Differentiating Partisan Portfolios using Volatility Modelling, Clustering and Factor Analysis

***Abstract*—At the center of the 2020 US presidential election, given a qualitatively selected set of US equities (Appendix Table XII) that are expected to exhibit differential performance based on the outcome of elections, we seek to explore if there is a difference in volatilities using a GARCH model and also investigate the rolling realized correlation of two portfolios. Micro-blogs mentioning pairs of companies around elections are used to identify clusters of stocks that could help delineate the two portfolios. Other aspects of portfolio returns are examined to look for any significant differences in factor exposures. We finally present a simple structured note to take advantage of our findings.**

***Index Terms*—GARCH, Twitter, Factor Exposure, Dummy-variable Regression, Structured Note, Butterfly Option**

I. Introduction

Two portfolios can be differentiated using many techniques. In this paper we explore both conventional and non conventional methods of differentiation. A brief introduction of each of the methods is described. The paper is organised into four key segments and each segment contains the description of data used, methodology and their corresponding results. The first segment models the volatility differences between the portfolios and tries to forecast them. The next segment uses alternative data from micro-blogs to cluster stocks into the two buckets. The third segment explores the factor exposures of the two portfolios and the final segment discusses the construction of a structured note based on our findings.

Firstly, volatility is an important factor in any financial return series and are usually time varying, clustered and not directly observable. Given two portfolios, we examine their conditional daily volatility using a uni-variate volatility model and GARCH [1].

The advent of social media especially micro-blogging has enabled investors to express their views publicly to a wide audience like never before. This has resulted in noisy yet abundant data that could be used to extract meaningful insights. Using the wisdom of crowds we try to obtain an aggregate estimate based on many individual observations. This method of using micro-blogs to differentiate democratic stocks from republican stocks has been primarily inspired from the work done by Sprenger et al. [2] where industry groups were identified based on investor perceptions of stocks on Twitter. They provide an alternative to popular methods such as SIC codes which have been questioned for their accuracy [3].

Equity factor premiums have been studied extensively in academia and practitioners ever since Fama French published their seminal paper in 1992 [5]. There have been numerous studies to extend the number of factors used [6]. Factors can be thought of as basic and objective characteristics that help explain excess returns of portfolios or stocks. Factors are usually constructed by taking hypothetical long, short positions in stocks after sorting on some metric. For example if we were constructing a value factor, we could sort our universe based on price-to-book ratio and take a long position/overweight stocks with high fundamental value (low P/B ratio) and a short/underweight stocks with low fundamental value (high P/B ratio). The resulting portfolio would in essence capture the value premium. Although Fama French factors are widely researched, we explore the use of factor indices provided by vendors like MSCI and FTSE to help decompose portfolio returns. The long-short approach used generally to construct factors assumes both legs contain information for asset prices despite the legs being subjected to different market dynamics. The work by Blitz et al. [7] argues that the long minus market approach has typically been more powerful than a long short approach especially in context of multi-factor combinations. The returns from long exposure subsume the short side in the overall factor premium. They also conclude that the effect is prevalent across both large cap and small cap universes which provides more conviction in the method. We follow a similar approach by adjusting market beta from long only factor indices. We hypothesize that if our portfolios are exposed to different factors, they would perform differently in the future.

II. Volatility difference and forecasting

A. Data

We firstly construct two portfolios: Democratic and Republican. The portfolios start from the earliest date when all stocks in their corresponding segment are listed (17 Nov 2011 for Democratic and 7 Jul 2015 for Republican). We construct an equal weighted portfolio on the start date and let the portfolio evolve with time.

B. Modeling

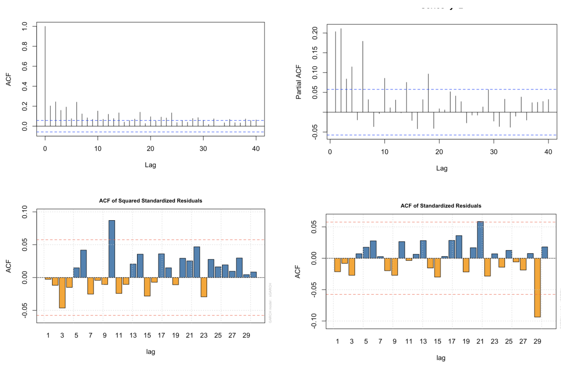
Price levels are not stationary hence we model their log return series using a GARCH process. We start with the Republican portfolio perform the following:

- Plot ACF and PACF for original series and select several candidates.
- Remove estimates that are not significant.
- Compare each model by AIC and BIC and choose the final candidate.

The final mean model for Republican was

$$\widehat{r_t} = \underset{(6.77)}{-0.00124} + \underset{(3.50)}{0.449 r_{t-5}} \underset{(-4.62)}{-0.551\epsilon_{t-5}} + \epsilon_t \quad \widehat{\sigma} = 0.012 \tag{2.1}$$

Then we check ARCH effects in residuals based on the first two plots in Figure I.



(a)

Fig. 1. Diagnostic Figures for Republic Model

Both ACF and PACF were significant at first four lags along with other higher lags. In order to keep our model parsimonious, we selected an ARCH(4) model for the variance equation. Results are summarized as follows, where the zero one dummy variable x_t takes one at the period when something political events happens, such as trade war and impeachment of President Trump. The result indicates that the volatility of republican portfolio surges during these times.

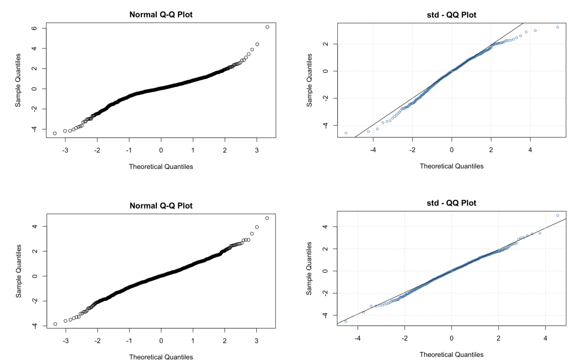
$$\widehat{r_t} = \underset{(7.99)}{0.00129} + \underset{(2.89)}{0.4866 r_{t-5}} \underset{(-3.66)}{-0.578\epsilon_{t-5}} + \epsilon_t \tag{2.2}$$

$$\begin{aligned}\widehat{\sigma_t^2} = & -0.000036 + 0.1944 r_{t-1}^2 - 0.1724 r_{t-2}^2 \\ & -0.1547 r_{t-3}^2 + 0.1564 r_{t-4}^2 + 0.000101 x_t\end{aligned} \tag{2.3}$$

Six parameters t value are 7.38, 3.37. 3.02. 2.79, 3.10 and 2.63, moreover, in our estimation, AR(8) and MA(8) term are also included, but their t value 0.34 and -0.74 indicate they are not significant, thus these two are not included in the equation. To ensure the model is adequate, we check whether the ARCH(4) model passes the diagnostic checks for model adequacy. We firstly pay attention to the residual serial correlation and remaining GARCH effects. ACF of residuals and square of residuals are shown as third and fourth plot of figure I.

ACF plot has a significant level at lag 29 while ACF of squared residual plot has significance at level 10 To get a reasonable estimate of volatility for our option pricing model in structure notes, we removed the significance at lag 10 by adding a lagged 10 term in the variance equation, although it may eliminate the effect, its AIC is larger indicating that the model is not simple enough. Thus we choose to ignore higher lags.

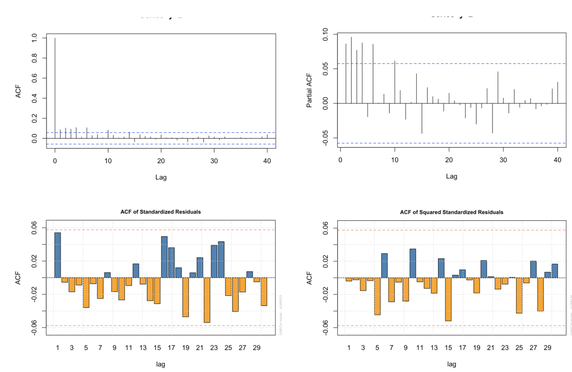
Then we check if the empirical distribution of residuals is consistent with our distribution assumption in our model. Since the QQ-plot of return series indicates a fat tail (first plot of figure 2), we assume the innovation at each period follows a student-t distribution. Below is a QQ-Plot(second plot of figure 2) of standardized residuals and we see a good fit between empirical and theoretical distributions.



(a)

Fig. 2. Q-Q plot for both models

The selection of model of Democratic portfolio follows a similar procedure and the final model along with its diagnostic plots are showed below.



(a)

Fig. 3. Diagnostic Figures for Democratic Model

Volatility model for Democratic portfolio is

$$\begin{aligned}\widehat{r_t} = & \ \underset{(3.44)}{0.000847} \ \underset{(-2.49)}{-0.0745 r_{t-4}} \\ & + \epsilon_t\end{aligned} \tag{2.4}$$

$$\widehat{\sigma_t^2} = \underset{(2.39)}{0.000002} + \underset{(6.91)}{0.08801 r_{t-1}^2} + \underset{(6.81)}{0.9039 \sigma_{t-1}^2} \tag{2.5}$$

As we can see from the squared residual ACF, residual ACF and QQ plot(the fourth plot of figure 2) of standardized residuals, there are no ARCH effects and the distribution assumption of our model is adequate.

With two adequate models at hand, we investigate the conditional daily volatility of two portfolios and plot them on the same graph.

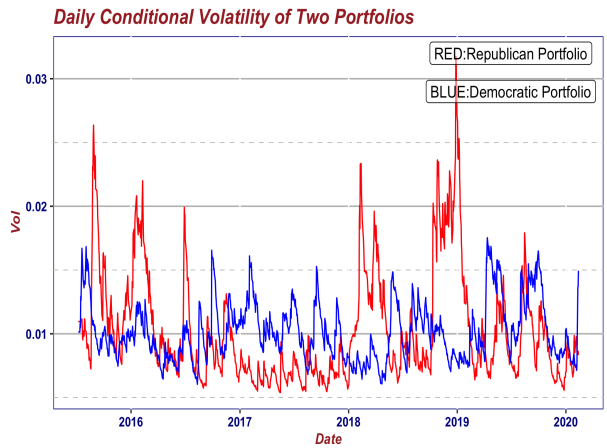


Fig. 4. Daily Conditional Volatility of Two Portfolios

There are some significant difference to be noted, particularly during early periods of 2016,2018 and 2019, the volatility of republic portfolio is evidently larger than the democratic one, while during other times such as from end of 2016 to 2018, that of democratic is slightly higher.

C. Forecasting

We follow Pascual et al.(2006) [9] and use GARCH bootstrap to improve accuracy of our forecasting. We use raw data of residuals to estimate an empirical distribution for bootstrap and take the uncertainty of parameter into consideration. 10-day ahead forecast is shown below. Forecast horizon start date is 2020-02-12. The first forecast value is for 2020-02-13.

TABLE I
VOLATILITY FORECASTED VALUE USED IN STRUCTURE NOTE CONSTRUCTION

Date	Democratic	Republic
2020-02-29	0.2232	0.1479

D. Difference of Realized Correlation

Another difference is realized correlation inside of two portfolios, we set rolling window as 50 and compute a time varying correlation. The formula is

$$\rho_{realized} = \frac{2}{n^2 - n} \sum_{i>j} \rho_{i,j} \tag{2.6}$$

, when volatility surges, correlation of republic tends to go up more as the figure shows.

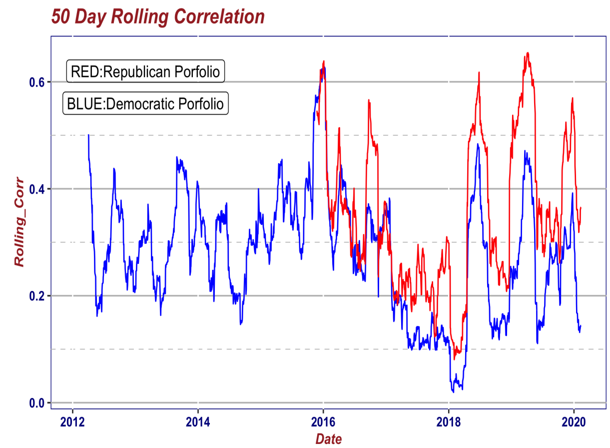


Fig. 5. 50 Day Rolling Correlation

III. CLUSTERING USING MICRO-BLOGS

A. Data

Online platforms have enabled investors to share stock related information and trading strategies. Das et al. (2005) [4] find that the majority of these users are retail investors and tend to be short term traders. Twitter is chosen as our data source since the platform streams millions of messages per day and has an active trading community. A common convention adopted by users on the platform is to tag stock related messages by a dollar sign followed by the relevant ticker (e.g $AMZN). A user who wishes to tag multiple stocks follows a similar convention (e.g $AMZN $WMT). Although there can be significant information in the content of the messages, we restrict ourselves to just the number of tweets that contain joint mentions of stocks in our interest. Tweets tagging only a single stock are therefore ignored. All tweets are weighted equally irrespective of the profile of the user (like followers) or the number of retweets. We study the 3-months surrounding elections (October-December) in two recent election years i.e 2012, 2016. Tweets for Aptiv PLC are not available and hence ignored from this analysis. We also use the data from each of the preceding years around the same period to correct for any sector related biases that can result in joint mention of stocks that need not necessarily be attributed to election outcomes. We investigate whether an increase in the proportion of joint mentions can serve as a measure for relatedness between stocks. Table II shows the total number of tweets that contain joint mentions of stocks in interest, the median and 75th percentile of the number of tweets with joint mentions as well as the percentage of all possible pairs that contain at least one joint mention. From the table it is quite clear that there are some stocks with significantly higher activity than others on Twitter. In order to account for differences in number of tweets between stocks, we first divide each entry by the total number of joint mentions of that particular stock.

$$Tweets^*(A, B) = \frac{Tweets(A, B)}{\sum_{I \subset U} Tweets(A, I)} \tag{3.1}$$

where, U is Universe of all stocks.

This can be interpreted as the fraction of tweets of stock A that also contain stock B. Stocks like AMZN and GOOG share a disproportionate number of joint tweets, so we take the log of the fraction previously calculated to avoid significant distortions in calculating similarity measures. The Euclidean distance between the column vectors $\widetilde{d} : (D_i, D_j)$ is calculated as

$$\widetilde{d}[D_A, D_B] = \sqrt{\sum_{i=1}^{N} (d_{A,i} - d_{B,j})^2} \tag{3.2}$$

where, $d_{A,i} = \log\left(Tweets^*(A, i)\right)$
similar to the method used for tree clustering in Prado et al [8]. This calculated distance metric spans over the entire space of stocks rather than each pair of stocks giving us a more robust measure of relatedness. Finally a dendrogram is constructed from the Euclidean distances for the two recent election years separately.

TABLE II
SUMMARY OF JOINT TWEET COUNT

	2016	**2015**	**2012**	**2011**
Total Number	21766	39325	12920	8451
Median	17	27	9	8
75% Percentile	55	94	28	23
% of pairs mentioned	92.3	96.1	76.8	70.4

B. Results

Though the interpretation of the graph can get quite subjective, from Figure 6 we see a cluster on the right(red) containing 12 republican stocks namely AMZN, GOOG, MRO, PYPL,CVX, V, AXP, COP, GILD, CRM, HON, MRK and 4 democratic stocks namely NEE, EXC, HD, MCD. Similarly the cluster on the left(green) contains EL, NSC, FSLR, STZ, SPWR, F, KO, WMT, CSX, SPG has 10 democratic stocks namely and 3 republican stocks namely FB, QCOM, C.

Using the data for 2011-2012 (Figure 7) we see that the pattern is not very straightforward. The cluster in middle(light blue) has 11 republican tickers (COP, AMZN, C, GOOG, CVX, CRM, MRO, HON, V, GILD, MRK) and 6 democratic tickers (MCD, WMT, KO, SPWR, F, FSLR). The outside cluster has 7 democratic (EXC, NEE, EL,SPG, STZ,HD, NSC) and 3 republican tickers(AXP, QCOM,CSX). PYPL, FB were not listed during the entire period, so they are ignored.

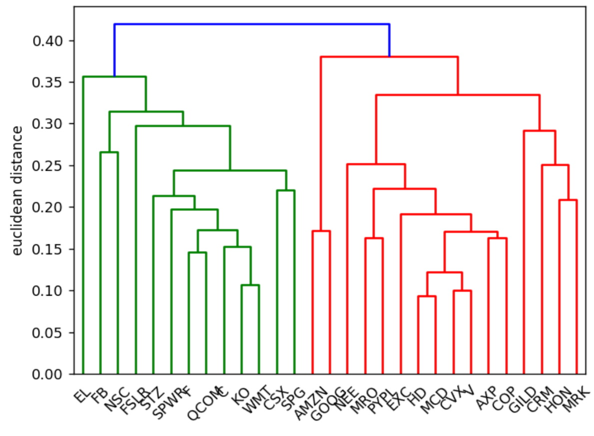


Fig. 6. Dendogram for 2015-2016

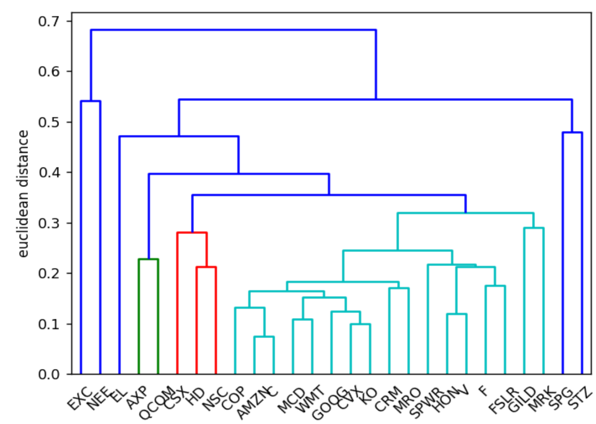


Fig. 7. Dendogram for 2011-2012

TABLE III
REGRESSION WITH MARKET FACTOR

Factor Index	**Beta**	**R-Square**
M2US000	0.883	0.777
M2USEV	1.130	0.893
M2USSNQ	0.988	0.964
M2US000G	1.065	0.944
M2USQU	0.990	0.937
M2US00MV	0.991	0.865
M2USSC	1.134	0.808
GSIN	0.954	0.916
GPVAN	0.874	0.892
SP5LVI	0.612	0.560

IV. FATOR EXPOSURE

A. Data

Factor investing is transforming the way investors construct and manage portfolios with smart-beta ETFs becoming ever so common. Since factors have been thought of as drivers of risk and return, we use well studied factors like Momentum, Value, Quality, Growth, Volatility, Size, Yield to discern portfolio returns. We also include a sustainability index in addition to the factors mentioned to take note of investors recent preference to sustainable stocks. We do not include the illiquidity factor, since it does not directly apply to the problem at hand. The Table XIII in Appendix contains the list of factor indices used along with their bloomberg ticker. Dividend adjusted prices from Jan 2012 to Dec 2019 are used to construct equal weighted portfolio returns of democratic and republican stocks.

Each of the mentioned indices focus on some specific characteristics of the underlying stocks. *MSCI USA Momentum Index* overweights stocks with high price momentum, high trading liquidity, investment capacity and moderate index turnover. Stocks in *MSCI USA Enhanced Value Index* exhibit value characteristics like lower price-to-book, price-to-forward earnings and enterprise value-to-cash flow from operations, whereas quality scores based on traits like high return-on-equity (ROE), low leverage and low earnings variability are emphasised in *MSCI USA Quality Gross Total Return Index*. A sector neutral *MSCI USA Sector Neutral Quality Index* is also used. The *MSCI USA Growth Index* captures large and mid-cap securities exhibiting overall growth style characteristics like long-term forward EPS growth rate, short-term forward EPS growth rate, current internal growth rate and long-term historical EPS growth trend as well as long-term historical sales per share growth. Securities in *MSCI USA Mid Value* and *MSCI USA Small Cap Index* measure the performance of mid cap and small cap securities in the US respectively. The *FTSE High Dividend Yield Index* consists of stocks that are characterized by higher-than- average dividend yields. *The S&P 500 Low Volatility Index* is designed to measure the performance of the 100 least volatile stocks of the S&P 500 Index. We have specifically included *FTSE KLD's Global Sustainability Index*, since it consists of a broad representation of top environmental, social and governance (ESG) performing companies across all sectors in North America, Europe and Asia Pacific. These indices primarily take only long positions in top stocks sorted based on the underlying factor. As discussed in the introduction, the first step in creating better factors is removing the market component from the indices. A simple OLS regression is run on monthly returns of these factors against the market index returns. The betas for the indices over the entire period are The monthly factor returns are then calculated as

$$x^*_{i,t} = x_{i,t} - \beta_i r_{M,t} \tag{4.1}$$

where $x^*_{i,t}$ is factor return of index *i* at time *t* adjusted for market factor.
$x_{i,t}$ is the original factor return of the index *i* at time *t*.
β_i is beta of the market factors for index *i*.
$r_{M,t}$ is market return at time *t*.

A dummy variable regression is performed on the portfolio returns with the factors constructed to find any significant differences in factor exposures between them. The outline of the method used is described below [10] [11]: Consider the two portfolio returns r_1, r_2 and common factors x^*_i. Regressions can be run on the portfolios separately.

$$\begin{aligned} r_{1,k} &= \sum_{i=1}^{n} c_{1,i} x^*_{i,t} \\ r_{2,k} &= \sum_{i=1}^{n} c_{2,i} x^*_{i,t} \end{aligned} \tag{4.2}$$

where r_1, r_2 are returns of the democratic and republican portfolios at time *t* respectively.
$c_{1,i}$ is the factor exposure of i^{th} factor to portfolio return.

This method of running separate regressions cannot determine whether the coefficients c_i are significantly different for the two portfolios. In order to tackle this, a dummy variable indicating whether it is a democratic portfolio is created.

$$I = \begin{cases} 1, \text{if democratic portfolio} \\ 0, \text{if republican portfolio} \end{cases} \tag{4.3}$$

We can now combine the two return series to run a new regression.

$$\begin{bmatrix} r_{1,1} & x^*_{1,1} & \cdots & x^*_{k,1} \\ \vdots & \vdots & \ddots & \vdots \\ r_{1,t} & x^*_{1,t} & \cdots & x^*_{k,t} \\ r_{2,1} & x^*_{1,1} & \cdots & x^*_{k,1} \\ \vdots & \vdots & \ddots & \vdots \\ r_{2,t} & x^*_{1,t} & \cdots & x^*_{k,t} \end{bmatrix}$$

$$r_t = \sum_{i=1}^{n} (\widetilde{c_i} + b_i I) x^t_{i,t} \tag{4.4}$$

Note, $c_{1,i} = \widetilde{c_i}, c_{2,i} = \widetilde{c_i} + b_i$

If the regression yields coefficients bis to be significant then it is reasonable to conclude that the two portfolios indeed have different exposure to the factor x^*_i

B. Results

From the results of the regression we see that the coefficient *M2US* (Market Index) is significant which comes as no surprise since we are considering long only portfolios. We observe that the coefficient *dem-M2USEV* is significant and positive indicating that the democratic portfolio is more exposed to the the enhanced value factor. Also, the democratic portfolio has a lower market exposure than the republican one as seen from the negative coefficient of *dem-M2US*. Another factor that is different is the *dem-SP5LVI* coefficient implying the lower volatility of democratic stocks. This reemphasises our results from the volatility modelling done earlier. Finally, we also note that the binary variable *isDem* is not significant indicating that there is no significant differences in the returns of the two portfolios after accounting for other factor exposures.

TABLE IV
DUMMY VARIABLE REGRESSION RESULTS

	Coefficient	**Std. Err.**	**T Value**	**P >| t |**
M2US	1.2001	0.064	18.734	0.0
M2US000	-0.0198	0.222	-0.089	0.929
M2USEV	-0.3785	0.264	-1.434	0.154
M2USSNQ	0.4642	0.518	0.897	0.371
M2US000G	-0.0293	0.721	-0.041	0.968
M2USQU	-0.7643	0.483	-1.581	0.116
M2US00MV	-0.2332	0.334	-0.698	0.486
M2USSC	0.1447	0.182	0.793	0.429
GSIN	0.3559	0.275	1.294	0.198
GPVAN	-0.227	0.491	-0.462	0.645
SP5LVI	-0.4308	0.207	-2.08	0.039
isDem	0.0024	0.004	0.615	0.54
dem-M2US	-0.2547	0.091	-2.811	0.006
dem-M2US000	-0.1405	0.314	-0.447	0.655
dem-M2USEV	1.0603	0.373	2.84	0.005
dem-M2USSNQ	-0.1894	0.732	-0.259	0.796
dem-M2US000G	0.5013	1.02	0.492	0.624
dem-M2USQU	0.8491	0.684	1.242	0.216
dem-M2US00MV	0.1695	0.473	0.359	0.72
dem-M2USSC	-0.1944	0.258	-0.753	0.452
dem-GSIN	0.3607	0.389	0.927	0.355
dem-GPVAN	0.2205	0.695	0.317	0.751
dem-SP5LVI	1.2439	0.293	4.247	0.0
constant	0.003	0.003	1.072	0.285

V. STRUCTURED NOTE

Structured notes can be decomposed into two segments: zero-coupon bond and a derivative instrument. Par of our structured note is designed to be 1000, thus, Julius Bear Bank, as the issuer, would receive 1000 dollars for one contract on the issuing date. To attract investors, payoff should be as high as possible at the maturity. In this section, we are going to demonstrate our design of the structured note, especially derivative parts and present the payoff graph at maturity.

A. Zero Coupon Bond

TABLE V
PARAMETERS OF ZERO COUPON BOND

Risk-free Rate (US Treasury Rate 1 year)	1.51%
Aa2 Credit Spread for JB	0.78%
Discount Rate	2.29%
Value of ZCB	977.6127
Balance of Funds	22.3873

The structured note is fully principal-protected, which means investors would get at least par value back at maturity whatever the outcome. This is achieved through zero-coupon bond accruing from its original issue value to face value. For Julius Baer Bank, the discount rate is 2.29%, thus, 977.6127 would be designed as zero-coupon bond, which is trivia but essential to principal protection.

B. Derivatives

We can calculate participation rate via balance of funds available after zero-coupon bond, in our case, 22.3873 divided by over-the-counter option price. Participation rate of 100% or even higher makes the product attractive to investors; therefore, our goal is to design "option portfolio" with lower price since our balance of funds is limited.

1) Index Compilation: Because stocks of each portfolio are all equally weighted, we compiled the portfolio index with the equation below.

$$I(t) = \frac{\sum P_i(t)}{\sum P_i(0)} * 100 \tag{5.1}$$

In our case, we set our base to be the issuing date. Therefore, Index level equals to 100 on the issuing date.

2) Option Pricing: We verified that the historical empirical CDF of the portfolio index is close to log normal. Naturally, we use Black-Scholes model to price OTC options. Pricing equations for both call and put options are as below.

$$c(t, S) = S\mathcal{N}(d_1) - e^{-r(T-t)}K\mathcal{N}(d_2) \tag{5.2}$$

$$p(t, S) = K\mathcal{N}(-d_2)e^{-r(T-t)} - \mathcal{N}(-d_1)S \tag{5.3}$$

where,

$$d_1 = \frac{ln(\frac{S}{K}) + (r + \frac{1}{2}\sigma^2(T-t))}{\sigma\sqrt{T-t}}$$

and

$$d_2 = \frac{ln(\frac{S}{K}) + (r - \frac{1}{2}\sigma^2(T-t))}{\sigma\sqrt{T-t}}$$

3) Option Strategy Design: As we discussed before, our goal is to lower option price in order to raise participation rate. Therefore, we tried to embed a butterfly spread in our structured note since butterfly spreads are relatively cheaper and flexible.

We observed and concluded in our second part that when a Republican candidate occupies the White House, volatility of Republican Index would increase dramatically, in contrast, Democratic Index would remain relatively low if a Democratic takes the House. Naturally, if investors expect volatility to increase, they would prefer more payoff at index level "away from" current level, otherwise, more payoff "around" current index level. Applying this logic, we design a short position in butterfly spread in Republican Structured Note and a long position in butterfly spread in Democratic Note.

a) Republican Structured Note: For Republican structured note, we go long on an ATM call and an ATM put, short 5% OTM put with strike 95 and 5% OTM call with strike 105 and put the extra money into coupon.

TABLE VI
REPUBLICAN OPTION PARAMETERS

S0	100 (initial index level)
σ	0.1429 (annualized)
Maturity	1 year
Discount Factor	1.51% (risk-free rate)

TABLE VII
OPTIONS FOR REPUBLICAN NOTE

Option Type	Option Price
ATM call with Strike 100	6.4342
ATM put with Strike 100	4.9355
5% OTM call with Strike 105	4.2404
5% OTM put with Strike 95	2.8845
Butterfly Spread (+ATM call + ATM put - OTM call - OTM put)	4.2448
Extra Coupon	18.1425

b) Democratic Structured Note: For Democratic Structured note, we short two ATM calls, long one OTM call and long one ITM call.

TABLE VIII
DEMOCRATIC OPTION PARAMETERS

S0	100 (initial index level)
σ	0.2232 (annualized)
Maturity	1 year
Discount Factor	1.51% (risk-free rate)

TABLE IX
OPTIONS FOR DEMOCRATIC NOTE

Option Type	Option Price
ATM call with Strike 100	9.5888
ATM put with Strike 100	8.0901
OTM put with Strike 90	3.8925
OTM call with Strike 110	5.6698
Butterfly Spread (-1 ATM call -1 ATM put + 1 OTM call + 1 OTM call)	-8.1166
Number of Butterfly per Contract	10
Extra Coupon	22.3873

4) Evaluation of Payoff: In order to evaluate each structured note, we calculated the conditional payoff. We assume that index follows log-normal distribution, of which PDF is the orange line in the graphs.

a) Conditional Payoff: Assume S_T applies to some PDF $f(s)$, and we have payoff function $g(s)$. As there are 2 strike price parameters we define

$$conditional \quad probability = P(S_T \in [K_1, K_2]) = \int_{K_1}^{K_2} f(s)ds \tag{5.4}$$

$$conditional \quad payoff = E[g(S_T)|S_T \in [K_1, K_2]] = \int_{K_1}^{K_2} g(s)f(s)ds \tag{5.5}$$

b) Advantages of Republican Structured Note: Conditional payoff is 1021.03, which is competitively high in the market. If a Republican candidate occupies the White House, the volatility of Republican Index tends to rise. Investors are more likely to get the maximum payoff of this note, which is 1023.56. Because the butterfly spread is very cheap, so that our investors are not only entitled to 100% of participation rate, but also extra coupon. The minimum payoff would be 1018.66, which is still attractive and competitive.

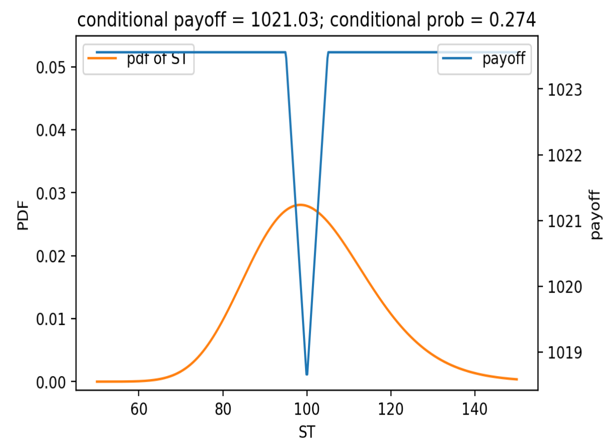


Fig. 8. Republican Structured Note Payoff

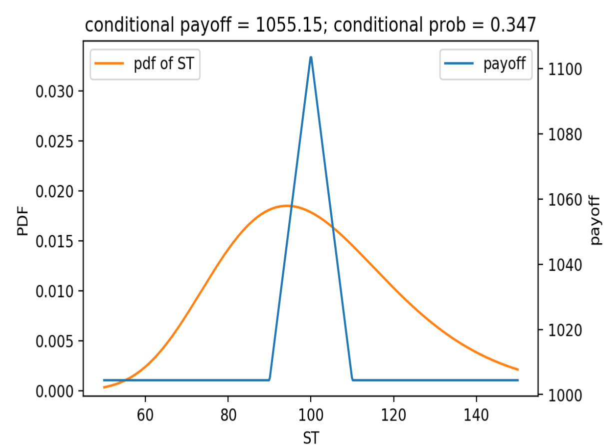


Fig. 9. Democratic Structured Note Payoff

c) Advantages of Democratic Structured Note: Conditional payoff is 1055.15, which is even higher than that of Republican Note. If a Democratic occupies the White House, the volatility of Democratic Index is relatively low. The payoff around current index level is very high. Investors would be more than happy to have return rate of up to 10%. For Democratic Structured Note, the maximum payoff could be 1103.41 and the minimum payoff is 1004.41.

VI. Final Term Sheet

TABLE X
1-Year Republican Structured Note Final Terms and Conditions

Issuer:	Julius Baer Bank(Moody's Aa2)
Offering:	Principal Protected Note due on Jan 29, 2020
Underlying Index:	Republican Index
Coupon	1.85%
Denomination/Principal:	$1,000
Issue Size:	$40,000,000
Issue Price:	100% (par)
Initial Index Level:	100
Redemption:	For each $1,000 principal amount of Securities a cash payment at maturity equal to: 1. principal: $1,000 2. coupon: $18.5 3. 100% butterfly spread payoff: $max(S_T - 100, 0) + max(100 - S_T, 0) -$ $max(S_T - 105, 0) - max(95 - S_T, 0)$
Maturity Date:	Jan 28, 2021
Determination Date:	Three business days before Maturity Date

TABLE XI
1-Year Democratic Structured Note Final Terms and Conditions

Issuer:	Julius Baer Bank(Moody's Aa2)
Offering:	Principal Protected Note due on Jan 29, 2020
Underlying Index:	Republican Index
Coupon	2.25%
Denomination/Principal:	$1,000
Issue Size:	$40,000,000
Issue Price:	1000 (par)
Initial Index Level:	100
Option Initial Premium:	+81.25
Redemption:	For each $1,000 principal amount of Securities a cash payment at maturity equal to: 1. principal: $1,000 2. coupon: $22.5 3. option initial premium 81 + 100% butterfly spread payoff: $-max(S_T - 100, 0) - max(100 - S_T, 0) +$ $max(S_T - 110, 0) + max(90 - S_T, 0)$
Maturity Date:	Jan 28, 2021
Determination Date:	Three business days before Maturity Date

VII. Conclusion

From the two GARCH models, we see volatility of Republican portfolio is more sensitive to external environment i.e. when an event occurs, its conditional volatility surges more than that of Democratic portfolio. The same effects are also reflected in the realized 50-day correlation of both portfolios. During periods of high volatility, average correlation between components also goes increases, bur more for the Republican portfolio.

Given the difficulty of bucketing stocks into two partisan portfolios, this study set out to use traditional methods as well as a unique dataset to find peer relationships. Though the method of using Tweets cannot be used to clearly delineate the democratic and republican portfolios, some meaningful relationships can be extracted from this simple methodology. We suspect the lower volume of tweets as well as continuation of the president's term may be the cause for the non existence of a clear pattern in 2012 compared to 2016.

From the factor regression, we see that there are a couple of coefficients that are different for the two portfolios indicating their differences in exposures to those factors. Assuming that portfolio returns can be decomposed into a sum its factor exposure returns, it is quite logical to conclude that these portfolios are indeed expected to perform differently going forward,

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APPENDIX

TABLE XII
PORTFOLIO STOCKS

Democratic Portfolio	Exelon Corp. (EXC) Ford Motor Co. (F) Aptiv PLC (APTV) Constellation Brands Inc. (STZ) Estee Lauder Cos. (EL) SunPower Corp. (SPWR) Coca-Cola Co. (KO) Walmart Inc. (WMT) Home Depot Inc. (HD) NextEra Energy Inc. (NEE) CSX Corp. (CSX) McDonalds Corp. (MCD) Simon Property Group Inc. (SPG) First Solar Inc. (FSLR) Norfolk Southern Corp. (NSC)
Republican Portfolio	Honeywell International Inc. (HON) Alphabet Inc. (GOOGL) ConocoPhillips (COP) Marathon Oil Corp. (MRO) Citigroup Inc. (C) Salesforce.com Inc. (CRM) QUALCOMM Inc. (QCOM) Gilead Sciences Inc. (GILD) Amazon.com Inc (AMZN) Chevron Corp. (CVX) Facebook Inc. (FB) Merck & Co. (MRK) PayPal Holdings Inc. (PYPL) American Express Co. (AXP) Visa Inc. (V)

TABLE XIII
FACTOR INDICES

Factors	**Index**	**Ticker**
Momentum	MSCI USA Momentum Index	M2US000
Value	MSCI USA Enhanced Value Index (USD)	M2USEV
Quality	MSCI USA Sector Neutral Quality Index	M2USSNQ
	MSCI USA Quality Gross Total return USD Index	M2USQU
Growth	MSCI USA Growth Gross total return USD Index	M2US000G
Size	MSCI USA Mid Value Gross Total return USD Index	M2US00MV
	MSCI USA Small Cap Gross Total Return USD Index	M2USSC
ESG	FTSE KLD Global Sustainability Index	GSIN
Yield	The FTSE High Dividend Yield Index	GPVAN
Volatility	S&P 500 Low Volatility Index	SP5LVI