty measures in that global economic and political events are significantly associated with the fluctuations of aggregate consumption and dividend volatilities.

References


Table 1: Summary Statistics

This table reports summary statistics of the variables used in the paper. $\Delta c$ and $\Delta d$ refer to consumption growth and dividend growth rates respectively, $r_s$ and $r_f$ stand for equity returns and the risk-free short-term interest rate respectively. $E(\cdot)$ is the expectation operator, and $\sigma(\cdot)$ is the volatility operator. Sample analogues are reported. Data series are at quarterly frequency and annualized. The second column to the fifth column represent the statistics for Australia, Canada, UK, and USA, respectively. The consumption of nondurables plus services for UK and USA and the consumption expenditure for Australia and Canada are used. The consumption data for Australia, Canada and USA are obtained from the Federal Reserve Bank of St. Louis and the consumption data for UK is from Datastream. For the dividend data, MSCI Price Index and MSCI Total Return Index for each country are used, obtained from Datastream. The consumption and the dividend are all expressed as real per capita. To calculate the equity returns $r_s$, we use MSCI Price Index for each country. For $r_f$, 3 month Treasury Bill(TB) rates for UK and USA are used and the government bond rates and the government securities TB rates are employed for Australia and Canada respectively. CPI data are also used to compute the real interest rates. All interest rates series come from the Federal Reserve Bank of St. Louis. All data period covers between 1970 and 2012.

<table>
<thead>
<tr>
<th></th>
<th>Australia</th>
<th>Canada</th>
<th>UK</th>
<th>USA</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E(\Delta c)$</td>
<td>0.01768</td>
<td>0.01868</td>
<td>0.02176</td>
<td>0.01768</td>
</tr>
<tr>
<td>$\sigma(\Delta c)$</td>
<td>0.02043</td>
<td>0.01566</td>
<td>0.02080</td>
<td>0.00888</td>
</tr>
<tr>
<td>$E(\Delta d)$</td>
<td>0.00539</td>
<td>0.00512</td>
<td>0.00616</td>
<td>0.00076</td>
</tr>
<tr>
<td>$\sigma(\Delta d)$</td>
<td>0.31226</td>
<td>0.09470</td>
<td>0.16670</td>
<td>0.06038</td>
</tr>
<tr>
<td>$E(r_s)$</td>
<td>0.06037</td>
<td>0.06632</td>
<td>0.07151</td>
<td>0.06570</td>
</tr>
<tr>
<td>$\sigma(r_s)$</td>
<td>0.19614</td>
<td>0.17443</td>
<td>0.20428</td>
<td>0.17142</td>
</tr>
<tr>
<td>$E(r_f)$</td>
<td>0.03116</td>
<td>0.02231</td>
<td>0.01619</td>
<td>0.01002</td>
</tr>
<tr>
<td>$\sigma(r_f)$</td>
<td>0.02146</td>
<td>0.01729</td>
<td>0.02715</td>
<td>0.01428</td>
</tr>
<tr>
<td>$E(r_s - r_f)$</td>
<td>0.02922</td>
<td>0.04401</td>
<td>0.05532</td>
<td>0.05568</td>
</tr>
</tbody>
</table>
Table 2: **Model Estimation Results** This table reports the estimation results of the global macroeconomic asset pricing model with uncertainty described in the paper. Each column presents parameter estimates for Australia (AUS), Canada (CAN), the United Kingdom (UK), and the United State of America (USA), respectively. A Bayesian estimation procedure is simultaneously used with General Method of Moment estimation to implement a Markov-Chain-Monte-Carlo (MCMC) method.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>AUS</th>
<th>CAN</th>
<th>UK</th>
<th>USA</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_c$</td>
<td>0.000016 (0.000011)</td>
<td>0.000011 (0.000010)</td>
<td>0.000011 (0.000010)</td>
<td>0.000002 (0.000001)</td>
</tr>
<tr>
<td>$\beta_c$</td>
<td>0.000202 (0.000046)</td>
<td>0.000093 (0.000023)</td>
<td>0.00186 (0.00033)</td>
<td>0.00039 (0.00012)</td>
</tr>
<tr>
<td>$\kappa_c$</td>
<td>$-0.0100$ (0.0001)</td>
<td>$-0.0999$ (0.0100)</td>
<td>$-0.0999$ (0.0100)</td>
<td>$1.9999$ (0.0100)</td>
</tr>
<tr>
<td>$\lambda_c$</td>
<td>0.1966 (0.0200)</td>
<td>0.0364 (0.0338)</td>
<td>0.0741 (0.0435)</td>
<td>0.0055 (0.0055)</td>
</tr>
<tr>
<td>$\sigma_c$</td>
<td>0.9404 (0.4521)</td>
<td>1.0225 (0.5080)</td>
<td>1.1208 (0.4790)</td>
<td>1.3395 (0.6695)</td>
</tr>
<tr>
<td>$\rho_c$</td>
<td>0.9995 (0.0031)</td>
<td>0.9993 (0.0168)</td>
<td>0.9995 (0.0329)</td>
<td>0.9775 (0.0047)</td>
</tr>
<tr>
<td>$\alpha_d$</td>
<td>0.001398 (0.000316)</td>
<td>0.000326 (0.000102)</td>
<td>0.000207 (0.000066)</td>
<td>0.000103 (0.000026)</td>
</tr>
<tr>
<td>$\beta_d$</td>
<td>0.3584 (0.1411)</td>
<td>0.0084 (0.0037)</td>
<td>0.0418 (0.0126)</td>
<td>0.0055 (0.0055)</td>
</tr>
<tr>
<td>$\kappa_d$</td>
<td>6.5325 (1.6004)</td>
<td>2.2239 (1.7374)</td>
<td>3.5812 (1.5483)</td>
<td>2.1709 (1.7032)</td>
</tr>
<tr>
<td>$\lambda_d$</td>
<td>0.7771 (0.2656)</td>
<td>0.8113 (0.2947)</td>
<td>0.8777 (0.2625)</td>
<td>0.5583 (0.3034)</td>
</tr>
<tr>
<td>$\sigma_d$</td>
<td>1.3557 (0.6155)</td>
<td>1.0717 (0.5385)</td>
<td>1.0421 (0.3967)</td>
<td>0.9489 (0.4280)</td>
</tr>
<tr>
<td>$\rho_d$</td>
<td>0.9996 (0.05918)</td>
<td>0.9997 (0.003911)</td>
<td>0.9994 (0.00902)</td>
<td>0.9976 (0.01985)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.0443 (0.0785)</td>
<td>0.1206 (0.0787)</td>
<td>0.0005 (0.0800)</td>
<td>0.0651 (0.0797)</td>
</tr>
<tr>
<td>$\chi$</td>
<td>2.2321 (0.7867)</td>
<td>1.7976 (0.8842)</td>
<td>1.9495 (0.7572)</td>
<td>3.1178 (0.8655)</td>
</tr>
<tr>
<td>$\rho_{\omega}$</td>
<td>0.9694 (0.0277)</td>
<td>0.9770 (0.0212)</td>
<td>0.9771 (0.0208)</td>
<td>0.9762 (0.0237)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Preferences and Global Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_{\omega}$</td>
</tr>
<tr>
<td>$\gamma$</td>
</tr>
<tr>
<td>$\psi$</td>
</tr>
</tbody>
</table>
Table 3: **Simulation versus Data** This table reports the key moments of the variables of interest generated by simulating the model using the estimated parameters in comparison with the actual sample moments from the data. Panel A displays the results for consumption growth and dividend growth rates at quarterly frequency, and Panel B shows the results for the asset pricing moments at annual frequency. The statistics for the model are based on 1000 simulations using the parameter estimates obtained from the global macroeconomic asset pricing model with uncertainty described in the paper.

<table>
<thead>
<tr>
<th>Panel A</th>
<th>Consumption Growth</th>
<th>Dividend Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data</td>
<td>Model</td>
</tr>
<tr>
<td>Australia</td>
<td>Mean 0.00442</td>
<td>0.00441</td>
</tr>
<tr>
<td></td>
<td>Std 0.01022</td>
<td>0.01078</td>
</tr>
<tr>
<td>Canada</td>
<td>Mean 0.00467</td>
<td>0.00467</td>
</tr>
<tr>
<td></td>
<td>Std 0.00783</td>
<td>0.00773</td>
</tr>
<tr>
<td>UK</td>
<td>Mean 0.00544</td>
<td>0.00545</td>
</tr>
<tr>
<td></td>
<td>Std 0.01040</td>
<td>0.01036</td>
</tr>
<tr>
<td>USA</td>
<td>Mean 0.00442</td>
<td>0.00443</td>
</tr>
<tr>
<td></td>
<td>Std 0.00444</td>
<td>0.00416</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B</th>
<th>Asset Prices</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>E($r_f$)</td>
</tr>
<tr>
<td>Data</td>
<td></td>
</tr>
<tr>
<td>Australia</td>
<td>0.03116</td>
</tr>
<tr>
<td>Canada</td>
<td>0.02231</td>
</tr>
<tr>
<td>UK</td>
<td>0.01619</td>
</tr>
<tr>
<td>USA</td>
<td>0.01002</td>
</tr>
</tbody>
</table>

| Model   |              |              |          |              |                |
|         | E($r_f$)     | $\sigma(r_f)$ | E($r_s$) | $\sigma(r_s)$ | E($r_s - r_f$) |
| Australia | 0.01854    | 0.00074      | 0.05398  | 0.07673      | 0.03544        |
| Canada  | 0.01779    | 0.00059      | 0.05960  | 0.10777      | 0.04181        |
| UK      | 0.01668    | 0.00099      | 0.07405  | 0.20663      | 0.05737        |
| USA     | 0.01828    | 0.00170      | 0.06328  | 0.10664      | 0.04500        |
Table 4: **Adverse Global Economic and Political Events and Shocks** This table reports the list of adverse global economic and political events and shocks with the duration of period recorded in media and prior studies. The first column shows the beginning quarter and the end quarter of the period of each event, and the second column labels and describes individual events. The total period covered is from 1970 to 2012. The period of the first oil shock (1973-1974) and the second oil shocks (1979) is based on Corbett (2013) and Graefe (2013). The period of the Mexican peso crisis (1994-1995) is defined from December 1995 to January 1996, which is based on Cole and Kehoe (1996) and Whitt Jr (1996). The Asian financial crisis clearly began in summer 1997 with the initial devaluation of Thailand. However, there is no agreement on when the crisis ended. In this study, the period of the Asian financial crisis including Russian currency crisis and Brazil’s devaluation is defined from July 1997 to January 1999, which is based on Baig and Goldfajn (1999), Chiodo and Owyang (2002), Johnson et al. (2000), and Caporale et al. (2005). The global financial crisis can be defined from August 2007 until March 2009. The choice of the global financial crisis period is based on official time lines provided by Federal Reserve Board of Governors and the Bank for International Settlements (BIS (2009)) among others.

<table>
<thead>
<tr>
<th>Period</th>
<th>Economic Events or shocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1973Q4-1974Q1</td>
<td>1973.10-1974.1 1st Oil shock</td>
</tr>
<tr>
<td>1979Q1-1979Q4</td>
<td>1979 2nd Oil shock</td>
</tr>
<tr>
<td>1987Q4</td>
<td>Black monday, 1987.10.19</td>
</tr>
<tr>
<td>1997Q3-1999Q1</td>
<td>1997.7-1999.1 Asian financial crisis</td>
</tr>
<tr>
<td></td>
<td>including Russian financial crisis and Brazil’s devaluation</td>
</tr>
<tr>
<td>2001Q3</td>
<td>2001. 9.11 attacks</td>
</tr>
<tr>
<td>2007Q3-2009Q1</td>
<td>2007.8 - 2009.3 global financial crisis</td>
</tr>
</tbody>
</table>
Table 5: Economic Recessions for Individual Country  This table reports the period of recessions for each country, Australia, Canada, UK, and USA. For the U.S. recessions, NBER recession records are used. In case of the United Kingdom, a recession is generally defined as two successive quarters of negative economic growth, as measured by the quarter-on-quarter figures for real GDP. The recessions for Australia are defined as at least two periods of consecutive negative real GDP growth rate. The reference dates for the recessions for Canada are from the C.D. Howe Institute (see Cross and Bergevin (2012)).

<table>
<thead>
<tr>
<th>Country</th>
<th>Dates</th>
<th>List of Recessions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>1971Q4-1972Q1</td>
<td>1971.4-1971.5 recession</td>
</tr>
<tr>
<td></td>
<td>1975Q3-1975Q4</td>
<td>1975.3-1975.4 recession</td>
</tr>
<tr>
<td></td>
<td>1977Q3-1977Q4</td>
<td>1977.3-1977.4 recession</td>
</tr>
<tr>
<td></td>
<td>1981Q3-1982Q1</td>
<td>1981.3-1981.4 recession</td>
</tr>
<tr>
<td></td>
<td>1982Q3-1983Q2</td>
<td>1982.3-1982.4 recession</td>
</tr>
<tr>
<td>Canada</td>
<td>1975Q1</td>
<td>1975.1-1975.3 recession</td>
</tr>
<tr>
<td></td>
<td>2008Q4-2009Q2</td>
<td>2008.8-2009.2 recession</td>
</tr>
<tr>
<td>UK</td>
<td>1973 Q3-1974Q4</td>
<td>Mid-1970s recessions</td>
</tr>
<tr>
<td></td>
<td>1975 Q2-1975Q3</td>
<td>1975.2-1975.3 recession</td>
</tr>
<tr>
<td></td>
<td>1980 Q1-1981Q1</td>
<td>Early 1980s recession</td>
</tr>
<tr>
<td></td>
<td>1990 Q3-1991Q3</td>
<td>Early 1990s recession</td>
</tr>
<tr>
<td></td>
<td>2008 Q2-2009Q2</td>
<td>Great Recession</td>
</tr>
<tr>
<td>USA</td>
<td>1973Q4-1975Q1</td>
<td>1973.4-1975.3 recession</td>
</tr>
<tr>
<td></td>
<td>1981Q3-1982Q4</td>
<td>1981.3-1982.4 recession</td>
</tr>
<tr>
<td></td>
<td>1990Q3-1991Q1</td>
<td>1990.3-1991.3 recession</td>
</tr>
<tr>
<td></td>
<td>2007Q4-2009Q2</td>
<td>2007.4-2009.2 recession</td>
</tr>
</tbody>
</table>

The reference dates for the recessions for Canada are from the C.D. Howe Institute (see Cross and Bergevin (2012)).
Table 6: Contribution of Global Uncertainty to Macro Volatilities

The Panel A in the table reports the regression coefficients ($\beta^g_w$) of projecting consumption volatility ($f_c(x_c)$) onto the volatility associated only with global uncertainty ($f_c(w^g)$) for each country $i = $ Australia, Canada, UK, and USA. The Panel B in the table reports the regression coefficients ($\beta^d_w$) of projecting dividend volatility ($f_d(x_d)$) onto the volatility associated only with global uncertainty ($f_d(w^g)$) for each country. The first row in the table displays countries. For each Panel, the first row shows the estimated coefficient $\beta$, the numbers in the second and third rows stand for standard errors and adjusted $R^2$, respectively. For $j =$consumption and dividend, the regression specification is written in the below.

$$f^j_i(x^j_{it}) = constant + \beta^g_w f^j_i(w^g_t) + e^j_{it}$$

<table>
<thead>
<tr>
<th></th>
<th>Australia</th>
<th>Canada</th>
<th>UK</th>
<th>USA</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Consumption</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.8016</td>
<td>0.7756</td>
<td>0.6939</td>
<td>0.3017</td>
</tr>
<tr>
<td>std. err.</td>
<td>0.0218</td>
<td>0.1030</td>
<td>0.0437</td>
<td>0.2676</td>
</tr>
<tr>
<td>Adj.$R^2$</td>
<td>0.8933</td>
<td>0.3054</td>
<td>0.5035</td>
<td>0.1025</td>
</tr>
<tr>
<td><strong>Panel B. Dividend</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.8634</td>
<td>0.7582</td>
<td>0.8794</td>
<td>0.5124</td>
</tr>
<tr>
<td>std.err.</td>
<td>0.1315</td>
<td>0.0448</td>
<td>0.0411</td>
<td>0.0102</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.2034</td>
<td>0.6288</td>
<td>0.7304</td>
<td>0.9378</td>
</tr>
</tbody>
</table>

Table 7: Correlation between the Gloabal Economic Uncertainty Factor ($w^g_t$) and Other Risk and Uncertainty Index Measures

This table shows correlations and their p-values between our global economic uncertainty factor and other existing measures of risk and uncertainty. Specifically, the second row displays the correlation, and the third row shows the corresponding p-values ($p-v$) for the null hypothesis, $\rho \neq 0$ vs the alternative hypothesis, $\rho > 0$. For the alternative risk and uncertainty measures, we use two volatility indices (VIX and VXO), National Financial Conditions Index (NFCI), and Global Economic and Political Uncertainty (GEPU). VIX and VXO are obtained from Chicago Board Options Exchange (CBOE). The data period of VIX is from 1990 to 2012 and the data period of VXO is from 1986 to 2012. NFCI between 1971 and 2012 is from Federal Reserve Bank of St. Louis and the data set covers between 1997 and 2012 for GEPU, which is provided Davis(2016).

<table>
<thead>
<tr>
<th></th>
<th>VIX</th>
<th>VXO</th>
<th>NFCI</th>
<th>GEPU</th>
</tr>
</thead>
<tbody>
<tr>
<td>correlation</td>
<td>0.3350</td>
<td>0.3019</td>
<td>0.2000</td>
<td>0.2142</td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.0005</td>
<td>0.0007</td>
<td>0.0047</td>
<td>0.0446</td>
</tr>
</tbody>
</table>
Table 8: Uncertainty Shocks and the Likelihood of Global Economic and Political Events

In order to examine the relationship between uncertainty shocks and the likelihood of global economic and political events, we use the probit, logit, and linear probability models. The form of the estimated equation is given by

\[ \text{Prob}(y_t = 1) = F(\alpha + \beta \Delta x_t), \]
\[ y_t = \begin{cases} 1 & \text{if an economic event or shock in quarter } t \text{ occurs} \\ 0 & \text{otherwise} \end{cases} \]

where \( F \) is the cumulative distribution function. The list of adverse global economic and political events and shocks with the duration of period recorded is previously defined. The probit model is based on the cumulative distribution function of the standard normal distribution and the logit model is based on the cumulative distribution for the logistic distribution. \( \Delta x_t \) in the equation represents \( x_t - x_{t-1} \) as uncertainty shocks, we use the difference of the estimated global uncertainty factor (\( w^g_t \)) and those of other risk measure index such as VIX, VXO, NFCI, and GEPU. The linear probability model is written in the below.

\[ y_t = \alpha + \beta \Delta x_t + \epsilon_t, \]

where \( y_t \) and \( \Delta x_t \) are same as in the above equation. \( R^2 \) represents McFadden \( R^2 \).

<table>
<thead>
<tr>
<th>Probit Model</th>
<th>( w^g_t )</th>
<th>VIX</th>
<th>VXO</th>
<th>NFCI</th>
<th>GEPU</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta )</td>
<td>0.8928</td>
<td>0.0230</td>
<td>0.0296</td>
<td>0.1805</td>
<td>0.0026</td>
</tr>
<tr>
<td>( p\text{-value} )</td>
<td>0.0020</td>
<td>0.2845</td>
<td>0.1220</td>
<td>0.3776</td>
<td>0.6081</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.0769</td>
<td>0.0141</td>
<td>0.0268</td>
<td>0.0059</td>
<td>0.0041</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Logit Model</th>
<th>( w^g_t )</th>
<th>VIX</th>
<th>VXO</th>
<th>NFCI</th>
<th>GEPU</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta )</td>
<td>1.8414</td>
<td>0.0418</td>
<td>0.0554</td>
<td>0.3205</td>
<td>0.0045</td>
</tr>
<tr>
<td>( p\text{-value} )</td>
<td>0.0015</td>
<td>0.2742</td>
<td>0.1081</td>
<td>0.3817</td>
<td>0.6024</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.0841</td>
<td>0.0144</td>
<td>0.0281</td>
<td>0.0057</td>
<td>0.0045</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Linear Probability Model</th>
<th>( w^g_t )</th>
<th>VIX</th>
<th>VXO</th>
<th>NFCI</th>
<th>GEPU</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta )</td>
<td>0.1976</td>
<td>0.0061</td>
<td>0.0076</td>
<td>0.0385</td>
<td>0.0008</td>
</tr>
<tr>
<td>( p\text{-value} )</td>
<td>0.0009</td>
<td>0.2749</td>
<td>0.1033</td>
<td>0.3843</td>
<td>0.6084</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.0635</td>
<td>0.0134</td>
<td>0.0251</td>
<td>0.0046</td>
<td>0.0043</td>
</tr>
</tbody>
</table>
Table 9: Uncertainty Shocks and the Likelihood of Global Economic and Political Events including Recession

This table repeats the empirical analysis in Table (8) incorporating economic recessions as well. Panel A reports the results when global recession is defined as an event if all countries are in recession. In Panel B, global recession is defined as an event with more than two countries (50%) experience recession.

<table>
<thead>
<tr>
<th>Panel A</th>
<th>$w_t^t$</th>
<th>VIX</th>
<th>VXO</th>
<th>NFCI</th>
<th>GEPU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probit Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.8981</td>
<td>0.0144</td>
<td>0.0260</td>
<td>0.1339</td>
<td>0.0026</td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.0017</td>
<td>0.4935</td>
<td>0.1695</td>
<td>0.5091</td>
<td>0.6081</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0767</td>
<td>0.0055</td>
<td>0.0203</td>
<td>0.0032</td>
<td>0.0041</td>
</tr>
<tr>
<td>Logit Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>1.8244</td>
<td>0.0265</td>
<td>0.0482</td>
<td>0.2386</td>
<td>0.0045</td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.0014</td>
<td>0.4814</td>
<td>0.1542</td>
<td>0.5125</td>
<td>0.6024</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0832</td>
<td>0.0058</td>
<td>0.0213</td>
<td>0.0031</td>
<td>0.0042</td>
</tr>
<tr>
<td>Linear Probability Model</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.2030</td>
<td>0.0040</td>
<td>0.0069</td>
<td>0.0294</td>
<td>0.0008</td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.0008</td>
<td>0.4854</td>
<td>0.1511</td>
<td>0.5155</td>
<td>0.6084</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0645</td>
<td>0.0055</td>
<td>0.0195</td>
<td>0.0026</td>
<td>0.0043</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B</th>
<th>$w_t^t$</th>
<th>VIX</th>
<th>VXO</th>
<th>NFCI</th>
<th>GEPU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probit Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.4997</td>
<td>0.0094</td>
<td>0.0142</td>
<td>-0.1762</td>
<td>0.0010</td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.0411</td>
<td>0.6323</td>
<td>0.4168</td>
<td>0.3269</td>
<td>0.8411</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0236</td>
<td>0.0024</td>
<td>0.0062</td>
<td>0.0056</td>
<td>0.0006</td>
</tr>
<tr>
<td>Logit Model</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.9382</td>
<td>0.0176</td>
<td>0.0273</td>
<td>-0.3400</td>
<td>0.0017</td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.0364</td>
<td>0.6175</td>
<td>0.3916</td>
<td>0.2982</td>
<td>0.8386</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0254</td>
<td>0.0026</td>
<td>0.0068</td>
<td>0.0063</td>
<td>0.0006</td>
</tr>
<tr>
<td>Linear Probability Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.1567</td>
<td>0.0031</td>
<td>0.0044</td>
<td>-0.0563</td>
<td>0.0003</td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.0341</td>
<td>0.6214</td>
<td>0.3940</td>
<td>0.3000</td>
<td>0.8417</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0264</td>
<td>0.0028</td>
<td>0.0069</td>
<td>0.0065</td>
<td>0.0007</td>
</tr>
</tbody>
</table>