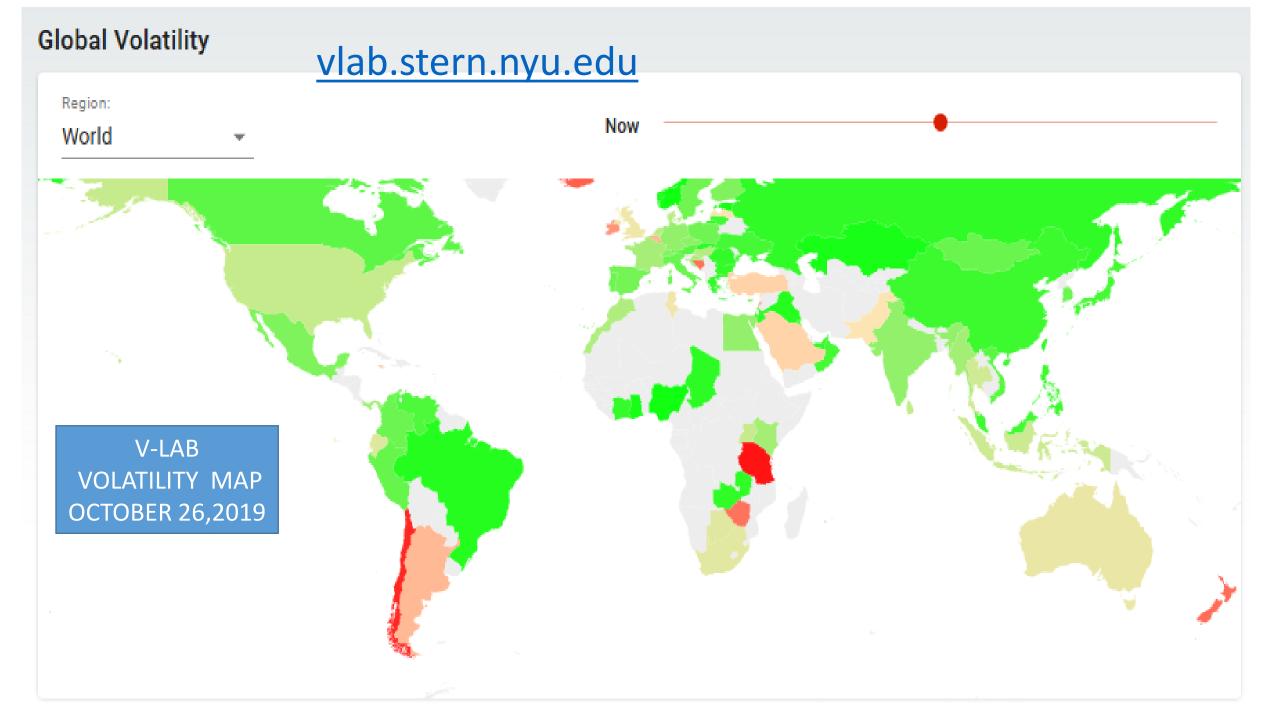
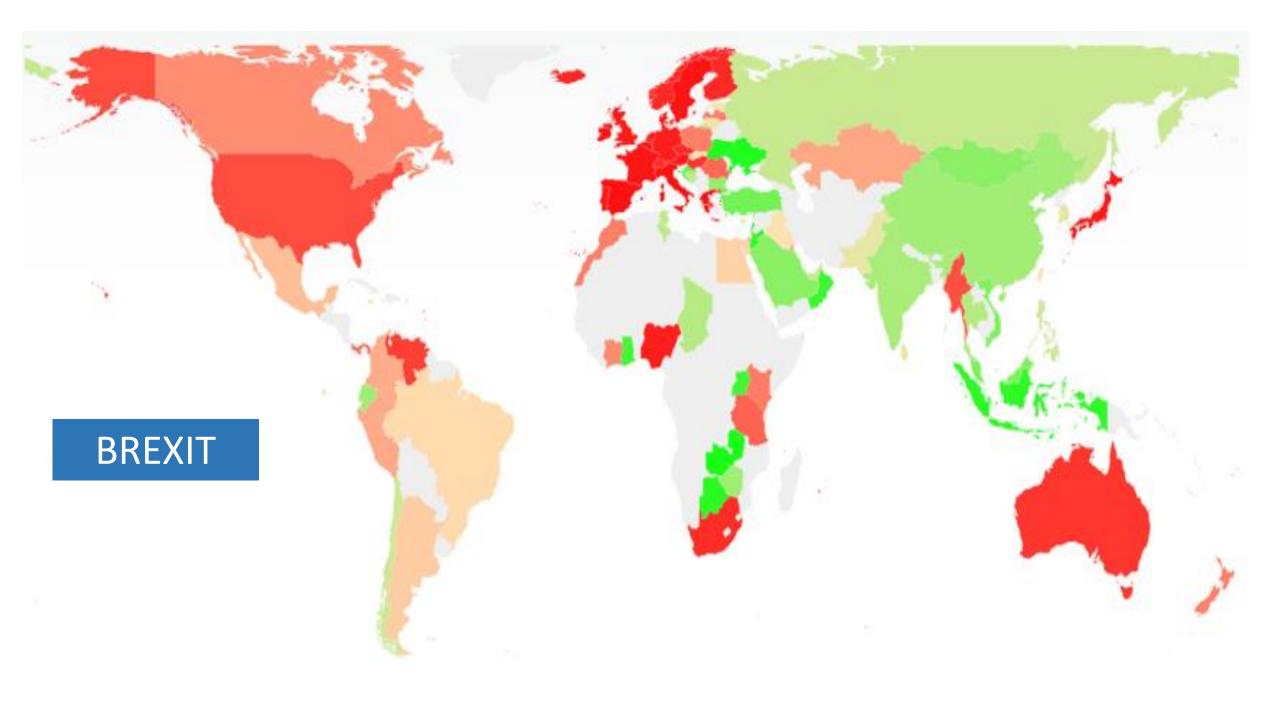
# MEASURING AND HEDGING GEOPOLITICAL RISK

Robert Engle and Susana Martins Volatility and Risk Institute at NYU Ster Climate Econometrics, Oxford Feb 16, 2021

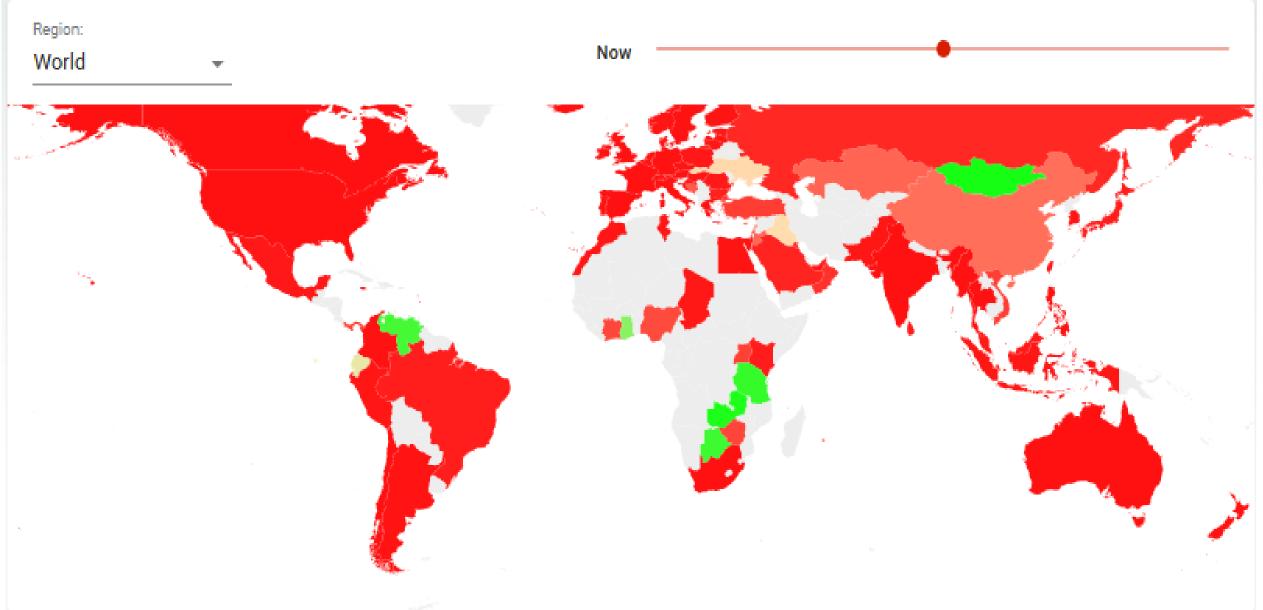
#### WHAT IS GEOPOLITICAL RISK?

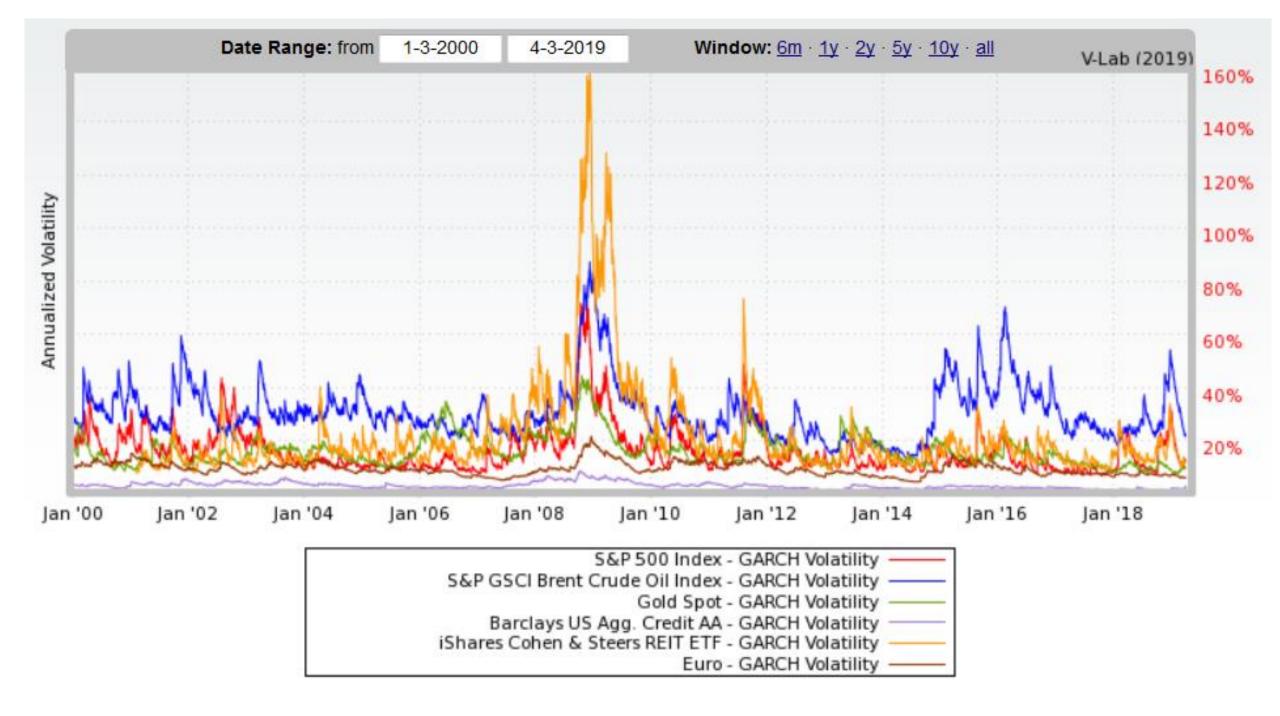
- Is it about politics or economics?
- Is it about terrorism, military risks, cyber risks or about elections, congressional actions and political movements?
- Is it about the level of risk or the surprise?
- Is it best measured in news or in financial markets?
- Rutherford D. Roger: "We are drowning in information and starving for knowledge."
- Hastie, Tibshirani and Friedman "the statistician's job is to make sense of it all - to extract important patterns and trends, and understand what the data says. We call this 'learning from the data.'





## 3/25/2020





#### STYLIZED FACT:

- Volatilities of most asset classes, sectors, countries, and even individual securities, tend to move together.
- A common view is that this is because they are all exposed to the same financial risk factors.
- Recent work by Herskovic, Kelly, Lustig, Von Nieuwerberg(2016) shows that this is also true after factors have been extracted. This follows a big literature on idiosyncratic volatility including Connor, Korajczyk and Linton(2006), Ang, Hodrick, Xing, Zhang(2006) and many others.

#### STYLIZED FACTS ABOUT VOLATILITY

- Although asset returns are difficult to forecast, volatilities are quite predictable
  - ARCH and GARCH style models show that shocks to volatility are persistent with long half lives.
  - The shocks to volatility can be extracted from volatility estimators.
- Because volatilities of many assets, asset classes, sectors and countries are correlated.
  - the shocks to volatilities must be correlated across assets
  - This is a new and testable observation

#### INTRODUCING - GEOVOL

- GEOVOL is a volatility factor that influences all financial assets, asset classes, and markets at the same time.
- When GEOVOL has a high value, it means that all asset returns are more volatile.
- Sometimes GEOVOL is due to political or military or terrorist activities and sometimes it is simply very impactful economic news. We think of it as geopolitical volatility.

#### MEASURING SHOCKS TO VOLATILITY

- From a volatility model, we can forecast the future variance. When returns around the mean are greater than this, we call it a volatility shock and measure it as a fraction of the predicted variance.
- For return r on day t, let h be the predicted variance of return, and m the predicted mean, then the variance shock is defined as:

$$e^2 = \frac{\left(r - m\right)^2}{h}$$

- The variance shock should have a constant mean of 1 and be serially uncorrelated. As they are unpredictable we call them innovations or shocks.
- In this notation, m is the mean that is predicted from the past and also from any common risk factors such as the market, Fama French Factors or Principle Components.

#### STANDARD STATISTICAL MODEL

- For a set of n assets and k risk factors:
- The standard data generating equation is

$$f_{t} = w_{t-1} r_{t}$$
$$r_{t} = r^{f} + f_{t}\beta + diag\left(\sqrt{h_{t}^{i}}\right)e_{t}^{i}$$

Where h and e are nx1 vectors. The vector  $e_t$  satisfies:

$$E_{t-1}\left(e_t^i e_t^i\right) = I$$

• Furthermore, without loss of generality factors can be rotated to be orthogonal and will have residuals that satisfy:

 $\{r_{i,t}\},\{f_{k,t}\}$ 

$$f_{t} = diag \left\{ \sqrt{h_{t}^{f}} \right\} e_{t}^{f}, \quad E_{t-1} \left( e_{t}^{f} e_{t}^{i} \right) = 0, \quad E_{t-1} \left( e_{t}^{f} e_{t}^{f} \right) = I$$
$$E_{t-1} \left( e_{t} e_{t}^{i} \right) = I, \quad for \quad e_{t} \equiv \left( e_{t}^{i} \right) = I, \quad e_{t}^{f} = \left( e_{t}^{i} \right)$$

• Hence

#### CROSS SECTIONAL CORRELATION

- By construction and definition of the set of risk factors, *e* should be serially and cross sectionally uncorrelated.
- Typically e<sup>2</sup> is also uncorrelated over time, but it is correlated across assets. Thus there is a common volatility shock which motivates our definition of GEOVOL.
- We can compute correlations between the volatility shocks of asset i and asset j using the standard formula for correlation:

$$\rho_{i,j} = \frac{1}{T} \sum_{t=1}^{T} \left( e_{i,t}^{2} - 1 \right) \left( e_{j,t}^{2} - 1 \right) / \kappa_{i} \kappa_{j}$$
$$\kappa = \frac{1}{T} \sum_{t=1}^{T} \left( e_{t}^{2} - 1 \right)^{2}$$

• In this formula we use kappa because this is the kurtosis-1 of e.

### TESTING THAT VOLATILITY SHOCKS ARE INDEPENDENT

- If there is no cross sectional correlation in volatility shocks, then there is no evidence for GEOVOL.
- We can apply standard tests that average correlations between a collection of returns are zero. If we reject this hypothesis, then there is some type of GEOVOL.
- We generally find that these correlations are almost all positive and very significant.
- However they are not equal. Thus there are differences in the exposure of different assets to the GEOVOL.

#### DEFINITION OF GEOVOL

- Let x be a latent variance with a conditional mean of 1. GEOVOL is its square root and is therefore a volatility.  $GEOVOL \equiv \sqrt{x}, E_{t-1}(x_t) = 1, V_{t-1}(x_t) = v_t$
- The information set in this notation is the past observations of {r}. Consequently, it is not possible to forecast x based on observed data although its variance can be forecast.
- However the main results hold under a weaker formulation:

$$E(x_t | r_{i,t-1}, ..., r_{i,t-k}, ...) = 1 \text{ for } i = 1, ..., N$$

• Now it is not possible to forecast x with any one asset history but perhaps it can be forecast with multivariate methods.

#### Factor Model for GEOVOL

- Now let asset j have a factor loading of s<sub>i</sub>.
- Then, for a given value of x, the variance of e is modeled as

 $V\left(e_{j}\left|x\right)=s_{j}\left(x-1\right)+1$ 

- This expression means that the unconditional variance, (when x is equal to its mean) is 1. Assuming s to be between zero and 1, the variance will always be non-negative, and the larger s, the more sensitive the asset variance is to GEOVOL.
- And as required

$$E_{t-1}\left(e_{t}e_{t}'\right) = I$$

#### INTERPRETATION OF X

- All elements of e have variance one.
- But on some days the squared return is bigger than one and some days it is smaller.
- When x is large, all returns are likely to be bigger than usual and when it is small, they are likely to be smaller than usual.
- When x is 4, and s=1, the standard deviation of returns is 2.
- When x is 4 but s=.1, the standard deviation of returns is 1.14

# ECONOMETRICS OF GEOVOL

#### GEOVOL

- Suppose asset j has variance shock  $g_{j,t}$  and  $\varepsilon_{i,t} \sim i.i.d.(0,1)$
- And let the data generating process be:

$$e_{j,t} = \sqrt{g_{j,t}} \ \varepsilon_{j,t}, \ g_{j,t} = s_j (x_t - 1) + 1$$

• The data are e, and the unobservables are parameters s and latent x

#### WHAT IS THE COVARIANCE MATRIX OF e<sup>2</sup> ?

• The Variance of each element is

$$V_{t-1}\left(e_{i,t}^{2}\right) = V_{t-1}\left(\varepsilon_{i,t}^{2}g_{i,t}\right) = E_{t-1}\left(\varepsilon_{i,t}^{4}\right)E_{t-1}\left(g_{i,t}^{2}\right) - 1 = \kappa s_{i}^{2}v_{t} + \kappa - 1$$

- And the covariance of each pair is  $Cov_{t-1}\left(e_{i,t}^2, e_{j,t}^2\right) = E\left(\varepsilon_{i,t}^2 \varepsilon_{j,t}^2 g_{i,t} g_{j,t}\right) - 1 = v_t s_i s_j$
- The matrix is equicorrelated if all s are the same.
- The average covariance matrix can be written as a factor matrix

$$\Psi = ss'\overline{v} + (\kappa - 1)\overline{v} diag\{s^2\} + (\kappa - 1)I, \quad s' = (s_1, ..., s_n)$$
$$= ss'\overline{v} + D$$

#### LIKELIHOOD FUNCTION

- Let s be an nx1 vector of parameters and x be a Tx1 vector of random variables and  $\varepsilon_{i,t} \sim IN(0,1)$ . Then assuming  $e_{i,t} = \sqrt{g_{i,t}} \varepsilon_{i,t}$
- the data augmented log likelihood is

$$L(s|e,x) = -.5\sum_{i=1,t=1}^{n,T} \log\left(g_{i,t} + \frac{e_{i,t}^2}{g_{i,t}}\right)$$

 The first order conditions are the partial derivatives with respect to s and x. Since each partial depends upon the other estimates, a joint maximum can be achieved if these are iterated to convergence. Interpretation as EM.

• 
$$\frac{\partial L(e;s,x)}{\partial s_i} = 0$$
,  $\frac{\partial L(e;s,x)}{\partial x_t} = 0$  for all *i* and *t*.

- These conditions define time series and cross sectional heteroskedastic regressions.
- For a discussion of data augmentation and EM models see Hastie, Tibshirani and Friedman(2009).

#### ESTIMATING S AND X

- An estimate of s is given by the factor loadings of the first principle component of e<sup>2</sup>. Works best with rank correlation matrix since data non-Gaussian.
- With an estimate of s we can estimate x with a cross sectional estimate for each time period using the relation:

$$e_{i,t} = \sqrt{\hat{s}_i (x_t - 1)} + 1 \quad \varepsilon_{i,t} \quad for \ i = 1, ..., n \ for \ each \ t$$

• Then from these estimates of x, a new estimate of s can be found from time series of the relation:

$$e_{i,t} = \sqrt{s_i (\hat{x}_t - 1) + 1} \quad \varepsilon_{i,t} \quad for \ t = 1, \dots T \ for \ each \ i$$

• Iterate to convergence (like Fama MacBeth)

#### NORMALIZATION

- Clearly the covariances that identify the matrix of squared returns will be unchanged if each s is multiplied by lambda and the variance of x is divided by lambda squared.
- x is non-negative with mean 1 and variance v
- s is between zero and one and normalized so the sum of squares is 1
- These normalizations are imposed in each estimation step.
- With these normalizations, the larger is n, the smaller must s be.

#### TWO MONTE CARLOS AND TWO APPLICATIONS

- Size and power of the test for a global volatility factor
- Performance of the estimator with a geopolitical volatility factor
- US Sector ETFs with n=9 and T=5177 (not fully presented to avoid fatigue)
- 12/23/1998 to 10/25/2018
- World country MSCI ETFs with n=45 and T= 5241
- 1/1/1999 to 2/1/2019 .

#### SIZE AND POWER OF THE GVF TEST

Table 1: Empirical rejection frequencies under $H_0: \bar{\rho} = 0$ .Table 3: Empirical rejection frequencies under $H_1: \bar{\rho} > 0$ when $v = 0.5$ .DGP $T$ $n$ $t_{r_1}$ $t_{r_2}$ $t_{r_3}$ $t_z$ $\xi$ Colspan="4">Colspan="4">Colspan="4">Colspan="4">Colspan="4">Colspan="4">Colspan="4">Colspan="4">Colspan="4">Table 3: Empirical rejection frequencies under $H_1: \bar{\rho} > 0$ when $v = 0.5$ .DGP $T$ $n$ $t_{r_1}$ $t_{r_2}$ $t_{r_3}$ $t_z$ $\xi$ Colspan="4">Colspan="4"Colspan="4">Colspan="4"Colspan="4"Colspan="4"Colspan="4"Colspa		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Table 1: Empirical rejection frequencies under $H_0: \bar{\rho} = 0$ .	Table 3: Empirical rejection frequencies under $H_1: \bar{\rho} > 0$ when $v = 0.5$ .
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	DGP $T$ $n$ $t_{r_1}$ $t_{r_2}$ $t_{r_3}$ $t_z$ $\xi$	$DGP \underline{T} \underline{n} \underline{t_{r_1}} \underline{t_{r_2}} \underline{t_{r_3}} \underline{t_z} \underline{\xi}$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\alpha = 0.01$	$\alpha = 0.01$
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	1  100  2  0.022  0.022  0.022  0.022  0.019	$1  100  2  0.148 \ 0.148 \ 0.150 \ 0.149 \ 0.131$
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		$2  100  5  0.637 \ 0.649 \ 0.639 \ 0.654 \ 0.626$
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		3 100 50 1.000 1.000 1.000 1.000 1.000
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		4  1000  2  0.676  0.676  0.676  0.685  0.679
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		5 1000 5 1.000 1.000 1.000 1.000 1.000
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		$6  1000 \ 50  1.000 \ 1.000 \ 1.000 \ 1.000 \ 1.000$
2 100 5 0.057 0.060 0.058 0.058 2 100 5 0.806 0.812 0.807 0.813 0.797   3 100 50 0.055 0.055 0.056 0.058 0.058 3 100 50 1.000 1.000 1.000   4 1000 2 0.055 <td></td> <td></td>		
3 100 50 0.055 0.065 0.066 0.058   4 1000 2 0.055 0.055 0.055 0.055 0.055   4 1000 2 0.843 0.843 0.843 0.843	1  100  2  0.063  0.063  0.064  0.063  0.059	$1  100  2  0.264 \ 0.264 \ 0.266 \ 0.264 \ 0.245$
4 1000 2 0.055 0.055 0.055 0.056 0.055 4 1000 2 0.843 0.843 0.843 0.846 0.843	2  100  5  0.057  0.060  0.058  0.060  0.058	2  100  5  0.806  0.812  0.807  0.813  0.797
	3  100  50  0.055  0.065  0.056  0.066  0.058	3 100 50 1.000 1.000 1.000 1.000 1.000
	4  1000  2  0.055  0.055  0.055  0.056  0.055	4 1000 2 0.843 0.843 0.843 0.846 0.843
	5  1000  5  0.053  0.053  0.053  0.055  0.054	5 1000 5 1.000 1.000 1.000 1.000 1.000
6 1000 50 0.050 0.051 0.050 0.052 0.052 0.052 6 1000 1.000 1		6 1000 50 1.000 1.000 1.000 1.000 1.000

#### ACCURACY MEASURE: R<sup>2</sup>

- After iteration, there are estimates of s and x.
- MSE(x) is the mean squared error of x. It is calculated by averaging the squares of all the elements of x.
- These R<sup>2</sup> indicate the improvement over using the unconditional values.

$$R_x^2 = 1 - \frac{MSE(x - \hat{x})}{MSE(x - 1)}, \quad R_s^2 = 1 - \frac{MSE(s - \hat{s})}{MSE(s - \overline{s})}$$

#### PERFORMANCE

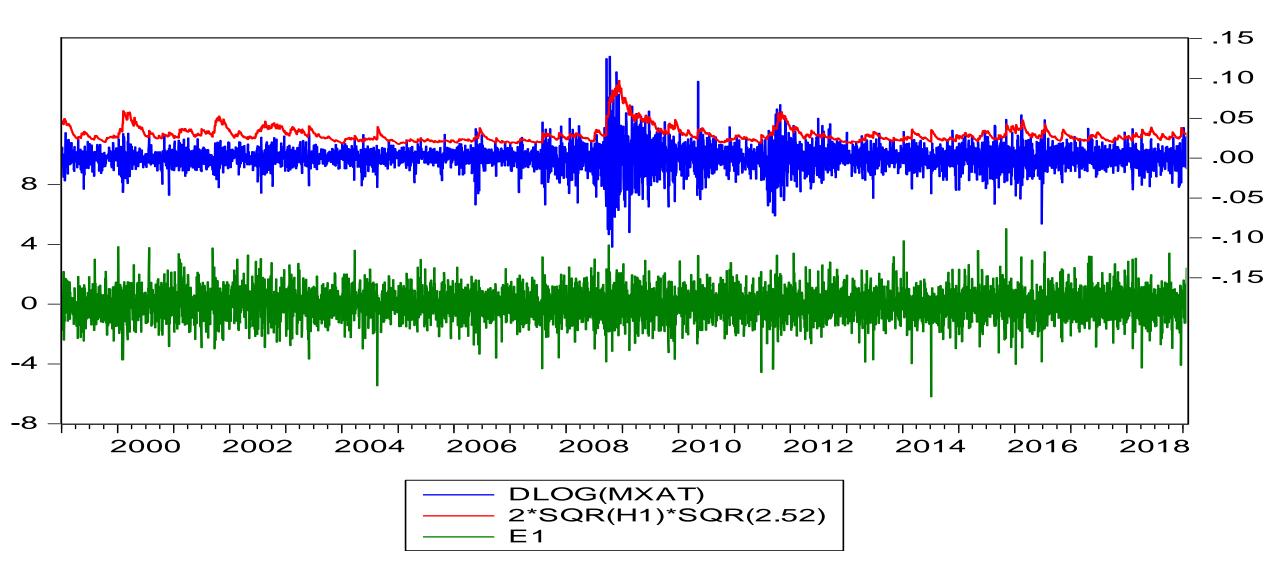
- S are drawn from uniform and normalized to s's=1. These s are reused for all simulations.
- X are drawn from exp(IN(0,u)) normalized to have mean 1.
- Epsilon are standard normal. Estimates are iterated to convergence.

	Table 9:	Results	from	the	simulations:	baseline	estimator.
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		T = 1000	)	T =	5000
	n = 10	n = 50	n = 100	n = 10	n = 50
$R^2_s$	0.833	0.695	0.399	0.956	0.935
$R^2_x$	0.761	0.873	0.891	0.774	0.882
Avg. correlation of $e^2$	0.210	0.079	0.054	0.233	0.091
Avg. empirical variance of $x$	28.21	32.25	32.23	35.83	36.88
Avg. number of iterations	30	32	31	26	23

# ACWI DATASET

#### AUSTRIA: RETURNS, VOL, STD RES



#### STEP 1

• Estimate factor model with GARCH errors for each asset

$$r_{i,t} = c_i + \beta_{i,k} f_{k,t} + \sqrt{h_{i,t}} e_{i,t}$$

- Factors are ACWI and first PC.
- Test whether the average correlation is equal to zero:  $\bar{\rho}_e = -.0099$
- Accept null of zero correlation.

#### STEP 2

- Compute standardized residuals and square them
  - Test whether average correlation of e squared is zero:
  - Test statistic is N(0,1) under H<sub>o</sub>
  - The result is 120 for MSCI ETF data

$$\overline{\rho}_{e^2} = 0.085$$

- Easily reject the null of no GEOVOL
- Compute principle components of squared covariance matrix
- Factor loadings are the initial estimate of s

#### CORRELATIONS OF e<sup>2</sup>

Spearman rank-order correlations:

	E1^2	E2^2	E3^2	E4^2	E5^2	E6^2
E1^2	1.000000					
E2^2	0.052096	1.000000				
E3^2	0.077126	0.098211	1.000000			
E4^2	0.051225	0.056661	0.058424	1.000000		
E5^2	0.057440	0.070854	0.047569	0.060105	1.000000	
E6^2	0.074792	0.057796	0.153607	0.065965	0.072646	1.000000
E7^2	0.053626	0.037686	0.073482	0.106101	0.080622	0.057293
E8^2	0.094876	0.135355	0.103920	0.062777	0.068836	0.090268
E9^2	0.044503	0.035886	0.088562	0.076848	0.065350	0.064221
E10^2	0.061097	0.034707	0.063540	0.042544	0.033291	0.069357
E11^2	0.057178	0.109938	0.161399	0.088484	0.059770	0.177131
E12^2	0.087924	0.044567	0.085903	0.066572	0.067164	0.108823
E13^2	0.041291	0.056253	0.019117	0.057774	0.036532	0.038267
E14^2	0.096191	0.101326	0.129824	0.064451	0.049110	0.102015
E15^2	0.113176	0.074267	0.086911	0.087135	0.036753	0.083550
E16^2	0.052127	0.094475	0.198587	0.076448	0.059473	0.196564

#### STEP 3: ITERATION

Estimate x<sub>t</sub> using cross sectional heteroskedasticity regression (x>0)

 $e_{i,t} = \sqrt{s_i \left( \mathbf{x}_t - 1 \right) + 1} \varepsilon_{i,t} \text{ for } i = 1, ..., n \text{ for each } t$ 

• Then estimate s using time series heteroskedasticity regressions (0<s<1)

$$e_{i,t} = \sqrt{s_i(x_t - 1) + 1} \varepsilon_{i,t} \text{ for } t = 1, ..., T \text{ for each } i$$

- Normalize after each step. Mean of x is 1, and s's=1
- Iterate to convergence.

#### **RESULTS FROM NEW VERSION NOW ON V-LAB**

- VLAB.STERN.NYU.EDU go to GEOPOLITICAL RISK ANALYSIS
- Data set is 47 US traded International ETFs 2000 to present
- Factors are ACWI and the first principle component

Top GEOVOL Events (new events in boldface)						
	Date	GEOVOL	Event			
1	Mar 9, 2020	51.28	COVID - All of Italy is locked down, Saudi Arabia / Russia oil price war			
2	Jun 24, 2016	49.13	Brexit			
3	Aug 5, 2019	39.36	China Trade War - China devalues its currency			
4	Apr 28, 2020	39.30	COVID - Market rally loses stream after tech share sell-off			
5	Sep 17, 2001	30.08	Market reopens after Sept 11th			
6	Feb 27, 2007	26.77	Chinese and European stock market crashes, Cheney assassination attempt, drop in durable goods orders			
7	Aug 24, 2015	23.45	Flash Crash, Chinese Black Monday			
8	Apr 24, 2017	22.07	Syrian sanctions			
9	Aug 5, 2011	18.21	Rumors of US credit rating downgrade			
10	Nov 9, 2016	18.08	Donald Trump elected president of the United States			
11	Apr 9, 2018	18.00	North Korea open to denuclearization, Missles hit Syrian air base			
12	May 18, 2017	17.18	Justice dept appoints Robert Mueller to head Russia investigation			
13	Mar 13, 2020	16.45	COVID - US declares national state of emergency			
14	Mar 12, 2020	16.19	COVID - Day after Trump address blocks visitors coming in from Europe			
15	Nov 9, 2020	16.07	COVID - Pfizer early trial data suggests vaccine is 90% effective, Joe Biden elected president of the United States			
16	Oct 10, 2008	15.22	Global Financial Crisis - Global stock market crash			
17	Mar 19, 2020	14.96	COVID - Coronavirus relief package signed			
18	Mar 12, 2001	14.81	Multiple tech stocks cut revenue guidance - Nasdaq slides below 2,000 for the first time in nearly 27 months			
19	Jul 23, 2002	14.56	Isreali/Palestinian Tension, Stock Market Crash			
20	Dec 17, 2014	14.50	Peshawar Pakistan school attacks, US/Cuba re-establish diplomatic relations			

GEOVOL Loadings		
Country	↓ Loading	VW Loading
Princ Comp #1	0.2614	0.4879
MSCI ACWI	0.2496	0.3900
France	0.2171	0.5813
Spain	0.1995	0.6305
Italy	0.1935	0.6156
Germany	0.1908	0.5286
Netherlands	0.1837	0.4575
Malaysia	0.1795	0.3430
Thailand	0.1758	0.5731
Belgium	0.1742	0.4214
Finland	0.1680	0.2983
United States	0.1636	0.2507
Egypt	0.1521	0.4701
Austria	0.1502	0.4504
Greece	0.1473	1.1217
Indonesia	0.1456	0.5074
South Korea	0.1403	0.6370
Singapore	0.1399	0.3678
Chile	0.1394	0.3975
China	0.1353	0.3102

OVOL Loadings		
untry	↓ Loading	VW Loading
ban	0.1325	0.2560
ng Kong	0.1310	0.3499
rway	0.1301	0.3277
ilippines	0.1300	0.2849
eden	0.1280	0.5086
wan	0.1273	0.4414
ited Kingdom	0.1260	0.2778
rtugal	0.1222	0.2529
tzerland	0.1188	0.2122
rico	0.1176	0.3861
h Africa	0.1169	0.5633
E	0.1150	0.2590
ombia	0.1146	0.3621
geria	0.1127	0.3601
tar	0.1122	0.2077
stralia	0.1112	0.3351
el	0.1105	0.2347
ssia	0.1095	0.4972
ızil	0.1092	0.6837
nada	0.1086	0.2318

GEOVOL Loadings		
Country	$\downarrow$ Loading	VW Loading
Ireland	0.1068	0.2153
Denmark	0.1023	0.1321
Pakistan	0.0994	0.3182
Peru	0.0954	0.1923
India	0.0942	0.2328
Turkey	0.0896	0.5322
Vietnam	0.0840	0.2229
Poland	0.0801	0.2543
New Zealand	0.0645	0.1037

GEOVOL data for < Dec 2010 >

#### Top GEOVOL Events (new events in boldface)

	Date	GEOVOL	Event
1	Sep 17, 2001	26.48	Market reopens after Sept 11th
2	Feb 27, 2007	23.23	Chinese and European stock market crashes, Cheney assassination attempt, drop in durable goods orders
3	Jul 23, 2002	15.78	Isreali/Palestinian Tension, Stock Market Crash
4	May 10, 2010	15.30	EU and IMF reveal a \$1 trillion plan to avoid a European debt crisis
5	Oct 10, 2008	15.18	Global Financial Crisis - Global stock market crash
6	Jan 22, 2008	14.25	Global Financial Crisis - Fed makes emergency 75 bps rate cut
7	Mar 12, 2001	13.97	Multiple tech stocks cut revenue guidance - Nasdaq slides below 2,000 for the first time in nearly 27 months
8	Jan 3, 2001	12.91	Fed surprise 50 bps interest rate cut
9	Mar 10, 2008	12.66	Global Financial Crisis - Continued signs of stress in the Financial sector, Fed term Ioan facility releases \$50 billion
10	Nov 8, 2007	12.13	Global Financial Crisis - Asian markets crash
11	Jan 30, 2003	10.66	Growing concerns that a war with Iraq may be inevitable, weak earnings estimates
12	Oct 6, 2005	10.63	Dallas Fed Bank chairman warns of inflation
13	Sep 2, 2008	10.35	Global Financial Crisis - Global growth concerns, flight to quality, liquidity contraction, Political Crisis in Thailand, Shooting in Washington state
14	Jun 28, 2010	10.30	Proposed G-20 deficit cuts causes global growth fears
15	Oct 28, 2008	10.07	Global Financial Crisis - Markets rebound after historic sell-off
16	Oct 25, 2000	9.98	Investors dump telecom stocks after disappointing results from Nortel Networks
17	May 6, 2010	9.94	Flash crash
18	Aug 9, 2007	9.85	Global Financial Crisis - Mortgage crisis goes global
19	Jan 25, 2008	9.84	Global Financial Crisis - Investors retreat after a two-day rally
20	Oct 13, 2008	9.54	Global Financial Crisis - Relief rally from details of bailout package, European bailout packages, and Federal Reserve actions

#### GEOVOL Loadings

Country	↓ Loading	VW Loading
Princ Comp #1	0.3349	0.7781
MSCI ACWI	0.3145	0.5913
France	0.2438	0.7575
Italy	0.2201	0.6822
Germany	0.2166	0.7150
Spain	0.2130	0.7234
Netherlands	0.2052	0.6622
Belgium	0.1959	0.6331
Malaysia	0.1955	0.4583
Japan	0.1864	0.4741
Thailand	0.1863	1.2376
South Korea	0.1850	1.2152
Singapore	0.1844	0.6998
Mexico	0.1810	0.7236
Austria	0.1685	0.6024
Sweden	0.1640	0.8906
Turkey	0.1578	1.8131
Brazil	0.1548	1.1532
South Africa	0.1501	0.8815
United States	0.1496	0.2798

#### GEOVOL Loadings

Taiwan 0.1	
Talwan 0.	1486 0.7747
United Kingdom 0.1	1415 0.3849
Canada 0.1	1386 0.3761
Switzerland 0.1	1374 0.3261
Australia 0.1	1365 0.4937
Hong Kong 0.1	1342 0.5051
Israel 0.1	1019 0.4288
Vietnam 0.0	0984 0.3616
Chile 0.0	0918 0.4208
Peru 0.0	0722 0.1554

### Recursive estimates of loadings are stable

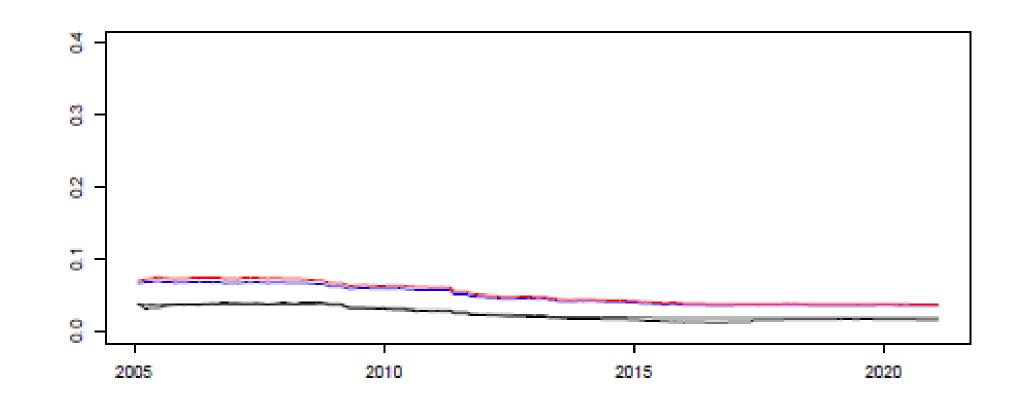


Figure 3: Re-scaled GEOVOL loading: cross-sectional average across all ETF loadings (gray), ACWI (blue), first principal component (red) and US (black).

# PORTFOLIO IMPLICATIONS

## PORTFOLIO IMPLICATIONS

- All portfolios will generally be sensitive to "GEOVOL" or geopolitical shocks.
- Even though a Markowitz optimal portfolio has a low variance, it will be sensitive to these shocks and its variability may be high.
- Since some assets are less sensitive to geopolitical shocks than others, these risks can be reduced by including an additional criterion in portfolio optimization. We call this *risk diversification*.

### THEORY

- Consider two assets with the same variance and expected return
- One has unit loading on GEOVOL, the other has zero.
- The Markowitz portfolio is equally weighted.
- This portfolio will have kurtosis proportional to the variance of GEOVOL and higher moments related to moments of GEOVOL.
- To reduce this kurtosis, the portfolio must reduce impact of the first asset and thereby increase variance.
- This tradeoff depends upon tolerance of tail risk and the size of tail risk.
- Such behavior will affect expected returns in equilibrium.

### Variance Weighted Factor Loadings

- Factor returns are given by:  $f_{kt} = \mu_k + \sqrt{h_{kt} \left(s_k \left(x_t 1\right) + 1\right)} \varepsilon_{kt}$
- Hence the variance of a factor conditional on x and the past is:

$$V_{t-1}(f_{kt} | x_t) = h_{kt} s_k (x_t - 1) + h_{kt}$$

• And the average variance conditional on x is

$$V(f_{kt}|x) = \sigma_k^2 s_k (x-1) + \sigma_k^2$$

• Thus the average loading on GEOVOL is the

Variance weighted GEOVOL loading:  $\tilde{s}_k = s_k \sigma_k^2$ 

### FOR ANY ASSET

• The variance conditional on GEOVOL can similarly be computed. For simplicity suppose the factors are uncorrelated. Then

$$V(r_{jt}|x) = (x-1)\left[\tilde{s}_{j} + \sum_{k=1}^{K} \beta_{j,k}^{2} \tilde{s}_{k}\right] + \left[\sigma_{j}^{2} + \sum_{k=1}^{K} \beta_{j,k}^{2} \sigma_{k}^{2}\right]$$

In matrix notation this is

 $V(r|x) = (x-1)(\beta diag\{\tilde{s}_f\}\beta' + diag\{\tilde{s}_i\}) + \beta diag\{\sigma_f^2\}\beta' + diag\{\sigma_i^2\}$ 

## PORTFOLIO OPTIMIZATION

### Maximize return

- Subject to volatility constraint
- And subject to sensitivity to geopolitical risk

$$\begin{aligned} &\underset{w}{Max \ w' \mu} \\ &subject \ to \ w' \Big[ \beta diag \left\{ \sigma_{f}^{2} \right\} \beta' + diag \left\{ \sigma_{i}^{2} \right\} \Big] w < \theta \\ ∧ \ w' \Big[ \beta diag \left\{ \tilde{s}_{f} \right\} \beta' + diag \left\{ \tilde{s}_{i} \right\} \Big] w < \theta_{2} \end{aligned}$$

### CORRELATIONS CHANGE WITH X

The covariance matrix between asset i and j conditional on x can be written as:

$$V_{i,j} = \left\{ \begin{bmatrix} \beta_i^2 & \beta_i \beta_j \\ \beta_i \beta_j & \beta_j^2 \end{bmatrix} \tilde{s}_f + \begin{bmatrix} \tilde{s}_i & 0 \\ 0 & \tilde{s}_j \end{bmatrix} \right\} (x-1) + \Omega$$

The correlation can be rewritten as:

$$\rho_{ij} = \begin{cases} \frac{\Omega_{ij}}{\sqrt{\Omega_{ii}\Omega_{jj}}} & \text{if } x = 1\\ \frac{\Omega_{ij}}{\sqrt{(\Omega_{ii} + \sigma_i^2(s_i - s_f)/s_f)}(\Omega_{jj} + \sigma_j^2(s_j - s_f)/s_f)} & \text{if } x \to \infty \end{cases}$$

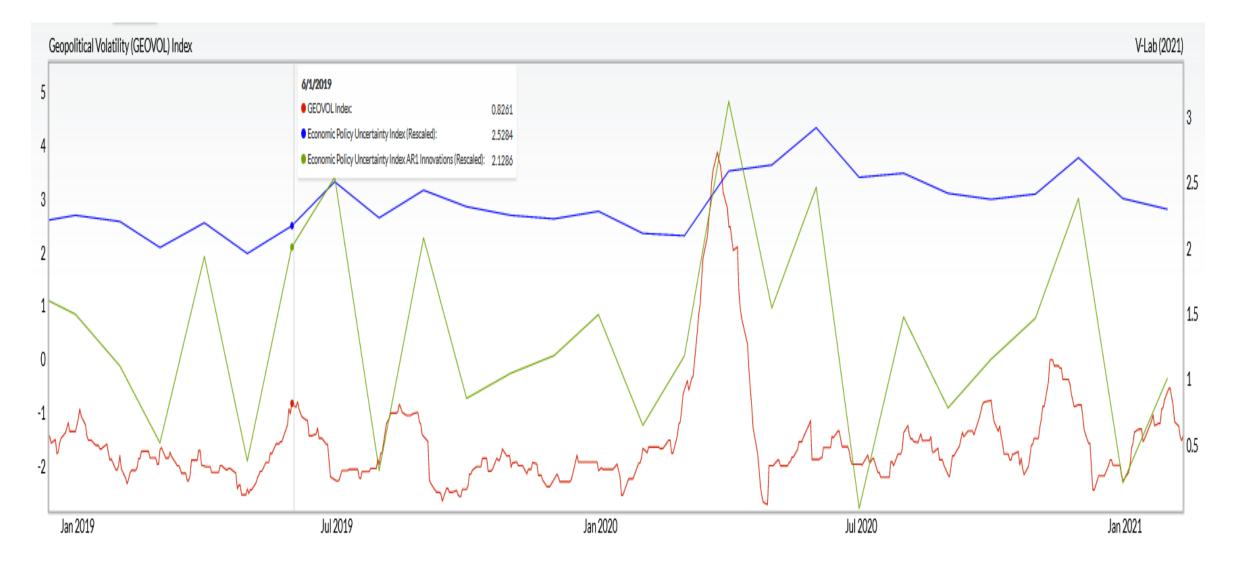
This will rise with x if  $S_f > S_i, S_j$ , which is typically satisfied.

### **GEOVOL PROPERTIES**

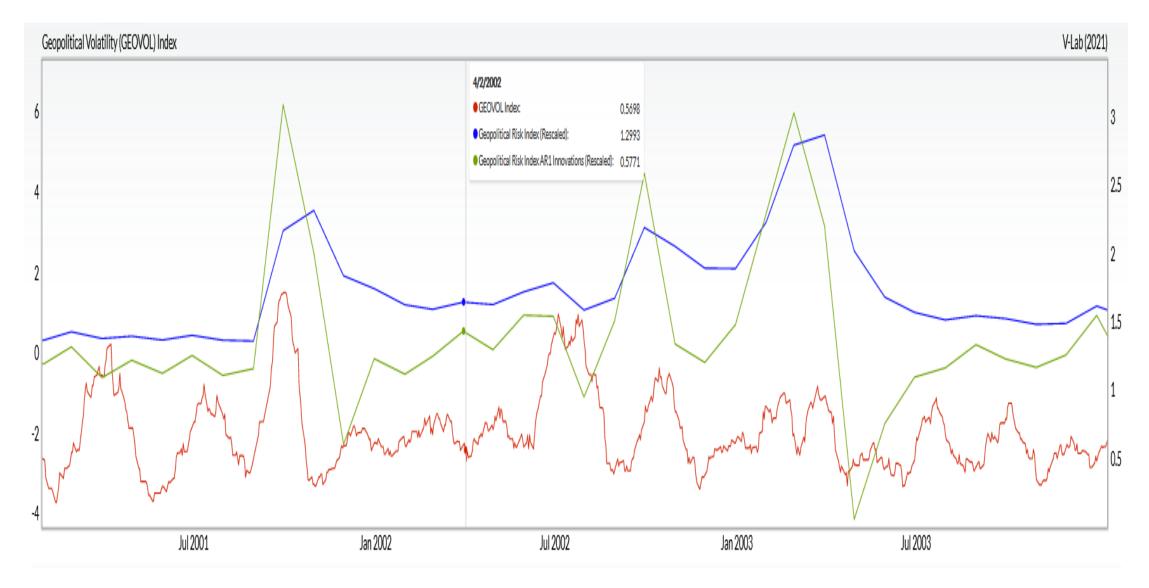
- When GEOVOL is high, correlations typically rise.
- When GEOVOL is high all assets and factors have higher volatility.
- When GEOVOL is very high, then most asset returns are tail events.
- Naturally an optimal portfolio will try to reduce this exposure.

# COMPARISONS

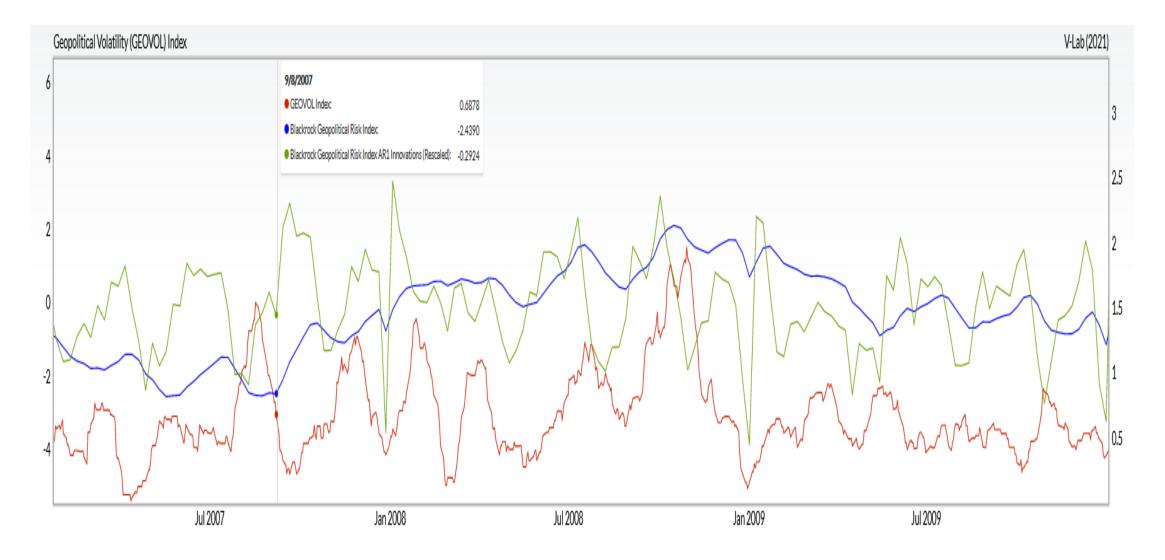
### COMPARISON WITH EPU OF BAKER BLOOM DAVIS



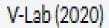
### COMPARISON WITH GPR OF CALDARA AND IACOVIELLO

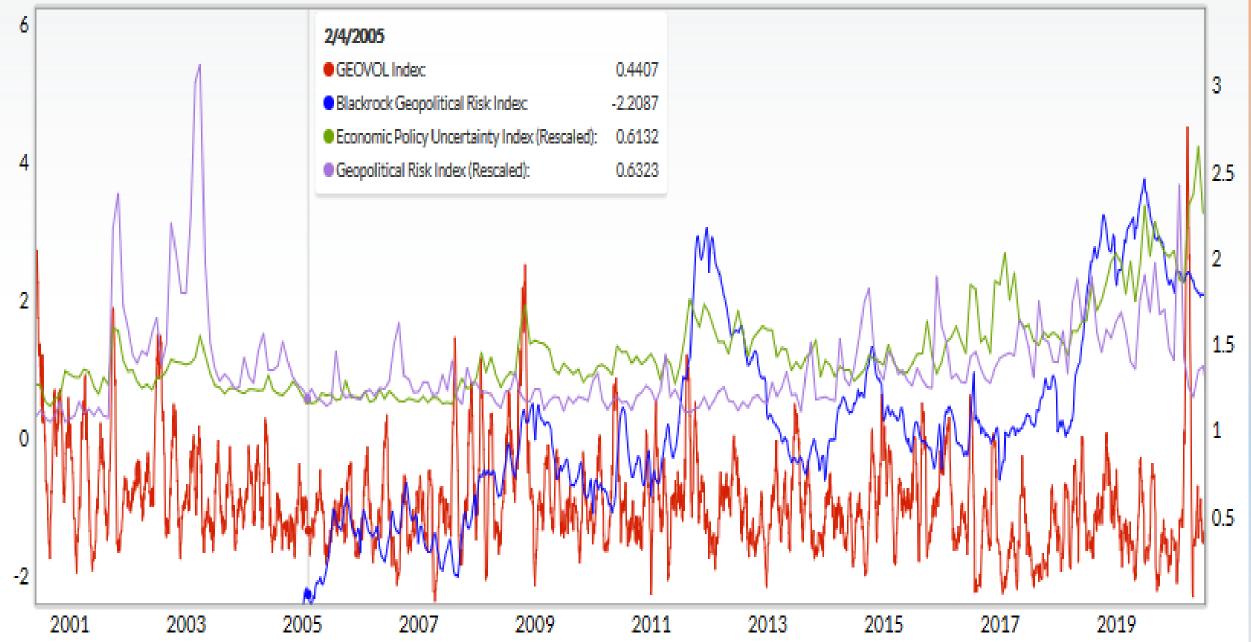


## COMPARISON WITH BLACKROCK



#### Geopolitical Volatility (GEOVOL) Index





# CORRELATIONS BETWEEN GEOVOL, AVGCOR AND d(GEPU) AND d(GPR)

- CORRELATIONS BETWEEN MONTHLY VALUES
- CORRELATIONS ARE HIGHEST BETWEEN GEOVOL AND dGEPU.

	AvgCor	$\mathbf{x}^m$	$\Delta \text{GEPU}$	$\Delta \mathrm{GPR}$
AvgCor	1	0.172	0.194	0.013
x <sup>m</sup>	0.172	1	0.399	0.156
$\Delta \text{GEPU}$	0.194	0.399	1	0.233
$\Delta \text{GPR}$	0.013	0.156	0.233	1

Table 1: Empirical correlation matrix.

### ASSET CLASS GEOVOL : ASSETGEOVOL

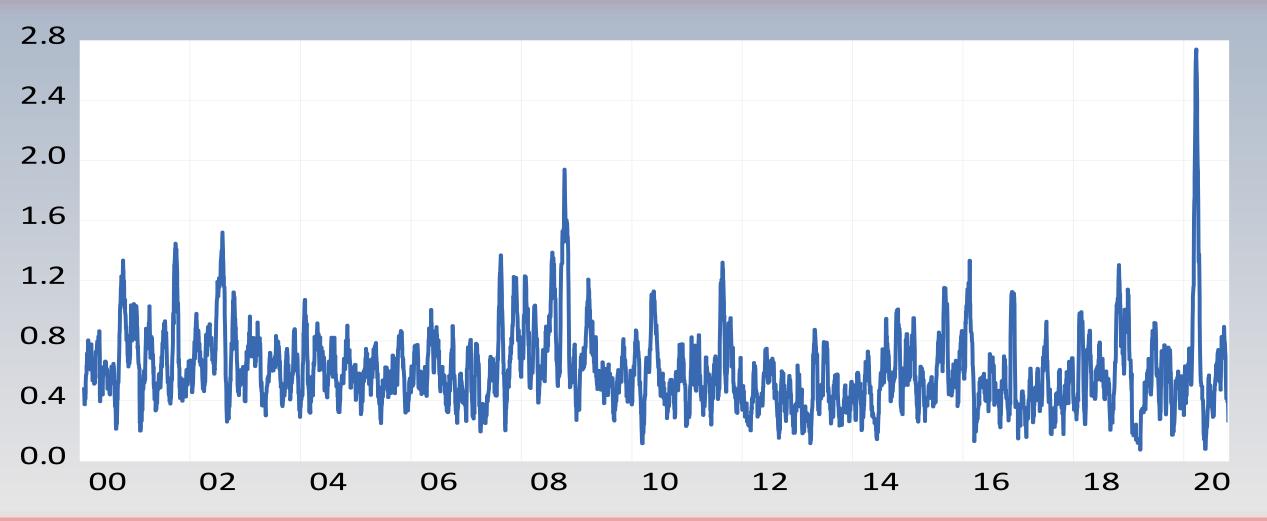
- Fixed Income, Commodities, Stock Style funds, Stock Sector Funds, International Funds, Exchange Rates, Real Estate: 23 funds
- One factor is the equal weighted average
- Average correlation of standardized residuals and t-stat: -.005, -6.9
- Average correlation of squared standardized residuals: 0.13, 161

### SORTED ASSET GEOVOL AND LOADINGS

	ASSETVOL	DATE		SHAT11	NAMELONG
7874 3054 7006 7546 6814 6794 2683 7560 2871 6498 5028 6908 7749 4898 6418 6534 5712 4899	ASSETVOL 6.662131 6.321569 6.308375 6.140162 5.942512 5.788944 5.308053 4.894078 4.675957 4.586077 4.476759 4.443259 4.245216 4.117005 4.104520 4.056355 4.038448 4.026468	DATE 2020-03-09 2001-09-17 2016-11-09 2018-12-05 2016-02-15 2016-01-18 2000-04-14 2018-12-25 2001-01-03 2014-11-28 2009-04-10 2016-06-24 2019-09-16 2008-10-10 2014-08-08 2015-01-19 2011-11-24 2008-10-13	8 11 7 16 19 17 24 14 13 5 1 12 9 6 10 20 4 22 3 23 21 18	0.265118 0.256220 0.251203 0.249021 0.234077 0.226975 0.226881 0.223477 0.222594 0.216629 0.201268 0.197895 0.188891 0.188405 0.187917 0.187684 0.178915 0.173482 0.170798 0.165238 0.157874	NAMELONG Russel 1000 Growth Global Energy ETF Russel 1000 Value ETF Energy Sector SPDR Technology Sector SPDR Financial Sector SPDR Average equally weighted of all assets GSCI WTI Crude Oil Index Stranded Asset Porfolio Gold Spot Barclays US Agg Credit Baa Barclays US Agg Credit Baa Barclays US Agg Gov Russel 2000 Value Cohen and Steers REIT ETF Russel 2000 Growth Consumer Staples SPDR EAFE ETF Health Care SPDR Emerging Markets ETF Consumer Discretionary SPDR Utilities Sector SPDR Industrial Sector SPDR
5654 6000	3.878905 3.798525	2011-09-05 2013-01-01	2 15	0.151853	US Dollar Index Materials Sector SPDR

# ASSET CLASS GEOPOLITICAL RISK: ASSETVOL

ASSETVOL\_M



# WHAT ABOUT A CLIMATE VOL FACTOR? CLIMATEVOL

- 179 funds are considered to be climate sensitive funds by Morningstar
- Some are low carbon, others are low E risk of ESG, others are sustainable sectors such as solar or wind energy
- Some are ETFs and others are open end mutual funds
- Some have 2 decades of history and others are very recent.
- Factors: investable FF3, transition risk, physical risk, oil futures, EW average

### PERFORMANCE TODAY

 Alpha computed from investable version of FF 3 factor over different horizons

Alpha Table	14	3Y	5Y	EW	Max
All	5.17	-0.29	-1.39	0.82	-1.27
Fossil Fuel Free	7.51	1.84	-0.80	2.02	-1.09
Low Carbon	-0.44	-2.96	-3.40	-2.30	-1.89
Low Environmental Risk	-4.34	-5.69	-5.36	-5.72	-1.94
Sustainability Mandate	5.63	0.10	-1.30	1.20	-1.51
Sustainable Sector	21.33	10.08	5.79	10.64	-0.92

# CLIMATEVOL (very preliminary results)

CLIMATEVOL	DATE
141.5379	2020-06-24
129.0493	2001-09-17
41.06480	2011-03-14
36.14899	2005-12-20
35.54124	2003-01-28
31.42308	2007-12-28
30.92800	2020-03-12
30.91908	2020-03-09
30.40776	2016-11-09
29.29859	2006-12-19
28.87536	2019-12-13
26.59563	2003-03-17
25.91626	2007-06-20
25.16425	2016-06-24
24.94105	2002-05-08
24.06985	2014-11-28
23.86352	2014-12-22
23.40897	2018-03-27
22.94598	2008-09-30
22.69361	2020-03-16

SHAT	NAME
0.190149	Domini Impact Equity Fund
0.168379	TIAA-CREF Social Choice International Equity Fund Inst
0.143281	Federated Hermes MDT Large Cap
0.128759	Invesco Oppenheimer Main Street Fund
0.125105	Nationwide Global Sustainable Equity Fund
0.123231	DFA International Sustainability Core 1 Portfolio
0.120132	TIAA-CREF Social Choice Low Carbon Equity Fund
0.118746	DFA US Sustainability Core 1 Portfolio
0.115917	FundX Sustainable Impact Fund
0.113963	Russell Sustainable Equity Fund
0.113654	BlackRock Advantage ESG US Equity Fund
0.113602	Calvert US Large Cap Core Responsible Index Fund
0.110561	Guinness Atkinson Funds - Alternative Energy Fund
0.108396	Calvert Social Investment Fund - Calvert Growth Allocati
0.108018	iShares MSCI USA ESG Select ETF

## CONCLUSIONS

- Geopolitical risks are shocks that impact many markets, sectors and asset classes.
- These can be observed as tail events in many asset returns.
- A Geopolitical Volatility Factor (GEOVOL) is introduced which has different loadings for different assets.
- Estimation and testing methods are introduced and examined by Monte Carlo.
- When applied to sector and country models, extreme events and factor loadings are identified.
- Portfolio implications are discussed.

YES, THERE IS ANOTHER WAY TO MANAGE GEOPOLITICAL RISKS

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