Academic Affiliate Paper Competition Winning Papers

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Team WOLT

Will the Julius Baer Election Notes Perform as Advertised?

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***Executive Summary*—In January 2020, Julius Baer (JB) Group Ltd. issued a pair of structured notes advertised to have differing performance dependent on the results of the U.S. 2020 presidential election[1]. The portfolios underlying these notes each consist of a basket of 15 stocks, with one expected to outperform the other depending on if President Trump, a Republican, wins reelection or is unseated by the challenging Democrat.**

In this paper we examine the JB Group's claim of differing expected performance of these two portfolios. To this end, we first examine the quantitative differences between the portfolios based on a set of fundamental, macroeconomic, and political features. We found that the portfolios do not perform as advertised in historical back test. We also found evidence that the Republican portfolio performance is correlated with oil price, and the Democratic portfolio is more immune to U.S. trade policy. An analysis of political donation data shows that the Republican portfolio on average has donated more to Democratic candidates in the 2020 election cycle than has the Democratic portfolio. Additionally, companies in the Republican portfolio generally have their headquarters in locations that vote much more heavily Democrat. Finally, we present evidence that the Republican portfolio constituent companies provide better health insurance than companies in the Democratic portfolio.

To predict the performance of the two portfolios conditioned on the results of the 2020 election, we incorporated some of these features into linear and ensemble machine learning models. We use the linear model to gain insight into our feature set, and we use the superior out-of-sample performance of the machine learning model to forecast portfolio returns. Under our best predictions, we found the spread between the two portfolios to favor the Republican portfolio in both election results. Additionally, we predict that a Democratic victory will favor both portfolios. However, in the framework of our model, these spreads are shown to not be statistically significant. Therefore, we cannot bolster the claims made by JB Group and have evidence to the contrary.

We use the same machine learning model to suggest portfolios that will perform as expected conditioned on a Republican or Democratic victory in 2020. After rearrangement of the assets in the JB structured notes, our model predicts spreads consistent with what is advertised of these portfolios. That is, a Democratic portfolio will perform better if a Democrat is elected rather than a Republican, and a Democratic portfolio will outperform a Republican portfolio in the case of a Democratic election victory. Likewise, the analogous case is predicted for a Republican portfolio. Finally, we propose novel portfolios with assets taken from the S&P 500 that will achieve the desired spreads with higher confidence.

[1] https://www.bloomberg.com/news/articles/2020-01-14/a-swiss-bank-is-selling-rich-clients-an-exotic-u-s-election-bet

1. The Julius Baer Structured Notes

The constituent assets of the JB Group Ltd. structured notes can be found in Table 1. These two portfolios are advertised to have differing performance based on the results of the 2020 U.S. Presidential Election. We will refer to the structured note that is expected to outperform the other conditioned on a 2020 Republican victory as the ”Republican portfolio”, and likewise for the ”Democratic portfolio”. Furthermore, in our analysis we will take these structured notes to be an equal weighting of a long position in each of the constituent companies.

Julius Baer Structured Notes

Democratic Portfolio		Republican Portfolio	
Asset	Ticker	Asset	Ticker
Exelon	EXC	Honeywell	HON
Ford	F	Alphabet Inc.	GOOG
Aptiv PLC	APTV	ConocoPhillips	CP
Constellation	STZ	Marathon Oil	MRO
Estee Lauder	EL	Citigroup	C
SunPower	SPWR	Salesforce	CRM
Coca-Cola	KO	Qualcomm	QCOM
Walmart	WMT	Gilead Sciences	GILD
Home Depot	HD	Amazon	AMZN
NextEra Energy	NEE	Chevron	CVX
CSX	CSXT	Facebook	FB
McDonald's	MCD	Merck & Co.	MRK
Simon Property	SPG	PayPal Holdings	PYPL
First Solar	FSLR	American Express	AXP
Norfold Southern	NS	Visa	V

TABLE 1: Constituent assets of the JB structured notes.

2. Quantitative Differences

We found significant quantitative differences between the two JB portfolios. In historical analysis of the portfolios, using portfolios built with companies present at the time, we found only three presidential elections since President Carter's election in 1976 where the portfolios performed as advertised. These were the 1992, 2008, and 2016 elections. An analysis of daily return spreads between the two portfolios and major news stories since 2016 suggested portfolio correlations with oil prices and U.S. trade policy worries. These hypotheses were given evidence with analysis of monthly returns correlation with oil prices and analysis of international revenue percentage. We found little crossover in industry classifications of the portfolios, with the Republican portfolio dominating in the energy and financial sectors, and the Democratic portfolio dominating in the utility and

Election Cycle	President Taking Power	Spread	D Portfolio % Return	R Portfolio % Return
1976	Jimmy Carter [D]	+0.58% R	3.08% (6)	3.67% (5)
1980	Ronald Reagan [R]	+8.99% D	35.67% (6)	26.68% (6)
1984	Ronald Reagan [R]	+11.34% D	29.05% (9)	17.71% (7)
1988	George H.W. Bush [R]	+13.40% D	42.13% (9)	28.73% (7)
1992	Bill Clinton [D]	+21.11% D	36.16% (9)	15.06% (9)
1996	Bill Clinton [D]	+20.62% R	16.21% (12)	36.83% (9)
2000	George W. Bush [R]	+1.66% D	8.91% (12)	7.24% (10)
2004	George W. Bush [R]	+11.29% D	20.17% (12)	8.88% (10)
2008	Barack Obama [D]	+7.91% D	−28.26% (14)	−36.17% (12)
2012	Barack Obama [D]	+15.68% R	15.43% (15)	31.11% (13)
2016	Donald Trump [R]	+16.68% R	8.26% (15)	24.94% (15)

TABLE 2: Historical performance of the Democratic and Republican portfolios. Spread refers to the difference in yearly returns between the two portfolios starting from the closest date to January 21st of the listed year. Green years indicate a matching election victory and spread direction. Numbers in parenthesis next to returns represent the number of companies present in the portfolio at that time.

consumer staples sectors. An analysis of headquarters location and location partisanship showed that the Republican portfolio was located in Democratic stronghold states, where Democrat partisanship has been steadily increasing since 1988. In an analysis of political donations, we found that both portfolios have donated more to Democratic candidates over the years. Additionally, we found statistical evidence that the Republican portfolio has donated more to Democratic candidates than the Democratic portfolio has in the 2020 election cycle. Finally, we found evidence that the Republican portfolio contains companies with higher rated healthcare than the Democratic portfolio.

2.1. *Historical Performance*

Yearly historical performance for each portfolio in every election cycle since President Carter is shown in Table 2. The Democratic and Republican portfolios were reconstructed each election cycle based on an equal weighting of companies that were present at the time. We will continue to use this reconstruction method as needed throughout this report when we historically analyze these portfolios. Time frames were chosen to start on the nearest date to January 29th with one year duration for presidential election years.

In the 11 presidential election cycles analyzed, there were 5 Democrat and 6 Republican victories. Out of all Democrat victories, the Democratic portfolio outperformed the Republican portfolio in 40% of cases. Out of all Republican victories, the Republican portfolio outperformed the Democratic portfolio in 17% of cases.

While the Republican portfolio outperformed the Democratic portfolio in the most recent presidential election in 2016, it also outperforms the Democratic portfolio in the 2012 election when President Obama [D] was elected for his second term. In fact, in only three cases has the dominating portfolios name matched the elected presidents party: President Clinton's first election in 1992, President Obama's second election in 2008, and President Trump's election in 2016.

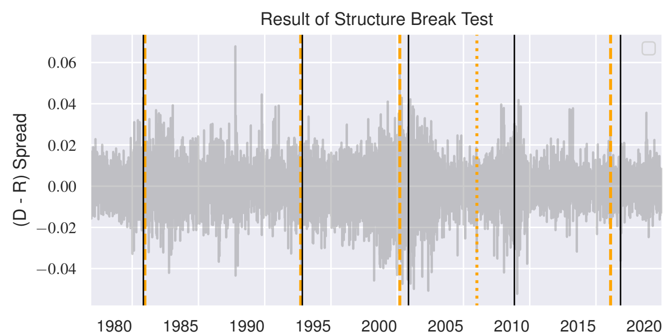

Fig. 1: Structural break test result. Solid lines represent election dates with a party switch. Orange dashed lines are break points close to an election. The orange dotted line is a break point far from any election.

To test if the two portfolios are sensitive to presidential elections, we conducted structural break tests [1] on historical daily spreads between the two JB portfolios. We chose the time period for a single test to be eight years long with one presidential election in the middle and we assumed one break point in each test. The results can be found in Figure 1. The break points in the years 1980, 1992, 2000, and 2016 are close to election dates, indicating that historically some election cycles have had daily impacts on the spreads between the two portfolios.

2.2. *News Effects in the Current Presidency*

We analyzed the time period between November 9th, 2016 and January 29th, 2020 for significant differences in daily returns between the Democratic and Republican portfolios. Historical daily summaries of financial

Date	Spread	News
11/9/16	+3.63% R	President Trump elected.
11/30/16	+2.29% R	Oil prices rise; Trump proposes fiscal stimulus measures.
12/7/16	+2.06% D	Trump intends to reduce drug prices.
2/17/17	+2.10% D	Trump proposes tax cuts and infrastructure plans.
10/10/18	+2.15% D	Concerns of rising interest rate and slowing global growth.
10/24/18	+3.57% D	Tech sector declines; Concerns of slowing global growth.
11/12/18	+2.26% D	Oil prices decline; Tariff worries.
12/26/18	+2.48% R	Strong retail sales; Oil prices rise; Tech stocks gain.
6/3/19	+2.25% D	Tech giants investigated against anti-trust laws.

TABLE 3: Daily return spreads and major news stories between the two portfolios on select dates between November 9th, 2016 to January 29th, 2020. Days were included if the spread between the two portfolios exceeded 2%. Blue or red highlighting indicates whether the Democratic or Republican portfolio outperformed, respectively.

news from Zacks Investment Research[2] allowed us to analyze news snapshots from when the spread of daily returns between the portfolio was substantial. Dates with daily return spreads between the two portfolios of over 2.00% are shown in Table 3 along with the major news stories of that day.

The relative returns compared with the news suggest that the Republican portfolio reacts positively to increasing oil price, and the Democratic portfolio is more immune to trade concerns. We quantify these suggested relationships by analyzing mean monthly correlation with oil prices and mean internationalization for both portfolios.

2.3. Oil Price Correlation

A company's sensitivity to oil prices is quantified by the correlation of monthly returns with monthly oil prices. Shown in Figure 2 is each company's correlation with oil prices along with portfolio averages. The time period analyzed was from a company's inception to January 2020, with data taken from the Federal Reserve Bank of St. Louis[3].

On average, companies in the Republican portfolio have stronger correlation with oil price than those in the Democratic portfolio. This significance is confirmed by a Welch's t-test on the means, which give a p-value of 0.04. The three companies most strongly correlated with oil price are Conoco Phillips, Marathon Oil, and Chevron, which are all part of the Republican portfolio. The three companies least correlated with

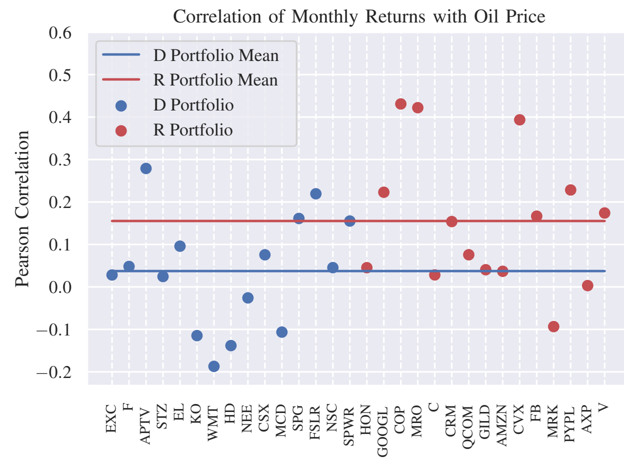

Fig. 2: Correlation of monthly returns with oil price for companies.

oil price are Walmart, Home Depot, and Coca-Cola, which are all part of the Democratic portfolio.

2.4. Internationalization

We quantify a company's internationalization by its proportion of overseas revenue in a fiscal year. Shown in Figure 3 is each company's internationalization level in fiscal year 2018 along with the Democratic and Republican portfolio means.

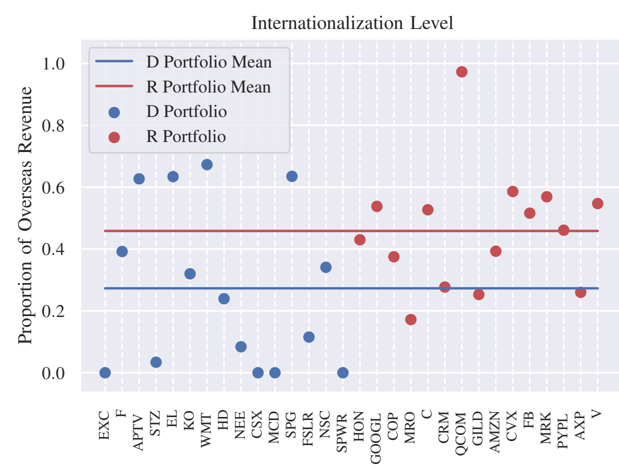

Fig. 3: Internationalization levels of companies.

The Republican and Democratic portfolios have mean internationalization levels of 45% and 27%, respectively. t-test results give evidence the difference in means is significant, with a p-value of 0.04. These results suggest that the Democratic portfolio is less internationalized and less sensitive to United States trade policy.

2.5. Sector Distribution

The sector distribution of each portfolio was analyzed using the GICS of each constituent company,

[2]https://www.zacks.com
[3]https://www.stlouisfed.org

Fig. 4: GICS industry classifications of companies.

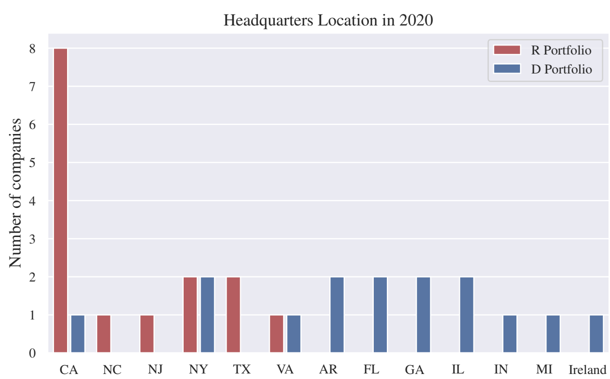

Fig. 5: Headquarters locations of companies in 2020.

with results in Figure 4.

Overall, there is relatively little crossover in industries between the two portfolios, with 73% of the Republican and 53% of the Democratic portfolios being invested in mutually unique sectors. Nearly half (47%) of the Republican portfolio is invested in the energy and financial sectors, while the Democratic portfolio contains no assets in these sectors. Likewise, nearly half (47%) of the Democratic portfolio is invested in the utility and consumer staples sectors, while the Republican portfolio is not at all. Both portfolios are 13% invested in the information technology sector.

2.6. Headquarters Location and PVI

The Cook Partisan Voting Index (PVI) is a measure of the relative partisanship of a state as compared with the nation[4]. For a particular party and election cycle, the PVI is calculated by comparing the most recent vote share to the average of the last two elections. We analyzed the two portfolios with respect to this measure by comparing constituent company headquarters locations with PVI. Company headquarters locations as of 2020 are shown in Figure 5.

Over half (53%) of companies in the Republican portfolio have their headquarters in California. Headquarters of companies in the Democratic portfolio are dispersed, with no more than 13% in any particular state. One company, Aptiv PLC has its headquarters outside of the United States in Dublin, Ireland.

For the companies with headquarters in the United States, we analyzed each portfolio by averaging the PVI of the constituent company's 2020 headquarters' state. PVI data was taken from the Cook Political Report[5]. Figure 6 shows the average PVI for each portfolio at each presidential election cycle since 1988. The PVI we use is measured on Democrat partisanship, i.e. the percentage of votes for the Democratic candidate over the national average. A positive PVI indicates Democrat leaning, while a negative PVI indicates a Republican leaning.

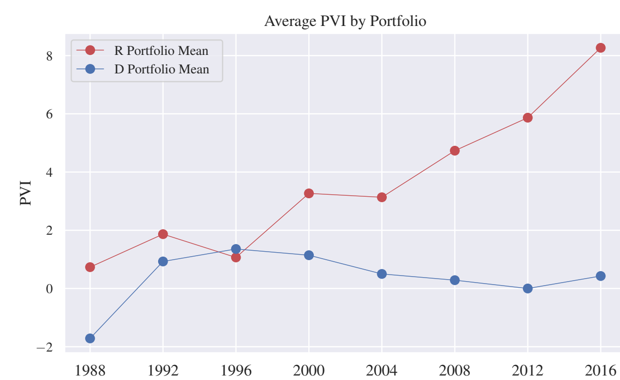

Fig. 6: Portfolio averaged PVI from 1998 to 2016 for each presidential election cycle. PVI for each company was taken to be the PVI of each company's headquarters' state.

Since 2000, the Republican portfolio on average has constituent company headquarters in locations that support the Democratic candidate more than the national average. This is an increasing trend since 2004, with the PVI growing at ∼55% per election cycle. Likewise, the Democratic portfolio with respect to this measure has shown relative non-partisanship through the years with a neutral average PVI and no clear upward or downward trend.

2.7. Political Donations

Using data from the Center for Responsive Politics (CRP)[6], we gathered political donations data of each company in the portfolios. Political donations by a company are defined to include donations made by the organization's political action committee (PAC),

[4]https://en.wikipedia.org/wiki/Cook_Partisan_Voting_Index

[5]https://cookpolitical.com/index.php/pvi-0

[6]https://www.opensecrets.org

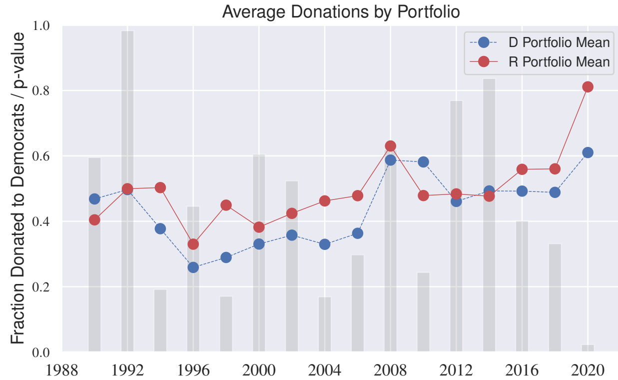

Fig. 7: Average political donations by portfolio for every presidential and midterm election cycle since 1988. Bars are the Welch's t-test p-value for the null hypothesis of equal means of the JB portfolios.

employees or owners of the company, and those individuals immediate family members. Portfolio averaged donations are shown in Figure 7, where donation partisanship for a particular election cycle is defined to be the percent of donations made to Democratic candidates out of total donations to both Republican and Democratic candidates. Portfolio averages are computed by an equal weighting of the constituent company's fraction donated to Democrats. Data for the 2020 election cycle consists of all donations made as of January 2020.

Some salient features emerge from these time series. On average, both portfolios from 1988 to 2006 generally donated more to Republican candidates. In 1996, the year President Clinton was elected for his second term, both portfolios donated most heavily to Republicans, with 78% donated to Republicans by the Democratic portfolio and 67% donated to Republicans by the Republican portfolio. Since 1996, both portfolios are shown to be trending toward donating a higher percentage to Democratic candidates. With respect to donations to Democratic candidates, 2020 thus far has been the most partisan year on record with 61% donated to Democrats by the Democratic portfolio and 81% donated to Democrats by the Republican portfolio.

There is not enough evidence to conclude different average donations of the portfolios with the exception of the 2020 election cycle. In the 2020 election cycle, a p-value of 0.024 gives evidence that the Republican portfolio has, as of January 2020, donated a higher percentage to Democratic candidates as compared with the Democratic portfolio.

Fig. 8: Health insurance ratings for companies in the JB portfolios.

2.8. *Health Insurance Ratings*

Under the conjecture that opinions on healthcare may be related to overall political affiliation of a company, we collected ratings of employee supplied healthcare from all companies in the two portfolios. Ratings data was taken from Glassdoor[7] from 2014 to the present. Glassdoor allows company employees to rate their health insurance from 1 to 5. The Republican portfolio has about 3000 reviews for company healthcare plans while the Democratic portfolio has 1300 reviews. Because of this imbalance, we applied a square root transformation to the number of reviews in each rating 1 to 5. A histogram of the transformed ratings for each portfolio is shown in Figure 8.

The Democratic portfolio has an average company healthcare rating of 3.23, while the Republican portfolio has an average rating of 3.55. The statistical significance of the difference between the means is supported by a t-test with a p-value of 0.006. These results suggest that the companies in the Republican portfolio issue better overall health care plans to their employees.

3. Expected Performance

To assess how the two JB portfolios will perform under a Republican or Democrat victory in the 2020 election, we constructed models to predict asset returns relative to the S&P 500 based on political, fundamental, and macroeconomic features. The set of assets we used for training are the yearly constituent companies of the S&P 500 since 1990. The starting year 1990 was chosen based on the availability of political donation and returns data. Our target variable is an asset's dividend adjusted yearly return from January 29$^{\text{th}}$ relative to the S&P 500. This return period was chosen

[7]https://www.glassdoor.com

to correspond to the term of the JB structured notes. The set of features we use are named and described in Table 4. After removal of missing data, our training set had a total of 10457 observations.

We built a linear model based on the standalone features and first order cross terms in Table 4, backward selecting significant features with p-values <0.1 [2]. Our linear model uses 231 variables including the intercept and achieves an adjusted R^2 of 19.69%.

We also built a stacked machine learning model to predict the quantile of relative returns based on the distribution of relative returns for any given year. All features in Table 4 were used. Compared with a random guess of quantile for a given asset and year, the stack model improved 26.5% out-of-sample with performance measured by distance from predicted quantile to correct quantile. This is an improvement over the linear model, which improved 24.7% in-sample over a random guess by the same performance metric.

We use both models to predict the performance of the JB structured notes in the 2020 Presidential Election. We define intended performance by two measures. Considering the Democratic portfolio as an illustrative example, the Democratic portfolio should outperform the Republican portfolio in the case of a Democratic election victory in 2020. Additionally, the Democratic portfolio should show better performance if a Democrat gets elected rather than a Republican. Both the linear model and stack model show that there is no evidence the portfolios will perform in this way, and there is weak evidence to the contrary.

3.1. Linear Model and Feature Significance

Our linear model includes features from Table 4 in addition to first order cross terms as independent variables. We selected these features for a mix of fundamental, macroeconomic, and political indicators. Fundamental features were chosen for their similarity to the Barra Risk Factors [3]. These features have been shown empirically to have explanatory power in asset cross sectional returns, and we include them to help discriminate non-political effects. Some macroeconomic features such as *GDP* were chosen to help alleviate outlier behavior in the 2001 and 2008 recessions. Others, such as *OilPrice* and *DollarIndex* were chosen based on inferences gained from Figures 2 and 3, respectively. All fundamental and macroeconomic data was taken from Bloomberg. We also include political donations in our feature set using data taken from the Center for Responsive Politics (CRP). Specifically, we include *DlogDonation* and *RlogDonation* along with *D%Donation* in light of the work by Cooper, Gulen and Ovtchinnikov [4], where political participation was shown to affect stock returns in election years.

Feature	Description
EffTaxRate	The effective tax rate a company pays. (OLY)
Beta	The beta against S&P 500. (OLY)
$Beta^3$	The cube of *Beta*. (OLY)
Momentum	The adjusted lag return. (OLY)
Profit	Simple average of ROE and ROA. (ELY)
Liquidity	Ratio of the traded volume to the market capitalization. (OLY)
Size	Log transformation of market capitalization. (ELY)
$Size^3$	The cube of *Size*. (OLY)
Value	Simple average of PE and PB ratio. (ELY)
Dividend	The dividend rate. (OLY)
Leverage	Ratio of total debt to total equity. (ELY)
Volatility	Simple average of 90D and 360D return standard deviation. (OLY)
Growth	Simple average of net income, EPS, sales and cashflow growth. (OLY)
OilPrice	Growth rate of the price of oil against the previous year's price of oil on the last trading day closest to January 29^{th}.
InterestRate	First order difference of the 10 year treasury yield against the previous year's yield on the last trading day closest to January 29^{th}.
DollarIndex	Annual growth rate of the U.S. dollar index on the last trading day closest to January 29^{th}.
CPI	First order difference of the consumer price index growth rate against previous year's December value.
GDP	First order difference of the GDP growth rate against the previous year's Q3 value.
Unempl	First order difference of the unemployment rate against the previous year's December unemployment rate.
D%Senate	Percent of the senate seats occupied by Democrats at the start of the year.
D%House	Percent of house seats occupied by Democrats at the start of the year.
D%Donation	Percent of political donations made to Democratic candidates.
DlogDonation	Log of the dollar amount donated to Democratic candidates.
RlogDonation	Log of the dollar amount donated to Republican candidates.
*GICS**	Ten indicators representing the industry, save one to avoid multicolinearity.
*XtY**	Four indicators active only if it is an election year where X is the party of the incumbent president and Y is the party of the incoming president. X and Y both belong to {R,D}.

TABLE 4: Description of features used for any given asset and year. ELY: variable calculated at the end of the lag year. OLY: variable calculated over the entire lag year. * indicates dummy variable.

In our linear model with n continuous variables and m dummy variables, we assumed an observation took

Significant Features in Panel Least Squares Regression											
Standalone Variables			Election & Fundamental Cross Terms			Election & Sector Cross Terms			Donation & Election/Sector Cross Terms		
Variable	Coef	*t*-stat	Variable	Coef	*t*-stat	Variable	Coef	*t*-stat	Variable	Coef	*t*-stat
DtD	−0.29	−7.40***	*DtR∗Volatility*	−0.09	5.90***	*DtR∗ConsumerCyclical*	−0.17	−4.37***	*DlogDonation∗RtD*	−0.08	−4.96***
DtR	0.20	6.70***	*RtD∗Momentum*	0.09	5.44***	*DtD∗Financial*	0.15	4.27***	*D%Donation∗Energy*	−0.31	−3.21***
Liquidity	0.30	6.22***	*DtR∗Momentum*	−0.09	−5.31***	*RtR∗Energy*	0.22	3.02**	*RlogDonation∗Technology*	−0.03	−2.65**
Momentum	0.27	6.20***	*RtR∗Liquidity*	−0.09	−4.89***	*DtR∗ConsumerNoncyclical*	−0.10	−2.94**	*D%Donation∗DtR*	−0.11	−2.54*
Profit	0.14	3.70***	*DtD∗Size*^{3}	0.07	4.83***	*RtD∗Energy*	−0.13	−2.56*	*D%Donation∗ConsumerCyclical*	−0.07	−2.51*
Technology	0.07	3.64***	*RtD∗Size*	0.46	4.06***	*DtR∗Communications*	−0.13	−2.47*	*DlogDonation∗Energy*	0.06	2.27*
RlogDonation	−0.13	−3.28**	*RtD∗Liquidity*	0.07	3.88***	*RtR∗Communications*	−0.16	−2.45*	*DlogDonation∗RtR*	0.04	2.15*
Energy	0.13	3.23**	*RtD∗Size*^{3}	−0.44	−3.86***	*RtD∗Financial*	−0.08	−2.09*			
Volatility	−0.13	−2.39*	*DtR∗Beta*	−0.05	−3.21**	*RtR∗BasicMaterials*	0.15	2.05*			
ConsumerCyclical	−0.33	−2.14*	*DtD∗EffTaxRate*	0.03	2.93**	*DtR∗Financial*	0.07	2.02*			

TABLE 5: Select significant features in least squares regression. p-value 0 - 0.01: ***, 0.01 - 0.05: **, 0.05 - 0.1: *.

the functional form of

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i^x x_i + \sum_{i=1}^{n}\sum_{j=1}^{i} \beta_{i,j}^{xx} x_i x_j + \sum_{j=1}^{m} \beta_j^d d_j + \sum_{j=1}^{m}\sum_{k=j+1}^{m} \beta_{j,k}^{dd} d_i d_j + \sum_{i=1}^{n}\sum_{j=1}^{m} \beta_{i,j}^{xd} x_i d_j + \varepsilon(0,\sigma^2),$$

where x_i is the i^{th} continuous variable, d_i is the i^{th} dummy variable, β are constant coefficients, y is our target of log returns relative to the S&P 500, and ε is a normally distributed random variable with mean 0 and variance σ^2. All continuous variables are standardized and winsorized at 5% and 95% quantiles.

Table 5 shows select features from the ordinary least squares regression with backward selection and their significance. The features shown are the most germane to the purpose of the model - predicting relative returns based on the political climate. We found that many of the political features crossed with fundamental and macroeconomic features were significant.

The standalone features *DtD* and *DtR*, which are dummy variables representing an election year in which the incumbent president is reelected, are shown to be significant. The negative coefficient of *DtD* indicates that all else being equal, the reelection of a Democratic president will have a negative effect on relative returns. The positive coefficient of *DtR* suggests the opposite, i.e. the defeat of an incumbent Democrat by a Republican will have a positive effect on relative returns.

Some election and sector cross terms showed significance as well. We found that *RtR∗Energy* and *RtD∗Energy* have a positive and negative coefficient in the regression respectively. This suggests that the energy sector reacts positively to the reelection of a Republican and negatively to the defeat of an incumbent Republican by a Democratic. We also found evidence of under performance in the consumer sector during a White House party switch from Democratic to Republican, and under performance of the communications sector when a Republican wins election, regardless of the previous party in the White House. Another sector sensitive to election results is the financial sector. The model suggests that a switch from a Republican to Democratic president will result in negative relative returns, while a switch from a Democratic to Republican president will result in positive relative returns.

The donation and election cross terms provide explanation of how political donations affect relative returns during election years. *DlogDonation∗RtD* and *DlogDonation∗RtR* are shown to be significant. Contrary to one's intuition, all else being equal, companies with a higher absolute monetary contributions to Democrats have lower relative returns when a Democrat replaces a Republican, and have higher relative returns when an incumbent Republican is reelected. The fraction of donations made to Democratic candidates, on the other hand, gives a more intuitive result. *D%Donation∗DtR* is shown to have a negative effect on relative returns if an incumbent Democrat is defeated by a Republican.

Linear model summary

		5 Quantiles		10 Quantiles	
R^2	Adj. R^2	L^1	L^2	L^1	L^2
21.46%	19.69%	1.24	1.65	2.56	3.31

TABLE 6: Performance of the linear model. The model has 10,457 observations and 231 backward selected variables. L^1 and L^2 are the in-sample mean absolute error and square root of mean squared error.

Performance of the linear model with backward selection can be found in Table 6. To compare performance with our machine learning model, we transform the relative returns into quantiles for each year and include a modified version of L^1 and L^2 distances as performance metrics. L^1 is the mean absolute error from predicted quantile to correct quantile, and L^2 is the square root of mean squared error. These measures have better penalization mechanisms than the simple accuracy score for stocks misclassified with large error.

3.2. Stack Model

Ensemble methods are commonly used to boost predictive accuracy by combining the predictions of

Stack Model Accuracy

Model	5 Quantiles L^1	5 Quantiles L^2	10 Quantiles L^1	10 Quantiles L^2
Stack Model	1.20	1.56	2.50	3.16
Random Forest	1.32	1.81	2.91	3.85
Gradient Boosting	1.34	1.80	3.03	3.95
Discriminant Analysis	1.36	1.80	2.92	3.80
Light GBM	1.39	1.86	2.98	3.87
XGBoost	1.41	1.89	2.93	3.81
Support Vector Classifier	1.45	1.92	3.19	4.11
AdaBoost	1.45	1.93	3.19	4.13
KNeighbors Classifier	1.48	1.92	3.10	3.98
Gaussian Naïve Bayes	1.48	1.93	3.19	4.07
Neural Network	1.52	1.99	2.99	3.93
Random Guess	1.60	2.00	3.40	4.06

TABLE 7: Stack model and constituent classification models with their L^1 and L^2 distance errors on the test set. Stack Model prediction is a weighted average of the classification model predictions.

multiple otherwise unrelated machine learning models [5], [6]. The idea is to combine so-called "weak" learners into one stacked model, resulting in a final ensemble that can have a higher prediction power. Using this method, we combined different multi-class classification models into one stack model to predict the relative returns quantile for a given asset and year. We chose to use discrete quantiles instead of continuous returns since we are chiefly interested in the relative performance between assets. Using quantiles preserves this relationship while being more forgiving in respect to the prediction accuracy. Scores were given to each individual member of our stack model based on their out-of-sample performance in a validation partition of our data set. Our stack model takes the accuracy score based weighted average of single model predictions to form the final quantile prediction. The detailed methodology for creating our stack model is as follows:

1) Discretize the asset returns relative to the S&P 500 into n quantiles year by year, so that the number of observations per quantile is balanced.
2) Randomly split the data set to form the training, validation, and test sets, with each taking 60%, 20%, and 20% of the observations, respectively.
3) Train 13 individual models using the training set and select the 10 best models based on their accuracy score in the validation set.
4) Determine weights of individual models by rank ordering their accuracy scores. A model with rank r out of 10 is assigned a weight $w_r = (11-r)/55$.
5) Evaluate the performance of the stack model with the test set.

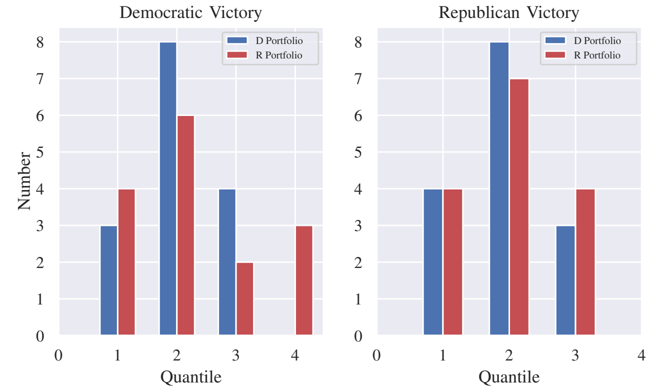

Fig. 9: 5 quantile stack model performance predictions.

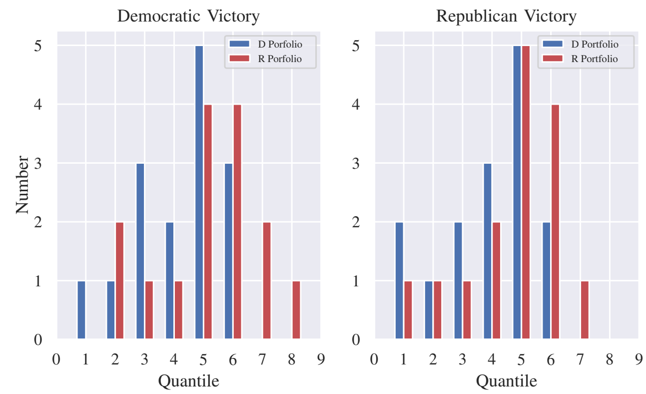

Fig. 10: 10 quantile stack model performance predictions.

To demonstrate robustness, we built two stack models that use 5 and 10 quantile classifications. From Table 7, we see that both stack models perform better than any of the individual constituent models and about 26% better than a random guess under L^1 and L^2 measures. These performance metrics refer to the total average distance error, measured by the same L^1 and L^2 norms as in the linear model, of observations' predicted quantile and actual quantile. Any individual model's performance in the test set is similar to its performance in the validation set, which suggests minimal overfitting.

3.3. Performance Predictions of the JB Portfolios

Using the linear and stack models, we predict the performance of the JB structured notes in the cases of a Democratic and Republican victory in 2020. Figures 9 and 10 show the performance predictions of the two portfolios using the 5 quantile and 10 quantile stack models, respectively. A comparison of the two models in Figure 11 shows that both predict the same outcomes, indicating robustness of the result. The stack models predict both portfolios will perform better if a Democratic wins election, and that the Republican

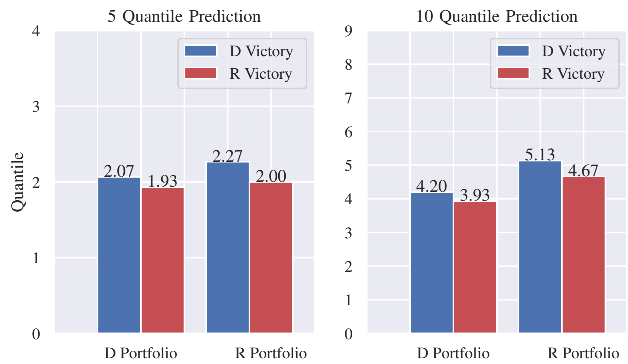

Fig. 11: Comparison of the 5 and 10 quantile model predictions.

portfolio will outperform the Democratic portfolio under both election results.

We use one tailed t-tests to measure the strength of the spread results. In our t-tests we use the alternative hypotheses that the portfolio spreads will perform as expected in relation to each other and across election results. For example, the Democratic portfolio should outperform the Republican portfolio in the case of Democratic victory, and the Democratic portfolio should have better performance under a Democratic victory as compared with a Republican victory. The analogous case should be true for the Republican portfolio.

Table 8 shows the performance predictions of the 10-quantile stack model and linear model. Both the linear and stack model do not give evidence of the advertised performance in any scenario, according to t-test results. The linear model even predicts the opposite of the advertised performance horizontally and vertically.

Linear Regression Model Predictions

	2020 Election Victor			
	Democrat	Republican	Spread	t-stat
D Portfolio % Returns	$-24.9\pm$ 9.2%	$-20.3\pm$ 12.6%	4.6%	-0.95
R Portfolio % Returns	$-14.3\pm$ 10.4%	$-30.5\pm$ 14.5%	16.3%	-2.53
Spread	10.6%	10.3%		
t-stat	-3.70	-2.57		

Stack Model (10 Quantile) Predictions

	2020 Election Victor			
	Democrat	Republican	Spread	t-stat
D Portfolio Quantile	4.2 ± 1.8	3.9 ± 1.6	0.3	$+0.46$
R Portfolio Quantile	5.1 ± 1.5	4.7 ± 1.6	0.4	-0.75
Spread	0.9	0.8		
t-stat	-1.55	$+1.23$		

TABLE 8: Performance predictions of the JB structured notes in the 2020 election. Spread cell color indicates direction. Blue favors Democratic type, red favors Republican type. p-value 0 - 0.01: ***, 0.01 - 0.05: **, 0.05 - 0.1: *.

4. Proposed Structured Notes

We propose two new sets of structured notes that have expected performance closer to the intended design of the original JB portfolios. One set of notes reshuffles the 30 companies in the JB portfolios and another novel set uses companies taken from the S&P 500. Since the stack models have better performance out-of-sample than the linear model does in-sample, and the stack model's results are robust across the 5 quantile and 10 quantile versions, we chose to use the 10 quantile stack model as our method for predicting relative asset returns. Our methodology for creating these new notes stays the same. First, we rank order all assets based on their difference in performance in the case of a Democrat victory in 2020 and a Republican victory in 2020. Next, we select the top 15 as the new Republican portfolio, and the bottom 15 as the new Democratic portfolio. The reshuffled JB portfolios and novel portfolio both exhibit clear performance differences in both election outcomes.

4.1. *Rearranged JB Notes*

Assets in the JB structured notes were rearranged to better approximate the desired performance. The new notes can be found in Table 9. We found that 40% of companies in each original portfolio would be better suited in the opposite portfolio. Predicted performance can be found in Table 10.

Under this arrangement, we predict the spreads to be consistent in both directions. In the framework of our model, we have 90% confidence that the Democratic portfolio will react better to a Democratic victory than a Republican victory, and 90% confidence that the Republican portfolio will outperform the Democratic portfolio in the case of a Republican victory. We have less than 90% confidence in all other spreads.

4.2. *Novel Portfolios*

Assets in the S&P 500 were ranked ordered according to performance in the cases of a Republican and Democratic victory in 2020. We believe the portfolios found in Table 11 have the highest likelihood of achieving election dependent performance.

The only company from the original JB portfolios that appears in the novel portfolios is Qualcomm. Originally in the Republican portfolio, it is now in the novel Democratic portfolio. Recall that significant features in our linear regression model (Table 5) suggested that

Rearranged JB Structured Notes

Democratic Portfolio		Republican Portfolio	
Asset	Ticker	Asset	Ticker
Qualcomm	QCOM	Norfolk Southern	NSC
Amazon	AMZN	Simon Property	SPG
Salesforce	CRM	SunPower	SPWR
Facebook	FB	Ford Motor	F
Marathon Oil	MRO	Constellation	STZ
Paypal	PYPL	CSX	CSX
Exelon	EXC	Honeywell	HON
Aptiv PLC	APTV	Alphabet	GOOGL
Estee Lauder	EL	Conoco Phillips	COP
Coca-Cola	KO	Citigroup	C
Walmart	WMT	Gilead Sciences	GILD
Home Depot	HD	Chevron	CVX
NextEra Energy	NEE	Merk & Co.	MRK
McDonalds	MCD	American Express	AXP
First Solar	FSLR	Visa	V

TABLE 9: Rearranged JB notes. Companies highlighted with purple have switched portfolios.

Novel Portfolios

Democratic Portfolio		Republican Portfolio	
Asset	Ticker	Asset	Ticker
Intuitive Surgical	ISRG	Whirlpool	WHR
Kraft Heinz	KHC	CH Robinson	CHRW
Brown-Forman	BF/B	Celanese	CE
Entergy	ETR	DXC Technology	DXC
Lam Research	LRCX	E-Trade	ETFC
MGM Resorts	MGM	Kimco Realty	KIM
Qualcomm	QCOM	Lincoln National	LNC
Hanesbrands	HBI	Union Pacific	UNP
Apple	AAPL	Corning	GLW
Boston Scientific	BSX	Alliance Data	ADS
NiSource	NI	News Corp	NWSA
ONEOK	OKE	Omnicom Group	OMC
Alexion	ALXN	Snap-on	SNA
AMD	AMD	Abiomed	ABMD
Becton Dickinson	BDX	Noble Energy	NBL

TABLE 11: Novel portfolios created for election dependent performance with assets taken from the S&P 500.

Rearranged JB Notes Predictions

	2020 Election Victor			
	Democrat	Republican	Spread	t-stat
D Portfolio Quantile	4.8 ± 2.0	3.8 ± 1.9	1.0	$+1.30^{*}$
R Portfolio Quantile	4.5 ± 1.4	4.8 ± 1.3	0.3	$+0.56$
Spread	0.3	1.0		
t-stat	$+0.43$	$+1.63^{*}$		

TABLE 10: Performance predictions of the rearranged JB notes. p-value 0 - 0.01: ***, 0.01 - 0.05: **, 0.05 - 0.1: *.

Novel Portfolios Predictions

	2020 Election Victor			
	Democrat	Republican	Spread	t-stat
D Portfolio Quantile	5.7 ± 2.5	3.3 ± 2.7	2.4	$+2.56^{***}$
R Portfolio Quantile	2.7 ± 1.6	4.9 ± 2.2	2.2	$+3.11^{***}$
Spread	3.0	1.6		
t-stat	$+3.99^{***}$	$+1.73^{**}$		

TABLE 12: Performance predictions for the novel portfolios. p-value 0 - 0.01: ***, 0.01 - 0.05: **, 0.05 - 0.1: *.

a Republican president would benefit the energy and financial sectors. The stack model may have also found this relationship, as the novel Republican portfolio includes the energy company Nobel Energy and financial companies Lincoln National and E-Trade.

In the framework of our model, we have 95% confidence that the Republican portfolio will outperform the Democratic portfolio under a Republican victory. For all other cases, we have 99% confidence that the spread will be consistent with expectations.

5. Conclusions

While we found substantial quantitative differences between the Julius Baer notes, we found no quantitative evidence that the portfolios will have the election dependent performance they advertise. In our best predictions, the Republican portfolio will outperform the Democratic portfolio in both election scenarios, and both portfolios will perform better in absolute terms if a Democratic challenger unseats President Trump. We do not have confidence, however, that these predicted spreads are statistically significant. We suggest a rearrangement that our model predicts will have the correct spreads in each direction, but only in two of the four spreads do we have 90% confidence that the spread is significant. As an alternative to the JB notes, we suggest our novel portfolios in which we have 99% confidence that three of the spreads will perform as expected, and 95% confidence that the final spread will perform as expected.

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Team Quant Avengers

An Opportunity to Speculate on Election: Structured Notes of Differentiated Returns on Election Results

An Opportunity to Speculate on Election: Structured Notes of Differentiated Returns on Election Results

Abstract:
Election effects on stock market are researched in this passage, and a structured note is designed to exploit on stocks' distinctive performance among different electoral scenarios. Historical data are tested on CAPM and Fama-French factors in different times, and βs are tested statistically stable. Then an optimized portfolio under mean-variance model has been established to form the basis of the structured note, with a fixed income security served as an insurance. Backtesting results show reliable differentiated returns under election scenarios.
Keywords: Optimization, Structured Notes

Contents

I. Introduction

US Stock market has been substantially affected by political events, especially presidential election each four years, due to the fact that election policy and its subsequential economic effect have drastic influence on macroeconomics and further, financial market. Therefore widespread concerns are concentrated on the 2020 election, which may be alleviated if possible financial instruments are available to protect investors from this systematic risk.

This article empirically tests on the historical performance of the given Democratic portfolio and Republican portfolio to see whether there are differences between these two portfolios under different party. Main contribution of this paper is the implementation of optimization method on selecting stocks to construct a portfolio and furthermore, to build structured notes which generate differentiated payoffs depending on the election outcomes. In this way, we can bet on the party-in-power for 2020 presidential election to realize different payoffs from the structured notes.

II. Data

We collect election, financial market and the Fama-French Three factors data from January 1980 to January 2020 to carry out empirical study on returns.

A. Election Data

For election data, we collect historical party-in-power data with the time range in which includes each president in the White House. These election data will be treated as an indicator variable in our later analysis.

B. Fama-French Data

For the Fama-French data, we obtain adjusted close stock prices, S&P 500 index, risk-free rate and the Fama-French Three factors data from Kenneth French Data Libaray. All data is collected on a daily basis. All these data will be needed for fitting regression model.

C. Financial Market Data

For the market data part, we collect all 30 given stocks' time series price data to carry out the historical statistically analysis and prediction on performance. These data are grabbed from Bloomberg terminal and the time span is from January 1980 to January 2020.

In the paper, we examine two equally weighted portfolio representing Democratic and Republican party respectively. The Democratic portfolio consists of following stocks: Exelon Corp., Ford Motor Co., Aptiv PLC, Constellation Brands Inc., Estee Lauder Cos., SunPower Corp., Coca-Cola Co., Walmart Inc., Home Depot Inc., NextEra Energy Inc., NextEra Energy Inc.,CSX Corp.,McDonald's Corp.,Simon

Property Group Inc.,First Solar Inc. and Norfolk Southern Corp. The Republican Portfolio includes the following stocks: Honeywell International Inc., Alphabet Inc., ConocoPhillips, Marathon Oil Corp., Citigroup Inc., Saleforce.com Inc., QUALCOMM Inc., Gilead Sciences Inc., Amazon.com Inc.,Chevron Corp.,Facebook Inc., Merck&Co., PayPal Holdings Inc.,American Express Co. and Visa Inc.

We initially look into the stocks' distribution among sectors devided by SPDR sector ETFs. An overview of the distribution is in the following graph, which illustrates that most democratic portfolio stocks are condensed in Consumer Discretionary, Consumer Staples, Utilities and sub sector semiconductor. And republican portfolio stocks are concentrated in Consumer services, Energy, Financials, Health Care and Technology.

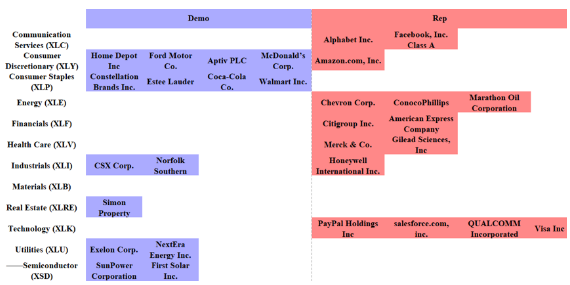

Fig. 1: Stock Sectors Overview

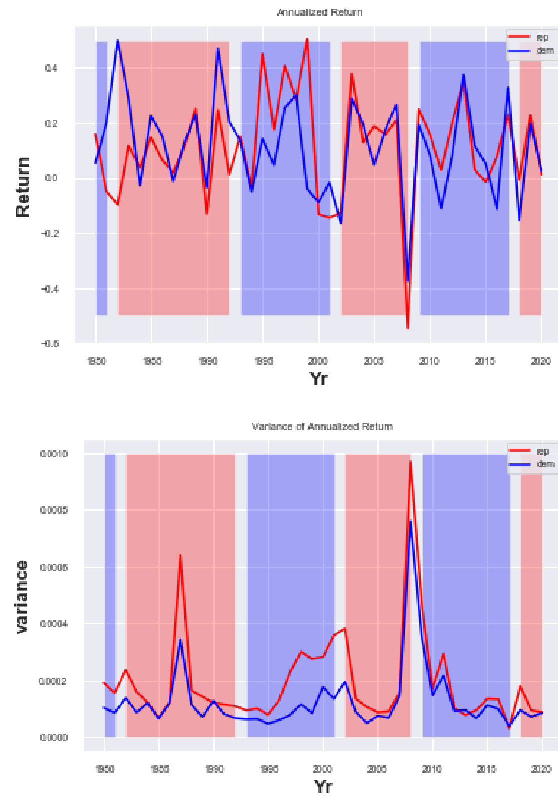

Fig. 2: Annualized Return and Variance of Two Portfolios

III. Statistical Analysis

The goal of our paper is to construct structured notes associated with these two portfolios which have differentiated payoffs according to the election result. The first thing is to differentiate these two portfolios in a quantitative way.

A. *Differentiate Two Portfolios by Quantitative Methods*

1) Portfolio Analysis

We utilize historical data to calculate annualized returns and volatility of the two portfolios.

From the annualized returns plotted in Figure 2, we notice that one portfolio outperforms the other in their corresponding governing periods, which implies that these two portfolios do represent two parties in some extent respectively.

As for the variance of annualized return, it is obvious that the variance of the democratic portfolio is smaller than that of republican portfolio in almost the whole history period.

The annualized return of republican portfolio is slightly higher than the democratic over the 40 years horizon. While the variance demonstrate periodic pattern, the volatility of portfolio is lifted up if its corresponding party empowers the White House.

Figure 3 shows that cumulative return of the democratic portfolio are greater than that of republican portfolio for the whole history period. At the same time, it depicts different growth trends in two portfolios: democratic one gains larger returns in the early time and the republican portfolio has rapid increase over the last two decades.

To check if these two portfolios have different variance, an F-test is implemented here with degree of freedom $n = m = 10311$.

The F statistic is derived from variance of two portfolios:

$$S_X^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2 = 0.013828^2$$

$$S_Y^2 = \frac{1}{m-1}\sum_{i=1}^{m}\left(Y_i - \overline{Y}\right)^2 = 0.011154^2$$

$$F = \frac{S_X^2}{S_Y^2} = 1.5369$$

The F statistic has a F distribution of degree of freedom n-1 and m-1 under null hypothesis, for which the 5% and 95% quantiles are 0.96 and 1.04 respectively. From this result, we can tell that there exists significant difference in variances of the two portfolios.

To evaluate these two portfolios, we can also look at the sharpe ratio and information ratio. It is not surprising to find that, the republican portfolio does possess higher Sharpe ratio and information ratio than the democratic portfolio in most of the time.

In addition, we can analyze these two portfolios' distribution. We plot the density of two portfolios and their $'qqplot'$ using annualized data.

Figure 5 is the result of $'qqplot'$ of these two portfolios. The distribution of republican portfolio has fatter tail and larger variance and the mean returns are close to each other. It is

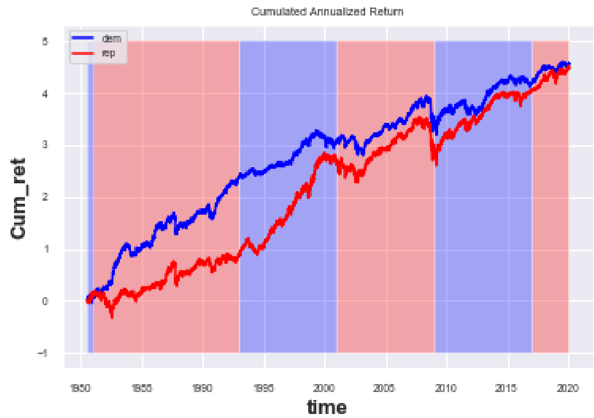

Fig. 3: Cumulative Return of Two Portfolios

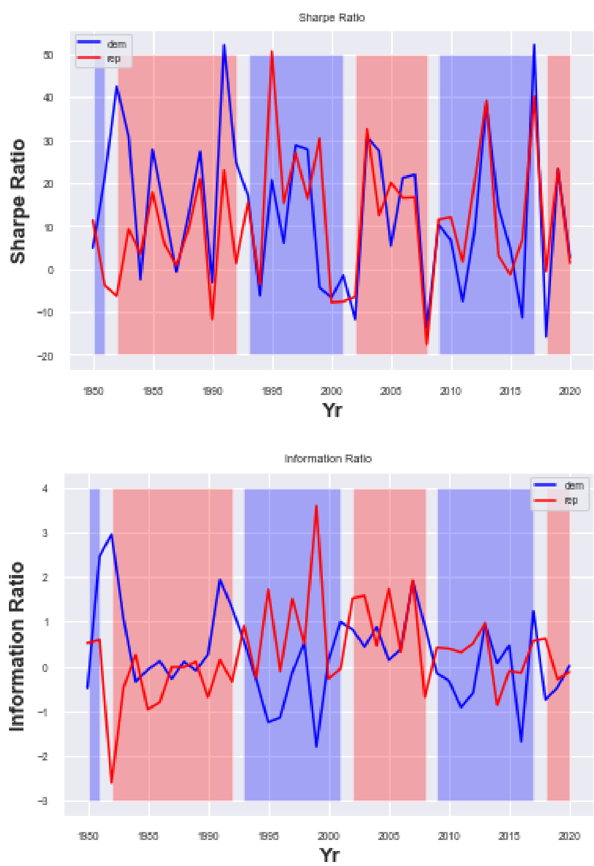

Fig. 4: Sharp Ratio and Information Ratio of Two Portfolios

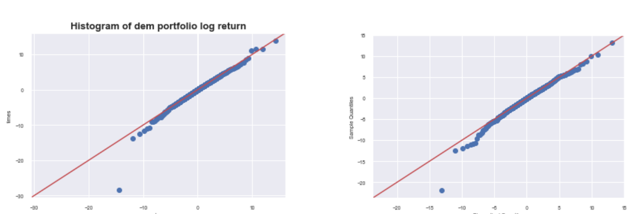

Fig. 5: Histogram of Annualized Portfolios Return

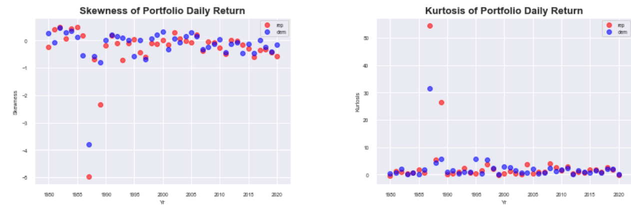

Fig. 6: Skewness and Kurtosis of Annualized Portfolios

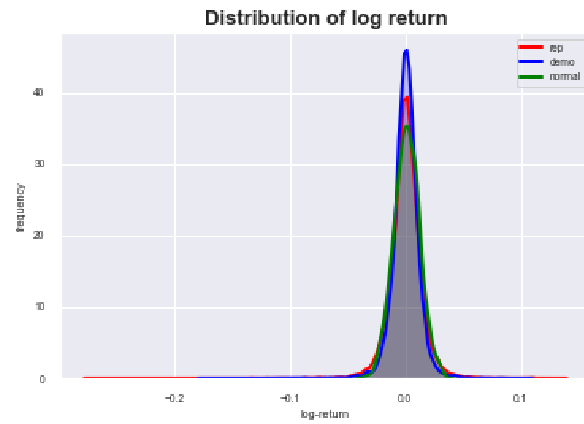

Fig. 7: Density Plot of Annualized Return

reasonable and it follows the variance analysis above.

From the density in Figure 6 &7, we can determine that the annualized return of both portfolios are asymptotically normal distributed. The extreme values of skewness and kurtosis appeared in 1980s, which is exactly the time period the U.S. financial market was experiencing the nominal oil crisis. Under this strong disturbance, the whole stock market suffered a huge downside effect and led to the appearance of bizarre statistics.

2) Correlation Analysis

Next, we adapt detailed analysis upon the correlation of stocks in two portfolios respectively. We visualize the correlation matrix using heat maps and find that the correlation of republican portfolio is much stronger. This implies that there may exist more related companies which are under the same industry. From this result, we can take a guess that the betas, which represent the sensitivity of the two portfolios to the market, should be different from each other.These results are demonstrated in Figure 8.

3) Sensitivity Analysis Under Financial Market

These two portfolios may have different levels of sensitivity to the performance of the whole market. In order to determine these characteristics, we first calculate the Sharpe ratio and information ratio based on risk-free rate and market return respectively. Figure 4 demonstrates the change of Sharpe ratio and information ratio of the two portfolios' returns from 1980 to 2020.

We continue our evaluation of market analysis upon the relation with financial market. By applying Capital Asset Pricing Model (CAPM) and Fama–French three-factor model to describe portfolio returns.

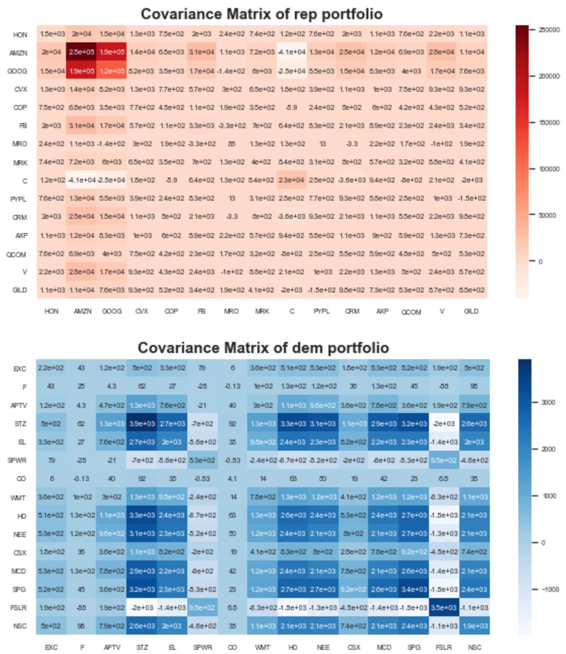

Fig. 8: Covariance Matrix of Two Portfolios

TABLE I: CAPM Coefficients of two portfolios

Coefficients	α	β
Republican	0.0012	1.0592
Democratic	-0.0011	0.9331

We test the significance of CAPM coefficients: α and β using bootstrapping method, where our null hypothesis is that the coefficients for the two regression are equal, namely $\beta_{dem} = \beta_{rep}$. Portfolio returns are randomly selected from our dataset and αs and βs are calculated subsequently. Then, we compute the difference between the two coefficients for the two portfolios and the standard deviation of these differences. The bootstrapping method does not have many strict assumptions and enables us to capture the correlation between each coefficients if there is any. We divide the difference of the coefficients in the two models by its standard error and get the p-value result for both parameters.

TABLE II: Bootstrap Significance Test for Coefficients

Coefficients	Dem - Rep	std. error	p-value
β	0.0001177794	0.0002516952	0.482785
α	-6.386094e-06	9.874519e-05	0.06467246

The p-value indicates that there is no significant difference of β between two portfolios. However, α has fairly significant difference on the regression of market excess returns. This implies the Republican is likely to beat the market performance while the Democratic may not.

The bootstrapping result for Fama-French three factor model does not indicate significant difference for all coefficients: MKT-RF, SMB and HML. However, there is evident difference in terms of the intercept, which yields the same outcome as

TABLE III: Fama French Coefficients of two portfolios

Coefficients	Mkt-RF	SMB	HML	intercept
Republican	-0.000335	0.002174	0.000662	0.0005
Democratic	-0.000037	0.00170	0.000732	0.00045

TABLE IV: Bootstrapping Significance Test for Coefficients

Coefficients	DEM - REP	std. error	p-value
MKT-RF	0.0002989607	9.557233e-05	3.128109
SMB	0.0004785483	0.0001757919	2.722243
HML	6.969441e-05	0.0001825584	0.381765
intercept	4.05432e-06	0.0001019589	0.03976426

the CAPM significance test.

Both regression results show higher sensitivity from market performance of the Democratic portfolio. In regards of the CAPM model, the Democratic portfolio has higher alpha value, which implies a higher excess return while it has a lower beta value. It means that it is less sensitive to the market.

B. *Portfolios Under Different Party*

1) *T-test for Returns under Different Party*

After doing basic statistical analysis for the Democratic and the Republican portfolio, we perform further analysis on the daily log returns of the two portfolios under different regimes, namely time period when a Democratic president is in the White House and that when a Republican president is in the White House.

The intuitive methodology comes in with the student t-test under unequal sample sizes and unequal variance, which testifies whether there is a statistical difference for portfolios' performance under different time regime.

To check the stability of variance among two different portfolios $n, m = 6009, 4302$,

$$F_1 = \frac{0.011557^2}{0.010565^2} = 1.196606$$

$$F_2 = \frac{0.014167^2}{0.013335^2} = 1.128677$$

The 95% confidence interval under null hypothesis for F statistics are (0.95,1.06), so it can be concluded that portfolios have different volatility regimes under different party-in-power times.

As a benchmark we examine the all-time difference for the two portfolios, which scrutinizes whether there is a fundamental difference among two portfolios. Then we test the t-test for two portfolios under the different time regimes. A t-statistic can be written as followed:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{s_{\bar{\Delta}}}$$

in which:

$$s_{\bar{\Delta}} = \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$$

Here, we have two t-statistics for the Democratic portfolio and the Republican portfolio respectively:

$$t_{demo} = \frac{\bar{X}_{demo-portfolio1} - \bar{X}_{demo-portfolio2}}{s_{\bar{\Delta}}}$$

$$t_{rep} = \frac{\bar{X}_{rep-portfolio1} - \bar{X}_{rep-portfolio2}}{s_{\bar{\Delta}}}$$

And we have the following result: comparing the t-statistic under all time, the t-statistics of different time is much larger indicating the fact that the portfolios have significant different performance under different party-in-power times.

TABLE V: T-test under different times

Test	t statistics	p-value
Benchmark	-0.04326123	0.96549373
Democratic Time	-1.16415997	0.24438323
Republican Time	1.40865812	0.15897431

2) Determine Differentiated returns

Further in the initial t-tests, the CAPM one factor model is a good way to quantify how these two portfolios perform comparing to the market benchmark. We use the log returns of the S&P500 index as the representation of the market return. Also, since we want to emphasize the influence of party-in-power, we also add a dummy variable ($party$) into the CAPM model, where a value of 1 indicates that a Democratic president is in the House and vice versa. Thus, our model for the two portfolios become

$$r_p - r_f = \alpha + \beta_{market} \cdot (r_m - r_f) + \beta_{party} \cdot party.$$

In this model, r_p and r_m are the daily log returns of the portfolio and the S&P 500 Index respectively. r_f is the risk-free rate.

The regression results are in the following table:

TABLE VI: Regression Results

Portfolio	β_{market}	β_{party}	p-value for β_{party}
Democratic	0.8615	-0.0004	0.000
Republican	1.1240	0.0001	0.370

The results are far from satisfying, the pre-selected equal-weighted portfolios fail to generate a significant difference in returns. The β_{party} may be robust but it has too tiny a value that may be wiped out by the volatility of stocks, therefore no investor should expect these two portfolios to generate differentiated returns and further optimization methods needed to be exploited to modify these portfolios to have differentiated returns.

IV. Structured Notes

For the construction of the structured notes, we first compute βs for the 30 stocks under different party using the CAPM model. Since the stock return in the given period is always proportional to β under the CAPM model, βs for the 30 stocks will serve as the proxy to their returns. Then, we use a Multivariate GARCH (generalized autoregressive conditional heteroskedasticity) model to forecast the covariance matrix of the 30 stocks. Consequently, we use mean-variance analysis to maximize the difference in total return under the two regimes. The calculated portfolio weights will be used to construct an at-the-money option on the basket of stocks, given investor's opinion on the upcoming election result.

A. Computation of βs

In order for our methodology to have an accurate and robust result, we need the following assumptions.

- Under the CAPM model, the true β for each stock will change only when the party in the White House changes.
- Variation in the estimate of β are pure noise if the party-in-power remains the same.
- The market excess return will be the same under either party.

If the above assumptions hold true, we are able to find two vectors of β_0 and β_1 such that for each stock i, β_{0_i} is the β under a Republican president and β_{1_i} is the β for the same stock under a Democratic president. All βs are estimated using the horizon of data available to us from 1980 to 2020. Table 7 shows the β for each stock under two regimes.

TABLE VII: βs for Stocks

Stocks	β_0	β_1
HON	1.096400	1.092213
AMZN	1.393088	1.434814
GOOG	1.003912	0.930824
CVX	0.920174	0.793759
COP	0.968508	0.819025
FB	1.282338	1.038358
MRO	1.133624	1.0416357
MRK	0.802783	0.783883
C	1.454651	1.763064
PYPL	1.383199	1.160870
CRM	1.318465	1.275001
AXP	1.397835	1.349551
QCOM	1.317994	1.296629
V	1.001132	0.948716
GILD	1.020100	0.995596
EXC	0.621669	0.446908
F	1.183358	1.090179
APTV	1.260605	1.319927
STZ	0.564559	0.700193
EL	0.657788	0.821496
SPWR	1.906496	1.705730
CO	0.066162	0.262401
WMT	0.880665	0.761713
HD	1.094164	1.061931
NEE	0.5741	0.435638
CSX	1.027078	1.015707
MCD	0.772930	0.617242
SPG	1.027344	0.844915
FSLR	1.499209	1.391855
NSC	0.979061	0.961210

B. Estimation of Covariance Matrix: Multivariate GARCH

In this part, we use the DDC model of Engel (2002) to estimate the covariance matrix, which can be defined as:

$$R_t = diag(q_{11,t}^{-1/2}...q_{NN,t}^{-1/2})Q_t diag(q_{11,t}^{-1/2}...q_{NN,t}^{-1/2})$$

where the N x N symmetric positive definite matrix $Q_t = (q_{ij,t})$ is given by:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha u_{t-1}u_{t-1}^{'} + \beta Q_{t-1}$$

$\bar{Q}$ is thhe N x N unconditional variance matrix of u_t, and α and β are non-negative scalar parameters satisfying $\alpha+\beta < 1$. The Q matrix is the covariance matrix that can be used in the optimization problem in next section.

C. Construction of Structured Notes

Once we have obtained the two vectors of βs and the covariance matrix, we can set up an optimization problem to construct a portfolio that will maximize the certainty equivalent of a given investor . Explicitly, the model we use is

$$\begin{aligned} \max \ & (\vec{\beta_0} - \vec{\beta_1})^{'} \vec{w} - \frac{1}{2} A \vec{w}^{'} \Sigma \vec{w} \\ \text{subject to} \ & \vec{w}^{'} I = \vec{1} \\ & \vec{w}^{'} X = 0.65, \end{aligned}$$

where X is a 30×1 column vector such that the first 15 entries of the vector are 1s and the rest are 0s. This constraint is to ensure that an investor will invest 65% of her asset in the Republican portfolio if she thinks a Republican president will win the election, and vice versa. Then, we can solve for w by:

$$w = \frac{1}{2A}\Sigma^{'}(R - G^T\lambda),$$

where Σ is a 30×30 covariance matrix, R is the difference between the βs under different president lead (aka. the vector $(\vec{\beta_0} - \vec{\beta_1})$), G is a 2×30 matrix consisting of 0s and 1s representing the two constraints and λ is the Lagrange multiplier.

Since we assume that the benchmark market excess return will not be affected by the president in the White House, we deliberately neglect the forecast of the market excess return. Then, this optimization problem maximize the difference of expected return when different party gets elected to the White House, while penalizing the return if the variance of the portfolio is too large. Moreover, the parameter A can be chosen for different investors with different relative risk aversion. In this case, we choose $A = 2$ to represent a typical risk averse investor.

Once we have the weight vector for the 30 stocks, we use this portfolio to construct an at-the-money option, where the strike price is just the weighted sum of the 30 stock price at the purchase date, January 29, 2020. Then, if an investor believes that a Republican president will win the election, he or she should buy the bet-on-Republican structured notes. On the other hand, if an investor believes that a Democratic president will win the 2020 election, he or she should buy the bet-on-Democratic structured notes. Table 8 and 9 give the weight of each stock when $A = 2$ when betting on different election result. A positive weight represent a long position of the stock whereas a negative weight represent a short position.

TABLE VIII: Optimized Weights with Only Risky Assets (Bet on Republican)

HON	AMZN	GOOG	CVX	COP
0.0988	-0.0081	0.0601	0.1006	0.0844
FB	MRO	MRK	C	PYPL
0.0387	-0.1027	0.0800	-0.0647	-0.0130
CRM	AXP	QCOM	V	GILD
-0.0168	0.1543	0.0503	0.0084	0.0531
EXC	F	APTV	STZ	EL
0.1266	0.0608	-0.0633	0.0320	-0.0523
SPWR	CO	WMT	HD	NEE
-0.0655	0.0969	0.0820	0.0004	0.1611
CSX	MCD	SPG	FSLR	NSC
-0.0388	0.1205	0.0610	-0.0281	-0.0167

TABLE IX: Optimized Weights with Only Risky Assets (Bet on Democratic)

HON	AMZN	GOOG	CVX	COP
0.0713	0.0228	-0.0069	0.0555	0.0620
FB	MRO	MRK	C	PYPL
0.0095	-0.0842	0.0751	0.0324	-0.0441
CRM	AXP	QCOM	V	GILD
-0.0166	0.1048	0.0447	-0.0240	0.0476
EXC	F	APTV	STZ	EL
0.0251	0.0470	-0.0441	0.0804	0.0236
SPWR	CO	WMT	HD	NEE
-0.0589	0.1187	0.0816	0.0279	0.2218
CSX	MCD	SPG	FSLR	NSC
-0.0185	0.1153	0.0538	-0.0283	0.0048

Furthermore, we also add a risk-free bond to further minimize the risk exposed to investment and add principal protection to our structured product. This asset allocation is based on the Merton Optimal Allocation formula,

$$w_{r_f} = \frac{\mu + \frac{1}{2}\sigma^2 - r_f}{\gamma\sigma^2}.$$

The portfolio mean return and standard deviation from our previous optimization problem is calculated and represented in the formula as μ and σ. Also, γ is the relative risk aversion of an investor and r_f is the risk-free rate. Hence, the weights for the 30 stocks can be represented as $w_i(1 - w_{r_f})$, for all $i \leq 30$ and $i \in N$.

Table 10 and 11 show the respective weights for each stock and the risk-free bond. With the optimized portfolio and principal protection of risk-free asset, we construct a bet-on-Republican structured note and a bet-on-Democrat structured note. Then we can use these weights and the stock price at the beginning of structure notes to calculate the strike price for the option. The strike price for bet-on-Republican portfolio is 212.65 and the price for bet-on-Democratic portfolio is 199.84.

TABLE X: Optimized Weights with Risky and Risk-free Asset (Bet on Republican)

HON	AMZN	GOOG	CVX	COP
0.0594	-0.0049	0.0361	0.0605	0.0508
FB	MRO	MRK	C	PYPL
0.0232	-0.0617	0.0481	-0.0389	-0.0078
CRM	AXP	QCOM	V	GILD
-0.0101	0.0927	0.0302	0.0050	0.0319
EXC	F	APTV	STZ	EL
0.0760	0.0365	-0.0380	0.0193	-0.0315
SPWR	CO	WMT	HD	NEE
-0.0394	0.0582	0.0493	0.0002	0.0968
CSX	MCD	SPG	FSLR	NSC
-0.0233	0.0725	0.0367	-0.0169	-0.0100
RF				
0.3988				

TABLE XI: Optimized Weights with Risky and Risk-free Asset (Bet on Democratic)

HON	AMZN	GOOG	CVX	COP
0.0389	0.0124	-0.0038	0.0303	0.0338
FB	MRO	MRK	C	PYPL
0.0052	-0.0459	0.0410	0.0177	-0.0241
CRM	AXP	QCOM	V	GILD
-0.0090	0.0571	0.0243	-0.0130	0.0259
EXC	F	APTV	STZ	EL
0.0137	0.0256	-0.0241	0.0439	0.0128
SPWR	CO	WMT	HD	NEE
-0.0321	0.0647	0.0445	0.0152	0.1209
CSX	MCD	SPG	FSLR	NSC
-0.0101	0.0629	0.0293	-0.0155	0.0026
RF				
0.4547				

V. Discussion

A. Backtesting Asset Allocation

In order to see whether our allocation methodology is valid and has the expected performance, we use previous stock data to backtest our portfolio selection. The backtest period is from the 2000 election to the 2016 election. For each election year, a portfolio that bet on a Republican President would be elected and a portfolio that bet on a Democratic President would be elected are constructed and set to be last one year which corresponds to the maturity of the 1-year structured notes. Then, the two portfolios' excess returns are compared to each other and of course, the market excess return.

For example, the detailed backtesting method is listed below for the 2012 election year.

- Use all daily stock return data prior to 2012 to compute two vectors of β, one under a Republican president and one under a Democratic president.
- Estimate future volatility and the covariance matrix by applying MGARCH model on the daily stock return data mentioned above.
- Maximize certainty equivalent using the objective function stated in the previous section and solve for the weight vector.
- Compute the two portfolios' cumulative return from January 2012 to January 2013 and compare with that of the market.

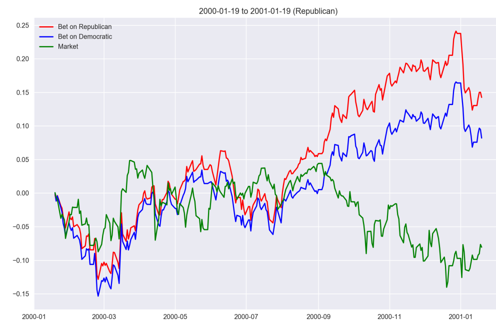

Fig. 9: Cumulative returns for the bet-on-Republican and bet-on-Democratic portfolio in 2000 elections

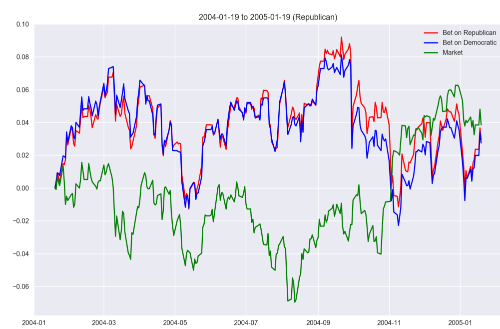

Fig. 10: Cumulative returns for the bet-on-Republican and bet-on-Democratic portfolio in 2004 elections

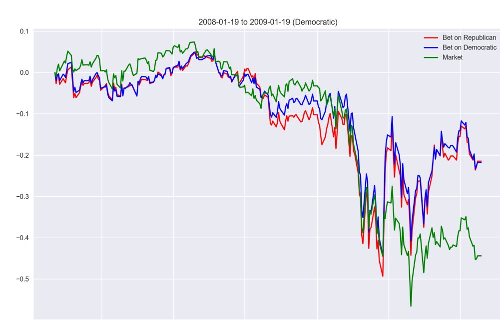

Fig. 11: Cumulative returns for the bet-on-Republican and bet-on-Democratic portfolio in 2008 elections

Figure 9-13 show our portfolio return VS. the market return for each selected election year.

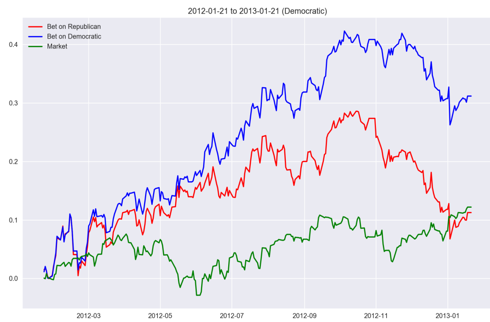

Fig. 12: Cumulative returns for the bet-on-Republican and bet-on-Democratic portfolio in 2012 elections

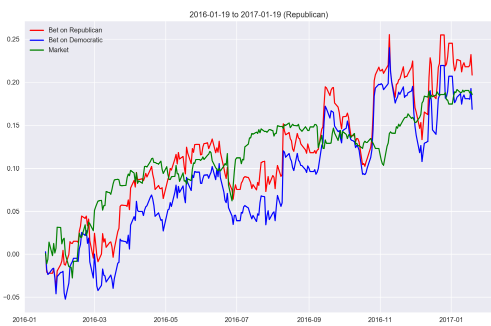

Fig. 13: Cumulative returns for the bet-on-Republican and bet-on-Democratic portfolio in 2016 elections

As we can see, except for the short period in 2004-2005, both of our portfolios, no matter of what party we bet on, perform better than the market return, which implies the profitability of our portfolios in most of the time. In particular, it is not hard to find that, if the party we bet was the same as the elected party, the corresponding portfolio's cumulative is distinguished from the one lost the bet. Specifically, the bet-on-Republican portfolio has higher cumulative return than the bet-on-Democratic portfolio's cumulative return from 2000 to 2001,2004 to 2005 and 2006 to 2007 which is exactly the time the Republican party was in power. Correspondingly, in 2008 and 2012, the bet-on-Democratic portfolio outperformed the bet-on-Republican one when the Democratic party was in power. This is what we want to differentiated the payoffs depending on the outcome of the election.

B. *Disadvantages and Improvements*

Although we constructed a structured notes that we expect will have differentiated payoff given different election results, we have made some assumptions that might not be true for financial time series data.

First of all, under the CAPM model, βs might change over time. However, since the 30 stocks given have uneven start date for which data is available, it is challenging for us to find a time period such that all stocks have underwent the leadership of both parties, or have been through a period such that there is a change from a Republican-led House to a Democratic-led House. Therefore, we made a compromise by using the entire 40 year period for all stocks and believe that the precision of estimation offered by high frequency daily data would compensate the time effect we might observe for βs.

Secondly, it is challenging for us to test the robustness and the predictability of the MGARCH model that we used to estimate the covariance matrix. Since the MGARCH model performs better under a short period of time, the accuracy of prediction for a one year span is still in question. However, we believe that past covariance matrix cannot be a representation of the future. Therefore, MGARCH or a stochastic volatility model seems more reasonable to predict volatility. If time permitted, we could also use a stochastic volatility model and backtest the performance of our selected stocks.

Even more, the structured product that we constructed serve as an at-the-money option of a selected portfolio. However, at-the-money option are always expensive to purchase and our paper does not discuss the pricing of our structured product. Also, if we are certain that a stock's return will go into one specific direction if a Democratic or Republican president was elected, the portfolio could then contain more out-of-the-money option, which will decrease the cost of purchasing the structured products but also increase the payoff if investor's bet is realized.

VI. Conclusions

To sum up, we have found some significant differences between the Democratic Portfolio and the Republican Portfolio. However, we do not find any significant difference between the return of the two portfolios. That is, we cannot find strong evidence indicating that the Democratic portfolio will perform better than the Republican portfolio if a Democratic president is elected in 2020.

Further, we construct a corresponding structured note that has differentiated payoffs depending on which party empowers the White House. However, in the process of generating such a derivative, we have adopted some assumptions which are not very robust in real financial time-series data.

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Team Quants by Ganges
He Wins or She Wins, You Win

He Wins or She Wins, You Win

Abstract

In the following paper, we take a closer look at past presidential elections in the US to see if we could infer some guidelines ahead of the results which are to be announced on November 3, 2020. The study empirically tests whether the US presidential elections do contain the important market inclusive information to explain the volatility and returns distribution of a pre-selected portfolio of stocks. We perform this event study on two portfolios, one for each National Political Party – the Democrats and the Republicans – that have been hand-picked by a major Swiss Bank. Empirical estimates conclude that the presidential elections in 2020 have a strong, significant relationship with investor's sentiment and stock market performance. Moreover, we show that election results can be capitalized to generate positive returns depending on which party takes control of the parliament. Finally, we construct two diversified portfolios – one for each political party – using quantitative techniques, that promise differentiated payoff contingent upon the respective party being voted into power. In addition, backtested performance of our strategy corroborate our results which indicate that a systematic investor can choose to bet on the elections outcome of 2020 to generate some profits at least in the short term.

I. Introduction

Political uncertainty and stock market performance remains the primary anxiety for market participants, analysts and policy makers. The stock markets' inefficiency and volatility occur due to political and economic ambiguity. In this research, we take a closer look at past presidential elections in the US and attempt to infer some guidelines ahead of the elections occurring in November 2020. Not being specialists in US Elections, we unfortunately have to restrict ourselves to observing how market participants have been influenced by the election periods and how they have expressed their preferences. The dataset is of course limited as our historical data starts in 1984 and we have only 9 elections to learn from. We look closely at two sets of portfolios that have been hand-picked by a major Swiss bank – Julius Baer. The bank claims that each portfolio is tied to a political party in the United States – Democrats and Republicans. Although, these portfolios are specifically constructed for the elections supposed to be occurring in 2020, we test the performance of portfolios that are constructed along the same guidelines as the hypothesized portfolios and conclude whether there is indeed any dependency of the portfolio performance upon which political party is voted into power in each election cycle. We not only review the performance of various "standard" equity portfolios (market, sectors, styles), but also compare the performance of the two party-linked portfolios with election betting markets and trends in polling data. We also look at whether political contributions made by corporations play a significant role in the 30 stocks being segregated into two party-linked portfolios.

We find that data from political betting markets, gathered from IOWA Electronic Markets (IEM) is a good indicator for the portfolio performance tied to each political party. While this anecdotal evidence is suggestive of the capitalization of the campaign platforms into equity prices, we acknowledge that it is difficult to separate the reaction of equity prices to this political event from other economic and financial developments. To build confidence in our model, we compare the idiosyncratic returns of each portfolio and find that the results are statistically significant. In section 2 of the paper we explain the various data sources used for our research and this event-study like framework. In section 3, we compare the two hypothesized portfolios and drill down into the differences between the two portfolios to explore factors that explain their risk and return profile. In section 4, we use various data sources to illustrate whether the hypothesized portfolios constructed by Julius Baer indeed are tied to their respective political party and whether successfully betting on a particular political party for 2020 can lead to outperformance of the respective hypothesized portfolio of stocks. In section 5, we dig deeper into the past election periods and find out whether this major political event can be used as an opportunity by investors for stock selection and generate differentiated returns at least in the short term. In section 6, we aim to build a model to construct two portfolios which are slightly different from the original portfolios yet are better tied to the respective political party. Finally, in section 7, we present our concluding remarks and takeaways from this event-study.

II. Data

Multiple data sources have been used in the following research to look at the event from various angles. We use fundamental data downloaded from Bloomberg such as stock returns, market capitalization, sector, and construct smart beta factors such as value, growth, momentum, etc. We have downloaded these scores for the S&P 500 Index constituents starting from January 1984. Utmost care has been taken to preserve Point-in-Time (PIT) data in order to avoid look-ahead bias and survivorship bias. We have used S&P 500 as a benchmark as most of the stocks in the hypothesized portfolio are a constituent of the index currently and all are large-cap stocks. The SP500 daily levels has been sourced from Yahoo Finance for the period from 1984 to 2020. The Winner Take All (WTA) data from IOWA Electronic Markets has been used as a proxy for the probability of each political party winning the elections in each period. The contract prices have been scaled to ensure that prices are between 0-1 such that they accurately measure probability of winning.

$$\pi_t^D = \frac{P_t^D}{P_t^D + P_t^R}$$

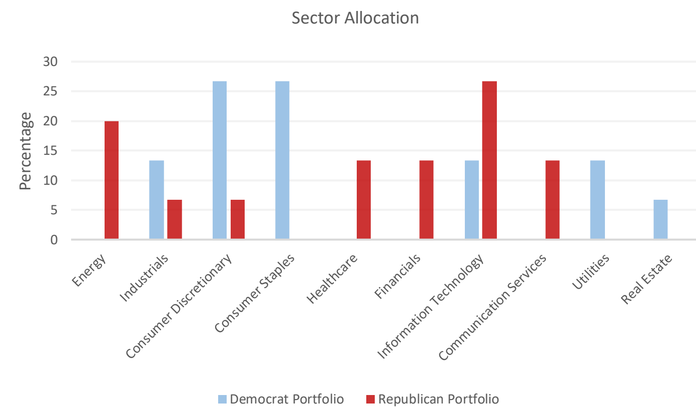
$$\pi_t^R = \frac{P_t^R}{P_t^D + P_t^R}$$

Here, π_t^D is the probability of Democrats winning at time t, π_t^R is the probability of Republicans winning at time t, P_t^D is the price of a WTA-Democrat contract at time t and P_t^R is the price of a WTA-Republican contract at time t.

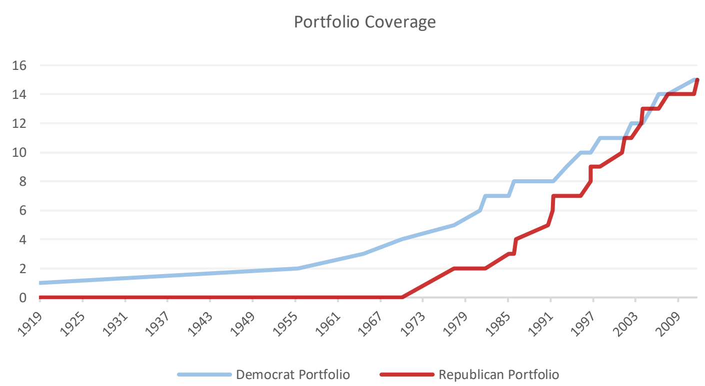
IEM has been developed by the University of IOWA and can be used as a forecasting tool. This is a real money futures market where contract payoffs will be determined by the popular vote cast in the 2020 U.S. Presidential Election. Traders can buy and sell real money contracts based on their belief about the outcome of the election. The payoff structure resembles an options contract that either pays $1 if the party receives majority of popular vote cast or 0$ otherwise. Polling data from RealClear Politics is used to track historical and latest trends in polling. Finally, the data for political contributions to each party by various companies is downloaded from the Center for Responsive Politics.

III. Are the two Portfolios Different?

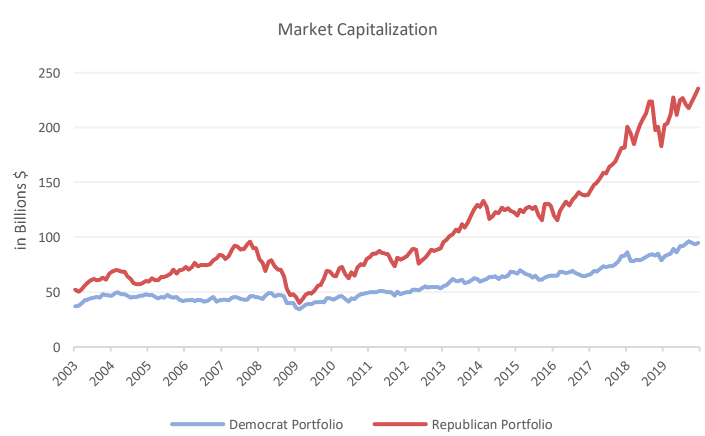
Skimming through the two portfolios hand-picked by Julius Baer tells that they are different in several ways.



Clearly, the two portfolios are invested in very different set of sectors. The Democrat Portfolio contains stocks majorly from Consumer Discretionary, Consumer Staples, Industrials and Utilities. Whereas, the Republican Portfolio contains stocks majorly from Information Technology, Energy, Healthcare, Financials, and Communication Services.



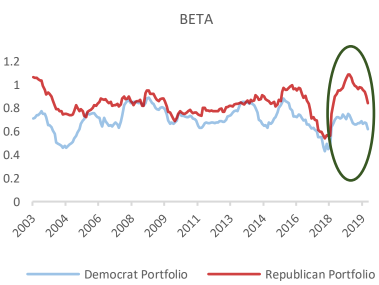
Looking at the year when each stock in the portfolio was listed as a public company, we can say that the Republican Portfolio is a much 'newer' portfolio, in that some of its stocks became public much later than their counterparts in the Democrat Portfolio. This led us to look at the two portfolios more closely and compare their performance and volatility with respect to market over time.

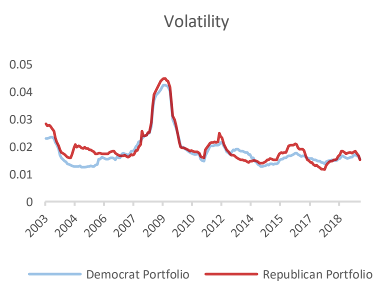


It can be seen that the Republican Portfolio is consistently worth more than Democrat Portfolio and that the spread has been increasing over time (here, Market Capitalization of the portfolio is calculated as an equally weighted average of the market cap of individual stocks in the portfolio). This is most likely because the Republican Portfolio contains majority of stocks from some of the biggest stocks within the Information Technology and Energy sector unlike Democrat Portfolio which contains around 50% of defensive stocks. This led us to compare the volatility and systematic risk – Beta, with respect to market – S&P500, of the two portfolios and how their risk profile has changed over time. Both volatility and beta are calculated for each stock in the portfolio using monthly returns over the last 3 years at each point in time. By performing a linear regression for excess stock returns above the risk-free rate against excess market returns, we get β for each stock along with its idiosyncratic or residual returns.

$$\boldsymbol{r_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_i(r_{m,t} - r_{f,t}) + \epsilon_{i,t}}$$

Here, r_f is the risk-free rate, $\boldsymbol{\epsilon_i}$ is the residual return for the stock *i,* and $\boldsymbol{r_m}$ is the S&P 500 return at time *t.*

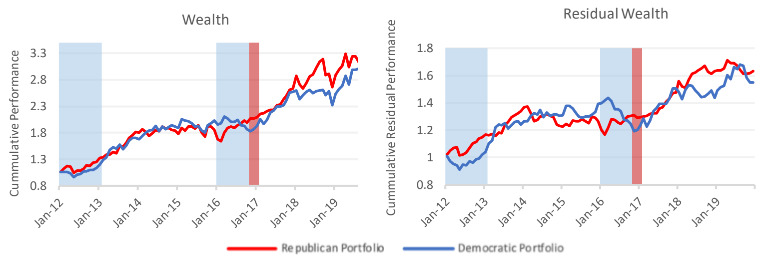




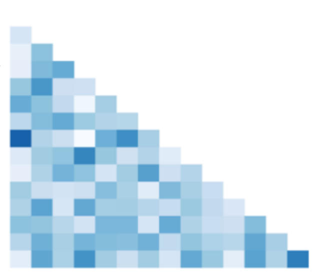
From both Beta and Volatility, it can be seen that Republican portfolio is consistently riskier than Democrat portfolio. Moreover, in the recent years, the Republican portfolio's beta has increased significantly in comparison to Democrat portfolio's beta.

We also check if there is any significant difference in the performance of both portfolios from the year 2012. We have chosen the year 2012 as the starting point to ensure that both portfolios have full coverage and to avoid missing information. Moreover, we acknowledge that the hypothesized portfolios are constructed specifically for the year 2020, so the performance of the same portfolios on a much earlier time period may not really be relevant to our research. For a more detailed explanation, we come back to this point in section IV.

It is clear that the Beta of both portfolios are significantly different, so we check cumulative performance of both portfolios using total returns and residual returns separately. Specific regimes for each term of the notes as structrued by Julius Baer have also been marked in the following graphs. The period of the notes are from Jan 29, 2020 to Jan 29, 2021. So, we have highlighted similar months in each election cycle to make a fair comparison of portfolio returns. We define a regime as the time period during which either political party was in power at the parliament.

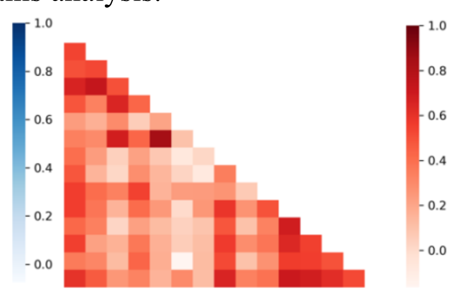


The Republican portfolio has outperformed the Democratic Portfolio during the time period from 2012 to 2020. Looking closely, it can be seen that majority of the outperformance occurs post 2016 election regime. We comment on the possible reason for this behavior in the forthcoming sections. However, here we look at the portfolio level diversification and pairwise correlations to see if the two portfolios are different in this regard. We compute stock pairwise correlations on each month of the year 2019 within the two portfolios and then calculate average pairwise correlation during this year. Stock correlations have been calculated using last 3 years monthly returns data – for both total and residual returns. We infer interesting results from this analysis.



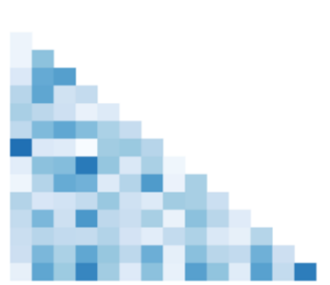
Democrat Portfolio – Total Returns

Average correlation = 29.88%



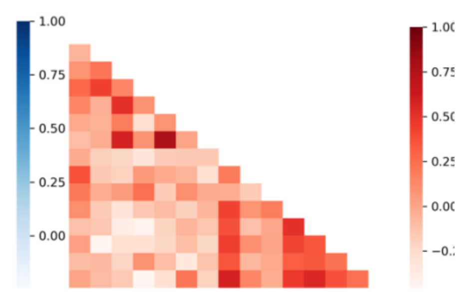
Republican Portfolio – Total Returns

Average correlation = 32.87%



Democrat Portfolio – Residual Returns

Average correlation = 14.21%



Republican Portfolio – Residual Returns

Average correlation = 2.51%

Firstly, we see that the average pairwise correlations, within the Republican Portfolio, computed using total returns for the last 3 years is higher than its counterpart Democrat Portfolio. On the contrary, if we use residual returns to compute stock pairwise correlations for the same time period, we find that the relationship is reversed. Again, this alludes to the fact that Republican Portfolio is more correlated with the market. We measure the percentage reduction achieved in portfolio volatility with Diversification Ratio of each portfolio.

$$DR_p = \frac{\sum w_i \sigma_i}{\sqrt{w^T V w}}$$

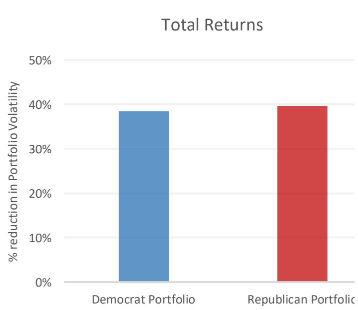
Here, V is the variance-covariance matrix of the portfolio p. In our case, since we are dealing with equal weighted portfolios, the above formula simplifies to:

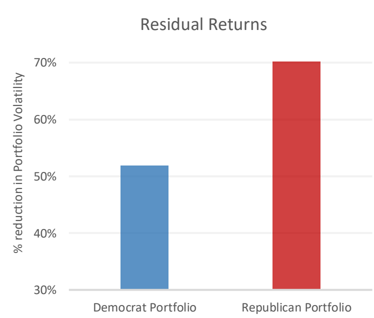
$$DR_p = \frac{\sum \sigma_i}{\sqrt{V}}$$

And, % reduction in portfolio volatility is calculated as:

$$1 - \frac{1}{DR}$$

which measures the reduction in portfolio volatility achieved as compared to the weighted average of component volatilities.





The Diversification Ratio gives us similar results. For the Democrat Portfolio, DR = 2.07 while for the Republican Portfolio, DR = 3.22 in the year of 2019. In conclusion, we find that Republican Portfolio tends to be much more diversified than the Democrat Portfolio once portfolio returns have been adjusted for market sensitivity.

Political Contributions

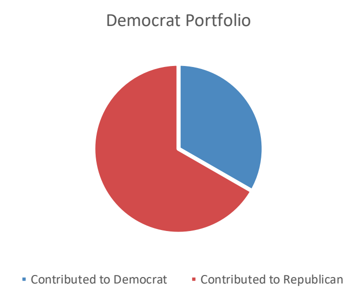
We look at the contributions made to either political party by each company in both portfolios for the two recent election cycles – 2016 and 2020. We do this to see if political contributions have any influence in the stocks being segregated into either portfolio. This data has been sourced from Centre for Responsive Politics

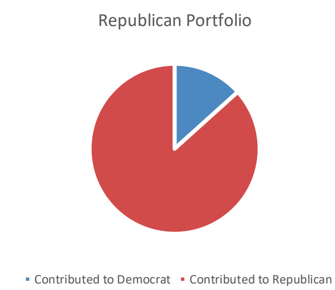
Average Portfolio Summary:

	Democrat Portfolio	*Republican Portfolio*
Coverage	*15*	*15*
CAGR	*14.43%*	*16.24%*
Sharpe Ratio	*1.04*	*1.15*
Maximum Drawdown	*-12.99%*	*-16.76%*
Annualised Volatility	*13.78%*	*14.70%*
Diversification Ratio	*2.07*	*3.22*
Hit Ratio	*0.68*	*0.67*

Portfolio statistics have been calculated for the period Jan 2012 to Jan 2020

which is an open source database that maintains political contributions by varioius committees and organisations for each political cycle. Our findings show that most companies have contributed to the Republican party in both election periods.



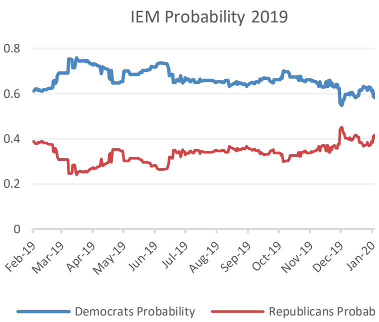


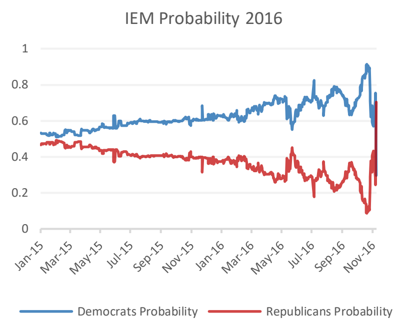
We conclude that political contributions alone are insufficient to conclude if they are the right measure to classify stocks into corresponding political portfolio.

IV. Do Elections Influence these Portfolios?

Using eveidence from the period preceeding the 2020 U.S. Presidential Election, this section attempts to test for the capitalization of election probabilities into equity prices for the sample of 30 firms hypothesized by Julius Baer. Two sources of daily data are incorporated: equity returns and candidate electoral prospects as implied by prices of political future contracts from the IOWA Electronic Market. The daily baseline estimates provide strong evidence that platforms are capitalized into equity prices. The evidence based upon weekly returns are strong suggesting a strong correlation of around 30%. To account for broader trends in equity markets during the sample period, we follow event study methodology and use abnormal/idiosyncratic returns in the analysis.

$$\boldsymbol{\epsilon_{i,t} = r_{i,t} - (\alpha_{i,t} + \beta_i\, r_{m,t})}$$





We denote the price of stock i at time t by $S_{i,t}$. The elections are held at time τ and the information on the election outcome is available at time τ+1. We assume that a majority voting for the Democratic candidate would lead to an additive change in the company's value at time τ+1 of D_i per share while a Republican president would lead to a change of R_i per share. For stocks that are affected by election outcome, either $D_i > R_i$ or $R_i > D_i$. For stocks that do not react to the election outcome, $D_i = R_i = 0$. The time t risk neutral probability for a Democratic (Republican) victory is π_{tD} (π_{tR}). Risk neutral event outcome probabilities are inferred from political betting markets (IEM Market).

The stock price may consist of two components: one that is independent of the direct effect of the election outcome (but may include indirect effects via the market return), denoted by $S_{i,t}.$, and one that represents a direct effect denoted by $S_{i,t}^{el}$.

$$S_{i,t}^{el} = \pi_t^D D_i + \pi_t^R R_i$$
$$= (1 - \pi_t^R) D_i + \pi_t^R R_i$$

If we look at the change in Stock prices,

$$\Delta S_{i,t}^{el} = \Delta\pi_t^R (R_i - D_i)$$

Here, Δ represents differences in time interval

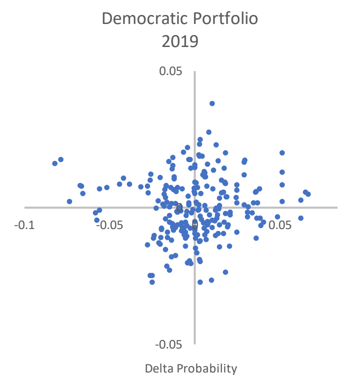
We use stock's residual/idiosyncratic returns for $\Delta S_{i,t}^{el}$ and $\Delta\pi_t^R$ is the change in probability for Republicans in the same time interval used to compute returns. Similarly, we can also write:

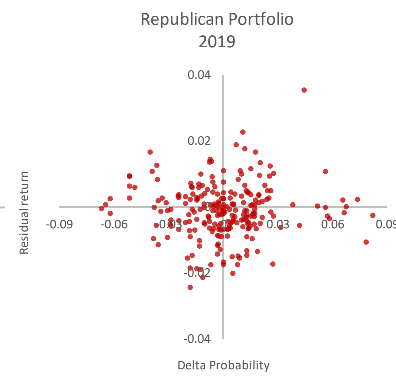
$$\Delta S_{i,t}^{el} = \Delta\pi_t^D (D_i - R_i)$$

where, $\Delta\pi_t^D$ is the change in probability for Democrats. From the above equations, we note that $(R_i - D_i)$ and $(D_i - R_i)$ are stock residual returns sensitivities to the change in probabilities $\Delta\pi_t^R$ $(\Delta\pi_t^D)$ for Republican and Democrats probabilities respectively.

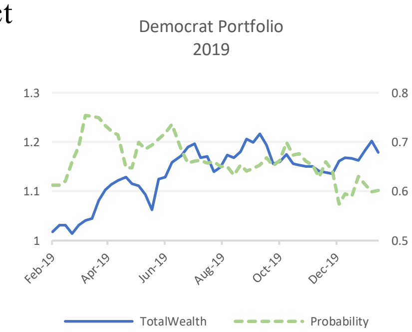
Empirically, we see that there is a lot of noise in daily time intervals. So, we run the following regressions using weekly time intervals for both Democratic and Republican portfolios.

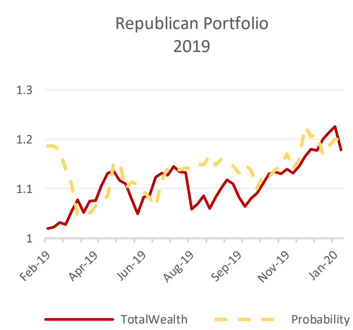
$$\epsilon_{i,t} = \alpha_{i,t} + \theta_i^R \Delta\pi_t^R + e_{i,t} \qquad i \in R$$
$$\epsilon_{i,t} = \alpha_{i,t} + \theta_i^D \Delta\pi_t^D + e_{i,t} \qquad i \in D$$





We see that there is no significant relationship between daily residual returns and change in probabilities for either portfolio. This led us to compare the cummulative performance of both portfolios with the risk neutral probability of winning of the respective party to visualise if there may be any relationship between the two at lower frequencies such as weekly or monthly.



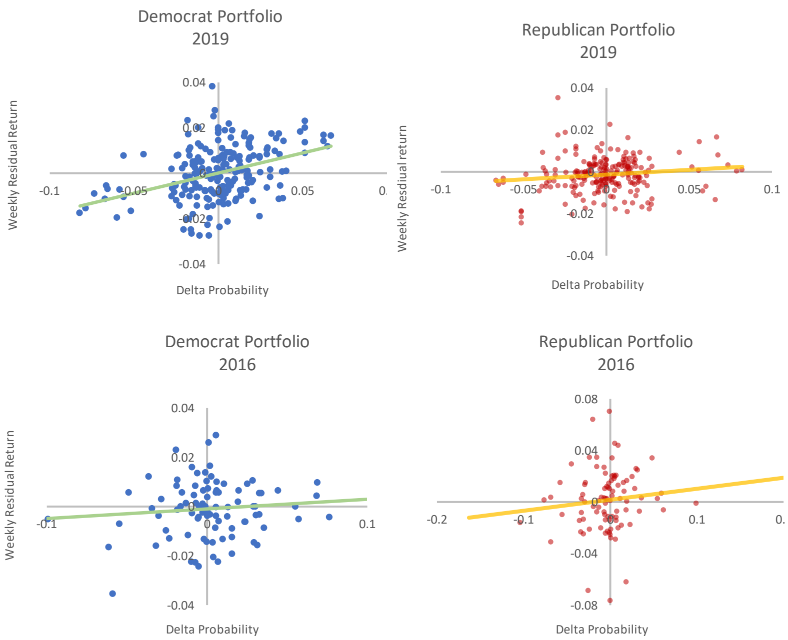


The two curves move together with correlation between cummulative performance of Democratic Portfolio and π^D = 10.62%, correlation between cummulative performance of Republican Portfolio and π^R = 8.03%.

From the equations defined above, stocks with a large positive θ_i^R are expected to benefit from a Republican victory and/or to suffer from a Democratic victory, while the opposite interpretation holds for stocks with a large θ_i^D. Stocks with θ_i^R *or* $\theta_i^D \sim 0$ should not react to the election outcome according to market expectations.

We use changes in event probabilities to validate the pre-selection, and in the forthcoming section, we use linear and non-linear machine learning techniques as the basis for selection of stocks, rendering our approach purely quantitative.

Next, we perform an OLS regression using weekly returns according to the equations defined above for 3 different portfolios – Democratic, Republican, and a long/short portfolio which goes long on the Democratic Portfolio and goes short on the Republican Portfolio. The results are quite interesting and are evidence of a strong linear relationship between weekly changes in probabilities measured from election betting markets vs weekly residual returns. We do the same for the election cycle of 2016 as well to check if the results are persistent and significant.



It is seen that the relationship within the Democratic Portfolio is stronger and more significant than the Republican Portfolio. This implies that average weekly abnormal returns of the democratic portfolio are explained more by the betting markets data than its counterpart republican portfolio, i.e. a lot of the returns within the republican portfolio is still unexplained even after accounting for effects of election in the portfolio.

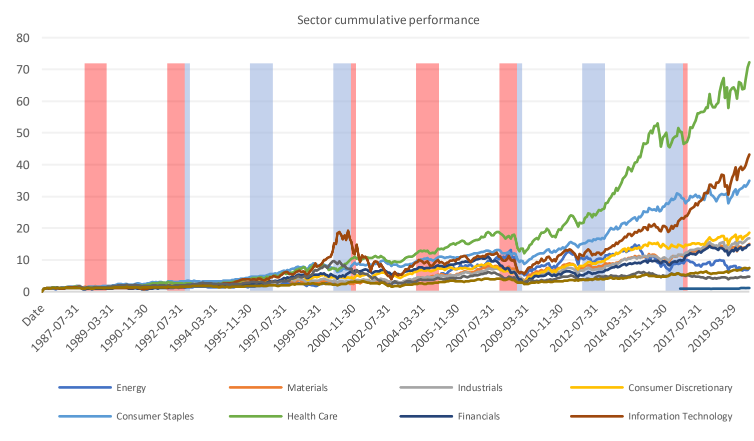
For the year 2016, we see that although the results are in line with the expected theoretical equation, but they are not significant. This implies that the hypothesized portfolios may be well suited for the 2020 elections but not for 2016 elections. The R^2 for the Democratic portfolio is around 15% while that for the Republican portfolio is merely 2.1%. We interpret this result by saying that the Democrat portfolio is a better tied to the Democratic party than the Republican portfolio is to the Republican party. The low R^2 reflects that while the electoral measures do not fully explain the variation in equity returns, news is incorporated into equity prices, and that this relationship is economically and statistically significant at least in the short term.

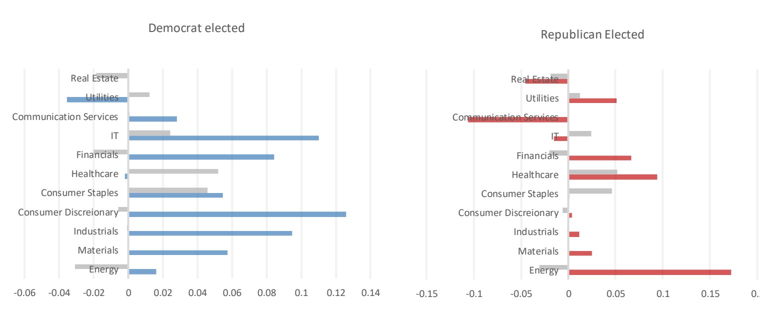
	Coeff Δπ	*Intercept*	*t-stat Δπ*	*Significant*	*R^2*
Dem_2016	0.041	-0.001	0.893	No	0.012
Rep_2016	0.0852	0.001	1.005	No	0.011
Dem_2019	0.1773	-0.0003	6.072	Yes	0.1512
Rep_2019	0.0452	-0.0013	2.005	Yes	0.021
Dem_Rep_2016	0.0451	-0.002	1.437	No	0.0224
Dem_Rep_2019	0.066	0	2.031	Yes	0.024

Regression stats for the hypothesized Democratic, Republican and long/short Democratic-Republican portfolio for the years 2015-2016 and 2019-2020.

Sector Analysis

We aim to check how various sectors (according to GICS classification) have performed during each election cycle in the past. We maintain our investment period from January of election year to January next year to be consistent with the investment horizon of the notes constructed by Julius Baer. A sector's return is calculated as the average return of all the stocks within the sector in S&P 500 at that time.





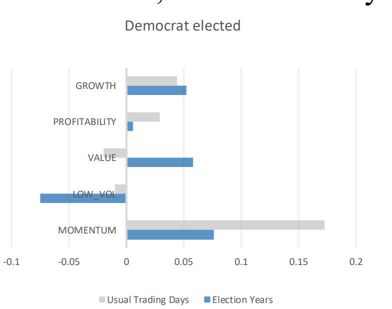
*Here, **when elected** is the January of election year to January of the next year when the party is elected, consistent with our investment horizon of the structured note. Usual trading days are all the days outside of our investoment horizon.*

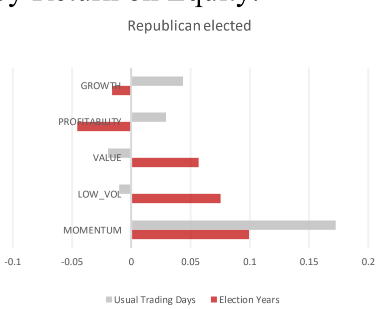
The sector returns comparison between usual trading days and when elected, from the year 1987, is done after adjusting for other macro effects which we assume is priced into the market. Our results indicate that election of a Democrat President is most favorable to sectors such as Consumer Discretionary, Industrials, Information Technology, and Consumer Staples. Looking at the sector allocation of the hypothesized Democratic Portfolio, we find that roughly 80% of the portfolio is invested in these 4 sectors.

The election of a Republican President is most favorable to sectors such as Energy, Healthcare, Financials, and Utilities. Looking at sector allocation of the hypothesized Republican portfolio, we find that roughly 50% of the portfolio is invested in these 4 sectors. An interesting difference to note is that IT and Communication Services hold up to 40% of the Republican portfolio while our analysis tells us that these two were one of the worst performing sectors during the investment period of our interest, when a Republican president is elected.

Style Analysis

Next, we repeat the same event analysis on the 5 styles that we have created – Value, Growth, Momentum, Low Volatility, Profitability. We measure Value by the trailing 12 months Earnings Yield, Growth by expected EPS growth, Momentum by last 12 months returns less last 1 month return, Low Volatility as inverse of realized volatility in the last 3 years calculated using monthly returns, and Profitability by Return on Equity.





Similar to sector returns, style returns have been calculated using residual returns to remove market effects. For each style, stocks within SP500 are ranked in decile (1-10) on a month *t*. A long/short portfolio is constructed which goes long on the top decile and goes short on the bottom decile. For this L/S portfolio average residual returns are calculated from the month *t* to *t*+1. This long/short return calculated is taken to be style return for the month *t*+1. This process is repeated for every month to get the style's return distribution.

We note that a Democratic elected president is favorable to Growth and Value stocks and is unfavorable to Low_Vol stocks. On the contrary, a Republican elected president is favorable to Value and Low_Vol stocks and unfavorable to Profitability and Growth stocks. Interestingly, we find that Value stocks perform better in both election regimes than usual trading days and Momentum stocks underperform in both election regimes than usual trading days.

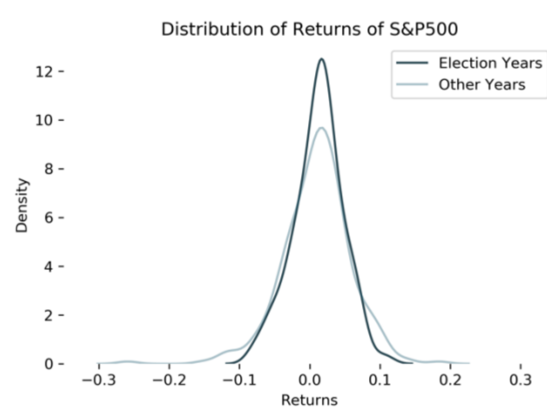
The above analysis enables us to deduce that both Democratic and Republican portfolios structured by Julius Baer show modest relationship with characteristics that have outperformed in the past election years. Although, the relationship is stronger in case of Democratic portfolio than Republican portfolio.

V. Is there an effect of elections on asset returns?

From 1984 there have been 9 elections. As shown below, the average monthly return of the S&P 500 index during the election years was 1.19% (annualized return = 14.28%) while the average monthly return during normal trading days was 0.98% (annualized return = 11.76%). In calculating average returns during elections, we have ommited the year 2008 considering the year as outlier. Our assumption is that in that year, elections must have had little effect in the market performance because of the recession and its influence on other macro indicators. We perform the Welch's t-test as a stististical significance test to check if the mean of the two distribution are equal.

$$t = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}}}$$

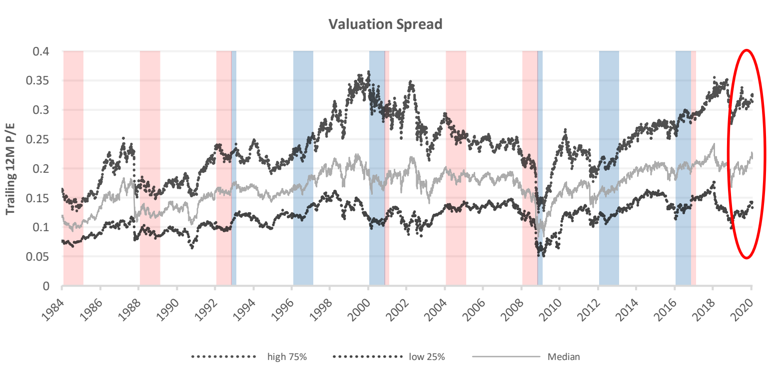
Here, $\overline{X_1}$ and $\overline{X_2}$ are the sample means of the two distribution, s_1 and s_2 are the sample standard deviations, N_1 and N_2 are the number of samples in each distributions.



Running this test, we get a t-statistic of 0.4654 and a corresponding p-value of 0.643. Thus, we fail to reject our null hypothesis that the means of the two distribution are equal, at the 5% level of significance. So, we dig deeper to look at other metrics for the effect of elections on the market as a whole.

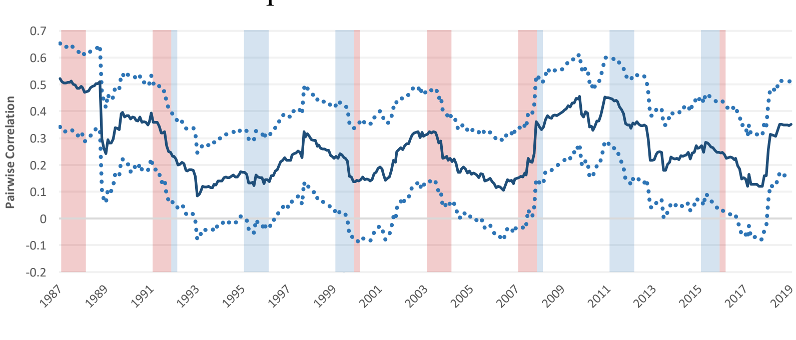
Opportunity Set

Another metric we look closely is the "opportunity-set" for investors. We think of this as the available opportunity for stock selection that investors can pursue to generate differentiated reutrns. We measure opportunity set in two different ways - valuation spread and stock pairwise correlation. Widening valuation spread typically indicates more stock level differentiation and therefore a better environment for stock selection. On the other hand, narrowing valuation spreads are indicative of lower levels of stock differentiation. The figure below shows the median, 25th percentile, and 75th percentile of trailing price to earnings for the S&P500 index constituents.



We see that the spread is increasing than prior months for most of the election periods and also for the current election period. This suggests that there may be some opportunity that investors can exploit to generate differentiated portfolio returns.

Closely related to the valuation spreads is the median pairwise correlation among stocks in the market. This is calculated by taking every possible pair of stocks and computing the correlation of their monthly returns based on the past 24 months of data and then taking the median across all those pairs.



It is easy to see that average pairwise correlations tend to decrease during all election years (except the year 2008 which we have considered as an outlier). This tells us that during the year of the election, stocks tend to trade more on their own merits, rather than being driven by common factors.

In conclusion, we find mixed results by looking at the reutrn and risk distribution of stocks during the year of the election versus other trading days. Nevertheless, since stock correlations decrease, we believe that investors may utilize this opportunity to create diversified portfolios while maintaining similar levels of expected returns to reduce the risk of their overall portfolio considerably.

VI. Portfolio Construction

In the final section we utilise all the results learnt so far to construct two long-only portfolios – Democratic and Republican portfolio. Each portfolio is constructed such that they are expected to outperform the market, contingent upon the election results – respective political party being elected into the parliament. Thus, we believe that the portfolios constructed can be used as a proxy for investors who are interested to bet on the outcome of U.S. Presidential Elections 2020. This assumption is in line with that of the construction of structured notes by Julius Baer that they intend to sell to institutional clients with similar interests. We also use state of the art quantitative and machine learning techniques to construct the two portfolios.

In our approach, we assume that the stocks are selected from the universe S&P 500. This is because the hypothesized portfolios constructed by Julius Baer are all large-cap stocks and 28 out of the 30 stocks are constituents of the S&P500 index. Secondly, both portfolios are U.S. large-cap long-only that contain 15 stocks in each portfolio. Again, this assumption is in line with the way that Julius Baer has constructed their structured notes.

The model incorporates a number of unique features including dynamic factor selection, a non-linear tree component, a linear classification model, and active style and sector rotation. Besides these, we have also included the factor that we have created using data from Iowa Electronic Markets. This 'alternative' factor measures the past correlation between stock's residual return with the probability of winning of a political party captured from political betting markets.

We have formulated the exercise as a supervised learning classification problem. We develop two models – one for each political party - using similar techniques. Each model is meant to select 15 stocks that are expected to outperform the most in the market contingent upon the respective political party being elected to form the parliament. In case of a conflict i.e. if a stock is predicted to be in both the portfolios, we put the stock in the portfolio where it is expected to outperform more based on its probability of outperformance. The target variable for the model is binary where 1 represents market outperformance between the period January of election year to January of next year. This is in line with the investment horizon of the structured note created by Julius Baer.

Our model is an ensemble of two different machine learning algorithms – 1. Logistic Regression that captures linear relationship between predictors and target (market outperformance) and, 2. XGBoost or Extreme Gradient Boosting that captures complex non-linear relationships between predictors and target. Finally, we use the average of the predicted probability from both algorithms as our final criteria for selecting stocks within the portfolios.

Logistic Regression

As mentioned in the previous section, one of the biggest challenges in this exercise is the limited number of election events. The small sample size poses significant difficulties on statistical inference.

$$logit(P) = log\left(\frac{P}{1-P}\right) = \beta_0 + \beta X^T$$

Here, P is the probability that a stock outperforms the market, β is the vector of weights as learned by the logit model for each predictor, and X^T is the transpose of a vector of predictors fed into the model.

XGBoost

The gradient boosting classifier is an additive model using classification trees of a fixed size as weak learners $h_m(x)$. Thus, we can denote our model $F(x)$ as a weighted sum of M weak learners.

$$F_M(x) = \sum_{m=1}^{M} \gamma_w \, h_m(X)$$

When the m_{th} learner is added to the model, it becomes

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

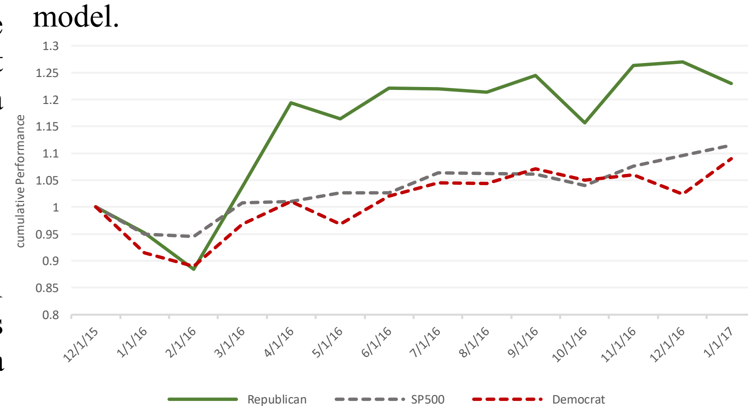
Results and recommendations

We trained our model using data from election years starting from 1984 and stocks that outperformed in those years and used the models to predict stocks that are expected to outperfrom in the 2020 elections. We get the following 15 stocks in each portfolio:

Democratic Portfolio	Republican Portfolio
Brighthouse Financial Inc	The Kraft Heinz Co
Allergan PL	Molson Coors Beverage Co
Hewlett Packard Enterprise Co	DENTSPLY SIRONA Inc
CenturyLink Inc	Facebook Inc.
News Corp	Coty Inc
Micron Technology Inc.	Kinder Morgan Inc.
Nektar Therapeutics	Incyte Corp
Xerox Holdings Corp	Alphabet Inc.
Western Digital Corp	McKesson Corp
Qorvo Inc	Cardinal Health Inc
Mylan NV	Zimmer Biomet Holdings Inc
DXC Technology Co	J.M. Smucker Co (The)
Perrigo Co Plc	Amazon.com Inc
Corning Inc	CVS Health Corp
Walmart Inc	Baker Hughes a GE Co

Backtest performance

We test the performance of our model on the election year 2016. To do this, we train our model using all the data before January 2015 and predict using the data from January 2015 to January 2016. Since Republicans were voted to form the government in 2016, we look at the performance of the republican portfolio, between January 2016 to January 2017, as predicted by our model.



The portfolio that our model predicted, generated an annualized return of 22.97% compared to 11.5% of S&P 500 index and has considerably outperformed the Democrat portfolio. This is strong evidence that the model has selected desirable portfolios that are more fine tuned bet on the result of the elections in 2016.

VII. Conclusion

Using evidence from past Presidential Elections, this paper has demonstrated that information from election betting markets are capitalized into equity prices for a sample of 30 firms in the US that are hypothesized to be tied to the political parties. To study investor preferences, we have looked at how characteristics from polling and political betting markets translate into returns for related stocks. We observe that we can find some of the relative valuation (i.e. the premia or discount applied by investors) by tracking correlation between stocks' abnormal returns with probability of winning of political party that the stocks are tied to. These correlations explain over 15% in the variation of the Democrat's portfolio's average residual returns; however, the relationship is not as strong in the case of Republican portfolio.

Looking at past elections and the way markets have performed in each regime, we found that the Democrats are most favorable to sectors such as Consumer Discretionary, Consumer Staples, IT, and Industrials while the Republicans are most favorable to sectors such as Energy, Healthcare, Financials, and Utilities. Thus, in case of anti-incumbency in the year 2020, there may be sufficient opportunity posed by sector rotation. On the contrary, in case of Republicans being re-elected, investors can capitalize by a higher exposer to styles such as Momentum, Value and Low Volatility.

We also noticed that elections have an effect on how the market performs at least in the short term. The average annualized return of the SP500 index during election years (January of election year to January of next year) is 14.28% while average annualized return during usual days in 11.26%. We see that stock pairwise correlations tend to decrease during election year which implies that there may be some opportunity for investors to construct portfolios with an aim to reduce their overall risk.

Finally, we used an ensemble machine learning approach to construct two long-only portfolios that are expected to be better tied to each of the two political parties. We suggest the portfolios predicted by the model with a belief that those portfolios better capture the relationship with respective political party than the hypothesized portfolio selected by Julius Baer. Backtest performance of the model on the year 2016, shows that our model picked a Republican portfolio that generated close to 23% returns during the period January 2016 to 2017 compared to 11.5% of the S&P 500 index and 9% of the Democratic portfolio selected by our model.

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Team Bobcat

Differentiating Partisan Portfolios using Volatility Modelling, Clustering and Factor Analysis

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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

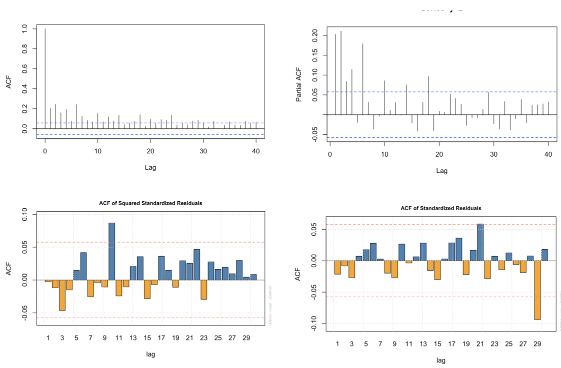
Price levels are not stationary hence we model their log return series using a GARCH process. We start with the Republican portfolio perform the following:

- 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.

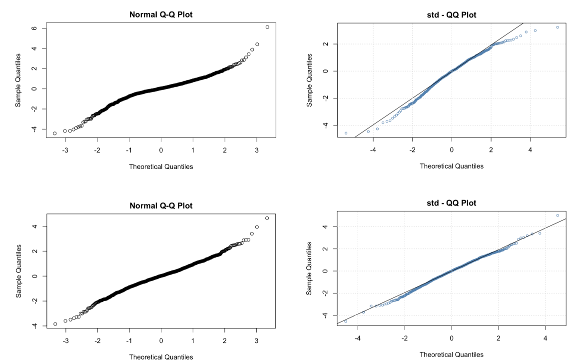
$$\widehat{r_t} = \underset{(7.99)}{0.00129} + \underset{(2.89)}{0.4866 r_{t-5}} \underset{(-3.66)}{-0.578\epsilon_{t-5}} + \epsilon_t \tag{2.2}$$

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

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.

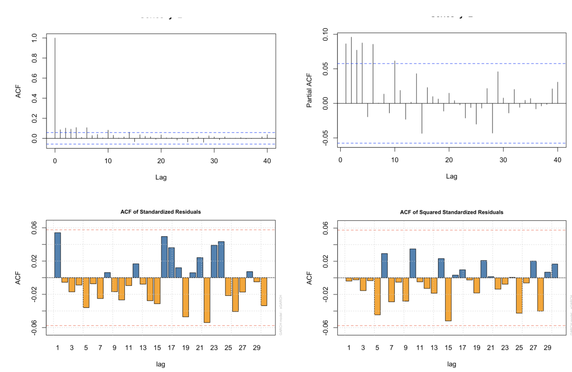
Then we check if the empirical distribution of residuals is consistent with our distribution assumption in our model. Since the QQ-plot of return series indicates a fat tail (first plot of figure 2), we assume the innovation at each period follows a student-t distribution. Below is a QQ-Plot(second plot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

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

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

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.

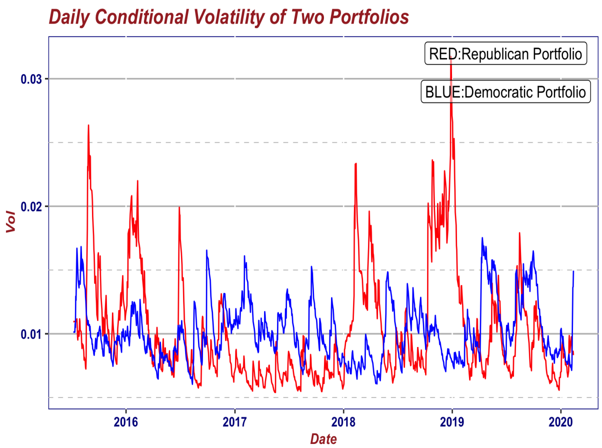


Fig. 4. Daily Conditional Volatility of Two Portfolios

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

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

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

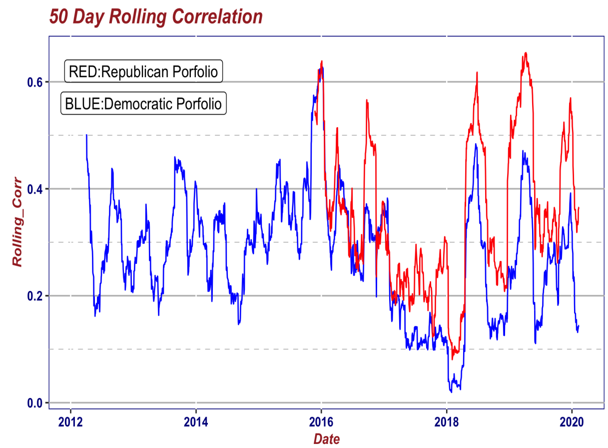


Fig. 5. 50 Day Rolling Correlation

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.

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

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, $d_{A,i} = \log{(Tweets^*(A, i))}$
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.

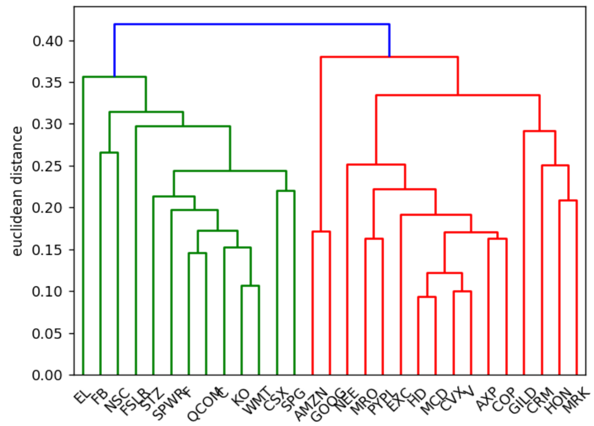


Fig. 6. Dendogram for 2015-2016

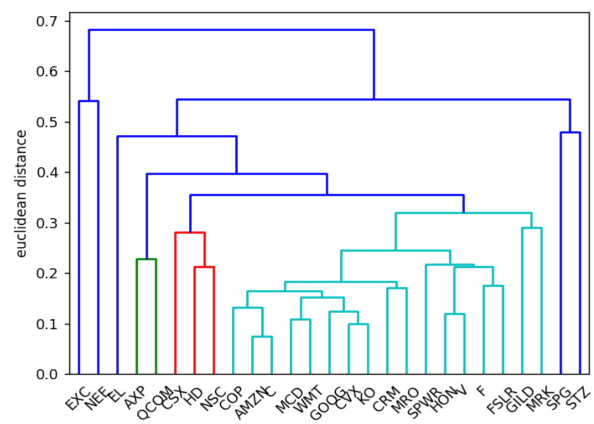


Fig. 7. Dendogram for 2011-2012

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.

$$\begin{bmatrix} r_{1,1} & x_{1,1}^* & \dots & x_{k,1}^* \\ \vdots & \vdots & \ddots & \vdots \\ r_{1,t} & x_{1,t}^* & \dots & x_{k,t}^* \\ r_{2,1} & x_{1,1}^* & \dots & x_{k,1}^* \\ \vdots & \vdots & \ddots & \vdots \\ r_{2,t} & x_{1,t}^* & \dots & x_{k,t}^* \end{bmatrix}$$

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

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

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

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

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.

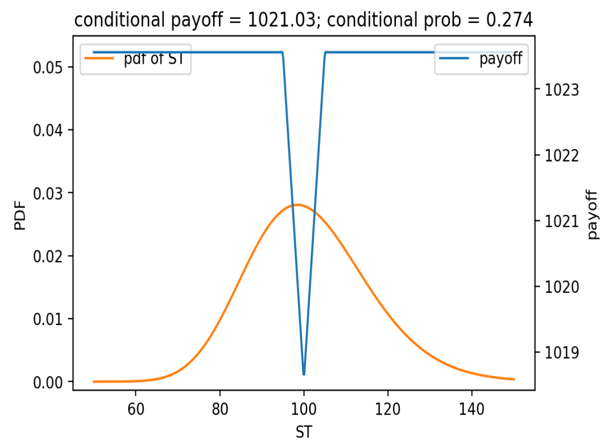


Fig. 8. Republican Structured Note Payoff

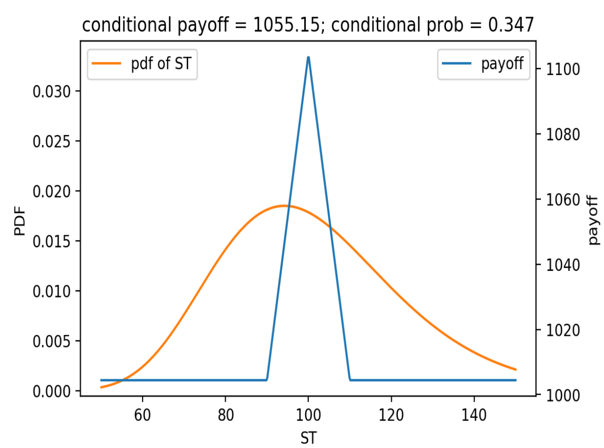


Fig. 9. Democratic Structured Note Payoff

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

Team QuAntiochus

A Multi-Strategy Structured Notes Solution: Hedging the 2020 U.S. Presidential Election

A Multi-Strategy Structured Notes Solution: Hedging the 2020 U.S. Presidential Election

***Abstract*—This paper studies the statistical differences between two equity portfolios and examines their performance characteristics within the context of the US presidential election. To leverage their different performance expectations, we subsequently design structured notes from the portfolios so as to explore possible trading opportunities. Two approaches are suggested in the construction process, i.e., utilizing options and swaptions.**

***Index Terms*—Financial Assets and Derivatives, Statistical Test, Linear Regression, Presidential Election, Structured Notes Construction**

I. Introduction

OVER the past few decades, the market has seen a proliferation of equity-linked structured products across a broad spectrum of asset classes. To meet the ever-shifting risk appetites of investors, banks have rolled out an inexhaustible variety of structured products linked to the underlying equity market, allowing for simultaneous investment participation and risk hedging.

Our goal is to cater to investors with a desire to participate in the equity market based on their opinions on the US presidential election outcome. To that end, we propose two canonical structured notes with their respective payoff mechanisms tied to two underlying portfolios that have been empirically tested to exhibit diverging returns depending on the outcome of the US presidential election.

Before giving the fact sheet of different structured notes, we perform statistical tests on *daily return*, *cumulative return*, and relevant financial factors to determine whether there are any significant differences between democratic and republican portfolios in Section II. After carefully analyzing the relationship between presidential election results and the performance of their respective portfolio using linear regression in Section III, we present solutions to constructing structured notes from the election portfolios with different payoffs based on the previous analysis in Section IV.

II. Quantitative Analysis

We retrieve all available price data of the 30 stocks from Yahoo Finance and calculate daily returns using adjusted-closing price. The dates range from 01/02/1972 to 01/17/2020. We also retrieve Form 10-K, the annual financial reports, from Bloomberg Terminal. Assuming equally weighted portfolios, we compute their returns as the arithmetic mean of all induvial stocks wherein.

A. Analysis of financial factors

To measure whether the two portfolios are in fact different from each other, we take financial factors into consideration. Take Weighted Market Capitalization of the portfolio as an example to illustrate how to calculate weighted factors of a portfolio. Suppose that we invest X dollars in a portfolio on December 31st every year, we divide the total investment amount into N parts evenly, corresponding into N stocks [1]. Each stock will then have a weight of W_i, measured as $1/N$.

Then, $F_{portfolio}$ is

$$F_{portfolio} = \sum_{i=1}^{N} W_i * F_i$$

where F_i is the Market Capitalization of stock i.

Having tested 25 financial factors, we find that two factors exhibit statistically significant difference between the Democratic and Republic portfolios: Weighted Market Capitalization and Weighted Asset Turnover.

Market capitalization is defined as number of outstanding shares multiplied by price per share. Since 2000, the Weighted MarketCap of democratic portfolio is 43.34% higher than that of republican portfolio on average.

[1]In some situations, there are some missing values of the financial factors. For example, some companies haven't published 2019 financial reports so that we cannot get their financial factors, while the stocks exist. Therefore, we choose N as the number of this factor that exists.

Debt_Capital is defined as the ratio of debt to total capital. From 2000 to 2002, the *Weighted_Debt_Capital* of republican portfolio is 33.01% higher than that of democratic portfolio on average. After 2002, the *Weighted_Debt_Capital* of democratic portfolio is 29.65% higher than that of republican portfolio on average.

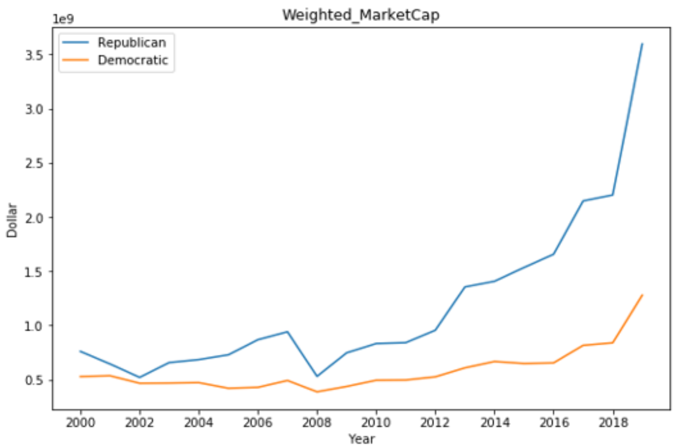


Fig. 1: Weighted Market Capitalization

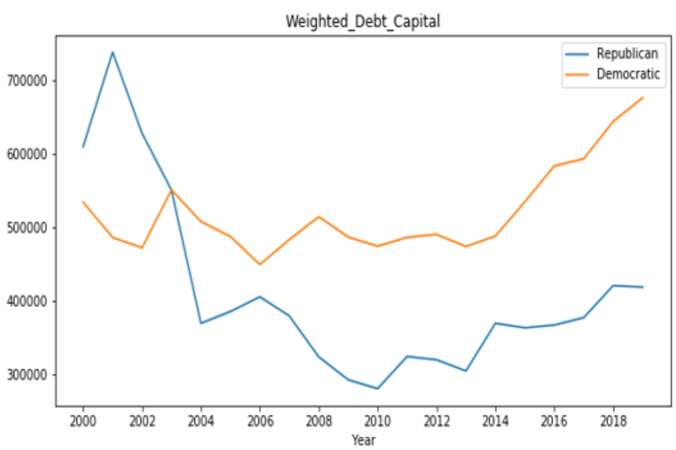


Fig. 2: Weighted Debt Capital

B. Exploratory Data Analysis and Hypothesis Construction

Before the inception of statistical analysis, we perform a data overview to ensure maximum empirical accuracy. We select three different time periods and four different metrics for examination. All time periods are backdated to 01/17/2020, the last date of our data sample.

From Table I and Table II, we observed some differences in performance between Democratic portfolio and Republican portfolio, especially over longer time spans such as four years and ten years. In order to gain a more intuitive sense of the portfolio performance for hypothesis construction, we graph the cumulative returns of the portfolios over different time spans.

TABLE I: Return Performace

	Cumulative return	Mean daily return
Democratic 1-Year	130.01%	0.107%
Republican 1-Year	125.59%	0.094%
Democratic 4-Year	182.65%	0.063%
Republican 4-Year	214.95%	0.081%
Democratic 10-Year	441.49%	0.064%
Republican 10-Year	464.78%	0.0067%

TABLE II: Risk Performace

	Annualized Volatility	Max drawdown
Democratic 1-Year	12.58%	-7.55%
Republican 1-Year	13.48%	-7.80%
Democratic 4-Year	13.61%	-16.69%
Republican 4-Year	15.33%	-21.94%
Democratic 10-Year	16.17%	-23.21%
Republican 10-Year	16.78%	-25.18%

According to Figure 3, over the past year, the democratic portfolio outperforms the republican portfolio, while the contrary is true for longer time spans. Since the cumulative return lines representing the two portfolios do not cross each other for most of the time, we build a hypothesis that the two portfolios have different characteristics. We examine our hypothesis quantitatively in the following sections.

C. Statistical Tests

We examine the differences between these two portfolios in two ways: one by daily returns, the other by cumulative returns. All tests are executed in Python for convenience and reproducibility.

1) Analysis of daily returns: Before we examine the differences in variance and mean, the data must pass the normality test. We choose Shapiro-Wilk model as a tool to test for normality. This model tests the null hypothesis that a sample $x_1, ..., x_n$ comes from a normally distributed population. The test statistic for the Shapiro-Wilk test is:

$$W = \frac{(\sum_{i=1}^{n} a_i x_{(i)})^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

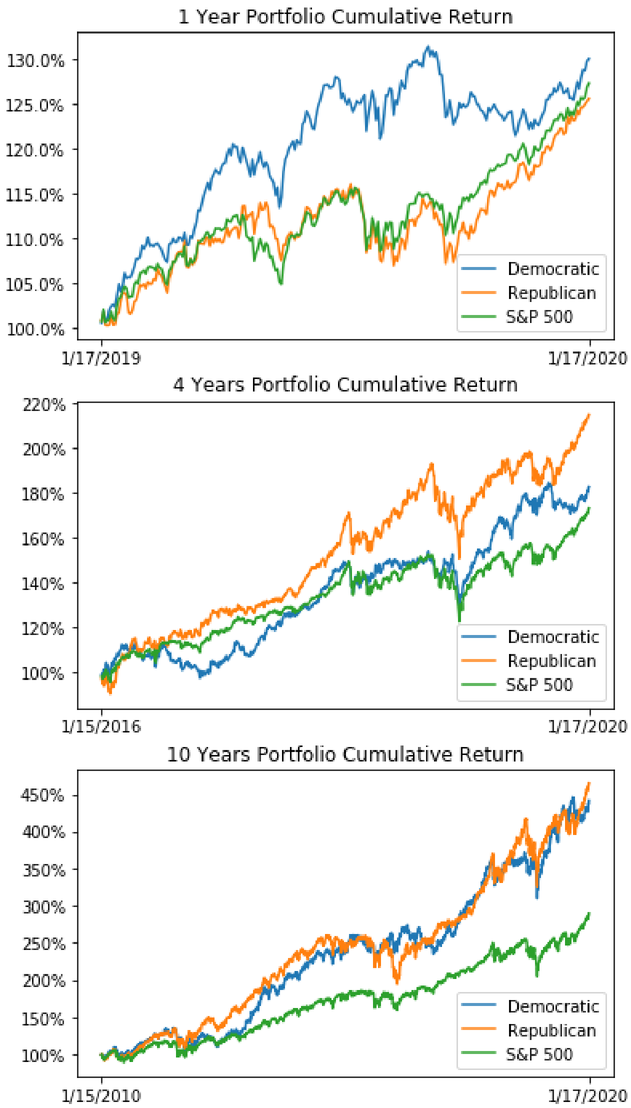


Fig. 3: cumulative portfolio returns of different time periods

where $x_{(i)}$ is the ith order statistic, and $\bar{x}$ is the sample mean.

We apply the Shapiro-Wilk model to test the daily returns of the portfolios for normality. The results are shown in the Table III.

TABLE III: Normality Test for Daily Return

Period	T-value	p-value
Democratic 1-Year	22.48	0.00
Republican 1-Year	23.76	0.00
Democratic 4-Year	72.30	0.00
Republican 4-Year	108.75	0.00
Democratic 10-Year	248.70	0.00
Republican 10-Year	184.52	0.00

From Table III, we observe p-values for all metrics are less than the significance level of 0.05, which gives us enough statistical evidence to reject the null hypothesis. All the daily returns data are not normally distributed; we cannot use the F-test for difference in variance and the standard T-test for the difference in mean, because both tests require the samples to be normally distributed.

As an alternative, we consider choosing between a paired samples T-test and a Wilcoxon signed-rank test. These tests test for the differences between two sets of paired data. In our study, the paired data is the daily returns of the two portfolios. In order to determine on an appropriate test, we test daily return difference between the two portfolios for normality. If the difference is normally distributed, a paired samples T-test can be used; otherwise, a Wilcoxon test is more appropriate.

TABLE IV: Daily Return Difference Test

Period	T-value	p-value
1-Year	1.95	0.38
4-Year	40.61	0.00
10-Year	145.78	0.00

From Table IV, the p-value for *1-year Daily Return Difference* is greater than the significance level of 0.05, therefore we cannot reject the null hypothesis. The next step is performing a paired samples T-test. In other cases, the p-values are less than 0.05, justifying the need for a Wilcoxon test with statistical evidence.

The paired T-test tests for the difference in mean with the null hypothesis that 2 related sets of data have identical expected values. The test statistic is:

$$t = \frac{\bar{X}_D - \mu_0}{\frac{s_D}{\sqrt{n}}}$$

where $\bar{X}_D$ and s_D are the mean and standard deviation of the differences between the pairs. The Wilcoxon signed-rank test is a nonparametric test that can be used to determine whether two sets of data have the same distribution. The test statistic is:

$$W = \sum_{i=1}^{N_r} [sgn(x_{(2,i)} - x_{(1,i)}) R_i]$$

TABLE V: paired samples T-test and the Wilcoxon signed-rank test

Period	Paired T-value	Paried p-value	Wilcoxon test stats	Wilcoxon test p-value
1-Year	0.32	0.75	-	-
4-Year	-	-	242427.5	0.22
10-Year	-	-	1559685.5	0.54

where sgn is the sign function, N_r is the reduced sample size after each ranking is done,R_i denotes the rank, and $x_{1,i}$ and $x_{2,i}$ denotes the measurements.

From Table V, every one of the tests returns a p-value greater than 0.05, indicating a lack of sufficient evidence to reject the null hypothesis. Whereas the two portfolios have the same mean for *1-year daily return* as stated in the null hypothesis, they have the same distribution for the *4-year* and *10-year daily return*.

No substantial conclusion can be made regarding any statistically significant difference between the two portfolios using daily return data. To more thoroughly test for quantitative differences, we then analyze cumulative return data.

2) Analysis of cumulative returns: The testing procedure of the cumulative returns is similar to that of the daily returns. For succinctness, we focus on interpreting the empirical results.

TABLE VI: Cumulative Returns Normality Test

Period	Republican p	Democratic p	Difference p
1-Year	0.015	0.000	0.000
4-Year	0.000	0.000	0.000
10-Year	0.000	0.000	0.005

Table VI shows resultant p-values of normality test across different time periods for both Republican and Democratic portfolios as well as the difference between the two. Following the rejection of null hypothesis for all three cases, we move forward with the Wilcoxon signed-rank test to test for difference in distribution.

TABLE VII: Cumulative Returns Wilcoxon signed-rank test

Period	Wilcoxon test statistic	Wilcoxon test p-value
1-Year	2.0	0.0
4-Year	6117.0	0.0
10-Year	868765.0	0.0

Table VII shows the results of Wilcoxon signed-rank test for cumulative returns. Given a p-value of zero across all three measures, we reject the null hypothesis and conclude the cumulative returns for the Democratic and Republican portfolios come from different distributions.

Combining this finding with the statistics from the exploratory data analysis (as Table VIII shows), we are able to come to a conclusion that the cumulative returns of the two portfolios exhibit significant differences in distribution. We continue to use this fact to test for the performance difference with regards to the election results in Section III.

III. Linear Regression Model

Building upon the significant differences in cumulative returns between the Democratic and Republican portfolios in Section II, we construct multivariate linear regression models to test for the statistical significance of explanatory variables in relation to portfolio performance.

To test whether the outcome of the election will significantly influence the performance of the two portfolios, we need to first introduce additional control variables to our model. According to existing academic studies , we select *max drawdown, volatility, Sharpe ratio, expected shortfall at 95% confidence interval*, and S&P 500 return as the control variables in our model. Because US presidential election is held every 4 years, the amount of historical data is limited. Consequently, our linear regression model draws on historical data from 1980 through 2016 to gauge the impact of election outcome on *portfolio return*.

The Descriptive Statistics Analysis of our control variables is shown in Table IX:

We use a dummy variable to represent the outcome of election outcome. A full representation of our regression model is shown as follows:

$$\begin{aligned} Return_x =& \beta_0 + \beta_1 Democratic_x + \beta_2 SP_x + \\ & \beta_3 MaxDD_x + \beta_4 Vol_x + \\ & \beta_5 Sharpe_x + \beta_6 ES_x + \epsilon \end{aligned}$$

To begin, we need to determine on an appropriate frequency level for portfolio return. We use x to

TABLE VIII: paired samples T-test and the Wilcoxon signed-rank test

Test Name	Daily return (1-year)	Daily return (4&10-year)	Cumulative return
Test for Normality	+ve	+ve	+ve
Test for Normality inDifference of Two Series	-ve	+ve	+ve
Test for Difference in Mean	-ve	n/a	n/a
Test for Difference in Distribution	n/a	-ve	+ve

TABLE IX: Descriptive Statistics Analysis of the variables

	Variables	Mean	Standard Deviation
	Count	10	
Dependent Variables	Daily Return_D	0.0090	0.0161
	Daily Return_R	0.0031	0.0071
	Monthly Return_D	-0.0021	0.0713
	Monthly Return_R	0.0006	0.0628
Independent Variable	Democratic	0.4000	0.5164
Control Variables	MaxDD_D	0.0437	0.0510
	Volatility_D	0.0578	0.0533
	Sharpe_D	0.3247	1.0787
	ES_D	-0.0217	0.0202
	MaxDD_R	0.0561	0.0533
	Volatility_R	0.0639	0.0527
	Sharpe_R	0.4163	0.9843
	ES_R	-0.0220	0.0176

substitute the time interval and the portfolio we choose . Upon reviewing the regression results, we find the daily return of both the Republican and Democratic portfolios are positively correlated to the dummy variable 'Democratic'. Such finding implies a shared positive shock of Democratic victory to both portfolios; that said, if the Democratic party wins the election, it is expected to observe an price increase in both portfolios. However, when switching portfolio return frequency from daily to a monthly basis, we arrive at different empirical results. While the monthly return of the Republican portfolio goes down following a Democratic party victory, that of the Democratic counterpart goes up as expected.

Thus, we infer from the regression results that the impact of election outcome on the return of Democratic portfolio is timely and continuous, as supported by a significantly positive relationship at 5% level between the success of the Democratic party and the increase in Democratic portfolio return, both on a daily and monthly basis. However, the story develops otherwise for Republican portfolio – Republican win does not have an immediate impact on its corresponding portfolio because daily return of the portfolio is significantly increased after the Democrat wins, albeit half that of its Democratic counterpart. Moreover, the monthly return of the Republican portfolio decreases following a the Republican defeat, which shows a lag effect of the election result on the portfolio return.

TABLE X: Linear Regression Results

$Return_x$	Coefficient β_1	T statistic
Democratic daily return	0.0098	1.98
Republican daily return	0.0044	1.72
Democratic monthly return	0.0331	2.46
Republican monthly return	-0.0136	-1.62

IV. STRUCTURED NOTES CONSTRUCTION

The investment thesis revolves around capturing the upside potentials on the underlying portfolio while limiting the downside risks should the US election outcome materializes otherwise. In the most conservative way, a structured note would guarantee principal protection while allowing partial participation in portfolio capital gain. This could be neatly modeled as a zero-coupon paying bond and a call option. Whereas the bond position guarantees principal payback, the call option maintains a long position that pays off in a stock rally.

A. *Underlying assets*

While most equity-linked structured notes are tied to an underlying market index (S&P 500, NSDAQ 100, or other broad stock indices), the ones in question are linked to an underlying portfolio. Because the portfolio was constructed specifically in such a way that its performance primarily hinges on US election outcome, its payoff structure is inherently

TABLE XI: Basic Information for Two at the Money OTC Options

	Volatility(%)	Start date	End date	Price(%)	Participation rate(%)
Democratic	12.44	01/29/2020	01/29/2021	5.78	51.07
Republican	13.61	01/29/2020	01/29/2021	6.23	48.14

risky or unpredictable at best, thereby necessitating a principal protection mechanism through bond investment. Since our structured notes are amenable to being decomposed into a combination of a zero-coupon paying bond and call options, their valuations can be broken down into an equivalent portfolio of financial instruments whereby each component is valued using the appropriate formula. By virtue of the decomposition approach, we can conveniently characterize the structured notes' payoff in terms of everyday financial products.

B. Valuation Approach

Consider a one-year zero-coupon paying bond as the capital preservation feature. Against the backdrop of a swiss private bank being the issuer, we set the prevailing interest rate at 3% in reference to an existing corporate bond issued by SWISS BK CORP, maturing on 07/15/2025 with a 3.4% yield [2] .

To account for the short duration of the bank's structured notes, we lower the rate by 40 bps to 3% as shorter maturity implies lower yield. Assuming no default risk, the bond position leaves approximately 3% (100% - 97%) of the principal available for call purchase. Depending on the cost of the OTC call option, we determine the participation rate accordingly, defined as the ratio of fund balance available to the call premium. Given a 40M principal value and a one-year investment horizon, we utilize Black-Scholes to compute the at-the-money call premium.

Structured Notes Payoff:

$$S + \max\{S \times P \times \frac{S_T - S}{S}, 0\}$$

Equivalent to:

$$S + \frac{S \times P}{S} \max\{S_T - S, 0\} = S + P \times \max\{S_T - S, 0\}$$

where S is the Principal Amount, S_T is the Portfolio Value, and P is the Participation Rate.

[2]"Bond Detail." Bonds Detail, http://finra-markets.morningstar.com/BondCenter/BondDetail.jsp?ticker=C27427&symbol=UBS.KG.

Note that the payoff function, $max\{S_T - S, 0\}$, translates effectively into a call option while the Principal Amount, S, represents a zero-coupon bond; that conveniently allows us to price the product separately by each component:

- Bond Value: $\frac{S}{1+r}$
- Call Option: $P[SN(d_1) - Ke^{-r}N(d_2)]$

The combined value of both components must add up to a principal amount of 40M, rendering P, Participation Rate, susceptible to manipulation.

We set risk free rate as 1.64% as this is the U.S. 10-Year Treasury yield on 01/28/2020. Assuming returns are identically independently distributed, we calculate portfolio volatility by averaging the daily return of 15 stocks in the portfolio from 01/28/2019, deriving the sample standard deviation and multiplying it by $\sqrt{252}$.

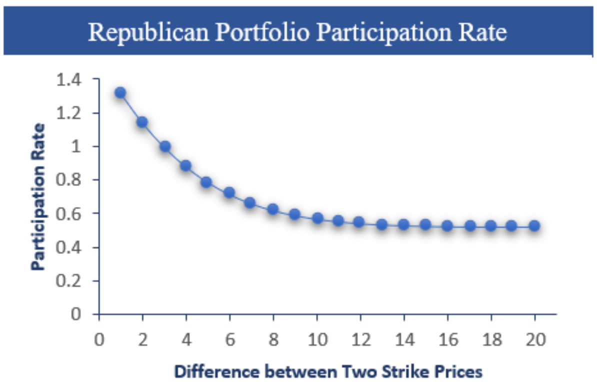
Table XI shows the basic information for two at the money OTC options.

C. Contingent Claims

With a zero-coupon bond and an ATM call option, the participation rate falls at 51%, which might seem somewhat unattractive to those looking for aggressive returns. To cater to investors' varied levels of risk appetites, we design a selection of participation rates through the following ways:

1) Investing in high yield corporate debt instruments
2) Capping upside gains through Bull-Spread Options

As the cost of bond investment is lowered, the remaining balance available for call option purchase becomes higher, enabling higher participation rates. However, investing in high yield corporate bonds introduces default risk and we may be no longer able to guarantee principal protection for investors. While modifying the debt component jeopardizes investor principal security, we can still achieve higher participation rates by adjusting the call position.



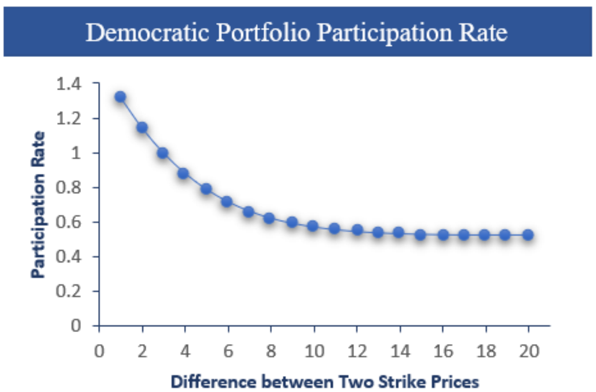


Fig. 4: Relationship of Profitable Interval and Participation Rate

One way of such realization would be to short sell an OTM (out-of-the-money) call option at a higher strike price in conjunction with the ATM (at-the-money) call option. This combination effectively constitutes a Bull-Spread strategy, profiting from underlying price rally while costing less than buying only the lower strike call. Despite having limited profit potential, this strategy performs best when the underlying portfolio rises moderately within a range between the lower and upper strike prices. The viability of the Bull-Spread strategy is further reinforced when drawing on empirical evidence – the benefiting portfolio of any particular US presidential election outcome generally will not rise above 10% in the quarter that follows.

Because of the inverse relationship between premium and strike price of call options, the higher the strike price of the short call, the lower the premium becomes; hence, translating into a lower participation rate when used to finance the ATM call option purchase.

We calculate the participation rate for the short call at different strike prices from 41M to 60M for two portfolios. The inverse relationship of profitable interval and participation rate is shown in Figure 4.

D. Swaption

To increase participation rate while keeping the possibility of gain higher returns, we can design an equity swap that the bank pay fixed rate and receive periodical return with respect to the return of underlying portfolio. Normally, the fixed rate is set to be about 6.5% annually. And then buy a swaption to have the right to enter in this swap nine month later, when the result of presidential election is almost certain. According to the result of Section III, we will not miss any impressive return but can escape from the uncertainty of election result now. The only shortage of this method is pricing the swaption is hard.

TABLE XII: Democratic Portfolio Bull-Spread Participation Rates

Targeted Realized Return	Targeted Return	Short Strike	Participation Rate
3.26%	2.50%	41M	130%
5.64%	5.00%	42M	113%
7.39%	7.50%	43M	98%
8.69%	10.00%	44M	87%
9.71%	12.50%	45M	78%
10.58%	15.00%	46M	71%
11.39%	17.50%	47M	65%
12.21%	20.00%	48M	61%
13.06%	22.50%	49M	58%
13.98%	25.00%	50M	56%

TABLE XIII: Republican Portfolio Bull-Spread Participation Rates

Targeted Realized Return	Targeted Return	Short Strike	Participation Rate
3.26%	2.50%	41M	130%
5.64%	5.00%	42M	113%
7.38%	7.50%	43M	98%
8.67%	10.00%	44M	87%
9.68%	12.50%	45M	77%
10.54%	15.00%	46M	70%
11.34%	17.50%	47M	65%
12.14%	20.00%	48M	61%
12.98%	22.50%	49M	58%
13.89%	25.00%	50M	56%

E. Equity Swaption

As an addition to our product offerings, we curate a third type of structured note specifically for investors looking for aggressive returns: a zero-coupon bond coupled with a nine-month equity swaption.

While this structured product has a higher potential upside, it no longer guarantees principal protection and puts investors at risk of capital loss, should their desired portfolio deliver poor performance following the presidential election in November. To understand the payoff mechanism of this swaption-like structured note, we analyze each component as follows:

1) The zero-coupon bond works the same as before to ensure principal delivery at expiration.
2) The equity swaption entitles us to enter into a swap transaction with a counterparty at maturity date (nine months later) with a predetermined fixed rate. The counterparty promises to pay the return on an underlying equity portfolio in exchange for a fixed rate from us. Given the timeline of US presidential election, the swaption comes into effect as of 1/27/2020 and matures on 11/03/220, a day after the US presidential election. Upon maturity, we only enter into the swap contract if the prevailing swap rate is higher than the predetermined fixed rate specified in the contract. By the same token, we take a loss of the swaption premium if the prevailing swap rate is lower than the fixed rate.

In case that we enter into the swap contract, an extra layer of risk is introduced through the uncertainty surrounding the floating return on the underlying portfolio for the 3 months after the US election outcome. So long as the portfolio return rises above the fixed rate, we are in a position to capture capital gains. However, if the portfolio delivers suboptimal returns, we suffer capital losses at the expense of investor's investment principal.

Our valuation methodology for equity swaption is cordially inspired by an academic study from Don el. 1998, who contends that pricing an equity swaption should be no different from pricing an interest rate swaption.

We define the value of portfolio at time t as $I(t)$, let $B(j,k)$ represent the value at time j of a zero-coupon bond with \$1 face value that matures at time k. Because we choose to enter into the swap nine months later, there is only one payment stream. As a fixed-rate payer, we receive

$$\frac{I(12)}{I(9)} - (1+R)$$

one year later, where R is the fixed rate we pay, determined in the ninth month after contract inception.

At any time j between 9th month and 12th month, the swap value should be:

$$V(j;9,12) = \frac{I(j)}{I(9)} - B(j,12) - RB(j,12)$$

Upon the initiation of the equity swap, the swap should have a value of zero and j = 9. Therefore, we have:

$$R = \frac{1-B(9,12)}{B(9,12)}$$

Now that we have equated a standard equity swap with a fixed rate on a plain vanilla swap, we can start pricing the swaption at time 0. If we denote the strike of swaption as K, the payoff at expiration is:

$$\max\{R-K,0\} \times B(9,12)$$

As shown in the former equation, portfolio value is excluded. Because immediately after exercising a swaption, the payer can always enter into an offsetting swap in the market to remain market neutral. Thus, the swaption is properly valued at expiration by executing a hypothetical arbitrage-free transaction.

We then apply Black-76 formula to value a payer swaption:

$$P \cdot e^{(-it_i)}(t_i - t_{i-1})[RN(d_1) - KN(d_2)],$$

$$where \quad d_1 = \frac{\ln\frac{R}{K} + \frac{1}{2}\rho_F^2 T}{\rho_F\sqrt{T}}, \quad d_2 = d_1 - \rho_F\sqrt{T}$$

Symbol	Description	Value
T	Expiry date of swaption	$\frac{3}{4}$
ρ_F	Volatility of swap rate	$70.41 \times \sqrt{0.25}$ [3]
P	Principal	40 million
i	$f(9,12)$	1.55% [4]

A typical annual rate of 6% is applied as the fixed rate, K, as seen across a wide array of equity swaptions in existing trading landscape. Results pertaining to the valuation process are shown in Table XIV:

TABLE XIV: Result of Pricing Swaption

$B(9, 12)$	R	$N(d_1)$	$N(d_2)$	price
0.9961	0.0039	1.35×10^{-5}	7.64×10^{-7}	0.0606

The swaption is refreshingly inexpensive because of the optionality to enter into a swap that trading at an annual spot rate of 1.55%, far lower than the annualized 6% we pay on the fixed leg. Unlike any traditional interest rate swaption, the underlying asset being discussed is portfolio return; that said, investor has the ability to capture portfolio return if their preferred party wins the election in 9 months.

When it comes to the calculation of participation rate, we formulate it by the rule of cash flow replication (i.e. outflow from fixed leg + inflow from portfolio return):

$$pr = \frac{return\ from\ purchasing\ bond}{price\ of\ swaption} \times (1 - \frac{K}{R})$$

Despite yielding an abnormally high participation rate, investor is nonetheless at risk of experiencing principal losses due to the uncertainty around future portfolio performance. To the extent of principal preservation, possible features can be introduced such as adding a floor to the float leg; however, investors are likely to find this type of structure unduly sophisticated and bafflingly opaque.

F. Caveat

With the attractive balance between risk and return as well as the feature of principal protection, we find it commercial enticing to present two types of portfolio-linked structured notes: 1) principally protected with a 51% participation rate for any upside return 2) principally protected with limited upside return and varying participation rates ranging from 51% to 130%. It is at the investor's discretion to select the appropriate product type according to their own risk tolerant level. Additional attention should be directed at the forgone interests that would otherwise be generated through investing in risk-free treasury bonds.

[3]From the close price of 01/27/2020, http://www.cboe.com/SRVIX

[4]From 3 month spot rate on 01/27/2020, https://www.treasury.gov/resource-center/data-chart-center/interest-rates/Pages/TextView.aspx?data=yieldYear&year=2020

V. Conclusion

This paper attempts to assess the implications of US presidential election outcome on equity market activities. Using historical data of two inherently different equity portfolios, we empirically test their characteristics and expected performance following US presidential election in a quantitative fashion.

Building upon empirical evidence, we construct two types of principally protected structured notes linked to the portfolios in question. By way of Black-Scholes Options Pricing Formula, we analytically compute the options premium and backward engineer the corresponding participation rate. Based on statistical analysis, we find it optimal to invest at a 87% participation given market sentiment often subdues gradually following the blistering presidential election.

In general, this paper provides strong evidence that US election has an important impact on equity market performance. Our findings in this study might shed some light on this subject area for future scholars.

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