Hedging Geopolitical Risk News

by

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1. Introduction

With recent significant risks and acts of geopolitical tension such as Covid-19, trade wars, political protests, and climate change, it is becoming increasingly more crucial to research and understand the effects of geopolitical risk on investments. The study of geopolitical tensions and other macroeconomic risks is gaining popularity in the research and investment communities, as more investors are finding value in understanding the impact of world events on their portfolios. A 2017 Gallup survey reported that 75% of investors were concerned about the effects of geopolitical risk on the business environment (Caldara).

In this paper, we try to understand and assess the impacts of geopolitical risk on asset prices using quantitative methods. The goal is to construct investment portfolios that achieve the best balance between such risks and returns.

The first step is to identify an index that quantifies, captures and records geopolitical risk on a consistent basis. Dario Caldara and Matteo Iacoviello's Geopolitical Risk Index is constructed on a monthly basis and counts the use of certain words related to geopolitical risk in prominent global newspapers through textual analysis. The index is broken down into the Benchmark Index (GPR), which starts in 1985 and uses eleven newspapers (e.g., Financial Times, Chicago Tribune), and the Historical Index (GPRH), which starts in 1899 and uses three newspapers. The two indices are further broken down into threats, acts, and a combination of the two; the indices measuring threats (GPR_THREAT and GPRHT) capture newspaper coverage only of risks of adverse geopolitical events, while the indices counting acts (GPR_ACT and GPRHA) only capture actual adverse events that have occurred. In this paper, we use the Benchmark Index as our measure of geopolitical risk, as it captures both the impacts of threats and acts from a variety of newspapers for over 30 years.

Using the GPR, we attempt to understand the relationship between geopolitical risk and asset prices on a monthly basis and use these relationships to create effective hedge portfolios. For statistical reasons, this requires two steps: first create so-called factor mimicking portfolios that "project" geopolitical risk on asset prices, and then use the results to construct a set of hedge portfolios.

To build on what previous research shows in relevant areas, we review those papers which we believe create a strong foundation to approach our guiding research questions. "Portfolios and Exact Arbitrage Pricing" (Huberman, Kandel, and Stambaugh) explored portfolio construction through factor mimicking. "Measuring Economic Policy" (Bloom, Baker, and Davis) developed a new index for economic policy uncertainty and measured its impact on investments, employment, and output in VAR models. "Economic Forces and the Stock Market" (Chen, Roll, and Ross) found that sources of macroeconomic risk are significantly priced in the market. "Economic Tracking Portfolios" (Lamont) discovered the usefulness of tracking portfolios in predicting macroeconomic variables and hedging economic risk. "Hedging Climate Change News" (Engle, Giglio, Kelly, Lee, and Stroebel) discussed climate change hedge portfolios that performed well compared to other hedge portfolios with industry tilts. These five papers, among others, create a framework and methodology for portfolio construction focused around macroeconomic events. We believe the methods used in these studies serve as great tools for understanding the relationship of geopolitical risk and investments.

2. Methodology and Data

This paper attempts to create successful hedge portfolios by going long a broad index, here the S&P 500 ETF, SPY, and short a factor mimicking portfolio—a tradeable portfolio maximally correlated with the GPR. Four mimicking portfolios are created: three using different collections of S&P 500 stocks and one using the Fama-French five-factor model. The first three methods draw monthly returns data from *Yahoo Finance* for individual S&P 500 stocks, while the final method uses monthly returns data for the five Fama-French factors from Kenneth French's data library. The data period used is from June 2000 to February 2020, allowing for 237 observations for each regression. This data period is chosen as it allows for complete returns data for over 300 of the current S&P 500 companies.

To create the factor mimicking portfolios in each method, we regress the monthly changes in the GPR on returns of the chosen factors (assets):

$$q_t = \sum_{i=1}^{N} w_i r_{i,t} + e_t = \hat{q}_t + \hat{e}_t$$

The time series we are looking to mimic, in this case the GPR, is represented by q_t, while $\hat{q}_t$ represents the values of the GPR predicted by the mimicking portfolio; w_i for each factor in these regressions serves as the respective factor's weight in the mimicking portfolio.

We want a hedge portfolio uncorrelated with q (GPR) but with minimum variance. To find the weights, we regress the returns of SPY on the prediction of the GPR from the mimicking portfolio, which plays the role of an instrumental variable:

$$r_t^M = \beta \hat{q}_t + h_t$$

To solve for the hedge portfolio, denoted h_t, we must find the difference between the returns of SPY and the product of the returns of the mimicking portfolio and its β:

$$h_t = r_{tM} - \beta \hat{q}_t$$

The negative of the beta of the mimicking portfolio in this second regression serves as the mimicking portfolio's weight in the hedge portfolio, while SPY is assigned a weight of 1 in the hedge portfolio. Therefore, each hedge portfolio consists of w(SPY) = 1 and w(Mimicking

Portfolio) = $-\beta$. Through this construction, h should be uncorrelated with q, creating a potentially valuable hedge portfolio.

3. Factor and Model Selection

Four different methods of factor selection are used to create the distinct mimicking portfolios. The first three methods contain the same first initial step of collecting the monthly returns of individual S&P 500 stocks and creating a correlation matrix for these returns with the change in the GPR. We then chose to further analyze the 20 S&P 500 stocks most correlated with the GPR, pictured below in **Figure 1**:

Rank	Stock	Correlation with GPR	Industry
1	NOC	0.1926	Aerospace & Defense
2	AJG	0.1846	Insurance
3	FLIR	0.1801	Thermal Imaging
4	WRB	0.1799	Insurance
5	NEM	0.1267	Gold Mining
6	VZ	0.1193	Telecom
7	MRK	0.1058	Pharmaceutical
8	T	0.1013	Telecom
9	AON	0.0991	Insurance
10	LHX	0.0977	Telecom/Defense
11	AZO	0.0962	Autoparts Retailer
12	PFE	0.0919	Pharmaceutical
13	LMT	0.0915	Aerospace & Defense
14	GD	0.0884	Aerospace & Defense
15	J	0.0735	Engineering
16	BSX	0.0732	Medical Device
17	WAT	0.0702	Life Science
18	FE	0.0696	Utilities
19	INTU	0.0676	Financial Software
20	CPRT	0.0568	Vehicle Remarketing

Figure 1: Top 20 S&P 500 stocks most correlated with GPR for the data period

The final method simply uses the five Fama-French factors to construct the mimicking portfolio.

3.1 Method 1: Stepwise Regression with Akaike Information Criterion

Method 1 uses the Akaike Information Criterion (AIC) model to estimate the out-of-sample prediction error of different models, therefore finding the model with the highest prediction quality. AIC approaches the impacts of overfitting and underfitting a model by weighing the goodness of fit of the model with its simplicity. With $\hat{L}$ as the maximum value of the likelihood function and *k* as the number of model parameters, AIC can be calculated as:

$$AIC = 2k - 2\ln(\hat{L})$$

The model with the lowest AIC value is the highest quality model, as it balances rewarding high goodness of fit and penalizing excessive parameters.

The factor selection process in Method 1 uses both forward and backward selection to choose the model with the lowest AIC value; the resulting model only used 4 stocks out of the original 20: NOC, AJG, FLIR, and LMT. This method used the least number of parameters of the four methods, but the stocks used were sensible from a qualitative standpoint given their industries. Northrop Grumman (NOC) and Lockheed Martin (LMT) are both aerospace and defense companies. FLIR Systems (FLIR) creates thermal imaging systems with some focus on government and military end markets. Arthur J. Gallagher & Co. (AJG), an insurance company, offers war risk underwriting through a variety of war risk coverage packages. These firms all have business models at least somewhat dependent on threats or acts of war, terrorism, and political tension, potentially explaining their higher correlations with the GPR and why they are suited to be factors in the GPR mimicking portfolio.

3.2 Method 2: Stepwise Regression with Subsets

Method 2's factor selection uses forward and backward selection in order to identify the best-fit model for a range of values of k parameters from $k = 1$ to k_{max}. This removes the dependency on a penalty model such as AIC in Method 1, as k is no longer a variable in model quality assessment. For this analysis, given there were 20 stocks used, k_{max} = 19 to form 19 total subsets; the selected stocks for each level of k are given a value of "*" and eliminated variables are given the value " ", as seen in **Figure 2**:

Stock

k	NOC	AJG	FLIR	WRB	NEM	VZ	MRK	T	AON	LHX	AZO	PFE	LMT	GD	J	BSX	WAT	FE	INTU	CPRT
1 (1)	"*"	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "
2 (1)	"*"	" "	"*"	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "
3 (1)	"*"	" "	"*"	" "	" "	" "	" "	" "	" "	" "	" "	" "	"*"	" "	" "	" "	" "	" "	" "	" "
4 (1)	"*"	"*"	"*"	" "	" "	" "	" "	" "	" "	" "	" "	" "	"*"	" "	" "	" "	" "	" "	" "	" "
5 (1)	"*"	"*"	"*"	"*"	"*"	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "
6 (1)	"*"	"*"	"*"	" "	"*"	" "	" "	" "	" "	" "	" "	" "	"*"	"*"	" "	" "	" "	" "	" "	" "
7 (1)	"*"	"*"	"*"	" "	"*"	"*"	" "	" "	" "	" "	" "	" "	"*"	"*"	" "	" "	" "	" "	" "	" "
8 (1)	"*"	"*"	"*"	" "	"*"	"*"	" "	" "	" "	" "	" "	"*"	"*"	"*"	" "	" "	" "	" "	" "	" "
9 (1)	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "	" "
10 (1)	"*"	"*"	"*"	"*"	"*"	"*"	" "	" "	" "	" "	" "	"*"	"*"	"*"	" "	" "	" "	"*"	" "	" "
11 (1)	"*"	"*"	"*"	"*"	"*"	"*"	" "	" "	" "	" "	" "	"*"	"*"	"*"	"*"	" "	" "	"*"	" "	" "
12 (1)	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	" "	" "	" "	" "	" "	" "	" "	" "
13 (1)	"*"	"*"	"*"	"*"	"*"	"*"	"*"	" "	" "	"*"	" "	"*"	"*"	"*"	"*"	" "	" "	"*"	" "	" "
14 (1)	"*"	"*"	"*"	"*"	"*"	"*"	"*"	" "	"*"	"*"	" "	"*"	"*"	"*"	"*"	" "	" "	"*"	" "	" "
15 (1)	"*"	"*"	"*"	"*"	"*"	"*"	"*"	" "	"*"	"*"	" "	"*"	"*"	"*"	"*"	" "	" "	"*"	" "	"*"
16 (1)	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	" "	" "	" "	" "
17 (1)	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	" "	"*"	"*"	"*"	"*"	" "	" "	"*"	"*"	"*"
18 (1)	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	" "	" "
19 (1)	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	"*"	" "

Figure 2: Factor selection through subsets for different levels of k

These 19 models were then ranked and compared by R^2 in **Figures 3 and 4:**

k	R-Squared	Rank
1	0.0371	19
2	0.0587	18
3	0.0706	17
4	0.0850	14
5	0.0792	16
6	0.0974	12
7	0.1004	11
8	0.1044	10
9	0.0834	15
10	0.1105	9
11	0.1138	8
12	0.0905	13
13	0.1166	6
14	0.1174	5
15	0.1179	4
16	0.1148	7
17	0.1189	1
18	0.1180	3
19	0.1183	2

Figure 3: The R^2 for each subset k with its ranking for the group

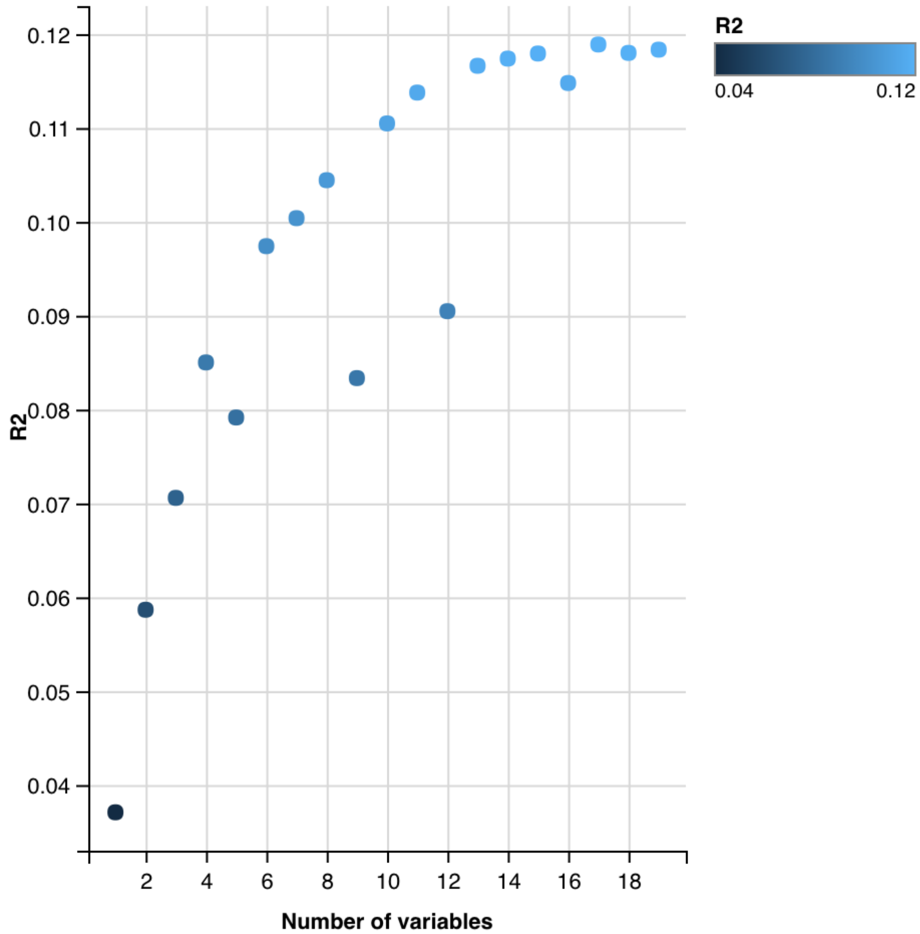

Figure 4: R_2 plotted for each model k

Although it does not have the most parameters among the subsets, the model $k = 17$ has the highest R_2, so it was selected as the model to implement for Method 2. Because this method does not penalize parameter quantity, it offers a distinct selection process from Method 1.

3.3 Method 3: Coefficient Elimination

In Method 3, the GPR was regressed on the 20 S&P 500 stocks, and those variables with coefficients > 0.5000 were selected, whereas the rest of the parameters were eliminated from the model, as seen in **Figure 5**:

Stock	Coefficient				
NOC	2.8049	T	-0.3915	J	-0.5425
AJG	1.5864	AON	-0.3435	BSX	0.0315
FLIR	0.9824	LHX	0.3747	WAT	0.0160
WRB	0.9318	AZO	-0.0883	FE	-0.6933
NEM	0.6735	PFE	-1.1110	INTU	0.1644
VZ	1.2116	LMT	-1.4421	CPRT	-0.2089
MRK	0.5450	GD	-1.1908		

Figure 5: Parameters in green are selected, as their coefficients > 0.5000; parameters in red are eliminated

This elimination process aims to keep the most significant, positively related variables with the goal of forming an efficient yet accurate model.

3.4 Method 4: Fama-French Five Factor Model

Method 4 uses the standard Fama-French five factors: excess return on the market (Mkt-RF), size (SMB), value (HML), profitability (RMW), and investment conservatism (CMA) to create a mimicking portfolio for the GPR.

4. Mimicking Portfolio Construction

The different factor weights for each method's mimicking portfolio are presented sequentially below as well as each mimicking portfolio's regression statistics and correlation matrix.

Method 1

Regression Statistics	
Multiple R	0.2916
R Square	0.0850
Adjusted R Square	0.0692
Standard Error	0.6383
Observations	237

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.0482	0.0432	1.1161	0.2655
NOC	2.5942	0.9257	2.8023	0.0055
AJG	1.4347	0.7500	1.9130	0.0570
FLIR	0.8793	0.3629	2.4232	0.0162
LMT	-2.1162	0.9854	-2.1477	0.0328

Factor	NOC	AJG	FLIR	LMT
Weight	2.5942	1.4347	0.8793	-2.1162

	NOC	*AJG*	*FLIR*	*LMT*
NOC	1.0000			
AJG	0.4060	1.0000		
FLIR	0.1854	0.2450	1.0000	
LMT	0.7243	0.4678	0.3009	1.0000

Figure 6: Method 1 mimicking portfolio regression statistics, weights and correlation matrix

Based on the regression for Method 1, the mimicking portfolio loaded positively on three out of four of its factors and loaded negatively on LMT, most likely due to the high correlation of 0.7243 between NOC and LMT; this high correlation is intuitive given NOC and LMT both operate in the aerospace and defense industry. The mimicking portfolio's positive weighting on the first three stocks can be justified, as each company serves segments driven by geopolitical tensions and acts of war.

Method 2

Regression Statistics	
Multiple R	0.1189
R Square	0.1189
Adjusted R Square	0.0505
Standard Error	0.6447
Observations	237

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.0287	0.0457	0.6290	0.5300
NOC	2.8062	1.0577	2.6530	0.0086
AJG	1.5989	0.9471	1.6880	0.0928
FLIR	0.9770	0.3926	2.4880	0.0136
WRB	0.9086	0.7768	1.1700	0.2434
NEM	0.6724	0.4240	1.5860	0.1142
VZ	1.1794	1.0981	1.0740	0.2840
MRK	0.5489	0.7720	0.7110	0.4779
T	-0.3860	1.0591	-0.3640	0.7159
AON	-0.3338	0.7479	-0.4460	0.6558
LHX	0.3763	0.6632	0.5670	0.5710
PFE	-1.1004	0.9719	-1.1320	0.2588
LMT	-1.4487	1.0996	-1.3180	0.1890
GD	-1.1954	0.9892	-1.2080	0.2282
J	-0.5375	0.5881	-0.9140	0.3618
FE	-0.6786	0.8067	-0.8410	0.4011
INTU	0.1624	0.4851	0.3350	0.7381
CPRT	-0.2155	0.5240	-0.4110	0.6814

Factor Weight	NOC	AJG	FLIR	WRB	NEM	VZ	MRK	T	AON
	2.8062	1.5989	0.9770	0.9086	0.6724	1.1794	0.5489	-0.3860	-0.3338
	LHX	**PFE**	**LMT**	**GD**	**J**	**FE**	**INTU**	**CPRT**	
	0.3763	-1.1004	-1.4487	-1.1954	-0.5375	-0.6786	0.1624	-0.2155	

	NOC	*AJG*	*FLIR*	*WRB*	*NEM*	*VZ*	*MRK*	*T*	*AON*	*LHX*	*PFE*	*LMT*	*GD*	*J*	*FE*	*INTU*	*CPRT*
NOC	1.0000																
AJG	0.4060	1.0000															
FLIR	0.1854	0.2450	1.0000														
WRB	0.3847	0.5623	0.2248	1.0000													
NEM	0.2129	0.0069	0.0637	0.0049	1.0000												
VZ	0.1551	0.2524	0.2370	0.0855	0.0650	1.0000											
MRK	0.2397	0.2848	0.1375	0.2094	0.1729	0.4480	1.0000										
T	0.1839	0.3404	0.2285	0.2180	0.0449	0.7416	0.4126	1.0000									
AON	0.3662	0.4771	0.1592	0.3929	0.0456	0.1741	0.2025	0.2144	1.0000								
LHX	0.4595	0.2460	0.2265	0.1140	0.1361	0.1784	0.1302	0.1368	0.2578	1.0000							
PFE	0.4143	0.4208	0.2696	0.2889	0.1911	0.3923	0.5279	0.3632	0.2335	0.2791	1.0000						
LMT	0.7243	0.4678	0.3009	0.3492	0.1091	0.1716	0.2609	0.2169	0.3458	0.4309	0.4146	1.0000					
GD	0.6466	0.4459	0.3312	0.2972	0.1096	0.2896	0.2950	0.3009	0.3297	0.5461	0.3978	0.6996	1.0000				
J	0.4472	0.3094	0.2352	0.3038	0.2459	0.2294	0.3088	0.2156	0.3489	0.3673	0.4065	0.4202	0.4228	1.0000			
FE	0.2006	0.2951	0.2438	0.2219	0.1058	0.2258	0.1299	0.2512	0.1192	0.1042	0.1680	0.1629	0.1642	0.1052	1.0000		
INTU	0.2182	0.1379	0.1179	0.0138	0.1251	0.2405	0.2128	0.1984	0.1844	0.2013	0.2610	0.1566	0.2863	0.2502	-0.0454	1.0000	
CPRT	0.2728	0.2034	0.2278	0.1930	0.1300	0.1998	0.2286	0.1841	0.1873	0.1905	0.2832	0.1990	0.3576	0.3117	0.1103	0.2644	1.0000

Figure 7: Method 2 mimicking portfolio regression statistics, weights and correlation matrix

Given it has the most parameters among the different methods, Method 2 had several positive and negative factor loadings.

Method 3

Regression Statistics	
Multiple R	0.2854
R Square	0.0814
Adjusted R Square	0.0533
Standard Error	0.6437
Observations	237

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.0313	0.0440	0.7117	0.4774
NOC	0.8771	0.7392	1.1866	0.2366
AJG	0.6622	0.8526	0.7767	0.4381
FLIR	0.6117	0.3668	1.6675	0.0968
WRB	0.7647	0.7425	1.0299	0.3041
NEM	0.6101	0.4116	1.4824	0.1396
VZ	0.5709	0.7949	0.7182	0.4734
MRK	-0.0600	0.7080	-0.0848	0.9325

Factor Weight	NOC	AJG	FLIR	WRB	NEM	VZ	MRK
	0.8771	0.6622	0.6117	0.7647	0.6101	0.5709	-0.0600

	NOC	AJG	FLIR	WRB	NEM	VZ	MRK
NOC	1.0000						
AJG	0.4060	1.0000					
FLIR	0.1854	0.2450	1.0000				
WRB	0.3847	0.5623	0.2248	1.0000			
NEM	0.2129	0.0069	0.0637	0.0049	1.0000		
VZ	0.1551	0.2524	0.2370	0.0855	0.0650	1.0000	
MRK	0.2397	0.2848	0.1375	0.2094	0.1729	0.4480	1.0000

Figure 8: Method 3 mimicking portfolio regression statistics, weights and correlation matrix

Method 3 loaded positively on all but one of its factors; its negative loading on MRK perhaps may be explained by its high correlation with VZ.

Method 4

Regression Statistics	
Multiple R	0.1717
R Square	0.0295
Adjusted R Square	0.0085
Standard Error	0.6588
Observations	237

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.0902	0.0454	1.9861	0.0482
Mkt-RF	-0.0010	0.0124	-0.0845	0.9328
SMB	0.0216	0.0184	1.1718	0.2425
HML	-0.0334	0.0192	-1.7451	0.0823
RMW	0.0052	0.0232	0.2229	0.8238
CMA	-0.0108	0.0278	-0.3892	0.6975

Factor	**Mkt-RF**	**SMB**	**HML**	**RMW**	**CMA**
Weight	-0.0010	0.0216	-0.0334	0.0052	-0.0108

	Mkt-RF	*SMB*	*HML*	*RMW*	*CMA*
Mkt-RF	1.0000				
SMB	0.3332	1.0000			
HML	0.0477	0.2505	1.0000		
RMW	-0.5334	-0.2703	0.2910	1.0000	
CMA	-0.2128	0.0719	0.5997	0.3068	1.0000

Figure 9: Method 4 mimicking portfolio regression statistics, weights and correlation matrix

Method 4's mimicking portfolio generally has low weights in each of its factors. Geopolitical risk appears to load negatively on the market's excess return; perhaps the market performs less in-excess of the risk-free rate in times of high geopolitical risk. The GPR loads positively on SMB, demonstrating that smaller firms may perform better than larger firms in times of higher geopolitical risk. A negative loading on HML suggests that growth stocks may perform better than value stocks when the GPR increases. The positive weighting on RMW suggests highly profitable firms perform better than those with weak operating profitability when the GPR rises. Lastly, geopolitical risk appears to load negatively on CMA suggesting firms that invest aggressively outperform those which invest conservatively when the GPR rises.

These distinct mimicking portfolios were then used to form hedge portfolios.

5. Hedge Portfolio Performance

Each hedge portfolio is measured by annualized expected return, annualized standard deviation, annualized Sharpe ratio, and final equity value of $100 invested at the beginning of the data period. The annualized risk-free rate is assumed to be 2.00%.

	w(MP)	w(SPY)	E[rP]	SD[rP]	SR[rP]	Final EQ
Method 1	-0.0228	1.0000	2.88%	14.73%	0.060	142.23
Method 2	-0.0116	1.0000	3.17%	**14.50%**	0.081	150.14
Method 3	-0.0260	1.0000	2.20%	14.71%	0.013	124.23
Method 4	-0.0071	1.0000	**4.02%**	14.81%	**0.137**	**177.60**
SPY	0.0000	1.0000	4.02%	14.81%	0.136	177.41

Figure 10: Performance for each hedge portfolio

While Method 2 had the lowest variance, Method 4 had the highest expected return, Sharpe Ratio, and final equity. The Fama-French five factor-based hedge portfolio slightly outperformed SPY on Sharpe ratio and final equity for the data period, demonstrating the value of the GPR hedge. The equity graphs for the four methods and SPY are plotted against the GPR below in **Figure 11**:

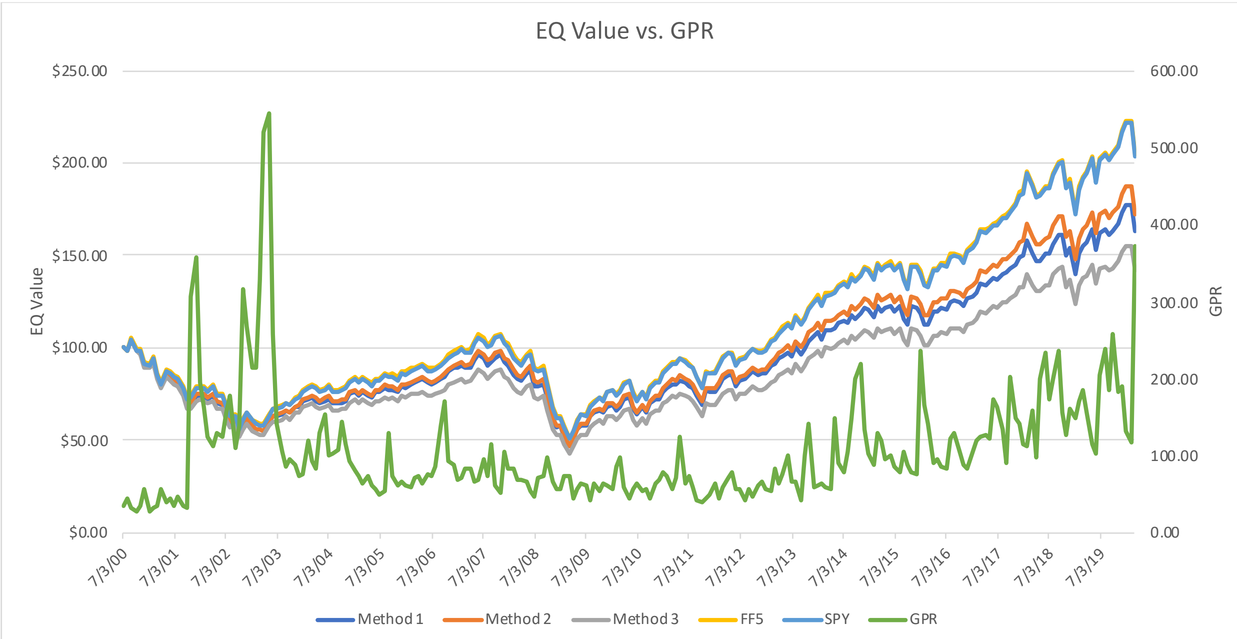

Figure 11: Equity values and GPR for the data period

As can be seen in the equity graph, SPY and Method 4 move almost identically, given the small weight of the hedge portfolio in Method 4. Method 4 is the most successful of the hedge portfolios in replicating the returns of SPY with less correlation to the GPR; this can be seen in **Figure 12**:

	Method 1	*Method 2*	*Method 3*	*Method 4*	*SPY*	*GPR*
Method 1	1.0000					
Method 2	0.9982	1.0000				
Method 3	0.9977	0.9974	1.0000			
Method 4	0.9948	0.9981	0.9935	1.0000		
SPY	0.9947	0.9981	0.9934	0.9998	1.0000	
GPR	-0.0196	-0.0109	-0.0224	0.0073	0.0106	1.0000

Figure 12: Correlation matrix of hedge portfolios, SPY, and GPR

Method 4 had the lowest weight in its respective mimicking portfolio, while Method 3 had the highest weight in its mimicking portfolio; this difference affected their directional relationships with the GPR. Because of the difference in their weighting schemes, Method 3 resulted in the most negative correlation with the GPR, while Method 4 had a slightly less positive correlation with the GPR than SPY did.

Of the four methods, Method 4 is most effective at constructing a hedge portfolio for geopolitical risk, as the resulting hedge portfolio is less correlated with the GPR than SPY is with the GPR. Method 4's hedge portfolio successfully replicates its benchmark, the S&P 500, while reducing an investor's exposure to fluctuations in geopolitical risk.

6. Conclusion and Further Exploration

This paper explores four different methods for constructing hedge portfolios using mimicking portfolios in order to hedge geopolitical risk. Using the GPR as the proxy for geopolitical risk, we were able to form an effective hedge portfolio consisting of the Fama-French five factors—Mkt-RF, SMB, HML, RMW, and CMA—and SPY. This hedge portfolio offers an investment product for investors looking to receive similar returns to that of the S&P 500 with reduced exposure to geopolitical risk. With a slightly higher Sharpe ratio and a higher final equity value than SPY, Method 4's hedge portfolio outperforms its benchmark for the data period analyzed in this paper.

Although we were able to form a successful hedge portfolio for geopolitical risk, there are many potential avenues for further exploration on this topic. Different factors can be explored to create a variety of mimicking portfolios that may result in more optimal hedge portfolios. Additionally, hedging the available separate aspects of geopolitical risk such as the threats and acts indices may provide more useful results; markets may sell on the threat of geopolitical risk and buy on the act. As proxies for geopolitical risk such as the GPR improve in accuracy with more data, hedge portfolios may be more effective. A world with increasing uncertainty and geopolitical tensions will demand further research on the relationship of asset returns and geopolitical risk.

References

1. Baker, Scott R., et al. "Measuring Economic Policy Uncertainty." *The Quarterly Journal of Economics*, vol. 131, no. 4, Nov. 2016, pp. 1593–1636., doi:10.2139/ssrn.2198490.
2. Caldara, Dario, and Matteo Iacoviello. "Measuring Geopolitical Risk." *International Finance Discussion Paper*, vol. 2018, no. 1222, 2018, pp. 1–66., doi:10.17016/ifdp.2018.1222.
3. Chen, Nai-fu, et al. *The Journal of Business, University of Chicago Press*, vol. 59, no. 3, July 1986, pp. 383–403.
4. Engle, Robert F., et al. "Hedging Climate Change News." *SSRN Electronic Journal*, 17 Jan. 2019, doi:10.2139/ssrn.3317570.
5. "Federal Reserve Economic Data: FRED: St. Louis Fed." *FRED*, Federal Reserve Bank of St. Louis, fred.stlouisfed.org/.
6. "Global Risk Briefing." *Bloomberg.com*, Bloomberg, www.bloomberg.com/graphics/global-risk-briefing/.
7. *Kenneth R. French - Data Library*, mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
8. Lamont, Owen A. "Economic Tracking Portfolios." *SSRN Electronic Journal*, Mar. 1999, doi:10.2139/ssrn.157772.
9. Pukthuanthong, Kuntara, et al. "A Toolkit for Factor-Mimicking Portfolios." *SSRN Electronic Journal*, 20 Feb. 2019, doi:10.2139/ssrn.3341604.
10. "Real-Time Financial Volatility, Correlation, And Risk Measurement, Modeling, And Forecasting." *V-Lab*, vlab.stern.nyu.edu/.

11. Roll, Richard, and Akshay Srivastava. "Mimicking Portfolios." *The Journal of Portfolio Management*, vol. 44, no. 5, 2018, pp. 21–35., doi:10.3905/jpm.2018.44.5.021.

12. "Yahoo Finance - Stock Market Live, Quotes, Business & Finance News." *Yahoo! Finance*, Yahoo!, finance.yahoo.com/.