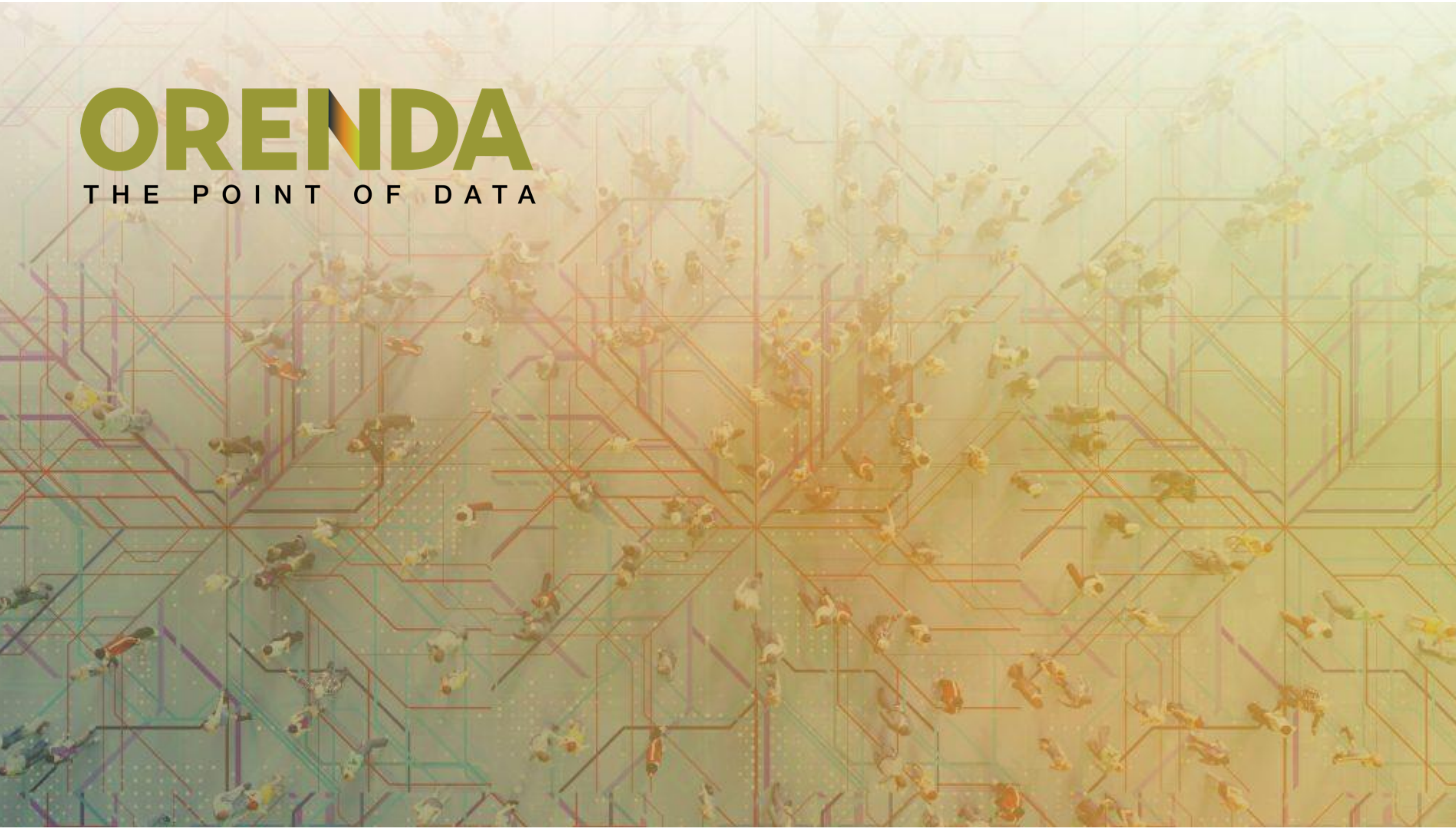

Multifactor Trading Model within the Russell 1000 WHITE PAPER

by ORENDA'S QUANT RESEARCH TEAM

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Multifactor Trading Model within the Russell 1000

Jose Jatar* and Ezequiel Machabanski ** and Tanya Seajay ***

October 27, 2020

Abstract

In this paper, we develop an expansion of Fama and French three-factor model. This was achieved by defining and incorporating Orenda's risk factor, as an efficient measure of corporate social alignment, with the objective of uncovering mispriced securities within the Russell 1,000, for the period of November 18th, 2015 to April 30th, 2020. Our hypothesis proposes that by applying statistical techniques to this newly designed asset pricing model, market participants could capitalize on long and short trading signals achieving superior risk adjusted and absolute returns.

Keywords: Multifactor, social positioning, alternative data, factor investing

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1. Background

Companies that thrive during dynamic times adhere to fundamental values that strengthen relationships with many stakeholders. These values have always been interconnected and are continuously under pressure. As issues emerge, as they always do, these values are tested, and the invariable nature of a company always surfaces.

During the current Global Pandemic, we have seen many great companies giving back to the communities where they do business and ensuring their employees and customers remain safe during difficult times and expecting nothing in return. We have also witnessed the opposite, and the swift reaction bad behavior incites when digitally empowered stakeholders are triggered. Although intricate and nuanced in modern times, the problems we face as a society are not the key determinants of our character, it is how likeminded, compatible, and committed we are when it comes to eradicating these problems. This is where Orenda focuses its technology, uncovering the degree society feels a company's daily and accumulative actions support the collective and widespread goals contained within ESG (Environmental, Social and Governance) ideals.

Social Positioning (noun)
The alignment of a company's values in comparison to the values of its stakeholders and others with interest or influence in its daily activities.

A company's social positioning score is used to compare against the social positioning score of its peers.

The scale Orenda uses to determine alignment between a company and its stakeholders is numerical, making it perfect for financial modeling. We use a 1-5 scale, with one being extremely negative. We extract text and organize it within our Social Positioning framework, and negative phrases such as "the CEO is a liar," erodes the company's score in real time.

The framework Orenda utilizes to calculate a company's social positioning score is shaped by eight fundamental values, such as the level of trust a consumer has that a company will do the right thing. We also include an overall value that encapsulates a company's average score in the eight categories. We ensure the technology remains timeless and adaptable to new and emerging topics of debate and discussion by using these scientifically proven relationship metrics as an effective standard and measurement for analysis. These fixed values provide a true representation of a company's real time alignment and a method of alerting when a company has fallen out of alignment.

Our methodology is purposely unique and effective when it comes to other ESG and Social Positioning data providers. We have proven that relying on company authored ESG reports provides a narrow and sluggish interpretation of the impact a company makes on people, the planet and global prosperity. Due to its nature, company reports may also contain biases or omit concerns. That is why our approach is to connect directly to streaming social media content to rapidly source the issues of the day and to calculate how aligned companies are with the people and the world around them. It all matters. And we prove it.

1 Introduction

Sharpe (1964), Lintner (1965), and Black (1972) provided academia and the financial industry a means of showing the relationship between the average returns on a portfolio or investments and the risk associated with it through their asset pricing models. This came to be known as the Capital Asset Pricing Model, commonly referred to as the CAPM. This asset pricing model predicts that the expected return of any security is a linear function of the risk associated with that investment, where the risk is measured as the covariance between the security's return and the return of the market from which it is drawn.

CAPM is an appealing model because it offers a powerful and intuitive prediction about the expected return and risk of any security. However, as explained by Ericsson and Karlsson (2004), the empirical evidence of the model is mixed. The collection of evidence from the equity markets during the years following the CAPM's development has provided clear indications that this asset pricing model provides an incomplete description of risk. Models incorporating multiple sources of systematic risk are more effective to estimate asset returns.

The ambiguous evidence about CAPM led to the consideration of multifactor asset pricing models, as introduced by Ross (1976) through the Arbitrage Pricing Theory. These asset pricing models suggest that the expected return on a security is a linear function of factor risk premiums and their respective factor sensitivities. The main difference between such multifactor models and CAPM is that they allow for an undetermined number of equally relevant factors.

Arguably the most famous multifactor asset pricing model was presented by Fama and French in which they propose that "many of the CAPM average-return anomalies are related, and they are captured by the three-factor model in Fama and French" (Fama and French, 1996). The model aims to explain returns on securities based on three factors: market premia, SMB and HML. This model has been widely tested and has become a standard tool for empirical studies of securities return. The factors are defined as follow:

- Market premia, computed as $R_M - R_F$, the return on a market value-weighted equity index in excess of the T-bill rate, and represents the equity risk premium, which is also used in the CAPM model.
- SMB (small minus big) a size (market capitalization) factor, SMB is the average return on three small-cap portfolios minus the average return on three large-cap portfolios. SMB represents the premium associated with small-cap stocks.
- HML (high minus low), is the average return on two high book-to-market portfolios minus the average return on two low book-to-market portfolios. HML represents a value return premium.

In this paper, we expand the Fama and French three factor model by incorporating the Orenda Risk Factor. The latter captures the difference in daily returns of a portfolio of high Socially Positioned companies against the returns of a portfolio of low Socially Positioned companies. We define the Orenda Risk Factor in section 4.3 of this paper. By adding this factor, we were able to perform a thorough analysis of the return characteristics of each stock, and more importantly, we used it to introduce statistical techniques that allowed us to use these four factors as the cornerstone of our multifactor trading model.

2 Orenda Social Positioning Scores

2.1. Orenda Background

Orenda Software Solutions was incorporated in 2015, after its founder, Tanya Seajay, completed a 20-year communication experience and social science research journey that concluded in 2014 at McMaster University, located in Hamilton, Ontario. The company's first objective was to leverage existing social science research by creating models that capture market perception of companies and their respective brands.

Orenda launched its first Social Positioning product as a retail solution for marketing managers and C-level executives. It subsequently transitioned into capital markets to close a gap that sentiment and Environmental, Social and Governance (ESG) data providers were not fulfilling. For example, many ESG data vendors supplied a company's self-reported metrics that might not conform with public perception. Orenda reports Social Positioning metrics from the opinion of such public. Many sentiment data vendors quantify fading emotions, such as joy, anger or happiness, lacking the stability and impactful effect on a company's long-lasting reputation. In contrast, Orenda solves this problem by quantifying relationship metrics that are needed to define a company's true Social Positioning among its peers.

2.2. Social Science

Orenda's social science models are based on 8-relationship metrics that were deemed necessary for a healthy relationship to establish and grow (Seajay, 2014). And although all eight metrics are paramount to efficiently assess how stakeholders perceive companies' social positioning, the existence of trust is crucial, as no relationship can exist without it. This builds on a significant body of research, including the six elements of a healthy relationship, as defined by Childers Hon and Grunig (1999). Orenda's relationship metrics include:

1. **Trust**: Measures the amount of integrity, dependability, and competence that the public has in a company and its brand and considers whether people believe that an organization could follow-through and deliver on its promises.
2. **Satisfaction**: Determines the amount of favorability the public expresses about a company and its brand, and measures whether people's expectations with a product or service are positively reinforced by their experiences.
3. **Corporate Social Responsibility**: Measures the level of confidence that people have in a company, in relation to its actions to improve or uphold the social fairness and environmental awareness of society.
4. **Commitment**: Measures the level of dedication that the public has to a company or brand in order to receive their desired benefits, as opposed to filling these needs using other products or services.
5. **Influence**: Analyzes the capacity that a company can affect the opinions of the public, and measures how the public judges a company's leadership, transparency, and authority on

industry topics.

6. **Exchange of Benefits**: Measures the level of reciprocity the public expects from a company for choosing its products or services rather than from competing companies.
7. **Character**: The distinct qualities that the public, according to industry standards, judges the unique traits of a brand in comparison to its competition.
8. **General**: Measures any remaining important social factors that have not been covered in any of the other categories.

Orenda weighs Trust along with the seven remaining relationship metrics to arrive at a company's Overall Social Positioning score. This is achieved by analyzing millions of online conversations, for publicly traded and privately held companies, and processing as well as quantifying such content through Orenda's AI and proprietary dictionaries. Orenda's technology collects content and updates social positioning scores every 10 minutes, providing a total of 144-daily updates per equity. The 10-minute intervals allow Orenda to collect enough content to deliver a statistically meaningful score. The scoring methodology employs a range of 1 to 5, representing an extremely low to extremely high Social Positioning score, respectively. Additionally, Orenda collects the number of conversations each update is comprised of, representing the degree of Social Engagement.

Figure 1 provides a sample Social Positioning dataset for Starbucks (NYSE: SBUX).

FIGI ID	TICKER	COMMITMENT	SOCIAL RESPONSIBILITY	INFLUENCE	EXCHANGE OF BENEFITS	GENERAL	CHARACTER	SATISFACTION	TRUST	OVERALL	GENERATED TIME	COUNTRY
BBG000CTQD87	SBUX	3.0541	3.3162	3.0408	3.0122	2.997	3.2861	3.2143	3.0726	3.1242	2015-03-31T10:30:00.000Z	US
BBG000CTQD87	SBUX	3.0544	3.3157	3.0401	3.0133	2.9964	3.2838	3.214	3.0733	3.1239	2015-03-31T10:40:00.000Z	US
BBG000CTQD87	SBUX	3.0556	3.3161	3.0396	3.0137	2.9977	3.2869	3.2153	3.0746	3.1249	2015-03-31T10:50:00.000Z	US
BBG000CTQD87	SBUX	3.0577	3.319	3.0398	3.0149	2.9993	3.2851	3.2156	3.0752	3.1258	2015-03-31T11:00:00.000Z	US
BBG000CTQD87	SBUX	3.0569	3.3213	3.0416	3.0144	2.9995	3.2926	3.2163	3.0747	3.1272	2015-03-31T11:10:00.000Z	US
BBG000CTQD87	SBUX	3.0568	3.3191	3.0416	3.0151	2.9984	3.291	3.2163	3.0717	3.1262	2015-03-31T11:20:00.000Z	US
BBG000CTQD87	SBUX	3.0581	3.3204	3.0401	3.0158	2.9999	3.2903	3.2181	3.0722	3.1269	2015-03-31T11:30:00.000Z	US
BBG000CTQD87	SBUX	3.0585	3.3212	3.0406	3.0176	3.0003	3.2934	3.2175	3.0701	3.1274	2015-03-31T11:40:00.000Z	US
BBG000CTQD87	SBUX	3.0599	3.3189	3.0395	3.019	2.9993	3.2958	3.2151	3.0703	3.1272	2015-03-31T11:50:00.000Z	US
BBG000CTQD87	SBUX	3.0618	3.3207	3.039	3.0192	3.0017	3.2963	3.2161	3.0711	3.1282	2015-03-31T12:00:00.000Z	US
BBG000CTQD87	SBUX	3.0619	3.322	3.0381	3.0195	3.0019	3.2895	3.2166	3.0696	3.1274	2015-03-31T12:10:00.000Z	US
BBG000CTQD87	SBUX	3.0613	3.3212	3.0398	3.0199	3.002	3.2886	3.2155	3.0693	3.1272	2015-03-31T12:20:00.000Z	US
BBG000CTQD87	SBUX	3.0626	3.3205	3.041	3.0192	3.0019	3.2903	3.2131	3.0698	3.1273	2015-03-31T12:30:00.000Z	US
BBG000CTQD87	SBUX	3.0637	3.3192	3.0418	3.02	2.9989	3.2814	3.2138	3.0627	3.1252	2015-03-31T12:40:00.000Z	US
BBG000CTQD87	SBUX	3.0665	3.3225	3.0432	3.0223	2.9988	3.2776	3.2136	3.0636	3.126	2015-03-31T12:50:00.000Z	US
BBG000CTQD87	SBUX	3.0682	3.3196	3.0436	3.0217	2.997	3.2812	3.2136	3.0643	3.1261	2015-03-31T13:00:00.000Z	US
BBG000CTQD87	SBUX	3.0672	3.3184	3.0434	3.0229	2.995	3.2874	3.2134	3.0645	3.1265	2015-03-31T13:10:00.000Z	US
BBG000CTQD87	SBUX	3.0644	3.3176	3.0413	3.0216	2.9971	3.2859	3.2115	3.0617	3.1251	2015-03-31T13:20:00.000Z	US
BBG000CTQD87	SBUX	3.0641	3.3181	3.0392	3.0223	2.9982	3.2821	3.2108	3.0629	3.1247	2015-03-31T13:30:00.000Z	US
BBG000CTQD87	SBUX	3.0673	3.3207	3.045	3.0286	2.997	3.2851	3.2142	3.0671	3.1281	2015-03-31T13:40:00.000Z	US
BBG000CTQD87	SBUX	3.0645	3.322	3.0431	3.029	2.9982	3.2884	3.2149	3.0651	3.1281	2015-03-31T13:50:00.000Z	US
BBG000CTQD87	SBUX	3.0597	3.3218	3.0438	3.0268	3.0019	3.2949	3.2126	3.0652	3.1283	2015-03-31T14:00:00.000Z	US

Figure 1

3. Orenda Social Positioning and Traditional Risk Factors

Orenda's Risk Factor was developed as a cross sectional variable and it can naturally be incorporated into multifactor models. For the last several decades, debates among capital market participants contemplate if factor loading capture risks or mispricing related to characteristics of individual securities. For example, Daniel and Titman (1997) and Chordia, Goyal, and Shanken (2017) found that high-BM stocks have higher expected returns regardless of their actual distress factor loadings; this implies that high-BM stocks are undervalued—that is, mispriced (Bruce I. Jacobs and Kenneth N. Levy, 2020). Orenda's objective is to introduce a factor that signals when securities are mispriced and provide market participants an opportunity to capitalize on such deviations from intrinsic values.

The ability to discern what is driving stock returns and if it can partially be assigned to a factor that does not conform to traditional factor loading, can represent significant gains. Orenda's unique dataset provides an opportunity to asset managers to introduce in diverse models the ability to discern missed priced securities and act accordingly. "Fama-French model, Jacobs and Levy (1988) developed a cross-sectional model that uses numerous factors to explain stock returns and takes into account their interrelationships. Jacobs and Levy (1988) used cross-sectional regressions at the individual stock level to disentangle multiple equity characteristics, or factors, to estimate the "pure" returns to each factor. Disentangling can reveal which factors really matter; it provides the pure return to each factor, uncontaminated by the effects of other factors" ((Bruce I. Jacobs and Kenneth N. Levy, 2020).

Although the proposed expansion to the Fama and French multifactor model does not contemplate a cross-sectional analysis, throughout this paper, we aimed at discovering mispriced securities by leveraging a globally accepted market asset pricing model. This conveys the message that Orenda's dataset can be easily modelled as a factor for risk loading or understanding security mispricing.

4. Research

4.1. Hypothesis

This research paper contemplates the hypothesis that constructing a trading strategy based on Orenda's expanded multifactor model, it provides superior risk adjusted results when compared to a predefined benchmark (iShares Russell 1000 ETF (NYSE Arca: IWB)) and it yields positive alpha after controlling for traditional market, size, value, investment and profitability risk factors.

4.2. Data & Benchmark Selection

The data for this paper includes end of day closing stock prices for the current and historical constituents of Russell 1,000, from November 2015 to April 2020. This pricing data was obtained from Yahoo Finance. Since the objective of this paper was to derive a short-term trading strategy from our newly expanded asset pricing model, we approached the lagging Fama and French three-factor with the following proxies:

- ***Market Risk (MKT)***: Calculated by obtaining the daily returns of iShares IVV, a market-cap-weighted ETF that tracks the Russell 1,000 performance, then subtracting the yield of the five years treasury bill. Formulaically, it would be represented by (1):

$$Mkt - RF = IVV_{Daily\ Returns} - {}^{\wedge}FVX_{Daily\ Returns} \tag{1}$$

- ***Small minus Big (SMB)***: This factor was computed by calculating the difference in daily returns of iShares IJR, a market-cap-weighted ETF of primarily small-cap US stocks, minus the daily returns of IVV. Formulaically:

$$SMB = IJR_{Daily\ Returns} - IVV_{Daily\ Returns} \tag{2}$$

- ***High minus Low (HML)***: Similarly, HML was computed by obtaining the difference in the daily returns of iShares IVE, a value ETF that tracks the performance of large-cap US stocks, minus the daily returns of iShares IVW, an ETF that tracks the performance of stocks with growth characteristics from the Russell 1,000. Formulaically:

$$HML = IVE_{Daily\ Returns} - IVW_{Daily\ Returns} \tag{3}$$

For the benchmark, it was determined that iShares IWB, a market-cap-weighted ETF that offers exposure to the 1,000 largest US companies, provided all of the desirable features of a suitable benchmark - it is unambiguous, measurable, investable, appropriate, and it was specified prior to developing and testing the model.

4.3. Orenda Risk Factor Design

The risk factor design aimed at introducing simple probability in Orenda's dataset. With this objective in mind, we delineated a model that allowed us to rebalance a paper portfolio quarterly. In our opinion, this provided the minimum amount of time that a security needs to materialize good or bad social positioning actions into stock price performance. Portfolio creation took place on December 31st, 2015 (Q4, 2015). Thereafter, we rebalanced with what is calculated to be highly regarded and socially aligned companies, as dictated by the model detailed below:

First step consisted of averaging monthly Social Positioning (4) scores:

$$Social\ Positioning\ Monthly\ Average = \frac{\sum(Social\ Positioning)_{Month\ t}}{\#\ of\ Days_{\ month\ t}} \tag{4}$$

the change in monthly social positioning (5) for the trailing twelve months. If variation was negative, we simply assigned a -1 (negative one) for that month. If positive, 1 (positive 1) or 0 (zero) if the Social Positioning score remained unchanged from the previous month. For the purpose of this paper, we called this transformation Simple Delta.

$$Simple\ Delta = \ln \frac{(Social\ Positioning\ Average)_{\ t}}{(Social\ Positioning\ Average)_{t-1}} = \{-1, 0, 1\} \tag{5}$$

We proceeded to aggregate the results of (5) into semiannual periods (6). For example, if the second half of calendar 2015, a particular security experienced consecutive monthly positive change in its social positioning score, it would enjoy a score of six. Should the security experience consecutive monthly negative change in its Social Positioning score, the semiannual score would amount to negative six.

$$\begin{aligned} &Semiannual\ Social\ Score \\ &= \sum (Monthly\ Simple\ Delta)_{\ Semiannual\ t} = \{-6 \ldots 6\} \end{aligned} \tag{6}$$

At every rebalancing point, we incorporated into the model the trailing two semiannual periods as quantified in (6). However, we assigned exponential weights giving the most recent semiannual period more importance into the score (7). We fixed the exponential weights at 41.42% & 58.58% for the first and second semiannual periods, respectively. For this paper, we reference (7) as a semiannual weighted social positioning score.

$$\begin{aligned} &Semiannuala\ Weighted\ Social\ Score \\ &= \sum((Semiannual\ Social\ Score_{\,Semiannual\ t-1} * 41.42\%) \\ &+ (Semiannual\ Social\ Score_{\,Semiannual\ t} * 58.58\%)) \end{aligned} \tag{7}$$

We proceeded to compute the weighted probability of each security experiencing an increase in its social positioning score (8) based on the trailing two semiannual periods. For example, if in the last 6 months (the most recent semiannual period), the security's social positioning increased consecutively for 6 months, then its standalone probability would be computed as 6 of 6 or 100%. If it did not increase and only eroded, then it would be 0 of 6 or 0%. We then assigned the same fixed exponential weights, employed earlier, of 41.42% & 58.58% for the first and second semiannual periods, respectively.

$$\begin{aligned} &Weighted\ Probability\ of\ an\ Increase\ in\ Social\ Positioning\ Score \\ &\quad = \sum((\,Standalone\ Probability_{Semiannual\ t-1} \\ &\quad * 41.42\%) + Standalone\ Probability_{Semiannual\ t} \\ &\quad * 58.58\%) \end{aligned} \tag{8}$$

The final step consisted of computing the product of the Semiannual Weighted social positioning (7) and the Weighted Probability of an Increase in social positioning (8) to arrive at what we refer to as the social positioning risk factor for security selection.

$$\begin{aligned} &Orenda\ Risk\ Factor \\ &\quad = (Semiannual\ Weighted\ Social\ Positioning \\ &\quad * Weighted\ Probability) \end{aligned} \tag{9}$$

While the Orenda risk factor is designed to produce security selections every six months, we computed the daily returns of these selections since November 2015 until April 2020 and introduced them into our multiple regression models to test for empirical alpha.

We have also defined the Orenda Risk factor by applying other statistical techniques, such as Monte Carlo Simulation with the intent of modelling social positioning, a proxy for sentiment, as a stochastic process. The idea behind this technique is that asset pricing models should be centered around the role of sentiment and, according to theory, this variable should be modeled as a stochastic process.

As proposed by Shefrin in his work titled "A Behavioral Approach to Asset pricing" (2008), he presents that asset pricing models incorporating sentiment could be decomposed into a stochastic process, pertaining to sentiment, meaning that market prices are efficient only if sentiment is uniformly zero. The notion of sentiment being zero is refuted by our data, statistical analysis, and financial models.

4.4. Model Design

Orenda's expanded multifactor asset pricing model contemplates market, size and value premia with the addition of Orenda's risk premia (10).

$$\begin{aligned} R_t - R_{f,t} = \alpha_{ff4} + \widehat{\beta_{mkt}}\left(R_{mt} - R_{ft}\right) + \widehat{\beta_{smb}}(SMB_t) \\ + \widehat{\beta_{hml}}(HML_t) + \widehat{\beta_{Orenda}}(Orenda_t) \end{aligned} \tag{10}$$

The traditional Fama and French factors were computed as previously presented in section 4.2 and Orenda's risk factor as computed under section 4.3. Orenda's portfolio of highly socially aligned companies were selected as the top 10% of the factor distribution while the poorly socially aligned companies formed the bottom 10% of the factor distribution.

We applied our expanded asset pricing model to all constituents of the Russell 1,000. We ran daily regressions comparing the daily returns for each constituent against the four independent factors and collected statistics from such regressions. For example, model coefficients, standard errors, t-statistics and more importantly, p-values on a daily basis. We then focused on the p-value statistic for each variable.

Subsequently, we analyzed the p-value of each regression to understand what the driving factors for stock returns were. We considered a p-value below 5%, for Orenda risk factor, to signal the presence of a Social Position premia attached to a particular security as a proxy for sentiment.

After considering the p-values for each of the four independent variables, we calculate the average for each factor for the last 100 days. We also tested the previous day, the average of the last 10, 20 and 30 days, and concluded that a 100-day average smooths the trend in the observed factor, and the model appears to perform better as more data was included in the computation of these parameters.

The following equation was applied to each one of the four independent variables:

$$If\ P_{value\ at\ t-1} \leq 0.05 = X_{avg\ last\ 100\ days} * \beta_{t-1} \tag{11}$$

Where X stands for the actual factor value, for example, the actual premium associated with small cap stocks when compared to large capitalization stocks for the last 100 days. β stands for the coefficients collected from the regression of that variable, and as indicated in the formula and earlier in this section, we used the previous day value of the coefficients. And finally, we only applied this formula when the p-value was less than or equal to 5%.

4.5. Selection Methodology

Considering that this is a short-term strategy, the model generated selections on a daily basis in both directions of the market, that is, each day buy and sell signals were produced by the model. There were no fixed number of selections, since this depended extensively on the overall market environment. For example, when we looked at the second quarter of 2019, specifically on the date 04/30/2020, the model generated 339 long signals, and 81 shorts. During this time, the overall conditions in the market were good and we were in the middle of great bull run. On the other hand, when we looked to the first quarter of 2020, when COVID-19 had major impact on global markets, our model produced a significant number of shorts prior to this time period.

The process of selecting securities that would be traded was relatively straightforward. Our model output allowed us to identify which factors were statistically meaningful and arrive at a required rate of return (RRR). This could be either negative or positive representing a premium or discount. When the required rate of return was negative, we generated a long signal for that stock and when positive, a short signal was produced. Notably, we only generated signals when the Orenda risk factor p-value was below 5%, as an indication that social positioning was least partially driving stock returns.

5. Empirical Evidence, Performance and Results

This section presents the empirical evidence, performance and risk adjusted results for the long-short strategy compares the results against the benchmark. Results reflect those of paper portfolios, assuming no transactions costs.

To validate the existence of positive alpha in the proposed model, after controlling for traditional factors, we employed time-series regressions on Orenda's long-short strategy's daily excess returns against the Fama-French 5 factors model. We decided to use the five factors model in our regressions because it added profitability and investment premiums to the traditional three factor model. Formulaically, it would be represented by the following equation:

$$R_{Orenda,t} - R_{f,t} = \alpha_{ff5} + \widehat{\beta_{mkt}}(R_{mt} - R_{ft}) + \widehat{\beta_{smb}}(SMB_t) + \widehat{\beta_{hml}}(HML_t) + \widehat{\beta_{rmw}}(RMW_t) + \widehat{\beta_{cma}}(CMA_t)\ e_{it} \tag{12}$$

Table 1 captures the coefficients estimates of Fama and French 5 factor model against the long-short strategy's daily excess return for the period of November 18th, 2015 to April 30th, 2020. As observed, Jensen's (daily) alpha is positive and significant a 95% confidence level (P-value of 0.005). The table also shows that this strategy's returns are slightly negatively correlated with market returns as measured by the statistically meaningful market beta of -0.1059.

LONG-SHORT REGRESSION OUTPUT	COEFFICIENTS	STD ERR	T	P>|T|	[0.025	0.975]
(INTERCEPT)	0.0005	0.0000	2.7910	0.0050	0.0000	0.0010
MKT-RF	-0.1059	0.0160	-6.6170	0.0000	-0.1370	-0.0750
SMB	-0.0078	0.0320	-0.2420	0.8090	-0.0710	0.0560
HML	-0.0791	0.0330	-2.3830	0.0170	-0.1440	-0.0140
RMW	-0.0746	0.0500	-1.4820	0.1390	-0.1730	0.0240
CMA	-0.0494	0.0620	-0.7950	0.4270	-0.1720	0.0730
No. Observations: 1117	R-squared: 0.059			F-statistic: 13.87		
	Adjusted R-squared: 0.055			Durbin-Watson: 1.938		

Table 1

Additionally, we computed the annualized Sharpe ratio for the predefined benchmark, and the long-short strategy, for the period of November 18th, 2015 to April 30th, 2020. Table 2 summarizes our findings.

LONG-SHORT	BENCHMARK (IWB)
1.251399	0.623049

Table 2

Figure 2 shows the performance of $1 invested in our long-short strategy since November 18th, 2015 until April 30th, 2020. As can be seen from the graph and the table, our long-short strategy beat the benchmark in both relative and absolute terms. $1 invested in such strategy at the beginning of this back-test period, would have reached $1.69, while a buy and hold strategy of the ETF IWB (benchmark) would have ended with $1.59. Although our long-short strategy has modestly outperformed the benchmark on absolute basis, the risk adjusted results have materially outperformed, with a Sharpe ratio of 1.25, while the benchmark produced 0.62.

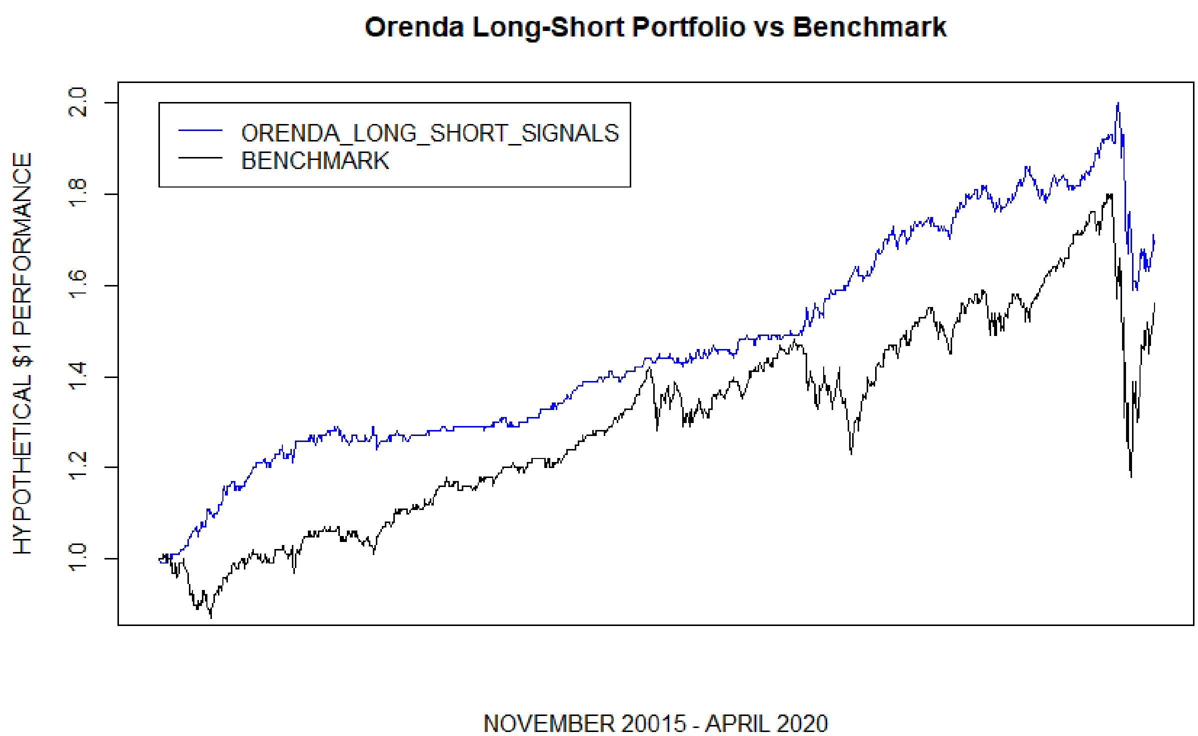

Figure 2

The long-short strategy is suitable for investors that want to reduce their exposure to the overall direction of the market, meaning that investors are equally likely to have long or short positions, depending on the overall market environment. This strategy aims for a correlation with the market as close as possible to 0, commonly known as Beta neutral. The regression output shows a correlation with the market close to 0 and negative, represented by the coefficient of -0.1059.

Although the long-short strategy might be attractive for institutional investors, asset managers, or hedge funds; generally speaking, most of the time investors would want to have long exposure, accordingly, we developed a long only strategy to satisfy this need. This strategy consists of buying on a daily basis the stocks that, according to the model, should see a positive return on the next day, hold them for one day and then liquidate such positions.

Similarly, to our long-short portfolio, we tested the long only strategy for empirical alpha after controlling for Fama-French five factors. Alpha is meaningful and positive at the 90% confidence interval, as showed in Table 3.

LONG REGRESSION OUTPUT	COEFFICIENTS	STD ERR	T	P>|T|	[0.025	0.975]
(INTERCEPT)	0.0008	0.0000	1.8310	0.0670	-0.0001	0.0020
MKT-RF	-0.2160	0.0370	-5.8890	0.0000	-0.2880	-0.1440
SMB	0.0968	0.0740	1.3030	0.1930	-0.0490	0.2430
HML	-0.0852	0.0760	-1.1200	0.2630	-0.2340	0.0640
RMW	0.1571	0.1150	1.3620	0.1740	-0.0690	0.3840
CMA	-0.1493	0.1430	-1.0470	0.2950	-0.4290	0.1300
NO. OBSERVATIONS: 1117	R-squared: 0.039			F-statistic: 8.976		
	Adjusted R-squared: 0.035			Durbin-Watson: 1.917		

Table3

Table 4 describes the performance of the long strategy against its benchmark on relative terms, meaning that we adjusted the annualized returns of both strategies by their respective annualized standard deviation. The long-only strategy has materially outperformed the benchmark.

LONG STRATEGY	BENCHMARK (IWB)
0.801705	0.623049

Table 4

Figure 3 shows the absolute performance of $1 invested in three different strategies. The red line represents the performance of the long only strategy, the blue line shows the long-short strategy, and the black line is the benchmark, representing the ETF IWB. The long only strategy produced the best performance among the three strategies on absolute terms. A $1 in the long portfolio on November of 2015, would have produced $1.99, compared to $1.69 and $1.56 for the long-short and benchmark, respectively.

As we can determine from this entire section, regardless of the strategy chosen, either long-short or long-only, both beat the benchmark on risk adjusted and absolute terms, and more importantly, validated at the 95% and 90% confidence levels, that such strategies produced empirical alpha after controlling for the Fama and French five factors model.

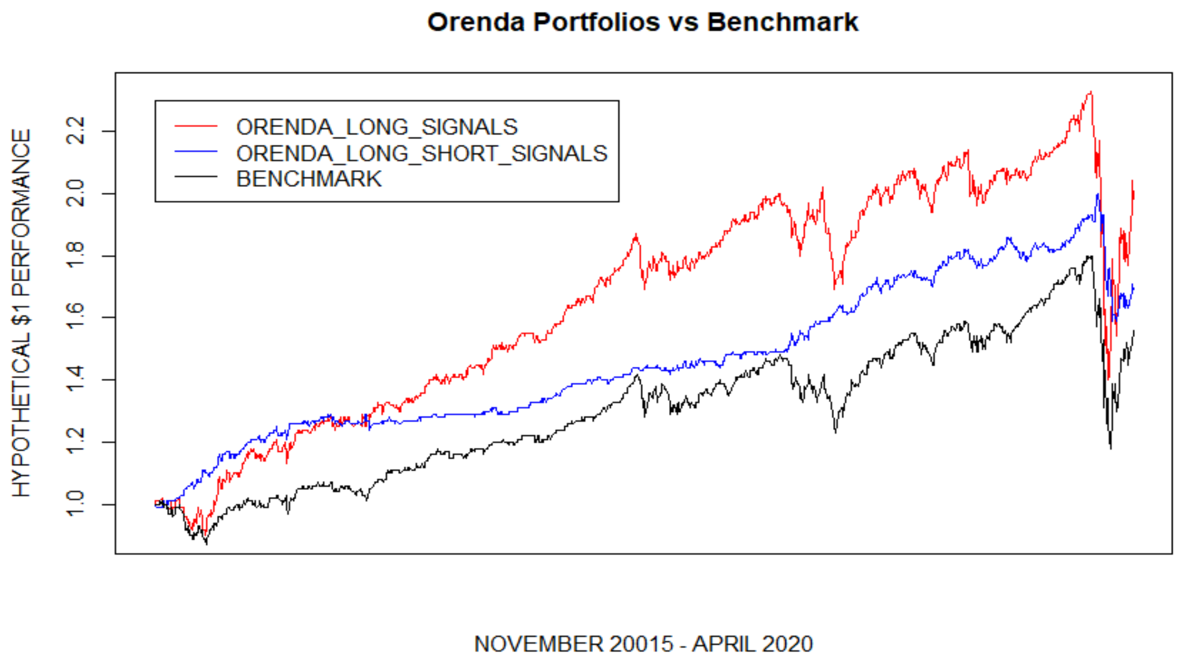

Figure 3

6. Conclusion

In the long run, valuations may drive stocks prices, but in the short-term, it is sentiment that moves prices. This creates investment opportunities for market participants that can identify whether a stock's return is partially driven by sentiment or not. This is where Orenda's data plays a critical role, as we can produce high-frequency data reflecting the social positioning of publicly traded companies.

Companies that are well-positioned in our social positioning rankings are considered worthy investments and having the ability to segregate those that enjoy a robust social positioning rating from companies that are considered unethical can lead to profitable trading strategies. Generally speaking, investors select securities according to how they feel about the stocks they choose to purchase, hold, sell, or ignore. For some investors, feeling good about a stock entails a concordance between the investor's personal values and characteristics of the company that correspond to those values. In this respect, financial portfolios bring both financial benefits and psychological benefits. An important challenge is to find a systematic way to quantify investors' values and the way they evaluate securities through the lens of those values. However, employing social positioning data for asset selection is challenging to say the least. Market participants are faced with unconsolidated, biased and outdated social positioning datasets that may not be accurate or modeled systematically.

Orenda addressed this problem directly by generating high frequency social positioning data from the perspective of the communities where these corporations are conducting business. As people issue opinions or statements on how corporations are behaving socially, with regards to the planet, Orenda quantifies this content in real time by employing a simple scoring methodology. This allows asset managers to introduce our datasets systematically for security selection, portfolio construction and alpha generation.

The multifactor factor model presented in this paper, is just one of the many forms Orenda's data could take to reflect the fact that sentiment is driving, partially, the returns of many stocks in the market. The two portfolios that we developed in this paper, the long-short and long-only strategies, both provided alpha after controlling for Fama and French 5 factors, which include market, size, value, profitability and investment premiums. Based on the statistical results, we were able to use Orenda's high frequency data to generate daily security selection for a period of almost five years and beat the benchmark on a risk adjusted and absolute basis in both strategies.

Both portfolios shown in this paper are short-term trading strategies that could be attractive to institutional investors, hedge funds, or asset managers in general that would like to move in and out of positions relatively quickly, and that are concerned about the long-term trend of the market as a whole.

More importantly, this is an evolving space and there is still room for improvement. This is a technique that can be effectively used to complement fundamental, quantitative, and/or technical analysis. As demonstrated in this paper, this model can be used by capital market participants as a stand-alone tool for investment decisions.

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