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Geopolitical risk and the stock market in Sweden

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Abstract

The recent country specific geopolitical risk index for Sweden (Caldara and Iacoviello, 2022) is applied on Swedish stocks where decile portfolios are created based on their firm beta estimates. The findings indicate a significant, positive alpha for the D10 (hedge) portfolio that improves upon the CAPM, FF5 and FF6 factor models. The highest nominal return in the long run fall to the market index, however in the short run when geopolitical risk is high the D10 portfolio provides both the best nominal and risk adjusted returns. When comparing D1, D10 and OMXSPI, the D10 portfolio had the highest yearly Sharpe ratio most often, but only slightly more often than the market index. During years when GPR was high, the D10 portfolio provided the best risk adjusted returns. The results for the D10 portfolio are robust to bootstrapping, but varying between decades, indicative of GPR sorting only being important when GPR is high. During spikes in GPR it becomes one of the most important factors driving stock returns. Therefore, it is important during turbulent times to consider GPR for contemporaneous investors seeking superior risk adjusted returns and in forecasting the future value of stock returns.

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1. Introduction

During recent years the interest in stock market investments among people in Sweden has grown considerably, with close to 3 million people owning stocks (Euroclear, 2025). With 30% of the population being private owners and close to everyone being affected by stock market movements through changes in pension savings, the importance of the stock market on everyday people cannot be overstated. The increase in investments further necessitates solid investment strategies and a natural question thus arises on what this strategy could be. The increased investment in stocks coincide with rising tensions in the world, such as the 2022 Russian invasion of Ukraine, the invasion of Gaza in 2023, the 12-day war in 2025 and recent airstrikes on Iran by the U.S. and Israel in 2026. The rising tensions were severe enough to end Sweden's 200 years of neutrality when in 2024 it joined NATO. The increasing tensions have pushed geopolitical risk, defined by Caldara and Iacoviello (2022) as the risk regarding adverse political events such as war and terror, to the forefront of investor concerns, becoming the "grey rhino" event: an event that is both highly probable and high impact, that investors are most concerned about (Cheng and Zhong, 2025).

The expansion of the capital asset pricing model (CAPM), (Sharpe, 1964; Lintner, 1965) in the intertemporal capital asset pricing model (ICAPM), (Merton, 1973) introduced not only the market-beta relationship as the sole factor, but also other covarying state variables that affect future changes in the investment opportunity set. One such plausible variable is geopolitical risk due to the evidence by Caldara and Iacoviello (2022) that found that spikes in GPR are predictors of future decline in investments. Risk-averse investors should thus seek to hedge this risk and demand compensation for holding a riskier asset through a risk premium.

To understand what geopolitical risk is and why it is important, some further background is needed. While the concept of geopolitics is old, with examples ranging from the writings of Aristotle (384-322 BC) to Montesquieu (1689-1755), the term geopolitics was coined more recently in the beginning of the 20th century by Rudolf Kjellén. A combination of geography and politics, it is a term used to describe how geography affects the power relationships in international politics. In general, it is a term often used interchangeably with international politics (Deudney, 2019). Applying this loose definition the geopolitical risk thus becomes the risks and effects of politics and of adverse events that affect the political climate, such as threats and realisations of war, terror attacks and nuclear threats. Attempts to quantify this geopolitical risk are multiple, the most prominent and the one used in this paper has been done by Caldara and Iacoviello (2022) in the geopolitical risk index. The historical index is created by analysing 10,000 articles per month from 3 different newspapers from the year 1900 to the present and counting the share of articles discussing negative geopolitical events and threats. A higher value is thus signalling of higher geopolitical risk. The recent geopolitical risk index for Sweden, which is the one used in this research paper, consists of 30,000 articles per month from 10 prominent U.S., U.K. and Canadian newspapers from the year 1985 to the present. The total sample of articles consists of about 25 million news articles.

While the relationship between geopolitical risk and stocks is well documented for larger combinations of countries such as the G7 and G20 countries and individual larger countries such as the U.S. and China, surprisingly little is known about the Swedish market on the firm level. With evidence of GPR being country specific (Zhang et al., 2022), the effect of GPR on Sweden needs to be further investigated, especially in the light of recent increased tensions and increased interest in investments. This begs the question if geopolitical risk can be used as a factor in an investment strategy to achieve better risk adjusted returns, or if the investor would be better off buying the market instead. Specifically, my research question is:

Can an investor using geopolitical risk achieve better risk adjusted returns?

The purpose of this thesis is to evaluate whether firm level exposure to geopolitical risk is priced in the Swedish stock market and to evaluate if this can be systematically leveraged by sorting stocks based on their firm beta estimates to achieve better risk adjusted returns. This study also aims to increase the awareness surrounding geopolitical risk in Sweden and how big the difference in return can be between two portfolios when the only variable changed is its sensitivity to geopolitical risk. If this is spread, it should make it harder for the intelligent investor to hold stocks without thinking about its exposure to GPR and should thus lead to investors only holding stocks that they truly believe in, for reasons they are aware of. At least in theory.

This sort of study is something that to the author's knowledge has not been done before for Sweden. Some might even wonder whether geopolitical risk is even something worth considering due to how protected Sweden has been regarding war and conflict. Precisely such doubts prove the importance of this study, where GPR is proven as a significant factor that when used correctly considerably improves upon models that do not incorporate it. By situating Sweden in the broader scheme of knowledge regarding GPR, this study expands upon the previous knowledge regarding geopolitical risk and investments through adding firm-level evidence from Sweden that can guide future investors in their pursuit of better investments, improving upon our previous understanding of what factors matter when looking for alpha beyond the CAPM and Fama French factors.

My structure for the rest of paper is as follows: Section 2 presents the literature review on what is known in the field, section 3 establishes the theoretical background based on ICAPM, section 4 discusses choice of methodology and decile sorting, section 5 presents the data and descriptive statistics, section 6 through 9 provides results, discussion, conclusion and references.

2. Literature review

Geopolitical risk has increased over the years and has become the "grey rhino" event that global investors are most worried about (Cheng and Zhong, 2025). Different from a black swan, the grey rhino as introduced by Michelle Wucker instead refers to events that are both highly probable and high impact, while often ignored. Multiple studies have been done previously tying together geopolitical risk and the stock market, many of which were published recently due to this being a currently popular field.

Studying the effect of the war in Iraq on U.S. financial markets it was found that an increase in war risk caused aggregate equity prices, treasury yields and the dollar to fall as well as an increase in oil prices (Rigobon and Sack, 2005). For the broader market, a stock's exposure to geopolitical risk is negatively related to its return (Baur and Smales, 2020). This is especially true for local geopolitical risk, something that is exacerbated for developed markets as compared to emerging markets and is more severe for high-risk as compared to low-risk markets. Further, global geopolitical risk is a priced factor meaning that investors are willing to accept a lower return to hold safer assets and demand a risk premium to hold riskier assets (Chen et al., 2026).

It has been found that stock prices are expected to fall at the announcement of a policy change, with the magnitude of the negative return increasing if uncertainty about the government policy is large (Pástor and Veronesi, 2010). This is because policy changes that increase the price are more expected than government policies that decrease it. It would therefore not be farfetched to expect stock prices to fall when the geopolitical risk is high, since the uncertainty about how the government will respond is large.

Findings by Brogaard and Detzel (2015) indicate that Economic Policy Uncertainty (EPU) is an economically important risk factor for stocks, where stocks with the lowest EPU beta outperform stocks with higher EPU beta and EPU positively forecast excess market returns. This again implies that whenever there is uncertainty about stock returns, be it regarding government policy or economic policy, then portfolios sorted on such state variables are likely to provide different returns from each other.

An increase in volatility of stock prices is found for GPR spikes by Zhang et al. (2022), when looking at 32 countries and regions the same is found by Pastor and Veronesi (2013), while it remains stable for G20 countries (Cheng and Zhong, 2025). Geopolitical risk increases downside risk to GDP growth (Caldara and Iacoviello, 2022), Cheng and Zhong (2025) see an increase in tail risk and tail risk connectedness for G20 countries. High geopolitical risk also increases contagion of downside risk and spreads through increased market pessimism and exchange rate volatility spreading from developed to less developed countries, a relationship that switches during crises. The same issue of contagion is seen by Foglia et al. (2025), where the larger economies of the U.S. and U.K. spread risk to the receiving G7 countries.

The effect of geopolitical risk is country specific and affect different countries and regions differently, with emerging markets, crude oil exporters and countries at peace being most affected (Zhang et al., 2022). Further, it is sector specific. Examining U.S. stocks, sectors react more strongly to terror threats than terror acts, and more strongly to escalations of war and military build ups than war threats and beginnings of war. Global peace and nuclear threats, while few, also contribute to volatility in certain industries (Chatziantoniou et al., 2025). The aviation industry and its corresponding stocks is one such sector that is more sensitive to geopolitical risk and were heavily affected both by COVID-19 and the Russian war on Ukraine. The relationship between geopolitical risk and airline stocks is stronger during turbulent market conditions and affects both tail ends, while geopolitical risk has little effect during normal market conditions, during extreme market conditions geopolitical risk becomes one of the most important factors determining the outcome of the airline stock (Song et al., 2025).

While geopolitical risk is both sector and country specific, the effect also varies by stock, justifying a cross-sectional approach such as Chen et al. (2026) has done prior. The different categories within the geopolitical risk index, such as the difference between geopolitical threats and acts are important, and which geopolitical risk category within the index that has the most impact varies by country (Chatziantoniou et al., 2025). Comparing four middle eastern economies; Israel, Egypt, Saudi Arabia and Turkey, military buildup had a consistent negative correlation with stock performance for Israel and Egypt, while Saudi Arabia and Turkey were most affected by war related events. Terrorism had a negative correlation with all four countries' stock markets (Eissa et al., 2024). These differences highlight the importance of the different categories and how the effect vary by country. Both threat and realization of geopolitical acts are important categories (Caldara and Iacoviello, 2022).

What about predictive power? Salisu et al. (2021) found global GPR to be a significant predictor of stock returns for the G7 countries and Schweiz, but not for Italy, outperforming models that do not include it. They also found geopolitical threats to have a larger impact than acts.

Foglia et al. (2025), again studying the G7 countries and Schweiz, state that global measures of geopolitical risk have predictive power at shorter horizons up to 6 months, while country-specific indices work better in the long run. Using the specific categories within the index improves the predictive power for U.S. stock market volatility and is robust across different U.S. stock market indices (Chatziantoniou et al., 2025). Stocks correlated with economic uncertainty carry a risk premium and earn more than stocks that are not correlated to economic uncertainty (Bali and Zhou, 2016). However, geopolitical risk is a distinct, separate factor that when high, predict economic disaster, lower economic return and decreased firm-level and sector-level investments (Caldara and Iacoviello, 2022).

Geopolitical risk affects investor sentiments negatively, while investor sentiments does not affect geopolitical risk. The effect on investor sentiments is time-varying, meaning that the effect of a geopolitical event is most important close to the event but decreases over time and investors respond more to domestic than global geopolitical events. Further, investor sentiment is equally affected by geopolitical risks, threats and acts (He, 2023). Investors react instantaneously to increases in geopolitical risk and during severe spikes the market panic-sells, while defence stocks act as hedges (Klein, 2024). Another hedge is gold and silver against geopolitical risk in general and particularly against geopolitical threats as compared to geopolitical acts (Baur and Smales, 2020).

The recent research into geopolitical risk and its effect on the stock market has been extensive. It has comprised most major nations individually at the firm level and smaller countries as part of larger groups at the country level. The same cannot be said about Sweden at the firm level, where little is known. To my knowledge, there only exists two papers discussing geopolitical risk and Sweden. A bachelor's thesis by Bergström and Larsson (2022) regarding the effect of geopolitical risk on the volatility of the Stockholm stock exchange and a master's thesis by Wikman (2025) conducted as an event study looking at the broader Nordic market. A firm level investigation into the stock market in Sweden and if investors can use geopolitical risk to achieve better risk adjusted returns has not been done before. My research expands upon the puzzle by placing the piece that is Sweden and situating it in the broader scheme of knowledge, further increasing what is known about geopolitical risk, and how investors can use it to achieve better risk adjusted returns.

3. Theoretical framework

The foundation for modern portfolio theory was put by Markowitz (1952) where it was established that return is something desirable and volatility undesirable and assumed that rational investors try to maximize their expected return while minimizing the volatility. Here investors are only compensated for bearing systematic risk, risk that cannot be diversified away. This led to the capital asset pricing model (CAPM) (Sharpe, 1964; Lintner, 1965) which states that in an efficient market assets are priced only depending on their market exposure. If the market is efficient, then no other factors should be able to provide excess return without increasing the risk. This leads to the efficient market hypothesis (Fama, 1970), which state that in a fully efficient market it should be impossible for anyone to consistently achieve better returns than the market since prices adjust immediately to new information.

In reality, markets seem to be efficiently inefficient (Garleanu and Pedersen, 2018), meaning that new variables such as state variables take time before they are fully integrated in the price, allowing for temporary anomalies.

The intertemporal capital asset pricing model (ICAPM) by Merton (1973) expands upon the original CAPM (Sharpe, 1964; Lintner, 1965) by stating that assets are priced not only depending on their market-beta exposure, but also on their covariance with other state variables. A state variable as defined by Merton (1973) is a variable that describes the state of the world and predicts future investment opportunities. One such possible variable is geopolitical risk due to the evidence by Caldara and Iacoviello (2022) that shocks in geopolitical risk predict lower future investments and output. This directly implies that geopolitical risk should be priced since risk-averse investors would want to buy assets that are positively affected by geopolitical risk so that in times of higher geopolitical risk, their investments would be safe through hedging. Empirical evidence by Chen et al. (2026) that find geopolitical risk to be a priced factor further strengthens this theory and gives it more credibility.

As an alternative to CAPM, the arbitrage pricing theory (Ross, 1976) instead gives more leeway in allowing for multiple risk factors that the stricter CAPM does not consider. Factors such as the ones suggested by Fama and French (2015, 2018) seem to explain a large part of the variety in returns.

If geopolitical risk really is systematic, as suggested by Pastor and Veronesi (2013), then this would further motivate a risk premium for GPR. This is made more likely by the flight to safety that is found by Klein (2024) where investors move into defence stocks and into gold and silver (Baur and Smales, 2020), into defence and aerospace companies (Zhang et al., 2022) when GPR is high.

4. Methodology

To investigate if geopolitical risk can be used as a factor providing better risk adjusted returns, a two-pass portfolio sorting procedure is done where first the geopolitical risk beta is estimated using individual stock time series data regressed on the geopolitical risk index (Caldara and Iacoviello, 2022). Then portfolios are created based on their corresponding geopolitical risk beta. The motivation for using the cross-section of Swedish stocks on the firm-level instead of only the index on the country-level is provided by Kelly and Pruitt (2013), where they found that the rich variety in individual stock data about future market expectations is removed in aggregation in a larger index.

Suggestions for how this is done is provided by Bali et al. (2017a), motivating the use of univariate portfolio sorts, that is using one factor such as GPR for predicting future stock prices by portfolio sorts. Further corroborating evidence for this method are provided by

Chen et al. (2026), Bali (2008), Anderson et al. (2009), Bali and Zhou (2016), Bali et al. (2017b).

Since geopolitical risk is not a tangible asset, such as gold, it cannot be bought by itself. To study it one needs to buy assets that are affected by it and respond to varying levels of GPR. By sorting stocks based on how they respond to GPR and placing said stocks into deciles it becomes possible to see larger patterns as well as differences that are both made invisible in the aggregation of an index as well as hard to spot among thousands of unsorted stocks. By sorting stocks based on characteristics such as GPR it is possible to see that stocks that were previously believed to be different respond similarly to a change in a common variable.

Since my research builds upon geopolitical risk as a factor that can help investors achieve better risk adjusted returns, the geopolitical risk index as created by Caldara and Iacoviello (2022) is used. The geopolitical risk index for Sweden is collected and used within the confines of the capital asset pricing model CAPM (Sharpe, 1964; Lintner, 1965), applied on Swedish stocks compared to a Swedish index, OMXSPI. First, the Swedish geopolitical risk index is used to create firm-specific estimates of their $\beta's$:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,MKT}\left(R_{OMXSPI,t} - R_{f,t}\right) + \beta_{i,GPR}(GPR_{Sweden,t}) + \varepsilon_{i,t} \quad (1)$$

Where $R_{i,t}$ is the return for stock i in time t, $R_{f,t}$ being the risk-free rate in time t, $R_{OMXSPI,t}$ is the return of the market index in time t and $GPR_{Sweden,t}$ is the recent country specific geopolitical risk index for Sweden in time t.

GPR can be used in its nominal form since the results from conducting the Augmented Dickey-Fuller test on the nominal GPR, market excess return and deciles 1 through 10 all indicate stationarity at the very least on the 5% level, results available in Table A1 in the appendix.

A rolling window approach with an estimation window length of preferably 60 months and a minimum of 36 months or greater is used. This means that if 60 months of data is available, then 60 months is used. If, however, only 36 months of continuous data is available, then that is the minimum used to create firm beta estimations. This ensures that the firm beta estimations are created using a sufficiently long time span, while not throwing out data that is available but missing only a few months. In practice this means that if for example 59 months of data is available, then the estimations are done using 59 months instead of not using the data at all. Since a rolling window approach is used the out of sample period is continuously rolled forward as the first portfolio is created in 1996 using 60 months of training data from the start of the stock returns in the beginning of 1991, the out of sample period moves forward one month at a time for an effective out of sample period of 30 years.

Then, once firm specific geopolitical risk estimates $\beta_{i,GPR}$ are created for each stock this is used to sort them into decile-portfolios based on their firm-specific geopolitical risk so that the decile 1 portfolio has the lowest (most negative) beta geopolitical risk, decile 2 slightly higher until the decile 10 portfolio that corresponds to the top 10% highest of beta geopolitical risk. The stocks in D10 would thus be the hedges, that is the stocks that react with a positive return when the GPR is high.

For the eleventh portfolio an important distinction is needed. Beta GPR signifies how much the return of the stock is affected by GPR, where a positive beta GPR leads to an increase in stock price when the GPR is high and a negative beta GPR leads to a decrease in stock price when GPR is high. An eleventh long-short portfolio is created that buys the lowest (most negative) beta GPR portfolio D1 and sells the highest (most positive) beta GPR portfolio D10. Since stocks with high beta GPR are safer, so that when GPR rises their return increases, risk averse investors should crave a risk premium for holding low beta GPR stocks, since all else equal a rational investor will only want to hold a riskier stock if it has a higher expected return. If the eleventh long-short portfolio is positive, this would be in agreement both with the predictions from the ICAPM (Merton, 1973), where a riskier asset must yield higher returns than a hedge, and in agreement with recent empirical findings such as Chen et al. (2026) that found riskier low beta GPR assets to yield higher returns than the safer hedges.

The portfolios are created using value weighting based on their market cap in the previous month and monthly rebalancing is done. Transaction costs are included for the full nominal wealth graph and the three decades of nominal wealth graphs. Transaction costs are not included in any of the tables. Where transaction costs are applied, the cost is 0.5% as suggested by DeMiguel et al. (2009) and Balduzzi (1999), where the cost is applied to the turnover with weights based on the market cap. Transaction costs are created following formula 16 by DeMiguel et al. (2009):

$$W_{k,t+1} = W_{k,t}(1 + R_{k,p})\left(1 - c \times \sum_{j=1}^{N} |\hat{w}_{k,j,t+1} - \hat{w}_{k,j,t^+}|\right), \qquad (16)$$

Where $W_{k,t}$ is the cumulative portfolio wealth in time t, $(1 + R_{k,p})$ is the gross return of the portfolio before costs, c being transaction cost and $\sum_{j=1}^{N} | \widehat{w}_{k,j,t+1} - \widehat{w}_{k,j,t} + |$ being the sum of the absolute difference between the target weight for the new month and the drifted weight at the end of the previous month, turnover.

It should be stated that the FF6 factors are the European factors (consisting of 16 European countries including Sweden), since they are not yet available for Sweden, so the study applies the assumption that the Swedish and European markets are similar enough for the study to hold. Depending on how large the difference is between the Swedish and European FF6 factors, and in what direction the difference is, this might bias the results. Since the Swedish factors do not exist, it is hard to say in which direction this biases the results. With the later findings that only the D10 portfolio was statistically significant on the 1% level when compared to the European FF6 factors, the results for the D1 to D9 and Long-Short portfolio can only be too conservative, if anything. Regarding the D10 portfolio, since the alpha instead is statistically significant, it could very well be that the results are too optimistic. What speaks against this is the evidence from the wealth graphs (Figure 2, 3, 4, 5) combined with the nominal GPR graph in Figure 1, that shows how differently the D10 portfolio behaves as compared to the other portfolios, especially when GPR is high.

The Swedish market rate (OMXSPI) is only available for the sample length through the price index (PI) instead of the total return index (RI) which includes reinvested dividends that the stock returns are calculated in, which leads to the market return curve being deflated. Any comparisons to the market return curve must thus be conservative, however since no cost is applied to the market index, the results should therefore be comparable.

The portfolios are then evaluated against the CAPM:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p\left(R_{OMXSPI,t} - R_{f,t}\right) + \varepsilon_{p,t} \quad (2)$$

Where $R_{p,t}$ is the return for portfolio p in time t, $R_{f,t}$ is the risk-free rate in time t and $R_{OMXSPI,t} - R_{f,t}$ is market excess return.

European Fama French 5 factor model (FF5), (Fama and French, 2015):

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{p,1}(MKT_t) + \beta_{p,2}(SMB_t) + \beta_{p,3}(HML_t) + \beta_{p,4}(RMW_t) + \beta_{p,5}(CMA_t) + \varepsilon_{p,t} \quad (3)$$

European Fama French 6 factor model (FF6), (Fama and French, 2018):

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{p,1}(MKT_t) + \beta_{p,2}(SMB_t) + \beta_{p,3}(HML_t) + \beta_{p,4}(RMW_t) + \beta_{p,5}(CMA_t) + \beta_{p,6}(Momentum_t) + \varepsilon_{p,t} \quad (4)$$

The evaluation against the three models CAPM, FF5 and FF6 to see if the α's are significant are done using the Gibbons Ross Shanken (GRS) test (Gibbons et al., 1989) and individual t-tests using Newey-West standard errors to correct for any autocorrelation or heteroskedasticity problems (Newey and West, 1994). Bootstrapping is used as a further robustness check and sub-sample analysis is used to see if the results are robust over time. Then summary statistics are created detailing the portfolio returns and behaviours, available in Table 1.

5. Data

The data collected is monthly data for the total return index (RI) for all Swedish stocks available from LSEG (dead and alive), price index (PI) for OMXSPI which incorporates corporate actions to be used as market reference, market cap (MV), a 1 month T-bill to be used as risk free rate (TRSD1MT), and classification for stock category, all collected from LSEG Refinitiv Workspace Datastream. The FF5- and FF6 factors are the European Fama French factors since the Swedish factors are not available, collected from the Kenneth R. French data library[1] and the GPR for Sweden is collected from Matteo Iacoviello's website[2]. All data is monthly and range from the 1st of January 1991 until 31st December 2025 for a period of 35 years. With the 60 month rolling regressions, the first portfolio created is available in the beginning of 1996 for 30 years of portfolio evaluation. The initial stock sample consists of 1383 Swedish stocks both listed and delisted on Nasdaq Stockholm, Spotlight Stockmarket (formerly Aktietorget), Nordic Growth Market and Burgundy Nordic MTF. The sample is believed by the author to be comprehensive, consisting of varying sizes, exchanges and categories which should therefore be representative of the Swedish stock

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[2] https://www.matteoiacoviello.com/gpr.htm

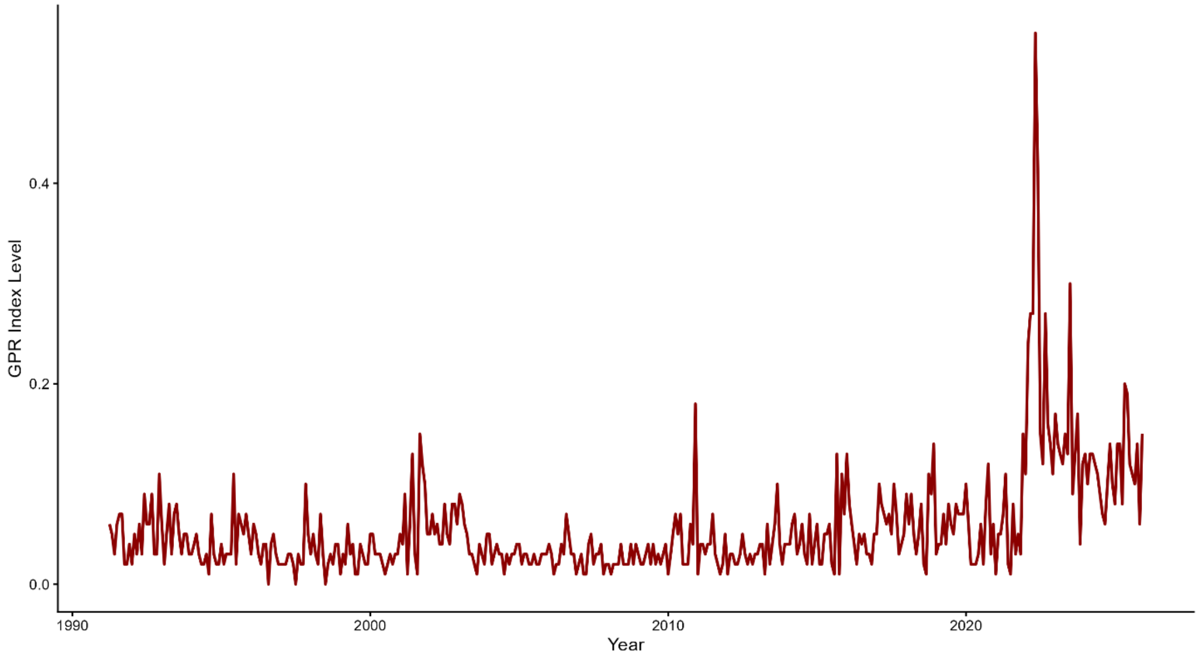
market as a whole. Keeping stocks that are both alive and dead does not introduce any survivorship bias, strengthening the robustness of the study.

The initial stock sample data collected from LSEG Refinitiv Workspace had various problems such as the return for small stocks being erroneously forced to only show two decimals. This caused small stocks to erroneously show returns in the 100's or 1000's of percent and stocks with a price less than 10 SEK was consequently removed from the sample. The sample sometimes recorded missing values as a 0, NA or even kept the same prices from month to month if the stock had been delisted. This was addressed by forbidding data to have the exact same return from one month to the other, excluding such values. Further errors causing stock returns to be impossibly high such as due to wrongfully recorded splits forced the use of data truncation. For each month data falling outside the 1st and 99th percentiles were removed, allowing some but not the most extreme of outliers. The resulting sample used is thus a little bit smaller than the initial 1383.

The categories of stocks for the initial sample are 42, ranging from Aerospace and defence to different industry categories to waste and disposal services. The full information on stock categories is available in Table A2 in the appendix. Of the 1383 stocks, 872 stocks are active and 511 are delisted.

In Figure 1 below the geopolitical risk index for Sweden is visualised in nominal terms. Considerable volatility seems to always be present with larger spikes clustered around events that raise geopolitical risk. The index spikes both fast and sharp and decrease quickly after the event. The largest spike is visible around 2022, likely capturing the Russian invasion of Ukraine. Other spikes are visible all throughout the sample period such as in 2001-2002 and 2011, however none as large as the one in 2022.

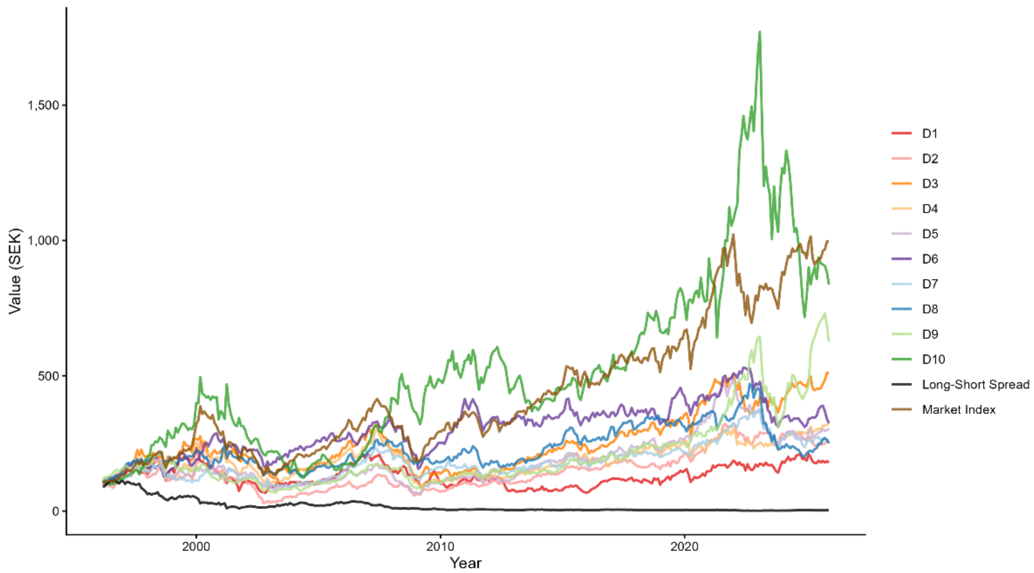
Figure 1: Nominal Geopolitical Risk (GPR) Index Over Time
Sweden-Specific Index.



6. Results

Once firm beta estimations are made, value weighted portfolios are created based on their corresponding firm beta, placing each portfolio into one of 11 portfolios, ranging from the most negative firm beta estimation D1 to the most positive D10. An additional long-short portfolio is created that buys the D1 portfolio and sells the D10 portfolio. An initial investment of 100 SEK. The results of such portfolios with monthly rebalancing and a transaction cost of 0.5% is shown in nominal terms in Figure 2 alongside the market index.

Figure 2: Cumulative Wealth (Net of 0.5% Transaction Costs)
Nominal scale. Initial investment 100 SEK.

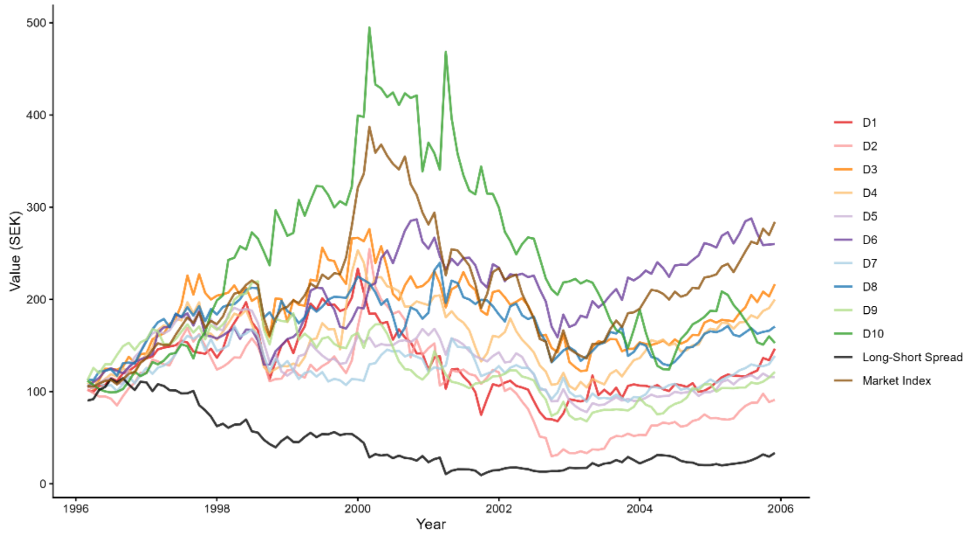


From Figure 2 it is clear that the D10 portfolio outperforms all the other portfolios except the market index in terms of pure nominal return, where an initial 100 SEK investment grow to roughly 1,700 SEK at its peak and ends at 900 SEK at the end of the research period, slightly below the market index. Comparing Figure 1 and Figure 2 the D10 portfolio catches the spikes in GPR in 2001, 2011 and 2022 remarkably well, spiking high and sharp in return whenever GPR spikes.

The important portfolio is seemingly the D10 portfolio, the hedge, that sometimes moves with the market line, sometimes opposite it, most clearly seen in 2022. The Long-Short portfolio performs the worst among all portfolios, even losing significant money over the period. The D1 portfolio is performing poorly as well, providing the next worst returns second to the Long-Short portfolio.

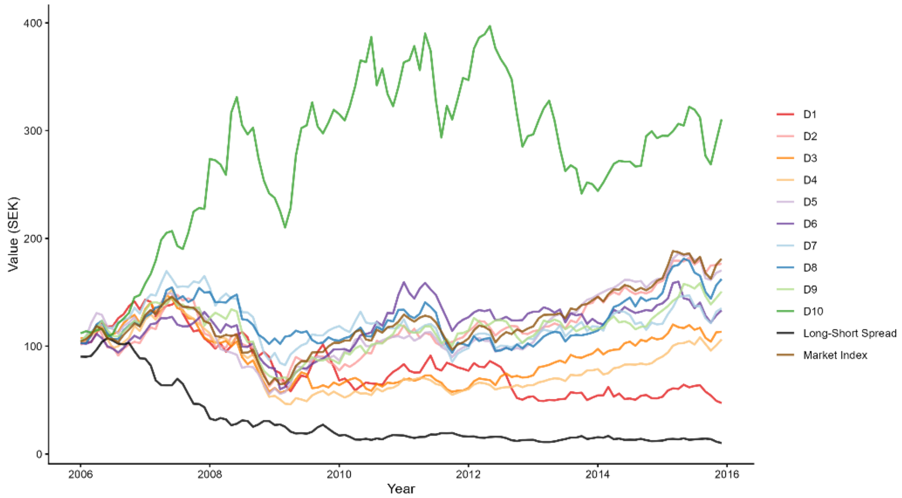
The results are made clearer when doing sub-sample analysis, where the research period is broken down into three decades, the results for the first decade being visible in Figure 3, with the D10 again standing out around the year 2000-2002. During the year 2000, the market index and D10 portfolios are seemingly mimicking each other, which changes in 2001 when they go opposite directions. Sorting based on GPR seems to provide little benefit over a long time if the GPR is low during that time, however whenever GPR spikes the hedge portfolio provides the best returns.

Figure 3: Cumulative Wealth - Era 1 (Nominal, Net of TC)
1996 - 2005.



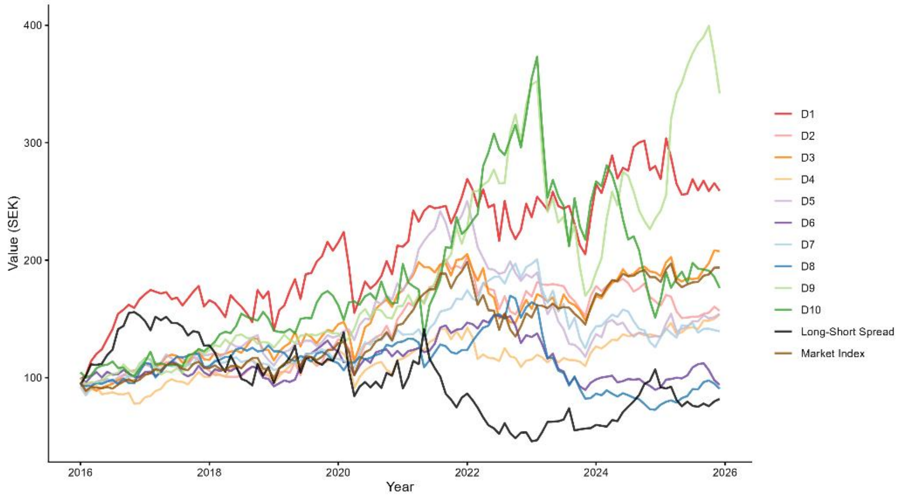
For the second decade the D10 portfolio dominates most of the time period, dwarfing all other portfolios that are more closely clustered together, visible in Figure 4.

Figure 4: Cumulative Wealth - Era 2 (Nominal, Net of TC)
2006 - 2015.



In Figure 5, the last decade, the invasion of Ukraine is visible as a spike in 2022, where both the D9 and D10 portfolios are providing good returns. The spike in GPR in 2025 is only caught by the D9 portfolio, which is unexpected.

Figure 5: Cumulative Wealth - Era 3 (Nominal, Net of TC)
2016 - Present.



From analysing Figure 1 through 5, though the results are turbulent a few visual heuristics can be learned. The D10 portfolio stands out, providing high excess returns when GPR is high, much higher than all the other portfolios. In 2022 when GPR is exceptionally high, the

D9 portfolio steps up, providing similar returns to D10. In periods when GPR is low, the sorting does not seem to provide any benefit.

For further analysis, the exact numbers for the portfolios need to be looked at, provided in Table 1.

Table 1: Summary statistics

Portfolio	Avg_Return	Max_Return	Min_Return	Volatility	Sharpe_Ratio	Sortino_Ratio	Skewness	Kurtosis	VaR_1pct	Exp_Shortfall_1pct	Lower_Partial_SD	Freq_Below_3Sig	Avg_GPR_Beta	Avg_Market_Cap	Avg_N_Stocks
D1	0.7649	29.63	-25.3942	7.6902	0.0787	0.1196	-0.0342	3.9594	-18.685	-22.384	5.0624	0.5587	-107.8129	12668	25
D2	0.9117	29.0048	-39.4854	7.2477	0.1038	0.1558	-0.3883	7.7418	-19.0167	-28.6899	4.8293	1.1173	-53.9895	24147	26
D3	1.0583	27.5702	-18.0207	6.1253	0.1467	0.2405	0.2074	4.667	-14.1997	-16.533	3.7376	0.2793	-34.0254	24674	27
D4	0.971	33.0198	-22.17	6.0276	0.1346	0.2108	-0.0037	5.8235	-15.9474	-19.0688	3.8492	0.838	-20.1779	17436	27
D5	0.968	26.2127	-13.5167	5.5205	0.1465	0.2377	0.1364	4.2653	-12.8292	-13.1073	3.4012	0	-8.5539	14181	27
D6	0.9692	17.8864	-23.7769	5.4446	0.1487	0.2326	-0.2743	4.3844	-13.1113	-17.252	3.481	0.838	2.7165	11905	27
D7	0.8679	24.224	-14.5501	5.5625	0.1274	0.1979	-0.0506	3.8072	-12.4043	-13.2398	3.5793	0	14.711	11486	26
D8	0.8297	26.1418	-17.9422	5.5535	0.1207	0.1821	-0.2568	4.7009	-14.7259	-16.3767	3.6814	0.5587	28.9138	8941	26
D9	1.0513	25.6075	-22.9783	6.3032	0.1415	0.2199	-0.1719	4.5442	-16.2401	-19.1163	4.0552	0.5587	49.3604	6272	25
D10	1.1241	38.4774	-22.4252	7.5258	0.1282	0.2252	0.6777	5.2739	-15.4293	-19.2853	4.2829	0.2793	109.9227	3108	24
Long_Short	-0.3592	34.9034	-63.8716	10.4109	-0.0498	-0.0663	-0.5925	7.0758	-24.8062	-40.0048	7.8279	0.838	-217.7356	NA	NA

Note: All return, volatility and risk measures are reported on a monthly basis. Average return calculated as arithmetic mean. All tables are reported without transaction costs

From Table 1 multiple interesting findings can be made regarding the summary statistics. The D10 portfolio stands out with both the highest average return and the highest maximum return. The lowest returns are awarded to the Long-Short portfolio, which is also underperforming in all measures, losing considerable money over the period. It will therefore not be further compared to the other portfolios but is noted here as the worst performing among almost all measures. The highest volatility is clustered around the top and bottom deciles. The corresponding Sharpe- and Sortino ratio are the worst for the D1 portfolio, but seems otherwise almost randomly distributed between deciles, providing no clear linear pattern between deciles over time. Most portfolios have a slight negative skew, the D10 has a clear positive one.

Regarding kurtosis, the normal distribution has the value 3, lower value signifying returns with less outliers and a higher value signifying fatter tails with both high risk of crashes and possibility for positive returns. All portfolios have values greater than 3.8, some around 4 or 5, with the highest kurtosis belonging to the D2 portfolio at 7.7. All portfolios therefore have fat tails and a higher risk than the normal distribution of both severe crashes and gains. The D1 and D2 portfolios have the most negative Value at Risk (VaR) and Expected Shortfall (ES) measures, the D9 and D10 also stand out from the rest of the portfolios with more negative values than many of the other portfolios. The Lower Partial Standard Deviation (LPSD) is also highest toward the top and bottom deciles.

The frequency of returns falling within 3 standard deviations (sigma) is 99.73% for normal distributions, leaving the mathematical probability of a return falling below 3 sigma 0.135%.

What is found for the portfolios is that the D5 and D7 have no observation of an extreme crash, all other portfolios have significantly higher risk of extreme crashes than is expected for the standard distribution.

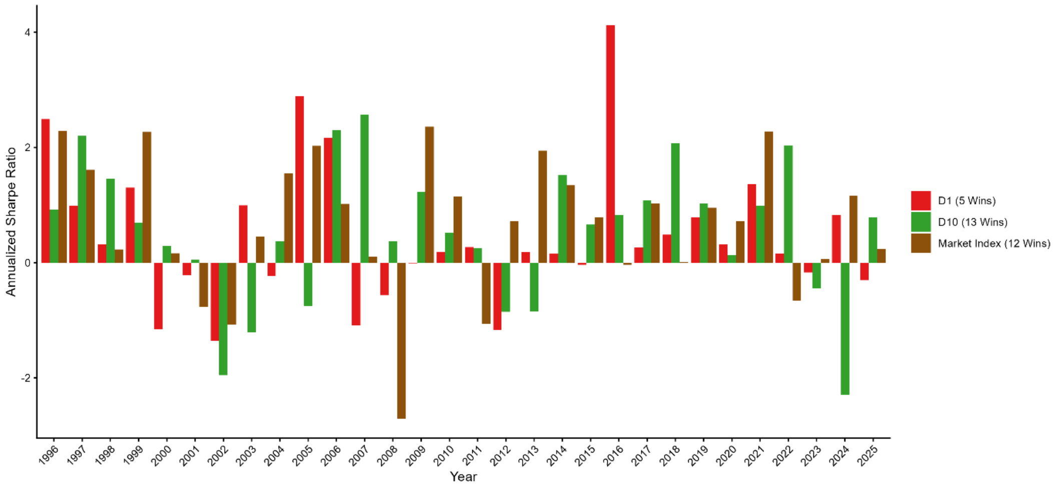
What is interesting is that the difference in average GPR beta between portfolios is the largest toward the top and bottom deciles, which seems to indicate that the most important portfolios are the D1 and D10 portfolios, since the rest of the portfolios are much closer together in difference in beta estimation.

The average market cap is the smallest for the D10 portfolio and increases almost perfectly linear as the deciles decrease, except for the D1 portfolio which is also smaller than the portfolios next to it. This might indicate that sorting based on firm beta GPR estimations is actually a disguise for size sorting. The hedge thus becomes a portfolio that is smaller in size since such companies might adapt better or quicker as compared to larger companies to spikes in GPR.

The average number of stocks is rather stable at 24 to 27 stocks for each portfolio, which is not a lot, though it should be noted that the variance is large, since fewer companies were listed in the beginning of the sampling period than toward the end.

Since the most important portfolio seems to be the D10 portfolio, it could be interesting to compare it to its opposite and see which of the two has the highest risk adjusted return not only over time, but within years. The results from such a question are provided below in Figure 6, where the sum of wins is included in the legend.

Figure 6: Annualized Sharpe Ratio by Year (Winner Count in Legend)
Calculated using Gross Returns.



From Figure 6 it is found that the D10 portfolio not only has the highest return, but also the highest Sharpe ratio as compared to the D1, but only slightly more often than the market index. Over the 30 years sample period, the D10 has the highest Sharpe ratio 13 times, the market index 12 times compared to the D1's 5 times. When it comes to risk adjusted returns, the D10 is therefore better than the D1 portfolio, however since it almost wins as often as the market index it is hard to suggest the use of the D10 portfolio as a buy-and-forget portfolio, but it should instead be used either as part of a larger portfolio or during shorter periods when the GPR is expected to rise, such as during 2022.

It seems evident that dependent on how and when you use it, using GPR can provide better risk adjusted returns as compared to the market index, but it should be used selectively. A natural question that arises is if using geopolitical risk is only a veil for other already established models that already explain a lot of the variation in stock prices and if GPR really provides anything new. Below, GPR is compared to other models to see if it provides any extra explaining power as compared to the CAPM, FF5 and FF6 factor models. The evidence for which is provided in Table 2, while using the more conservative Newey West standard errors.

Table 2: GPR vs CAPM, FF5 and FF6

Portfolio	CAPM_Alpha	CAPM_P	CAPM_Sig	CAPM_MKT	FF5_Alpha	FF5_P	FF5_Sig	FF5_MKT	FF5_SMB	FF5_HML	FF5_RMW	FF5_CMA	FF6_Alpha	FF6_P	FF6_Sig	FF6_MKT	FF6_SMB	FF6_HML	FF6_RMW	FF6_CMA	FF6_WML
D1	0.3361	0.299		0.6756	0.3811	0.2754		0.6846	0.099	-0.0537	-0.3871	0.4182	0.2372	0.5446		0.6793	0.0736	0.0308	-0.5338	0.3141	0.1977
D2	0.2904	0.2696		0.9788	0.3636	0.2608		0.9393	0.385	-0.1386	-0.0677	-0.0443	0.4475	0.1941		0.9424	0.3999	-0.1878	0.0177	0.0163	-0.1151
D3	0.5208	0.0073	***	0.8469	0.2995	0.1463		0.8695	-0.0229	0.1193	0.538	0.2317	0.2893	0.1824		0.8691	-0.0247	0.1253	0.5275	0.2243	0.014
D4	0.4569	0.0221	**	0.8099	0.2949	0.135		0.7872	0.1295	0.2933	0.3843	-0.2563	0.2186	0.3225		0.7844	0.116	0.3381	0.3065	-0.3115	0.1048
D5	0.4861	0.0257	**	0.7593	0.3172	0.1451		0.7366	0.1604	0.3266	0.3139	-0.1845	0.3787	0.0966	*	0.7388	0.1713	0.2905	0.3767	-0.14	-0.0846
D6	0.5674	0.0363	**	0.6329	0.362	0.1941		0.6522	-0.0764	0.2543	0.3426	0.1452	0.4241	0.1513		0.6545	-0.0655	0.2179	0.4058	0.1901	-0.0853
D7	0.4537	0.0448	**	0.6525	0.2767	0.2081		0.6445	-0.011	0.3996	0.2486	-0.1889	0.3021	0.1936		0.6455	-0.0065	0.3847	0.2746	-0.1705	-0.0349
D8	0.5786	0.0424	**	0.3957	0.4671	0.101		0.3826	0.1977	0.152	0.1644	0.071	0.3703	0.2116		0.379	0.1806	0.2088	0.0657	0.001	0.133
D9	0.7289	0.0377	**	0.5079	0.6285	0.0821	*	0.4921	0.1012	0.2645	0.083	-0.1059	0.5282	0.1387		0.4884	0.0835	0.3234	-0.0193	-0.1785	0.1378
D10	0.9681	0.0118	**	0.2457	1.1492	0.0067	***	0.2394	-0.1749	-0.1202	-0.3014	-0.3378	1.216	0.0075	***	0.2418	-0.1631	-0.1594	-0.2333	-0.2895	-0.0918
Long_Short	-0.6321	0.1875		0.4299	-0.768	0.1526		0.4452	0.2739	0.0666	-0.0857	0.756	-0.9788	0.1144		0.4374	0.2367	0.1902	-0.3005	0.6037	0.2895

Table 2 provides evidence that using GPR provides positive significant alphas at the very least on the 5% level that cannot be explained by the CAPM. The results are however not significant for the D1, D2 and Long-Short portfolios. Comparing the portfolios to the European FF5 and FF6 factor models the results are instead insignificant for most portfolios, except for the D10 portfolio where the results are highly significant on the 1% level. These findings indicate that geopolitical risk can be an important factor when forming hedging portfolios, improving upon prior models that do not include it. However, it only holds true for a portfolio that has the most positive of firm beta estimations, which does not allow for any half measures. When sorting based on GPR, only the most sensitive stocks matter that react positively when GPR is high. The joint result for the GRS test is also highly significant for the CAPM, but insignificant for the FF5 and FF6 factor models, provided in Table 3.

Table 3: GRS test

Model	GRS_Statistic	P_Value
CAPM	2.2243	0.0161
FF5	1.4281	0.1661
FF6	1.4428	0.1599

Returning to the factor loadings for the FF6 model in Table 2, they explain why the portfolios behave the way they do by exposing how much they are exposed to different factors. Since only the D10 portfolio is significant, the focus will be on understanding what separates it from the other portfolios. First off, it moves less with the market than any of the other portfolios. This could be indicative of something else guiding the portfolio, and with the prior findings it is likely that GPR causes the portfolio to move, more so than the market which however still has some impact. All other factor loadings are negative for the D10 portfolio. This means that the portfolio is more exposed to smaller companies rather than larger, more exposed to growth stocks than value stocks, companies with weaker as compared to stronger operating profitability, aggressively spending rather than conservatively spending companies and slightly more exposed to companies that are currently losing as compared to momentum stocks. The Long-Short portfolio has positive factor loadings for all except robust minus weak. The other portfolios have varying factor loadings.

Table 4: Bootstrapping

Portfolio	Original_Alpha	Boot_Lower_95	Boot_Upper_95	Boot_P_Value	Boot_Sig
D1	0.2372	-0.5468	1.1025	0.5272	
D2	0.4475	-0.1811	1.0614	0.1736	
D3	0.2893	-0.1542	0.7354	0.1822	
D4	0.2186	-0.2305	0.6959	0.3228	
D5	0.3787	-0.0528	0.8137	0.0822	*
D6	0.4241	-0.0726	0.9344	0.0952	*
D7	0.3021	-0.1647	0.7727	0.2042	
D8	0.3703	-0.2061	0.9588	0.2152	
D9	0.5282	-0.1186	1.2141	0.1144	
D10	1.216	0.392	2.0651	0.0042	***
Long_Short	-0.9788	-2.2342	0.3253	0.1476	

Note: 10,000 iterations.

A natural question that arises is if the results for the alpha from the portfolio creations were just driven by luck. As a robustness test, bootstrapping is done for the most rigorous method, the FF6 model and the results are significant on the 1% level for the D10 portfolio and insignificant for all portfolios except for on the 10% level for the D5 and D6 portfolios. The bootstrapping is done with 10,000 iterations, ensuring that the results are robust without assuming normality, results are available in Table 4.

Table 5: Subsample analysis

Portfolio	Era1_Alpha	Era1_P	Era1_Sig	Era2_Alpha	Era2_P	Era2_Sig	Era3_Alpha	Era3_P	Era3_Sig
D1	-0.1402	0.856		0.2242	0.7589		0.5989	0.1728	
D2	0.3575	0.6101		0.9177	0.0291	**	0.2941	0.2221	
D3	0.52	0.36		0.0088	0.9803		0.4778	0.0325	**
D4	0.4261	0.4572		0.0684	0.8408		0.2936	0.3023	
D5	-0.3102	0.4563		0.8445	0.0081	***	0.434	0.2016	
D6	0.5061	0.2707		0.644	0.0806	*	0.1964	0.6364	
D7	-0.2608	0.5787		0.5686	0.1053		0.4379	0.322	
D8	0.1265	0.8327		0.5427	0.1553		0.2092	0.6772	
D9	-0.4124	0.4961		0.6182	0.1628		1.0531	0.0964	*
D10	1.3554	0.1306		1.547	0.0141	**	0.9142	0.2232	
Long_Short	-1.4956	0.2371		-1.3228	0.1371		-0.3153	0.6966	

Returning to subsample analysis (Table 5) where the portfolios' alphas are divided into decades between 1996-2005, 2006-2015 and 2016-2025, a few key insights can be learned. The alphas were insignificant across all portfolios for the first decade, indicating that geopolitical risk was not an important factor providing excess return over the FF6 factor model.

For the second and third decade, the results are mixed. During the second decade the D2 and D5 are significant on the 5% level, the D5 on the 1% level and D6 significant on the 10% level. During the third decade the D3 portfolio is significant on the 5% level and the D9 on the 10% level. These results are not necessarily bad, but rather indicative of GPR being a factor which's importance varies with time and as GPR increase or decrease. The results become nuanced as other portfolios than the D10 are proven to be important during different times. Further breaking down the results not only by decades, but by year and month are likely to provide even more interesting results.

However, since the L-S portfolio has an insignificant alpha across all three decades, there is still no evidence that such a strategy would prove fruitful and no evidence that it provides excess return that cannot already be explained by the FF6 factor model.

7. Discussion

Sorting Swedish stocks based on their firm beta geopolitical risk estimates creates significant excess returns that generate high alphas that cannot be explained by the CAPM. This holds for all deciles except the D1 and D2, indicating that when sorting based on GPR exposure the important portfolios are not the risky ones, but rather the safer portfolios.

When comparing the portfolios to the FF5 and FF6 factor models, only the D10 portfolio was significant on the 1% level. The results were also varying by decade, signifying that the importance of GPR varies, and which portfolio is important also varies over time.

The attempt to create a long-short portfolio that buys the stocks that fare worse when GPR is high and sells the stocks that go up when GPR is high was however fruitless. That is not necessarily indicative of GPR being a bad factor, but that GPR can mask an underlying mix of assets that knowingly or not employ a FF6 factor strategy. It is also likely that stocks that have certain characteristics and exposures to the FF6 factors behave differently in relation to GPR due to their innate resilience that come with the factors.

The finding that the D10 portfolio has high alpha further cements the importance of focusing on that portfolio rather than on portfolios in the other deciles. There was some evidence of hedging visible in the short run by the D10 portfolio, where it went in opposite direction compared to the market index, however the importance of the D10 portfolio in the long run is only large if GPR is high. This is not necessarily evidence of the D10 portfolio not being a good portfolio, but that the hedging effect of the D10 portfolio is only active during the short, quick spikes that make up the GPR index, Figure 1 in the data section for reference.

While the Long-Short portfolio is grounded in the theoretical prediction of the ICAPM that a riskier asset (D1) should hold a risk premium over a less risky asset (D10), its failure to provide a positive, significant alpha needs to be further analysed.

Among the decile portfolios, the D1 did have both the lowest average return and the highest volatility as well as some of the worst downside risk measures, with no empirical indication of it carrying the risk premium suggested by the ICAPM. The D10 portfolio on the other hand carried both high values for return and volatility and its downside risk measures were better than the D1. This caused the empirical findings to be the opposite of the theoretical predictions since the Long-Short portfolio will only gain money if the D1 has higher returns than the D10 portfolio.

This led to the Long-Short portfolio that is made up of both portfolios to fail in the long run. Further, the risk with constructing a Long-Short portfolio is that in the shorter time span, in times of a GPR spike, then the returns would become double negative since both portfolios are expected to lose money when GPR is high. It would essentially be a peacetime strategy. This is because the return of the D1 portfolio goes down when GPR is high, and by shorting the D10 portfolio (the hedge) you would lose money from both portfolios. This makes it a bad portfolio for handling the shorter, faster GPR spikes. The empirical result from this study refutes the theoretical prediction of the Long-Short portfolio providing positive returns in the long run.

What about reversing the portfolio? If we instead created a portfolio that buys the D10 portfolio (the hedge) and sells the D1 (the risky portfolio), that portfolio would also fail since the formula for calculating the p-value for the alpha does not change. Such a portfolio would still provide insignificant results, only that the sign for the estimates such as alpha and factor loadings would flip. Its short run effectiveness, however, remains untested.

An investor with a long time horizon only caring about absolute return would be quite disappointed buying any of the portfolios as they all provided poor returns as compared to the market index. This is especially true with the hassle of monthly rebalancing and its corresponding transaction costs that are associated with such a strategy. The same monthly rebalancing is not needed for investors buying the market index, as it is done automatically. However, what about the risk adjusted measures?

Except for the Long-Short portfolio providing a negative Sharpe- and Sortino ratio, no other portfolio clearly stands out regarding risk adjusted measures in the long run. Comparing yearly Sharpe ratio of the D1 to the D10 and market index, the D10 is the better portfolio, but only slightly better than the market index, which makes it hard to suggest as a long-time portfolio providing better risk adjusted returns. Its importance remains in the short run.

The study, while pointing to important findings regarding geopolitical risk and investing, has its limitations. In hindsight its focus should have been on the short-run performance of portfolios, incorporating daily stock returns behaviour around GPR spikes and forecasting when such events happen. With the focus of the study being more towards identifying the effect of GPR in the long run, it becomes less clear if GPR matters. The results are also focused on Sweden and with priorly provided evidence of GPR being country specific, the results might not extrapolate to other regions.

With data for Sweden being hard to come by in some instances, the study was limited by the availability of data. The FF5 and FF6 factors are not currently available for Sweden, so the factors for Europe had to be collected instead with the assumption that Europe and Sweden are similar. For factors to be significant a large time span is needed, and a time span of 35 years was employed in this study. The problem with that is that toward the beginning of the sampling period the number of companies with available data drops, so that the portfolios have a smaller sample in the beginning, risking outliers driving the results, the sample grows over time as more companies are available for collection. It would be good to supplement this study with not only monthly, but also daily data as well for robustness tests, but due to restrictions in the amount of data that can be collected for an academic license, this was made harder. The time restrictions of a bachelor thesis further limit the extent of the study, employing Fama Macbeth style regressions could also improve the robustness and knowledge gained from the research, but with limited time this was not possible.

Some scrutiny can be put on if using the geopolitical risk index by Caldara and Iacoviello (2022) is a good idea for Sweden, since it is a measure on the share of other countries' newspapers mentioning Sweden and GPR events. It seems evident that the index works, and that stocks react to its spikes, but not clear what it actually measures. With Sweden's acceptance into NATO the country specific index for Sweden might increase since more news articles are likely to discuss Sweden since it is now part of a larger global alliance, where events on the other side of the world are more likely than before to spike the index. The prediction from this is that the country specific index and the global index are likely to converge since global events and Swedish events become intertwined. It raises scrutiny on if the period before the NATO acceptance in 2024 and the period after are similar, especially since this study mostly captures the period before 2024. It also begs the question on which events, both global and local, that are included as spikes in the index, and future research could be made that further investigates this. A local GPR measure if available would maybe provide other evidence and conclusions than those made by this study so the creation of a Swedish GPR index is likely to be important.

Using portfolios sorted on firm beta GPR is likely to improve the characteristics when included in a broader portfolio, but a full investigation into GPR and how it interacts as part of a broader portfolio is beyond the scope of this research paper.

Future research could be made using Fama Macbeth regressions to better determine if GPR is priced or not in Sweden and even attempts to create a GPR index for Sweden so that the results are made more robust, credible and clear in what they mean. The creation of FF6 factors for Sweden to be used as comparison to portfolios created based on GPR sorting would also provide more robustness and results that do not rely on as many assumptions as was needed by this study due to the availability of data and proper comparison models. Using daily data in a similar study would also prove interesting, since GPR can change quickly and since the impact of geopolitical threats and acts might be different a study that separates the GPR into those factors and based on sectors would provide a fuller picture.

8. Conclusion

To conclude, there is evidence to suggest that an investor in Sweden can use geopolitical risk to achieve better risk adjusted returns, with significant alphas that cannot be explained by prior models such as the CAPM, FF5 or FF6 models. The significance of these findings remains clustered around the D10 portfolio, the hedge that includes stocks that react with positive returns when GPR is high. The importance of GPR as a factor lies in the short run and only matter during the quick spikes that make up the geopolitical risk index.

The results from decile sorting indicate that a portfolio sorted on the most positive firm beta GPR estimation (D10) would provide the highest return among all portfolios, but only slightly better Sharpe ratio than the market index on a yearly basis. In the long run the D10 portfolio does not provide an average monthly Sharpe- or Sortino ratio that is that much different as compared to the other portfolios. As compared to the CAPM all portfolios except the D1, D2 and Long-Short portfolio provide positive significant alphas that cannot be explained by the CAPM, however only the D10 portfolio beat both the FF5 and FF6 factor models.

The results indicate that the average market cap was smaller for the top and bottom deciles than the middle deciles, and that the D10 portfolio had the smallest market cap with the market cap increasing as deciles decrease. This indicates that portfolios that respond positively when GPR is high tend to consist of smaller companies.

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Appendix

Table A1: ADF test

Variable	ADF_P_Value	Significance	Conclusion
Raw Nominal GPR	0.01	**	Stationary
Market Excess Return (MKT.RF)	0.01	**	Stationary
Decile 1 (D1)	0.01	**	Stationary
Decile 2 (D2)	0.01	**	Stationary
Decile 3 (D3)	0.01	**	Stationary
Decile 4 (D4)	0.01	**	Stationary
Decile 5 (D5)	0.01	**	Stationary
Decile 6 (D6)	0.01	**	Stationary
Decile 7 (D7)	0.01	**	Stationary
Decile 8 (D8)	0.01	**	Stationary
Decile 9 (D9)	0.01	**	Stationary
Decile 10 (D10)	0.01	**	Stationary

Note: results from the Augmented Dickey-Fuller test. Due to using the "tseries" package in R studio the p-values are capped at 0.01. Real p-values are even lower

Table A2: Count of stocks by sector

Sectors	Count of Sectors
Aerospace and Defense	9
Alternative Energy	22
Automobiles and Parts	11
Banks	9
Beverages	8
Chemicals	20
Construction and Materials	45
Consumer Services	14
Electricity	10
Electronic and Electrical Equipment	67
Finance and Credit Services	8
Food Producers	23
General Industrials	17
Health Care Providers	19
Household Goods and Home Construction	19
Industrial Engineering	40
Industrial Materials	14
Industrial Metals and Mining	23
Industrial Support Services	56
Industrial Transportation	26
Investment Banking and Brokerage Services	74
Leisure Goods	59

Media	24
Medical Equipment and Services	99
Non-life Insurance	3
Oil, Gas and Coal	17
Open End and Miscellaneous Investment Vehicles	8
Personal Care, Drug and Grocery Stores	16
Personal Goods	9
Pharmaceuticals and Biotechnology	132
Precious Metals and Mining	13
Real Estate Investment and Services	98
Real Estate Investment Trusts	2
Retailers	54
Software and Computer Services	183
Technology Hardware and Equipment	35
Telecommunications Equipment	30
Telecommunications Service Providers	15
Tobacco	1
Travel and Leisure	44
Unclassified	1
Waste and Disposal Services	5
Grand Total	**1382**