101 Formulaic Alphas

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Abstract
We present explicit formulas – that are also computer code – for 101 real-life quantitative trading alphas. Their average holding period ranges from approximately 0.6 to 6.4 days. The average pairwise correlation of these alphas is low, at 15.9 percent. The returns are strongly correlated with volatility, but have no significant dependence on turnover, directly confirming an earlier result based on a more indirect empirical analysis. We further find empirically that turnover has poor explanatory power for alpha correlations.

Keywords
formulaic alpha, turnover, cents-per-share, volatility, quantitative trading, correlation

1. Introduction
There are two complementary – and in some sense even competing – trends in modern quantitative trading. On the one hand, more and more market participants (e.g., quantitative traders, inter alia) employ sophisticated quantitative techniques to mine alphas.[1] This results in ever fainter and more ephemeral alphas. On the other hand, technological advances allow us to essentially automate (much of) the alpha-harvesting process. This yields an ever-increasing number of alphas, whose count can be in the hundreds of thousands or even millions, and with the exponentially increasing progress in this field will likely be in the billions before we know it…

This proliferation of alphas – albeit mostly faint and ephemeral – allows combining them in a sophisticated fashion to arrive at a unified "mega-alpha." It is then this "mega-alpha" that is actually traded – as opposed to trading individual alphas – with the bonus of automatic internal crossing of trades (and thereby crucial-for-profitability savings on trading costs, etc.), alpha portfolio diversification (which hedges against any subset of alphas going bust in any given time period), and so on. One of the challenges in combining alphas is the usual "too many variables, too few observations" dilemma. Thus, the alpha sample covariance matrix is badly singular.

Also, naturally, quantitative trading is a secretive field and data and other information from practitioners is not readily available. This inadvertently creates an enigma around modern quant trading. For example, with such a large number of alphas, are they not highly correlated with each other? What do these alphas look like? Are they mostly based on price and volume data, mean-reversion, momentum, etc.? How do alpha returns depend on volatility, turnover, etc.?

In a previous paper, Kakushadze and Tulchinsky (2016) took a step toward demystifying the realm of modern quantitative trading by studying some empirical properties of 4000 real-life alphas. In this paper we take another step and present explicit formulas – that are also computer code – for 101 real-life quant trading alphas. Our formulaic alphas – albeit most are not necessarily all that "simple" – serve the purpose of giving the reader a glimpse into what some of the simpler real-life alphas look like.[2] They also enable the reader to replicate and test these alphas on historical data and do new research and other empirical analyses. Hopefully, they will further inspire (young) researchers to come up with new ideas and create their own alphas.

We discuss some general features of our formulaic alphas in Section 2. These alphas are mostly "price–volume" (daily close-to-close returns, open, close, high, low, volume, and vwap[3])-based, albeit "fundamental" input is used in some of the alphas, including one alpha utilizing market cap, and a number of alphas employing some kind of binary industry classification such as GICS, BICS, NAICS, SIC,[4] etc., which are used to industry-neutralize various quantities.[5]

We discuss the empirical properties of our alphas in Section 3 based on data for individual alpha Sharpe ratio, turnover, and cents-per-share, and also on a sample covariance matrix. The average holding period ranges from approximately 0.6 to 6.4 days. The average (median) pairwise correlation of these alphas is low, at 15.9 percent (14.3 percent). The returns R are strongly correlated with the volatility V and, as in Kakushadze and Tulchinsky (2016), we find an empirical scaling

$$R \sim V^X \tag{1}$$

with $X \approx 0.76$ for our 101 alphas. Furthermore, we find that the returns have no significant dependence on the turnover T. This is direct confirmation of an earlier result by Kakushadze and Tulchinsky (2016), which is based on more indirect empirical analysis.[6]

We further find empirically that the turnover per se has poor explanatory power for alpha correlations. This is not to say that the turnover does not add value in, e.g., modeling the covariance matrix via a factor model.[7] A more precise statement is that pairwise correlations Ψ_{ij} of the alphas (where $i, j, = 1, \ldots, N$ label the N alphas, $i \neq j$) are not highly correlated with the product $\ln(\tau_i)\ln(\tau_j)$, where $\tau_i = T_i/\mu$ and μ is an a priori arbitrary normalization constant.[8]

We briefly conclude in Section 4. Appendix A contains our formulaic alphas with definitions of the functions, operators, and input data used therein. Appendix B contains some legalese.

2. Formulaic alphas

In this section we describe some general features of our 101 formulaic alphas. The alphas are proprietary to WorldQuant LLC and are used here with its express permission. We provide as many details as we possibly can within the constraints imposed by the proprietary nature of the alphas. The formulaic expressions – that are also computer code – are given in Appendix A.

Very coarsely, one can think of alpha signals as based on mean-reversion or momentum.[9] A mean-reversion alpha has a sign opposite to the return on which it is based. For example, a simple mean-reversion alpha is given by

$$-\ln(\text{today's open} / \text{yesterday's close}) \tag{2}$$

Here, yesterday's close is adjusted for any splits and dividends if the ex-date is today. The idea (or hope) here is that the stock will mean-revert and give back part of the gains (if today's open is higher than yesterday's close) or recoup part of the losses (if today's open is lower than yesterday's close). This is a so-called "delay-0" alpha. Generally, "delay-0" means that the time of some data (e.g., a price) used in the alpha coincides with the time during which the alpha is intended to be traded. For example, alpha (2) would ideally be traded at or, more realistically, as close as possible to today's open. More broadly, this can be some other time, e.g., the close.[10]

A simple example of a momentum alpha is given by

$$\ln(\text{yesterday's close} / \text{yesterday's open}) \tag{3}$$

Here it makes no difference if the prices are adjusted or not. The idea (or hope) is that if the stock ran up (slid down) yesterday, the trend will continue today and the gains (losses) will be increased further. This is a so-called "delay-1" alpha if the intent is to trade it today (e.g., starting at the open).[11] Generally, "delay-1" means that the alpha is traded on the day subsequent to the date of the most recent data used in computing it. A "delay-*d*" alpha is defined similarly, with *d* counting the number of days by which the data used is out-of-sample.

In complex alphas, elements of mean-reversion and momentum can be mixed, making them less distinct in this regard. However, one can think of smaller building blocks of such alphas as being based on mean-reversion or momentum. For instance, Alpha#101 in Appendix A is a delay-1 momentum alpha: if the stock runs up intraday (i.e., close > open and high > low), the next day one takes a long position in the stock. In contrast, Alpha#42 in Appendix A essentially is a delay-0 mean-reversion alpha: rank(vwap – close) is lower if a stock runs up in the second half of the day (close > vwap) as opposed to sliding down (close < vwap). The denominator weights down richer stocks. The "contrarian" position is taken close to the close.

3. Data and empirical properties of alphas

In this section we describe empirical properties of our formulaic alphas based on data proprietary to WorldQuant LLC, which is used here with its express permission. We provide as many details as possible within the constraints of the proprietary nature of this dataset.

For our alphas we take the annualized daily Sharpe ratio S, daily turnover T, and cents-per-share C. Let us label our alphas by the index i ($i = 1, \ldots, N$), where $N = 101$ is the number of alphas. For each alpha, S_i, T_i and C_i are defined via

$$S_i = \sqrt{252}\,\frac{P_i}{V_i} \tag{4}$$

$$T_i = \frac{D_i}{I_i} \tag{5}$$

$$C_i = 100\,\frac{P_i}{Q_i} \tag{6}$$

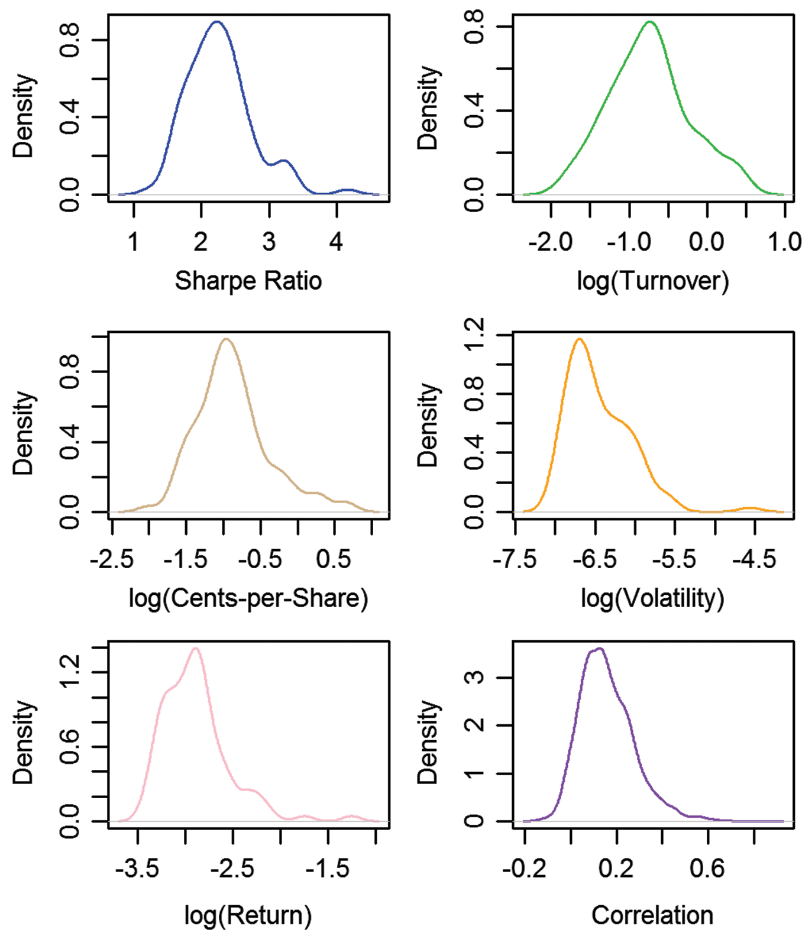
Here: P_i is the average daily profit and loss (P&L, in dollars); V_i is the daily portfolio volatility; Q_i is the average daily shares traded (buys plus sells) by the ith alpha; D_i is the average daily dollar volume traded; and I_i is the total dollar investment in said alpha (the actual long plus short positions, without leverage). More precisely, the principal of I_i is constant; however, I_i fluctuates due to the daily P&L. So, both D_i and I_i are adjusted accordingly (such that I_i is constant) in Equation (4). The period of time over which this data is collected is Jan 4, 2010–Dec 31, 2013. For the same period we also take the sample covariance matrix Υ_{ij} of the realized daily returns for our alphas. The number of observations in the time series is 1006, and Υ_{ij} is nonsingular. From Υ_{ij} we read off the daily return volatility $\sigma_i^2 = \Upsilon_{ii}$ and the correlation matrix $\Psi_{ij} = \Upsilon_{ij} / \sigma_i \sigma_j$ (where $\Psi_{ii} = 1$). Note that $V_i = \sigma_i I_i$ and the average[12] daily return is given by $R_i = P_i / I_i$.

Table 1 and Figure 1 summarize the data for the annualized Sharpe ratio S_i, daily turnover T_i, average holding period $1/T_i$, cents-per-share C_i, daily return volatility σ_i, annualized average daily return $\widetilde{R}_i = 252\, R_i$, and $N(N-1)/2$ pairwise correlations Ψ_{ij} with $i > j$.

Table 1: Summary (using the R function `summary()`) for the annualized Sharpe ratio S_i, daily turnover T_i, average holding period $1/T_i$, cents-per-share C_i, daily return volatility σ_i, annualized average daily return $\widetilde{R}_i$, and pairwise correlations Ψ_{ij} with $i > j$ (see Section 3). The performance figures are exclusive of any trading or transaction costs, price impact, etc.

Quantity	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
S	1.238	1.929	2.224	2.265	2.498	4.162
T	0.1571	0.3429	0.4752	0.5456	0.6474	1.604
$1/T$	0.6235	1.545	2.104	2.391	2.916	6.365
C	0.1324	0.3125	0.3969	0.4814	0.5073	2.031
$10^3 \times \sigma$	0.9318	1.194	1.395	1.747	2.019	10.44
$100\% \times \widetilde{R}$	3.285	4.4	5.441	6.015	6.296	28.72
$100\% \times \Psi_{ij}$	–15.09	7.457	14.31	15.86	22.91	87.33

Figure 1: Density (using the R function `density()`) plots for the annualized Sharpe ratio S_i, daily turnover T_i, cents-per-share C_i, daily return volatility σ_i, annualized average daily return $\widetilde{R}_i$, and pairwise correlations Ψ_{ij} with $i > j$ (see Table 1 and Section 3). The "extreme" outliers in S_i, σ_i and $\widetilde{R}_i$ are due to the delay-0 alphas (see Section 2).



3.1 Return vs. volatility and turnover

We run two cross-sectional regressions, both with the intercept, of $\ln(R_i)$ over (i) $\ln(\sigma_i)$ as the sole explanatory variable and (ii) $\ln(\sigma_i)$ and $\ln(T_i)$. The results are summarized in Tables 2 and 3. Consistent with Kakushadze and Tulchinsky (2016), we have no statistically significant dependence on the turnover T_i here, while the average daily return R_i is strongly correlated with the daily return volatility σ_i and we have the scaling property (1) with $X \approx 0.76$.

3.2 Does turnover explain correlations?

If we draw a parallel between alphas and stocks, then alpha turnover is analogous to stock liquidity, which is typically measured via an average daily dollar volume (ADDV).[13] The log of ADDV is routinely used as a style risk factor[14] in multifactor risk models[15] for approximating the stock portfolio covariance matrix structure, whose chief goal is to model the off-diagonal elements of the covariance matrix, that is, the pairwise correlation structure.[16] Following this analogy, we can ask if the turnover – or more precisely its log – has explanatory power for modeling alpha correlations.[17] It is evident that using the turnover directly (as opposed to its log) would get us nowhere due to the highly skewed (roughly log-normal) turnover distribution (see Figure 1).

Table 2: Summary (using the R function `summary(lm())`) for the cross-sectional regression of ln(*R*) over ln(σ) with the intercept. See Subsection 3.1 for details; also see Figure 2

	Estimate	Standard error	*t*-Statistic	Overall
Intercept	−3.509	0.295	−11.88	
ln(σ)	0.761	0.046	16.65s	
Mult./adj. *R*-squared				0.737 / 0.734
F-statistic				277.2

Table 3: Summary for the cross-sectional regression of ln(*R*) over ln(σ) and ln(*T*) with the intercept. See Subsection 3.1 for details

	Estimate	Standard error	*t*-Statistic	Overall
Intercept	−3.435	0.324	−10.60	
ln(σ)	0.775	0.052	14.84	
ln(*T*)	−0.023	0.040	−0.57	
Mult./adj. *R*-squared				0.738 / 0.732
F-statistic				137.8

To answer this question, recall that in a factor model the covariance matrix is modeled via

$$\Gamma_{ij} = \xi_i^2 \delta_{ij} + \sum_{A,B=1}^{K} \Omega_{iA} \varphi_{AB} \Omega_{jB} \qquad (7)$$

Here: ξ_i^2 is the specific risk; Ω_{iA} is an $N \times K$ factor-loadings matrix corresponding to $K \ll N$ risk factors; and φ_{AB} is a factor-covariance matrix. In our case, we are interested in modeling the correlation matrix Ψ_{ij} and ascertaining whether the turnover has explanatory power for pairwise correlations. Whether the volatility and turnover are correlated is a separate issue.

So, our approach is to take one of the columns of the factor-loadings matrix as $\ln(T_i)$. More precisely, a priori there is no reason why we should pick $\ln(T_i)$ as opposed to $\ln(\tau_i)$, where $\tau_i = T_i / \mu$ and μ is some normalization factor. To deal with this, let us normalize τ_i such that $\ln(\tau_i)$ has zero cross-sectional mean, and let $v_i = 1$ be the unit N-vector (the intercept). Then we can construct three symmetric tensor combinations $x_{ij} = v_i v_j$, $y_{ij} = v_i \ln(\tau_j) + v_j \ln(\tau_i)$, and $z_{ij} = \ln(\tau_i)\ln(\tau_j)$. Let us now define a composite index $\{a\} = \{(i,j) | \, i > j\}$, which takes $M = N(N-1)/2$ values (i.e., we pull the off-diagonal lower-triangular elements of a general symmetric matrix G_{ij} into a vector G_a). This way we can construct four M-vectors Ψ_a, x_a, y_a, and z_a. Now we can run a linear regression of Ψ_a over x_a, y_a and z_a. Note that $x_a = 1$ is simply the intercept (the unit M-vector), so this is a regression of Ψ_a over y_a and z_a with the intercept. The results are summarized in Table 4. It is evident that the linear and bilinear (in $\ln(\tau_i)$) variables y_a and z_a have poor explanatory power for pairwise correlations Ψ_a, while x_a (the intercept) simply models the average correlation Mean(Ψ_a). Recall that by construction, y_a and z_a are orthogonal to x_a, and these three explanatory variables are independent of each other.

Let us emphasize that our conclusion does not necessarily mean that the turnover adds no value in the factor-model context, it only means that the turnover per se

Figure 2: Horizontal axis: $\ln(\sigma)$; vertical axis: $\ln(R)$. The dots represent the data points. The straight line plots the linear regression fit $\ln(R) \approx -3.509 + 0.761 \ln(\sigma)$. See Table 2.

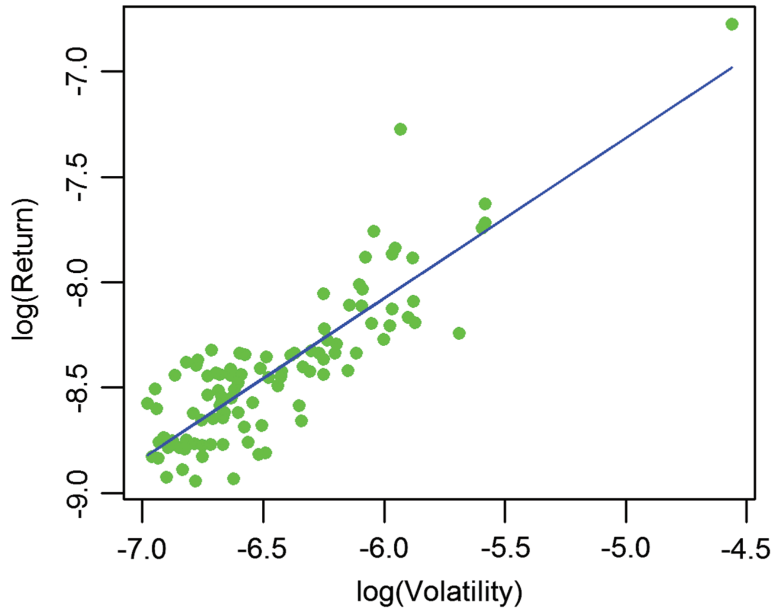


Table 4: Summary for the cross-sectional regression of Ψ_a over y_a and z_a with the intercept. See Subsection 3.2 for details; also see Figure 3.

	Estimate	Standard error	*t*-Statistic	Overall
Intercept	0.1587	0.0017	95.18	
y_a	0.0067	0.0023	2.907	
z_a	0.0474	0.0063	7.537	
Mult./adj. *R*-squared				0.0127 / 0.0123
F-statistic				32.55

Table 5: Summary for the cross-sectional regression of $\ln(\sigma)$ over $\ln(T)$ with the intercept. See Subsection 3.2 for details; also see Figure 4.

	Estimate	Standard error	*t*-Statistic	Overall
Intercept	−6.174	0.062	−100.1	
$\ln(T)$	0.368	0.068	5.412	
Mult./adj. *R*-squared				0.228 / 0.221
F-statistic				29.29

does not appear to help in modeling pairwise alpha correlations. The above analysis does not address whether the turnover adds explanatory value to modeling variances, e.g., the specific risk.[18] Thus, a linear regression of $\ln(\sigma)$ over $\ln(T)$ (with the intercept) shows nonzero correlation between these variables (see Table 5), albeit not very strong. To see if the turnover adds value via, e.g., the specific risk requires using certain proprietary methods beyond the scope of this paper.[19]

Figure 3: Horizontal axis: $w_a = 0.0067\, y_a + 0.0474\, z_a$; vertical axis: Ψ_a – Mean(Ψ_a). See Table 4 and Subsection 3.2. The numeric coefficients are the regression coefficients in Table 4.

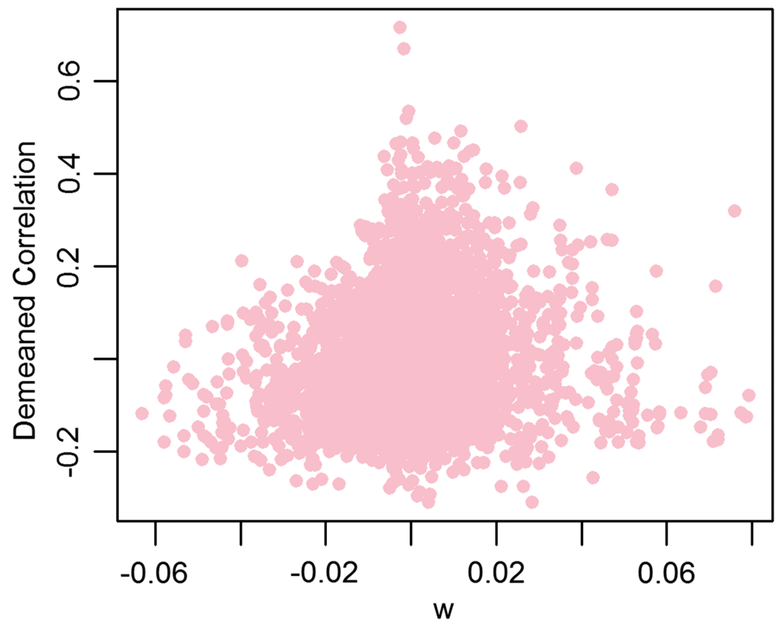
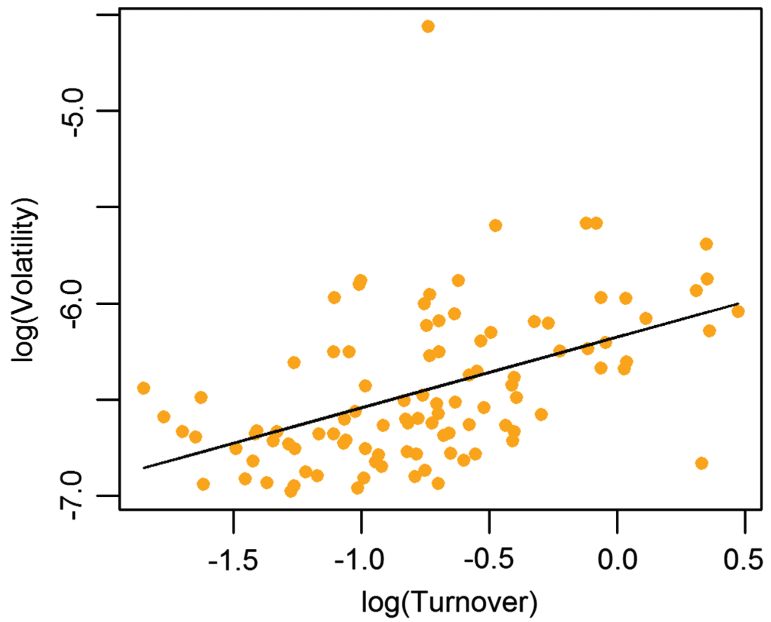


Figure 4: Horizontal axis: $\ln(T)$; vertical axis: $\ln(\sigma)$. The dots represent the data points. The straight line plots the linear regression fit $\ln(\sigma) \approx -6.174 + 0.368 \ln(T)$. See Table 5.



4. Conclusions

We emphasize that the 101 alphas we present here are not "toy" alphas but real-life trading alphas used in production. In fact, 80 of these alphas are in production as of this writing.[20] To our knowledge, this is the first time that such a large number of real-life explicit formulaic alphas has appeared in the literature. This should come as no surprise: naturally, quant trading is highly proprietary and secretive. Our goal here is to provide a glimpse into the complex world of modern and ever-evolving quantitative trading and help demystify it, to any degree possible.

Technological advances nowadays allow the automation of alpha mining. Quantitative trading alphas are by far the most numerous of the available trading signals that can be turned into trading strategies/portfolios. There are myriad permutations of individual stock holdings in a (dollar-neutral) portfolio of, e.g., 2000 most-liquid US stocks that can result in a positive return on high- and mid-frequency time horizons. In addition, many of these alphas are ephemeral and their universe is very fluid. It takes quantitatively sophisticated, technologically well-endowed, and ever-adapting trading operations to mine hundreds of thousands, millions, or even billions of alphas and combine them into a unified "mega-alpha," which is then traded with the added bonus of sizeable savings on execution costs due to automatic internal crossing of trades.

In this spirit, we end this paper with an 1832 poem by the Russian poet Mikhail Lermontov (translated from the Russian):

The Sail

A lonely sail seeming white,
In misty haze mid blue sea,
Be foreign gale seeking might?
Why home bays did it flee?

The sail's bending mast is creaking,
The wind and waves blast ahead,
It isn't happiness it's seeking,
Nor is it happiness it's fled!

Beneath are running ázure streams,
Above are shining golden beams,
But wishing storms the sail seems,
As if in storms is peace it deems.

Appendix A: Formulaic alphas

In Subsection A.1 we provide our 101 formulaic alphas. The formulas are also code once the functions and operators are defined. The functions and operators used in the alphas are defined in Subsection A.2. The input data is elaborated upon in Subsection A.3. The code in Subsection A.1 is in a proprietary coding language. Readers unfamiliar with this language can port the formulas in Subsection A.1 into the language of their own choosing (e.g., R, Python, etc.) by simply porting the underlying functions and operators defined in Subsection A.2. This is the beauty of formulaic alphas – they are readily portable.

A.1 Formulaic expressions for alphas

```
Alpha#1: (rank(Ts_ArgMax(SignedPower(((returns < 0) ? stddev(returns, 20) : close), 2.), 5)) - 0.5)
Alpha#2: (-1 * correlation(rank(delta(log(volume), 2)), rank(((close - open) / open)), 6))
Alpha#3: (-1 * correlation(rank(open), rank(volume), 10))
Alpha#4: (-1 * Ts_Rank(rank(low), 9))
Alpha#5: (rank((open - (sum(vwap, 10) / 10))) * (-1 * abs(rank((close - vwap)))))
Alpha#6: (-1 * correlation(open, volume, 10))
Alpha#7: ((adv20 < volume) ? ((-1 * ts_rank(abs(delta(close, 7)), 60)) * sign(delta(close, 7))) : (-1 * 1))
Alpha#8: (-1 * rank(((sum(open, 5) * sum(returns, 5)) - delay((sum(open, 5) * sum(returns, 5)), 10))))
Alpha#9: ((0 < ts_min(delta(close, 1), 5)) ? delta(close, 1) : ((ts_max(delta(close, 1), 5) < 0) ? delta(close, 1) : (-1 * delta(close, 1))))
Alpha#10: rank(((0 < ts_min(delta(close, 1), 4)) ? delta(close, 1) : ((ts_max(delta(close, 1), 4) < 0) ? delta(close, 1) : (-1 * delta(close, 1)))))
Alpha#11: ((rank(ts_max((vwap - close), 3)) + rank(ts_min((vwap - close), 3))) * rank(delta(volume, 3)))
Alpha#12: (sign(delta(volume, 1)) * (-1 * delta(close, 1)))
Alpha#13: (-1 * rank(covariance(rank(close), rank(volume), 5)))
Alpha#14: ((-1 * rank(delta(returns, 3))) * correlation(open, volume, 10))
Alpha#15: (-1 * sum(rank(correlation(rank(high), rank(volume), 3)), 3))
Alpha#16: (-1 * rank(covariance(rank(high), rank(volume), 5)))
Alpha#17: (((-1 * rank(ts_rank(close, 10))) * rank(delta(delta(close, 1), 1))) * rank(ts_rank((volume / adv20), 5)))
Alpha#18: (-1 * rank(((stddev(abs((close - open)), 5) + (close - open)) + correlation(close, open, 10))))
Alpha#19: ((-1 * sign(((close - delay(close, 7)) + delta(close, 7)))) * (1 + rank((1 + sum(returns, 250)))))
Alpha#20: (((-1 * rank((open - delay(high, 1)))) * rank((open - delay(close, 1)))) * rank((open - delay(low, 1))))
Alpha#21: ((((sum(close, 8) / 8) + stddev(close, 8)) < (sum(close, 2) / 2)) ? (-1 * 1) : (((sum(close, 2) / 2) < ((sum(close, 8) / 8) - stddev(close, 8))) ? 1 : (((1 < (volume / adv20)) || ((volume / adv20) == 1)) ? 1 : (-1 * 1))))
Alpha#22: (-1 * (delta(correlation(high, volume, 5), 5) * rank(stddev(close, 20))))
Alpha#23: (((sum(high, 20) / 20) < high) ? (-1 * delta(high, 2)) : 0)
Alpha#24: ((((delta((sum(close, 100) / 100), 100) / delay(close, 100)) < 0.05) || ((delta((sum(close, 100) / 100), 100) / delay(close, 100)) == 0.05)) ? (-1 * (close - ts_min(close, 100))) : (-1 * delta(close, 3)))
Alpha#25: rank(((((-1 * returns) * adv20) * vwap) * (high - close)))
```

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Alpha#26: (-1 * ts_max(correlation(ts_rank(volume, 5),
ts_rank(high, 5), 5), 3))
Alpha#27: ((0.5 < rank((sum(correlation(rank(volume),
rank(vwap), 6), 2) / 2.0))) ? (-1 * 1) : 1)
Alpha#28: scale(((correlation(adv20, low, 5) + ((high +
low) / 2)) - close))
Alpha#29: (min(product(rank(rank(scale(log(sum(
ts_min(rank(rank((-1 * rank(delta((close - 1), 5))))),
2), 1))))), 1), 5) + ts_rank(delay((-1 * returns), 6), 5))
Alpha#30: (((1.0 - rank(((sign((close - delay(close,
1))) + sign((delay(close, 1) - delay(close, 2))))
+ sign((delay(close, 2) - delay(close, 3)))))) *
sum(volume, 5)) / sum(volume, 20))
Alpha#31: ((rank(rank(rank(decay_linear((-1 *
rank(rank(delta(close, 10)))), 10)))) + rank((-1 *
delta(close, 3)))) + sign(scale(correlation(adv20, low,
12))))
Alpha#32: (scale(((sum(close, 7) / 7) - close)) + (20 *
scale(correlation(vwap, delay(close, 5), 230))))
Alpha#33: rank((-1 * ((1 - (open / close))^1)))
Alpha#34: rank(((1 - rank((stddev(returns, 2) /
stddev(returns, 5)))) + (1 - rank(delta(close, 1)))))
Alpha#35: ((Ts_Rank(volume, 32) * (1 - Ts_Rank(((close +
high) - low), 16))) * (1 - Ts_Rank(returns, 32)))
Alpha#36: (((((2.21 * rank(correlation((close - open),
delay(volume, 1), 15))) + (0.7 * rank((open - close))))
+ (0.73 * rank(Ts_Rank(delay((-1 * returns), 6), 5))))
+ rank(abs(correlation(vwap, adv20, 6)))) + (0.6 *
rank((((sum(close, 200) / 200) - open) * (close -
open)))))
Alpha#37: (rank(correlation(delay((open - close), 1),
close, 200)) + rank((open - close)))
Alpha#38: ((-1 * rank(Ts_Rank(close, 10))) * rank((close
/ open)))
Alpha#39: ((-1 * rank((delta(close, 7) * (1 - rank(
decay_linear((volume / adv20), 9)))))) * (1 +
rank(sum(returns, 250))))
Alpha#40: ((-1 * rank(stddev(high, 10))) *
correlation(high, volume, 10))
Alpha#41: (((high * low)^0.5) - vwap)
Alpha#42: (rank((vwap - close)) / rank((vwap + close)))
Alpha#43: (ts_rank((volume / adv20), 20) * ts_rank((-1 *
delta(close, 7)), 8))
Alpha#44: (-1 * correlation(high, rank(volume), 5))
Alpha#45: (-1 * ((rank((sum(delay(close, 5),
20) / 20)) * correlation(close, volume, 2)) *
rank(correlation(sum(close, 5), sum(close, 20), 2))))
Alpha#46: ((0.25 < (((delay(close, 20) - delay(close,
10)) / 10) - ((delay(close, 10) - close) / 10))) ? (-1 *
1) : (((((delay(close, 20) - delay(close, 10)) / 10) -
((delay(close, 10) - close) / 10)) < 0) ? 1 : ((-1 * 1) *
(close - delay(close, 1)))))
Alpha#47: ((((rank((1 / close)) * volume) / adv20) *
((high * rank((high - close))) / (sum(high, 5) / 5))) -
rank((vwap - delay(vwap, 5))))
Alpha#48: (indneutralize(((correlation(delta(close,
1), delta(delay(close, 1), 1), 250) * delta(close, 1)) /
close), IndClass.subindustry) / sum(((delta(close, 1) /
delay(close, 1))^2), 250))
Alpha#49: (((((delay(close, 20) - delay(close, 10)) / 10)
- ((delay(close, 10) - close) / 10)) < (-1 * 0.1)) ? 1 :
((-1 * 1) * (close - delay(close, 1))))
Alpha#50: (-1 * ts_max(rank(correlation(rank(volume),
rank(vwap), 5)), 5))
Alpha#51: (((((delay(close, 20) - delay(close, 10)) / 10)
- ((delay(close, 10) - close) / 10)) < (-1 * 0.05)) ? 1 :
((-1 * 1) * (close - delay(close, 1))))
Alpha#52: ((((-1 * ts_min(low, 5)) + delay(ts_min(low,
5), 5)) * rank(((sum(returns, 240) - sum(returns, 20)) /
220))) * ts_rank(volume, 5))
Alpha#53: (-1 * delta((((close - low) - (high - close)) /
(close - low)), 9))
Alpha#54: ((-1 * ((low - close) * (open^5))) / ((low -
high) * (close^5)))
Alpha#55: (-1 * correlation(rank(((close - ts_min(low,
12)) / (ts_max(high, 12) - ts_min(low, 12)))),
rank(volume), 6))
Alpha#56: (0 - (1 * (rank((sum(returns, 10) /
sum(sum(returns, 2), 3))) * rank((returns * cap)))))
Alpha#57: (0 - (1 * ((close - vwap) /
decay_linear(rank(ts_argmax(close, 30)), 2))))
Alpha#58: (-1 * Ts_Rank(decay_linear(correlation(
IndNeutralize(vwap, IndClass.sector), volume, 3.92795),
7.89291), 5.50322))
Alpha#59: (-1 * Ts_Rank(decay_linear(correlation(
IndNeutralize(((vwap * 0.728317) + (vwap * (1 -
0.728317))), IndClass.industry), volume, 4.25197),
16.2289), 8.19648))
Alpha#60: (0 - (1 * ((2 * scale(rank(((((close -
low) - (high - close)) / (high - low)) * volume)))) -
scale(rank(ts_argmax(close, 10))))))
Alpha#61: (rank((vwap - ts_min(vwap, 16.1219))) <
rank(correlation(vwap, adv180, 17.9282)))
Alpha#62: ((rank(correlation(vwap, sum(adv20,
22.4101), 9.91009)) < rank(((rank(open) + rank(open)) <
(rank(((high + low) / 2)) + rank(high))))) * -1)
Alpha#63: ((rank(decay_linear(delta(IndNeutralize(close,
IndClass.industry), 2.25164), 8.22237)) -
rank(decay_linear(correlation(((vwap * 0.318108) + (open *
(1 - 0.318108))), sum(adv180, 37.2467), 13.557),
12.2883))) * -1)
Alpha#64: ((rank(correlation(sum(((open * 0.178404) +
(low * (1 - 0.178404))), 12.7054), sum(adv120, 12.7054),
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16.6208)) < rank(delta((((high + low) / 2) * 0.178404) +
(vwap * (1 - 0.178404))), 3.69741))) * -1)
Alpha#65: ((rank(correlation(((open * 0.00817205) +
(vwap * (1 - 0.00817205))), sum(adv60, 8.6911), 6.40374))
< rank((open - ts_min(open, 13.635)))) * -1)
Alpha#66: ((rank(decay_linear(delta(vwap, 3.51013),
7.23052)) + Ts_Rank(decay_linear(((((low * 0.96633) +
(low * (1 - 0.96633))) - vwap) / (open - ((high + low) /
2))), 11.4157), 6.72611)) * -1)
Alpha#67: ((rank((high - ts_min(high, 2.14593)))^rank(
correlation(IndNeutralize(vwap, IndClass.sector),
IndNeutralize(adv20, IndClass.subindustry), 6.02936))) *
-1)
Alpha#68: ((Ts_Rank(correlation(rank(high), rank(adv15),
8.91644), 13.9333) < rank(delta(((close * 0.518371) +
(low * (1 - 0.518371))), 1.06157))) * -1)
Alpha#69: ((rank(ts_max(delta(IndNeutralize(vwap,
IndClass.industry), 2.72412), 4.79344))^Ts_Rank(
correlation(((close * 0.490655) + (vwap * (1 -
0.490655))), adv20, 4.92416), 9.0615)) * -1)
Alpha#70: ((rank(delta(vwap, 1.29456))^Ts_Rank(
correlation(IndNeutralize(close, IndClass.industry),
adv50, 17.8256), 17.9171)) * -1)
Alpha#71: max(Ts_Rank(decay_linear(correlation(Ts_Rank(
close, 3.43976), Ts_Rank(adv180, 12.0647), 18.0175),
4.20501), 15.6948), Ts_Rank(
decay_linear((rank(((low + open) - (vwap + vwap)))^2),
16.4662), 4.4388))
Alpha#72: (rank(decay_linear(correlation(((high +
low) / 2), adv40, 8.93345), 10.1519)) / rank(
decay_linear(correlation(Ts_Rank(vwap, 3.72469),
Ts_Rank(volume, 18.5188), 6.86671), 2.95011)))
Alpha#73: (max(rank(decay_linear(delta(vwap, 4.72775),
2.91864)), Ts_Rank(decay_linear(((delta(((open *
0.147155) + (low * (1 - 0.147155))), 2.03608) / ((open
* 0.147155) + (low * (1 - 0.147155)))) * -1), 3.33829),
16.7411)) * -1)
Alpha#74: ((rank(correlation(close, sum(adv30, 37.4843),
15.1365)) < rank(correlation(rank(((high * 0.0261661) +
(vwap * (1 - 0.0261661)))), rank(volume), 11.4791))) *
-1)
Alpha#75: (rank(correlation(vwap, volume, 4.24304)) <
rank(correlation(rank(low), rank(adv50), 12.4413)))
Alpha#76: (max(rank(decay_linear(delta(vwap, 1.24383),
11.8259)), Ts_Rank(decay_linear(Ts_Rank(correlation(
IndNeutralize(low, IndClass.sector), adv81, 8.14941),
19.569), 17.1543), 19.383)) * -1)
Alpha#77: min(rank(decay_linear(((((high + low) / 2) +
high) - (vwap + high)), 20.0451)), rank(
decay_linear(correlation(((high + low) / 2), adv40,
3.1614), 5.64125)))
Alpha#78: (rank(correlation(sum(((low * 0.352233) +
(vwap * (1 - 0.352233))), 19.7428), sum(adv40, 19.7428),
6.83313))^rank(correlation(rank(vwap), rank(volume),
5.77492)))
Alpha#79: (rank(delta(IndNeutralize(((close * 0.60733)
+ (open * (1 - 0.60733))), IndClass.sector), 1.23438)) <
rank(correlation(Ts_Rank(vwap, 3.60973), Ts_Rank(adv150,
9.18637), 14.6644)))
Alpha#80: ((rank(Sign(delta(IndNeutralize(((open *
0.868128) + (high * (1 - 0.868128))), IndClass.industry),
4.04545)))^Ts_Rank(correlation(high, adv10, 5.11456),
5.53756)) * -1)
Alpha#81: ((rank(Log(product(rank((rank(correlation(
vwap, sum(adv10, 49.6054), 8.47743))^4)), 14.9655))) <
rank(correlation(rank(vwap), rank(volume), 5.07914))) * -1)
Alpha#82: (min(rank(decay_linear(delta(open, 1.46063),
14.8717)), Ts_Rank(decay_linear(correlation(
IndNeutralize(volume, IndClass.sector), ((open *
0.634196) + (open * (1 - 0.634196))), 17.4842), 6.92131),
13.4283)) * -1)
Alpha#83: ((rank(delay(((high - low) / (sum(close, 5)
/ 5)), 2)) * rank(rank(volume))) / (((high - low) /
(sum(close, 5) / 5)) / (vwap - close)))
Alpha#84: SignedPower(Ts_Rank((vwap - ts_max(vwap,
15.3217)), 20.7127), delta(close, 4.96796))
Alpha#85: (rank(correlation(((high * 0.876703) + (close
* (1 - 0.876703))), adv30, 9.61331))^rank(correlation(
Ts_Rank(((high + low) / 2), 3.70596), Ts_Rank(volume,
10.1595), 7.11408)))
Alpha#86: ((Ts_Rank(correlation(close, sum(adv20,
14.7444), 6.00049), 20.4195) < rank(((open + close) -
(vwap + open)))) * -1)
Alpha#87: (max(rank(decay_linear(delta(((close
* 0.369701) + (vwap * (1 - 0.369701))), 1.91233),
2.65461)), Ts_Rank(decay_linear(abs(correlation(
IndNeutralize(adv81, IndClass.industry), close,
13.4132)), 4.89768), 14.4535)) * -1)
Alpha#88: min(rank(decay_linear(((rank(open) +
rank(low)) - (rank(high) + rank(close))), 8.06882)),
Ts_Rank(decay_linear(correlation(Ts_Rank(close,
8.44728), Ts_Rank(adv60, 20.6966), 8.01266), 6.65053),
2.61957))
Alpha#89: (Ts_Rank(decay_linear(correlation(((low *
0.967285) + (low * (1 - 0.967285))), adv10, 6.94279),
5.51607), 3.79744) - Ts_Rank(decay_linear(delta(
IndNeutralize(vwap, IndClass.industry), 3.48158),
10.1466), 15.3012))
Alpha#90: ((rank((close - ts_max(close, 4.66719)))^
Ts_Rank(correlation(IndNeutralize(adv40,
IndClass.subindustry), low, 5.38375), 3.21856)) * -1)
Alpha#91: ((Ts_Rank(decay_linear(decay_linear(
correlation(IndNeutralize(close, IndClass.industry),
volume, 9.74928), 16.398), 3.83219), 4.8667) - rank(
decay_linear(correlation(vwap, adv30, 4.01303),
2.6809))) * -1)
```

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Alpha#92: min(Ts_Rank(decay_linear(((((high + low) / 2)
+ close) < (low + open)), 14.7221), 18.8683),
Ts_Rank(decay_linear(correlation(rank(low),
rank(adv30), 7.58555), 6.94024), 6.80584))
Alpha#93: (Ts_Rank(decay_linear(correlation(
IndNeutralize(vwap, IndClass.industry), adv81, 17.4193),
19.848), 7.54455) / rank(decay_linear(delta(((close
* 0.524434) + (vwap * (1 - 0.524434))), 2.77377),
16.2664)))
Alpha#94: ((rank((vwap - ts_min(vwap, 11.5783)))^
Ts_Rank(correlation(Ts_Rank(vwap, 19.6462), Ts_Rank
(adv60, 4.02992), 18.0926), 2.70756)) * -1)
Alpha#95: (rank((open - ts_min(open, 12.4105))) <
Ts_Rank((rank(correlation(sum(((high + low) / 2),
19.1351), sum(adv40, 19.1351), 12.8742))^5), 11.7584))
Alpha#96: (max(Ts_Rank(decay_linear(
correlation(rank(vwap), rank(volume), 3.83878),
4.16783), 8.38151), Ts_Rank(decay_linear(
Ts_ArgMax(correlation(Ts_Rank(close, 7.45404),
Ts_Rank(adv60, 4.13242), 3.65459), 12.6556), 14.0365),
13.4143)) * -1)
Alpha#97: ((rank(decay_linear(delta(IndNeutralize(((
low * 0.721001) + (vwap * (1 - 0.721001))),
IndClass.industry), 3.3705), 20.4523)) - Ts_Rank(
decay_linear(Ts_Rank(correlation(Ts_Rank(low, 7.87871),
Ts_Rank(adv60, 17.255), 4.97547), 18.5925), 15.7152),
6.71659)) * -1)
Alpha#98: (rank(decay_linear(correlation(vwap, sum(adv5,
26.4719), 4.58418), 7.18088)) - rank(decay_linear(
Ts_Rank(Ts_ArgMin(correlation(rank(open), rank(adv15),
20.8187), 8.62571), 6.95668), 8.07206)))
Alpha#99: ((rank(correlation(sum(((high + low)
/ 2), 19.8975), sum(adv60, 19.8975), 8.8136)) <
rank(correlation(low, volume, 6.28259))) * -1)
Alpha#100: (0 - (1 * (((1.5 * scale(indneutralize(
indneutralize(rank(((((close - low) - (high - close))
/ (high - low)) * volume)), IndClass.subindustry),
IndClass.subindustry))) - scale(indneutralize((
correlation(close, rank(adv20), 5) - rank(
ts_argmin(close, 30))), IndClass.subindustry))) * (
volume / adv20))))
Alpha#101: ((close - open) / ((high - low) + .001))
```

A.2 Functions and operators

(Below, "{ }" stands for a placeholder. All expressions are case-insensitive.)

abs(x), log(x), sign(x) = standard definitions; same for the operators "+", "-", "*", "/", ">", "<", "==", "||", "x ? y : z"

rank(x) = cross-sectional rank

delay(x, d) = value of x d days ago

correlation(x, y, d) = time-serial correlation of x and y for the past d days

covariance(x, y, d) = time-serial covariance of x and y for the past d days

scale(x, a) = rescaled x such that sum(abs(x)) = a (the default is a = 1)

delta(x, d) = today's value of x minus the value of x d days ago

signedpower(x, a) = x^a

decay_linear(x, d) = weighted moving average over the past d days with linearly decaying weights d, d – 1, …, 1 (rescaled to sum up to 1)

indneutralize(x, g) = x cross-sectionally neutralized against groups g (subindustries, industries, sectors, etc.), i.e., x is cross-sectionally demeaned within each group g

ts_{O}(x, d) = operator O applied across the time series for the past d days; non-integer number of days d is converted to floor(d)

ts_min(x, d) = time-series min over the past d days

ts_max(x, d) = time-series max over the past d days

ts_argmax(x, d) = which day ts_max(x, d) occurred on

ts_argmin(x, d) = which day ts_min(x, d) occurred on

ts_rank(x, d) = time-series rank in the past d days

min(x, d) = ts_min(x, d)

max(x, d) = ts_max(x, d)

sum(x, d) = time-series sum over the past d days

product(x, d) = time-series product over the past d days

stddev(x, d) = moving time-series standard deviation over the past d days

A.3 Input data

returns = daily close-to-close returns

open, close, high, low, volume = standard definitions for daily price and volume data

vwap = daily volume-weighted average price

cap = market cap

adv{d} = average daily dollar volume for the past d days

IndClass = a generic placeholder for a binary industry classification such as GICS, BICS, NAICS, SIC, etc., in indneutralize(x, IndClass.level), where level = sector, industry, subindustry, etc. Multiple IndClass in the same alpha need not correspond to the same industry classification.

Appendix B: Disclaimer

Wherever the context so requires, the masculine gender includes the feminine and/or neuter, and the singular form includes the plural and vice versa. The authors of this paper ("Authors") and their affiliates including without limitation Quantigic® Solutions LLC ("Authors' Affiliates" or "their Affiliates") make no implied or express warranties or any other representations whatsoever, including without limitation implied warranties of merchantability and fitness for a particular purpose, in connection with or with regard to the content of this paper including without limitation any formulae, code, or algorithms contained herein ("Content").

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Zura Kakushadze received his PhD in theoretical physics from Cornell University, and was a Postdoctoral Fellow at Harvard University and an Assistant Professor at the C.N. Yang Institute for Theoretical Physics at Stony Brook. He received the Alfred P. Sloan Fellowship in 2001. After expanding into quantitative finance, he was a Director at RBC Capital Markets, Managing Director at WorldQuant, Executive Vice President and substantial shareholder at Revere Data, and Adjunct Professor at UConn. Currently he is the President and co-owner of Quantigic® Solutions and a Full Professor at the Free University of Tbilisi. He has 110+ publications in physics and finance.

ENDNOTES

1. "An alpha is a combination of mathematical expressions, computer source code, and configuration parameters that can be used, in combination with historical data, to make predictions about future movements of various financial instruments" (Tulchinsky *et al*., 2015). Here, "alpha" – following the common trader lingo – generally means any reasonable "expected return" that one may wish to trade on, and is not necessarily the same as the "academic" alpha. In practice, often detailed information about how the alphas are constructed may not even be available. For example, the only data available could be the position data, so "alpha" then is a set of instructions to achieve certain stock (or other instrument) holdings by some times $t_1, t_2, \ldots$ (e.g., a tickers-by-holdings matrix for each t_s).
2. We picked these alphas largely based on simplicity considerations, so they can be presented within the inherent limitations of a paper. There also exist myriad other, "non-formulaic" (coded and too-complex-to-present) alphas.
3. Here "vwap," as usual, stands for "volume-weighted average price."
4. GICS = Global Industry Classification Standard; BICS = Bloomberg Industry Classification System; NAICS = North American Industry Classification System; SIC = Standard Industrial Classification.
5. More precisely, depending on the alpha and industry classification used, neutralization can be w.r.t. sectors, industries, subindustries, etc. – different classifications use different nomenclature for levels of similar granularity.
6. In Kakushadze and Tulchinsky (2016), the alpha return volatility was not directly available and was estimated indirectly based on the Sharpe ratio, cents-per-share, and turnover data. Here, we use direct realized volatility data.
7. Depending on a construction, a priori the turnover might add value via the specific (idiosyncratic) risk for alphas.
8. Here we use the log of the turnover as opposed to the turnover itself as the latter has a skewed, roughly log-normal distribution, while pairwise correlations take values in (–1, 1) (in fact, their distribution is tighter – see below).
9. On longer horizons, for a discussion of mean-reversion (contrarian) and momentum (trend-following) strategies, see, e.g., Avellanida and Lee (2010) and Jegadeesh and Titman (1993), respectively, and references cited therein.
10. Four of our 101 alphas in Appendix A, namely the alphas numbered 42, 48, 53, and 54, are delay-0 alphas. They are assumed to be traded at or as close as possible to the close of the trading day for which they are computed.
11. In contrast, if alpha (3) is executed as close as possible to yesterday's close, then it is delay-0.
12. Here the average is over the time series of the realized daily returns.
13. Perhaps a more precise analogy would be between the turnover and the ratio of ADDV and market cap; however, this is not going to be critical for our purposes here.
14. For liquidity as a style risk factor, see, e.g., Pastor and Stambaugh (2003) and references cited therein.
15. See, e.g., Grinold and Kahn (2000) and references cited therein.
16. Variances are relatively stable and can be computed based on historical data (sample variances). It is the off-diagonal elements of the sample covariance matrix – to wit, the correlations – that are out-of-sample unstable.
17. The log of the turnover as a factor for risk models of alpha portfolios was suggested by Kakushadze (2014).
18. Suppressing alpha weights by the turnover can add value but be highly correlated with volatility suppression.
19. Roughly speaking, when the specific risk is computed via nontrivial (proprietary) methods, the column in the factor loadings matrix corresponding to the turnover is no longer proportional to $\ln(\tau_i)$ but is a more complex function of the turnover, the specific risk also depends on the turnover nontrivially and is not quadratic in $\ln(\tau_i)$.

20 For proprietary reasons, we are not at liberty to state precisely which ones.

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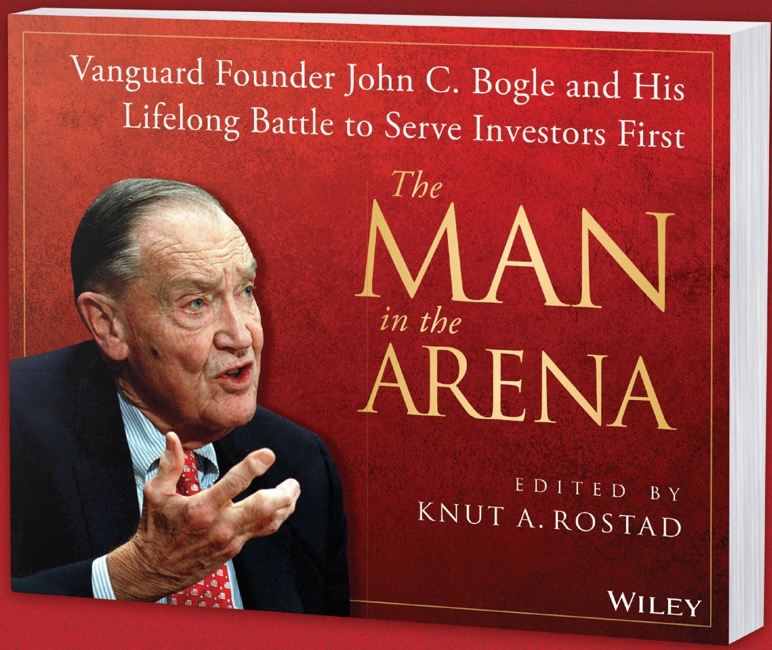

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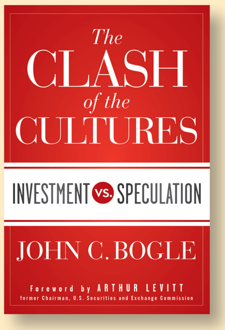

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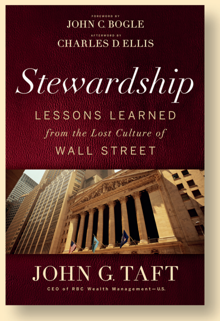

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