Reviewing the Quality Factor

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Summary

Perhaps overshadowed by the focus on Value factor performance in recent years, the Quality factor has experienced an unusually steep drawdown as well. However, whereas vaccine news and an influx of Retail trading activity seems to have sparked a resurgence in Value, those events only exacerbated Quality's underperformance. This note reexamines the Quality factor's viability, both from an empirical data perspective and from a softer viewpoint of why it should work in the first place. In both regards Quality still looks appealing: it satisfies all the key quantitative criteria WEDGE looks for in a factor, and its recent struggles align with its defensive nature and tilt against certain Retail investor behaviors.

Key Takeaways

1. Empirical returns and behavioral studies continue to support a Quality factor, with high Quality stocks outperforming low Quality ("Junk") stocks, on average. Both approaches suggest that advantage is nonlinear, with the greatest impact coming from Junk stock underperformance.
2. The Quality factor is defensive in nature, with negative correlations to other common factors like Market Beta, Small Size, and Value. Quality also tends to lag when longshot or "Lottery" stocks, typically preferred by Retail investors, go on big runs like they have in the past year.
3. Because of the above points, WEDGE prefers to implement Quality either as an exclusionary filter (e.g. avoid the lowest Quality stocks) or in combination with other factors (e.g. buy stocks with strong Value, Momentum, etc. and above average Quality characteristics).

History of Quality Investing

Investment Philosophy

The concept of investing in high quality companies sounds embarrassingly simple, so it is no surprise that musings about a "Quality" focus date back to at least Benjamin Graham (1949), if not earlier. As one of Graham's students, Warren Buffett extolls similar virtues, which in 2018 researchers quantified in terms of distinct factor exposures (Frazzini et al.). Specifically, both Berkshire Hathaway's stock returns and the performance of its public 13D holdings were shown to exhibit a statistically significant, positive exposure to the Quality factor, distinct from an also significant exposure to Value.

Quantitative Factor

Academic research on Quality as a defined factor has been a more recent movement, though it is less clear when practitioners started using it. Robert Novy-Marx (2013) led the academic charge by adding a profitability factor to the orthodox Fama-French three factor model of that time. Fama and French themselves then introduced a five-factor model in 2015, using a different profitability measure plus a new investment[1] factor. Three years later, AQR proposed a composite Quality factor which coalesces a handful of common definitions together (Asness et al., 2018). The data for all three of these papers is publicly accessible, and for the latter two is updated each month. These datasets provide a convenient way to study the Quality factor broadly, without digressing into specific WEDGE factors and models.

Amorphous Definition

One of the most confusing aspects of the Quality factor is that it lacks a clear definition. All Value factors boil down to "Price over Something," but Quality has no universal component. Novy-Marx chose to use gross profits scaled by total assets for his factor; Fama and French divide operating profitability by book equity; and the AQR composite includes measures of profitability, profitability growth, safety, and capital return. This ambiguity extends beyond academia. Both iShares and Invesco offer Quality factor ETFs with a few billion dollars of AUM, but the former includes a component for "stable earnings growth" while the latter seeks low accrual ratios (in addition to ROE and leverage measures which they do have in common).

No resolution to this murkiness is proposed here; it is only mentioned as a word of caution. Some investors may know Quality by a different word entirely; followers of Novy-Marx and Fama-French tend to adopt their nomenclature of a "Profitability" factor rather than "Quality."

Recent Performance

Over the past few years Quality by most definitions has performed poorly, which is especially frustrating for quantitative investors since much of that underperformance has coincided with a historic drawdown in the Value factor. Moreover, while the success of COVID-19 vaccines, economic reopening, and a surge in Retail trading have all supported a rebound in the Value factor, those same events accelerated losses to Quality. The Retail component is particularly intriguing, as new dynamics such as Reddit message boards and free trading apps have led some to question whether a Quality tilt is outdated. When the returns of individual, outlier stocks are even more extreme than usual (e.g. GameStop, AMC, etc.), the natural reaction is to try to catch some of those high-octane, "Home Run" stocks in the future.

[1] The investment factor is contrarian, shorting stocks with high balance sheet growth and going long those with lower growth.

Table 1. Recent Quality Performance

Annualized long-short returns for Fama-French and AQR factors; annualized active returns vs. S&P 500 for domestic ETF products (both shown in %s).

	Domestic Factors		Global Factors		Quality ETFs	
Starting Date	**FF**	**AQR**	**FF**	**AQR**	**iShares**	**Invesco**
12/31/17 (Value Drawdown)	0.49	-1.05	5.28	3.87	-0.52	-1.01
12/31/19 (Pandemic)	0.18	-8.47	3.86	-2.53	-1.72	-1.56
10/31/20 (Post-Vaccine) **	-0.35	-2.05	-0.53	-2.24	-0.12	-0.35

Source: Kenneth R. French and AQR data libraries, FactSet, and WEDGE Capital Management. All data are simple, monthly returns, ending March 2021.
**Return spreads shorter than one year are not annualized.

Empirical Tests

Before addressing the question of whether recent events have created a paradigm shift, it makes sense to first verify that the historical data is compelling. A prior WEDGE paper outlined five broad criteria for assessing a factor's viability. In truth, many other metrics and statistical properties are worth studying too, but these criteria are unique in that they are open-ended; there is no algorithm or threshold that factors must pass before they can be used in live models. At WEDGE, those decisions are made by the investment staff with an "I'll know it when I see it" approach to the entire mosaic of the analysis.

1. Robust Standalone Power

The first, rather obvious, hurdle for any factor is that its historical performance needs to be robust. More specifically, the measuring stick of what is "robust" should be stricter for investment factors than what is required for almost any other scientific endeavor. This extra skepticism is necessary because the same financial datasets have been available for decades now, with powerful incentives encouraging researchers to find new factors and patterns in that data. Since there is no way to tell how many attempts were made before an interesting result is published, it would be naïve to follow the traditional statistics habit[2] of blindly scanning research results for t-statistics greater than 2.

The top panel of Table 2 shows various definitions of the Quality factor all exhibit positive return spreads beyond that naïve statistical rule. Novy-Marx's factor shows the greatest statistical confidence, which is interesting as it is the only one formed on an intra-industry basis. Quality also stands out as being distinct from other common factors. The bottom panel of Table 2 presents time series regressions which control for a handful of other equity factors. These results only enhance Quality's profile further: it has a demonstrably negative relationship with most other factors, which magnifies its unexplained alpha and suggests that it could be a potent addition to multifactor models.

[2] The habit arises because a t-statistic of 2 corresponds to a widely accepted, easy to remember, confidence threshold of 5%.

Table 2. Long-Term Quality Factor Returns

Time series regression of monthly long-short factor returns (in %s) for Novy-Marx, Fama-French, and AQR factors; t-statistics shown in brackets.

	Domestic Factors			Global ex-US	
	NM	FF	AQR	FF	AQR
Average Return (Annualized)	3.68	3.03	4.11	4.23	5.88
t-statistic	[5.40]	[3.05]	[4.30]	[4.96]	[4.76]
Factor Regression Coefficients					
Alpha (Monthly)	0.28	0.38	0.49	0.47	0.51
	[5.72]	[4.90]	[8.16]	[7.63]	[6.79]
Market	-0.07	-0.08	-0.21	-0.12	-0.22
	[-6.71]	[-4.08]	[-15.03]	[-8.65]	[-14.46]
Size	-0.06	-0.23	-0.31	-0.09	-0.15
	[-6.07]	[-8.71]	[-13.76]	[-2.92]	[-4.03]
Value	-0.05	0.16	-0.19	-0.13	-0.18
	[-4.58]	[4.51]	[-8.39]	[-3.71]	[-5.03]
Momentum	0.05	—	-0.01	—	0.10
	[7.47]	—	[-0.70]	—	[3.65]
Investment	—	-0.28	—	-0.21	—
	—	[-5.16]	—	[-4.59]	—

Source: Robert Novy-Marx, Kenneth R. French and AQR data libraries, and WEDGE Capital Management. Novy-Marx data covers July 1963 – December 2012; French covers July 1963 – March 2021 (domestic) and July 1990 – March 2021 (international); AQR covers July 1957 – March 2021 (domestic) and July 1987 – March 2021 (international). Explanatory factors for each regression use the factors and definitions preferred by those authors.

These negative relationships already help clarify Quality's recent underperformance. Quality has a negative slope (i.e. beta) with the market factor, meaning that high Quality stocks tend to outperform when stocks underperform bonds, all else equal (i.e. the phrase "Flight to Quality" is a real thing). Conversely, when stocks outperform, or when small caps outperform large caps, or when Value outperforms Growth… Quality tends to lag. All those ingredients were present in magnitude during the past year, creating a very difficult environment for high Quality stocks to outperform.

In the long-run, most quantitative products will want to tilt towards those Market, Size and Value factors anyways, so the decision of how to implement Quality without disturbing the other factors' power is worth considering (more on this later).

2. Long, Consistent Track Record

WEDGE's second criterion is to see whether a factor has outperformed across different macro environments and events. Economic cycles can be very long, with specific events stubbornly sparse. For example, interest rates have been on a downward trajectory for over thirty years now, and the last meaningful corporate tax increase in the U.S. happened way back in 1968. A factor backtest with even a few decades of history could have a built-in bias to falling interest rates or taxes[3].

In the case of the Quality factor, Table 3 segments its long-short returns from Table 2 into decades, revealing a surprisingly consistent pattern of outperformance across periods. Quality did well during the rising interest rates of the 1980s, and has continued to outperform in more recent decades as quantitative investing has become more mainstream.

Table 3. Quality Factor Returns by Decade

Annualized long-short factor returns for Fama-French and AQR factors (shown in %s).

	Domestic Factors			Global ex-US	
Decade	**NM**	**FF**	**AQR**	**FF**	**AQR**
1960s	0.44	1.28	2.12	—	—
1970s	1.09	-0.56	1.36	—	—
1980s	4.68	4.85	6.86	—	11.79
1990s	4.81	2.50	5.11	6.41	5.60
2000s	5.83	8.50	6.81	2.17	5.83
2010s	5.15	1.35	4.22	4.26	6.97
2020s	—	0.18	-8.47	3.86	-2.53

Source: Robert Novy-Marx, Kenneth R. French and AQR data libraries, and WEDGE Capital Management. Novy-Marx data covers July 1963 – December 2012; French covers July 1963 – March 2021 (domestic) and July 1990 – March 2021 (international); AQR covers July 1957 – March 2021 (domestic) and July 1987 – March 2021 (international).

3. Appalachian Return Profile

One of the great challenges to investing is that the market is always trying to learn and improve too. This circuitous relationship means even strong data patterns can be arbitraged away if there is no underlying force behind them. Thus, to believe a factor's outperformance will persist, it should come from either a risk source or behavioral bias (or a combination of them). Either (1) some element of risk makes the factor less appealing to a subset of market participants, so they avoid those stocks; or (2) behavioral biases prevent optimal decision making and repeatedly leave alpha on the table.

[3] There are tests and adjustments that could rule out specific linkages like this, but the broader message is that a long, diverse data history provides confidence that a factor can work through new, "unknown unknowns" it will encounter in the future.

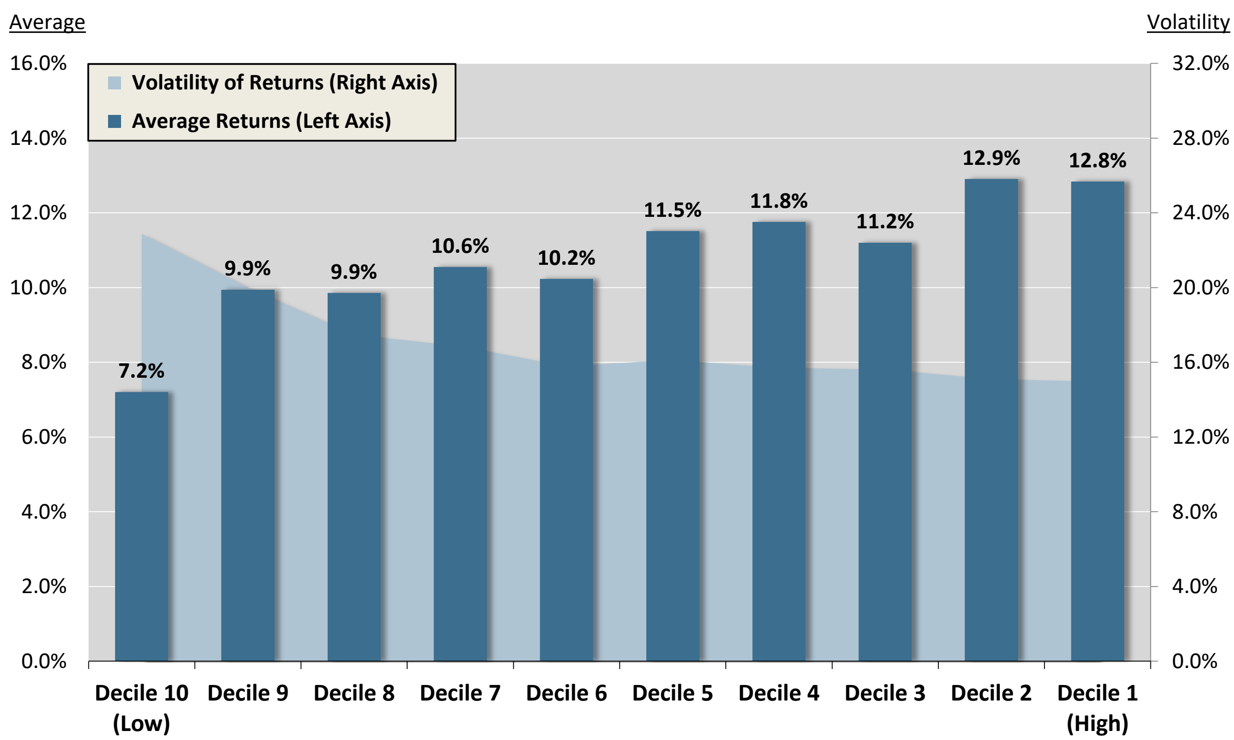
Fortunately, either possibility suggests that a certain *shape* should emerge when sorting a factor's returns into deciles (or quintiles, etc.). If there is a source causing the historical outperformance, then one should expect a relatively smooth ascent across portfolios formed by increasing dosages of the proxy for that source (i.e. the factor). At WEDGE this property is analogized as preferring Appalachian Mountain returns over Rocky Mountain returns.

This shape preference can be demonstrated with an unrelated, but very simple, example of causality. GPS watch data has shown that marathon runners who cover a higher weekly mileage in their training run faster in the race, on average (Eberhardt, 2017). That sounds rather obvious, but the improvement builds steadily. As average weekly mileage rises from 40 to 50, 60, 70, etc., average race times keep improving. Surely that trend cannot extend forever – at some point physical limitations will make additional miles counterproductive – but the performance pattern would never drop down and then jump back up again in a "V" shaped, Rocky Mountain pattern. Because training directly *causes* athletic improvement, the proxy measurement for more of it shows an Appalachian increase in performance.

Similarly, seeing a smooth ascent in decile-sorted factor returns provides confidence that some underlying force(s) is causing those returns. Return plots that jump up and down in a jagged pattern are concerning, as they may indicate an enticing factor return spread is just some lucky data mining.

Figure 1. Simple Returns of Quality-Sorted Portfolios

Annualized, long-only simple returns of domestic, decile-sorted portfolios formed according to AQR Quality factor.



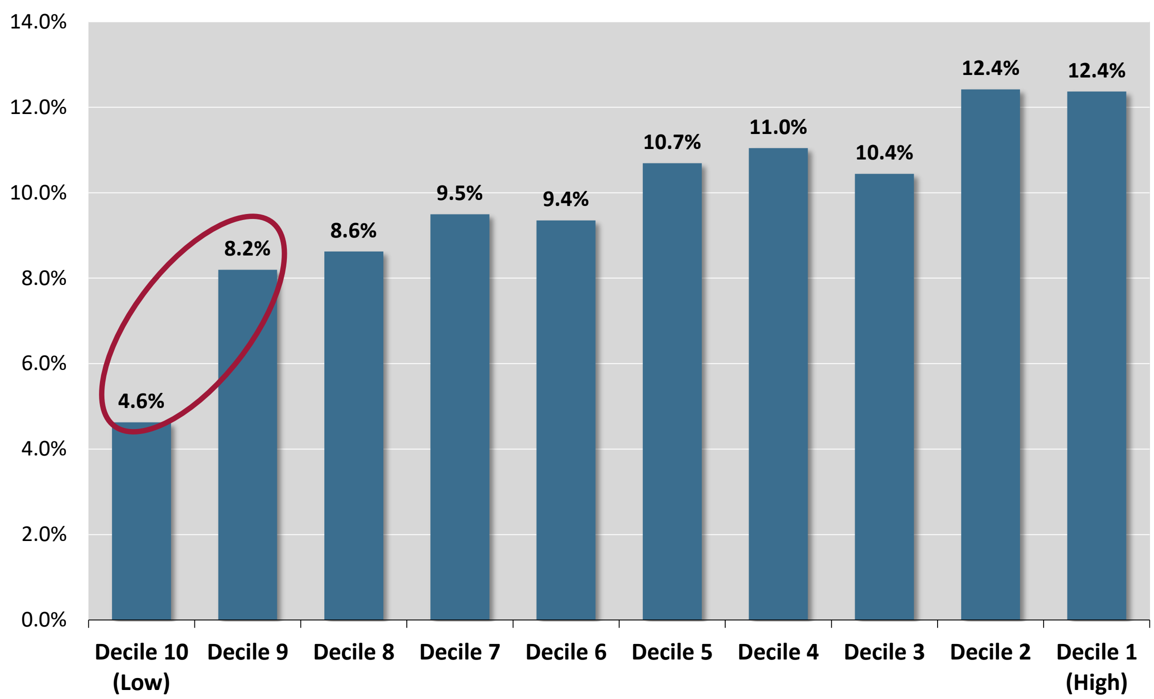
Source: AQR data library and WEDGE Capital Management. Monthly returns data spans from July 1957 to March 2021.

Figure 1 plots this analysis by showing the average long-only returns for Quality-sorted portfolios using the AQR definition, along with the standard deviation of those returns. Moving from low Quality to high Quality produces a gradual, upward ascent of performance, whereas the volatility of returns smoothly declines. There are some minor fluctuations along the way, but nothing that would undermine the basic idea that there is some underlying source for why "more Quality is good; less is bad."

Figure 2 combines these simple return and volatility effects by graphing the same portfolios' compound returns. A similar Appalachian pattern is present, but here the worst Quality decile stands out as excessively bad compared to the general upward trend from deciles 9 to 1. Such a steep drop is not concerning because it occurs at the bottom decile. In fact, seeing this excessively bad combination of low returns and high volatility demonstrates how factor effects can be nonlinear and Appalachian at the same time. In the case of Quality, avoiding the very worst stocks has historically been the most potent first step to take, whereas there seems to be less performance gain from distinguishing between good and great Quality. For that reason, WEDGE prefers to use Quality either as an exclusionary filter (e.g. filter out the lowest Quality stocks) or in combination with other factors (e.g. new purchases should have high Value, high Momentum, etc. and at least a decent reading on Quality).

Figure 2. Compound Returns of Quality-Sorted Portfolios

Annualized, long-only compound returns of domestic, decile-sorted portfolios formed according to AQR Quality factor.



Source: AQR data library and WEDGE Capital Management. Monthly returns data spans from July 1957 to March 2021.

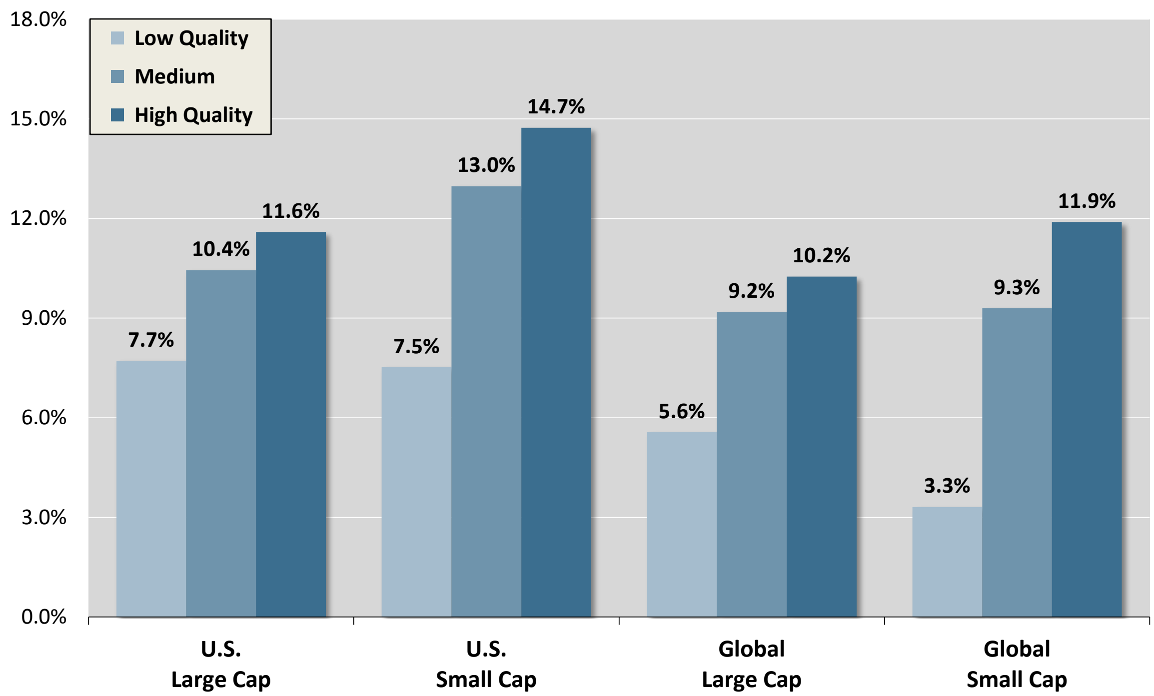
4. Out of Sample Evidence

An additional reliability check is to see how a factor works in other asset classes. The goal of any model is to work well on future data and shocks it was never trained for, which is not an easy task. An overfit backtest can be completely useless once it goes live, so reviewing how a factor performs in asset classes beyond its intended use serves as proxy for this kind of "out of sample" analysis.

Figure 3 breaks up the AQR data into four different asset classes, forming low, medium, and high Quality-sorted portfolios within two broad geographic regions. In each segment, the lowest Quality portfolios again exhibit the weakest compound returns, although the underperformance of low Quality is more pronounced in the Small Cap universes.

Figure 3. Quality Portfolio Returns by Size and Region

Annualized, long-only compound returns of tercile-sorted portfolios formed according to AQR Quality factor.



Source: AQR data library and WEDGE Capital Management. Domestic data begins July 1957, global in July 1987, with both ending March 2021.

5. Practical

Finally, a factor should pass some common sense checks. First, its turnover and liquidity should be acceptable for live portfolios. Quality factors have been operating in live WEDGE products for over 25 years now, and the prior section already described a low turnover application of the factor – simply screen out the lowest Quality stocks. This precise approach is used for fundamental research products at WEDGE, which better aligns with their investment horizons.

Secondly, there should be some rough outline of economic rationale for why a factor works. That description does not have to be perfectly formed or proven out, but if it is a struggle to even start down the path, then how can the factor really be expected to keep working into the future?

The Quality factor is interesting in this regard, since in most walks of life higher quality commands a higher price, which would suggest high Quality stocks deserve *lower* returns – not higher returns. In fixed income markets, for example, higher credit quality is priced for lower yields. This paradox makes it hard to envision a risk-based explanation for the Quality factor, especially when one sees that the lowest Quality stocks also have the highest return volatility. That leaves behavioral finance as the more promising avenue. Fortunately, there is already a robust literature documenting related behavioral biases and their connection to the Quality factor.

Behavioral Explanations

Favorite-Longshot Bias

The favorite-longshot bias describes the tendency for people to overpay for opportunities with a low probability of success but a large payoff if successful. The fact that anyone plays the lottery is the simplest example of this phenomenon, but more nuanced insights come from betting behavior at horse races. In 2010 researchers uncovered that bets on longshot horses provided an average ROI of −61%, whereas a strategy of always betting the favorite returned −6% (Snowberg and Wolfers). Presumably there is some nonmonetary benefit that makes going to the track enjoyable in the first place (otherwise the best strategy is to stay home). Once at the track though, a very simple strategy could save gamblers a lot of money. The tactic is so simple that it should be learnable, which implies that either bettors habitually overestimate the chances of longshots winning, or they experience greater enjoyment the more their payoff diagram resembles a lottery.

Both reasons seem to have a place in describing the Quality factor. It seems natural to draw a linkage between low Quality, "Junk" stocks and lottery outcomes. Companies with less of a profitability cushion are essentially levered to a change in their fortunes, more so than companies with a margin of safety. Investors can easily picture in their mind what a turnaround scenario would look like for a Junk stock, which may cause them to overestimate the probability of that scenario coming to fruition.

Overestimating Probabilities

Known as the availability bias, the tendency to overestimate longshot odds was one of the first behavioral biases ever documented (Kahneman and Tversky, 1973). More recently, researchers were able to draw an explicit connection between inaccurate probability estimations and the Quality factor's performance (Bouchard et al., 2016). That analysis compared realized stock returns to prior sell-side analyst price targets, which presumably should be forecasting those returns. The first cut of the data revealed a blanket, excessive bullishness by the sell-side analysts, which is a separate and unrelated bias. Once that bullishness was controlled for though, analyst price targets tended to "systematically underestimate the future return of high-quality firms, compared to low quality firms." These results avoid the "more fun" explanation of seeking lottery payoffs, since sell-side analysts stand to receive better compensation and career advancement the more accurate their price targets are.

Desirability of Lottery Payoffs

In 2009, Alok Kumar, a professor focused on behavioral finance topics, explored the question of who owns Junk stocks in a paper aptly titled "Who Gambles in the Stock Market?". He found that "at the aggregate level, individual investors prefer stocks with lottery features, and like lottery demand, the demand for lottery-type stocks increases during economic downturns." A truncated look at his analysis is shown in Table 4 below: it compares the excess weight held by Retail and Institutional investors in their portfolios, according to various stock characteristics.

To start with, Kumar's analysis confirms the zero-sum game relationship of alpha: Retail investors tend to be underweight stocks that will outperform, while Institutional investors hold more weight in those stocks, on average. Beyond the return outcomes, Retail investors prefer stocks with a high skewness of returns, greater unexplained volatility, and smaller companies with cheaper share prices.

Table 4. Characteristic Preferences of Investor Types

Average overweight/(underweight) of a given stock characteristic with respect to the passive, cap-weighted market portfolio. t-statistics in brackets.

	Overweight vs. Mkt			Overweight vs. Mkt	
Characteristic	**Retail**	**Inst'l**	**Characteristic**	**Retail**	**Inst'l**
Mean (Future) Return	-0.96	1.36	Stock Price	-0.20	0.29
	[-24.43]	[40.46]		[-23.69]	[21.84]
Skewness	0.41	-0.11	Log(Firm Size)	-0.68	2.70
	[29.87]	[-7.64]		[-35.42]	[21.03]
Idiosyncratic Volatility	0.91	-0.26	Prior Month's Return	0.04	-0.05
	[33.14]	[-19.93]		[2.55]	[-5.61]

Source: Kumar (2009). Who Gambles in the Stock Market? Table II (selection portions; only statistically significant coefficients with differing signs between investor types are shown here). Retail data covers the monthly brokerage holdings for 77,995 U.S. households from 1991 – 1996. Institutional holdings data populated through 13F filings via Thomson Financial.

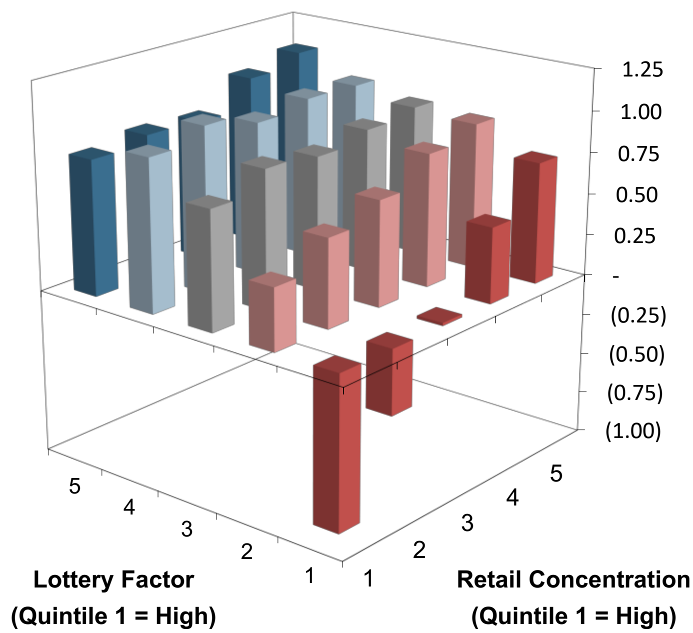
Lottery Stocks as a Factor

Retail Investor Connection

More recently, academics have expressed the idea of lottery-like features as its own equity factor (Bali et al., 2017). Their definition is tied to the skewness of a stock's recent return history[4] rather than underlying fundamentals, but it captures similar market segmentation effects between Retail and Institutional investors. Figure 4 provides a visualization for how the underperformance of Lottery stocks is isolated to those with high Retail ownership. For stocks that have a high level of Institutional ownership, there is not nearly as much return dispersion between high and low Lottery measures.

Figure 4. Lottery Returns and Retail Ownership

Bivariate, dependent portfolio sorts based on Institutional ownership share and "FMAX" Lottery factor. Returns shown are monthly, average returns (%).



Source: Bali et. al (2017) and WEDGE Capital Management. Data covers July 1963 – November 2012, as published in Table 8 of Bali et. al. The original data table of 100 portfolios is shown above, condensed into a 5x5 plot, by averaging the returns of adjacent 10x10 decile portfolios into one quintile.

Relationship with Quality

The Lottery concept overall lacks the factor robustness that Quality was shown to have earlier. Figure 4 already reveals some "Rockiness" in the Lottery factor's returns, but an even more telling test is presented in an appendix. The Quality factor retains a significant alpha even after the Lottery factor is used as a confounding variable to explain it, but the reverse is not true. When Quality is introduced into a regression of the Lottery factor's performance, Lottery's alpha loses its statistical significance.

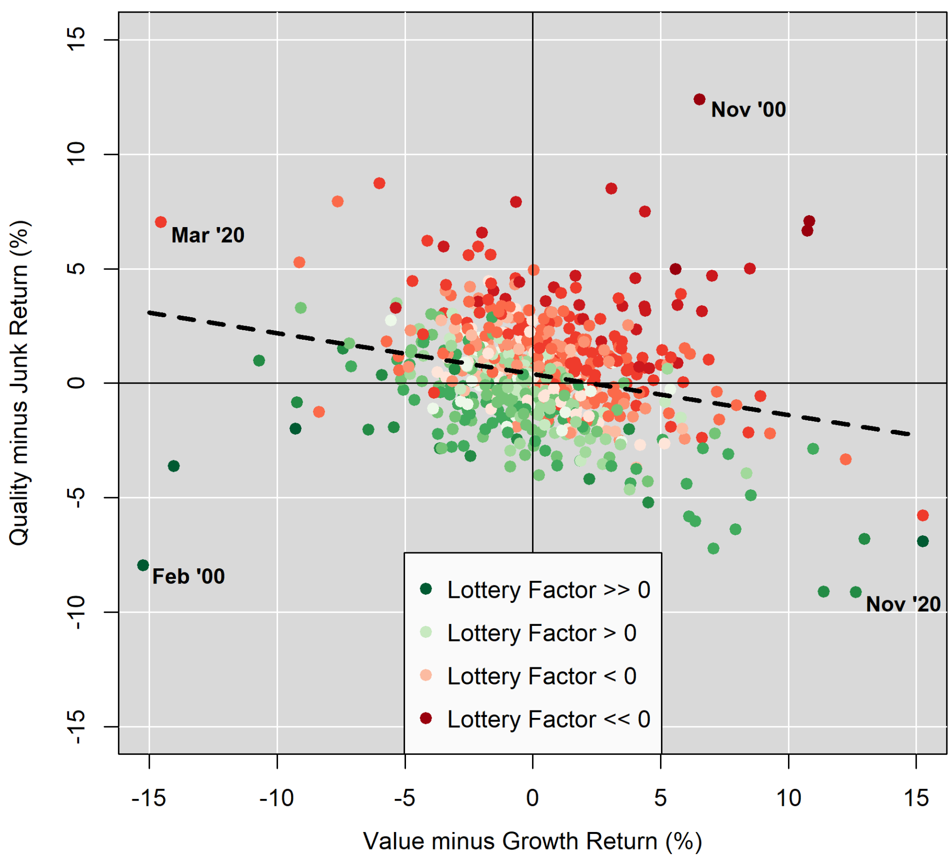
[4] Specifically, the FMAX factor is created by sorting stocks based on the average of their five highest individual daily returns over the past month. Stocks with high up days are considered to have more lottery potential for large future pops.

Nevertheless, the concept of Lottery stocks is still useful for understanding contemporaneous Quality returns. Figure 5 shows a scatter plot of monthly Quality and Value factor performance. These factors were already shown to have a negative relationship with each other, and the dotted line sloping down across the chart depicts that negative correlation. In practice, actual observations deviate far away from that trend line though. However, those deviations tend to widen or shrink based on how Lottery stocks did in that same period. When Lottery stocks do very well (darkening green colors), Quality's performance tends to be noticeably weaker than would otherwise be predicted. That effect was certainly present when Pfizer announced its vaccine results in November 2020 (bottom right corner), and it was also present in February 2000 – the final gasp of the Dot-Com Bubble (bottom left corner).

Conversely, when Lottery stocks do poorly (darkening red colors), Quality tends to post higher returns. This effect was present in the March 2020 crash, but not to the same extent that November 2020 was a headwind. That imbalance is surprising, as those two months have a clear, disease vs. cure relationship. The strongest Lottery effect ever happened after the Dot-Com Bubble burst, in November 2000.

Figure 5. Monthly Performance of Quality, Value, and Lottery Factors

Monthly, long-short domestic factor returns of HML Value factor (x-axis), QMJ Quality factor (y-axis), and FMAX Lottery factor (color scale).



Source: AQR Data Library, Turan G. Bali Data Library, and WEDGE Capital Management. Data of monthly returns spans from July 1963 – December 2020.

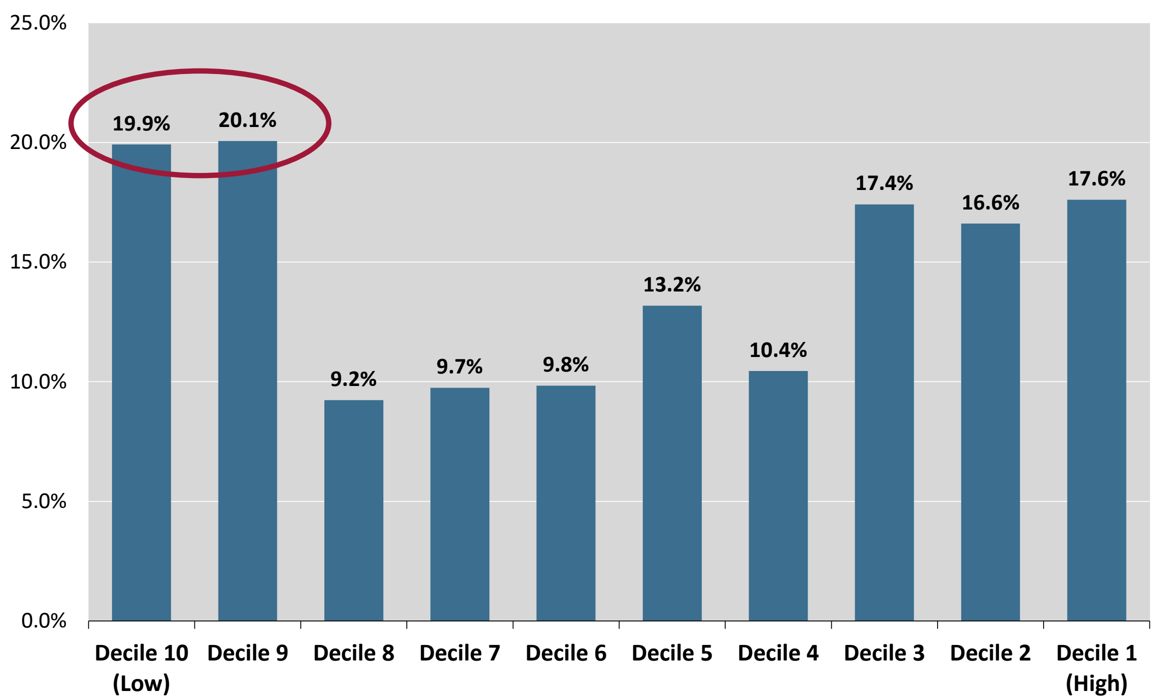
Recent Quality Weakness

Quality's relationship with Lottery-ness and Retail investor preferences is critical for understanding its recent underperformance, as a concoction of events led to a sudden rise in Retail investor participation. Retail trading commissions dropped to zero, multiple rounds of government stimulus were paid out, COVID-19 lockdowns created a surge in free time, and smartphone apps (e.g. Robinhood) and message boards (e.g. Reddit) promoted the excitement of day-trading. It is no surprise then that the increased Retail participation funneled into the types of stocks Retail investors tend to prefer, which in turn pushed the prices of those stocks higher. Figure 6 below plots the compound portfolio returns of the same Quality decile-sorted portfolios shown earlier, but only since 12/31/17. The overall underperformance of the Quality factor is due solely to the bottom quintile's high returns.

Adding to those Retail headwinds, the traditional equity factors Quality tends to hedge against all posted large, positive returns during the past year. Thus, the real surprise in Quality's recent performance is that it was already lagging before the past year's factor and COVID headwinds. Value and Size factors were underperforming back in 2018 and 2019, but the normally diversifying Quality factor was not helping to ease those burdens the way its long-term correlations would suggest.

Figure 6. Post-2017 Compound Returns of Quality-Sorted Portfolios

Annualized, long-only compound returns of domestic, decile-sorted portfolios formed according to AQR Quality factor.



Source: AQR data library and WEDGE Capital Management. Monthly returns span January 2018 (start of steep Value drawdown) to March 2021.

Conclusions

Despite its recent underperformance, WEDGE continues to view Quality as a viable factor. The long-term empirical data remains attractive, and the behavioral rationale for why Quality should work in the first place still makes sense. However, because Quality tends to move against most other factors, and its greatest benefit seems to come from the short end of its spectrum, WEDGE prefers to use it as an exclusionary filter rather than a portfolio characteristic to maximize.

In recent years this approach has been perhaps the worst one possible, as the lowest Quality stocks with Lottery features have had the best performance. However, WEDGE does not view that recent performance as a sea change that negates the favorable long-term evidence. In particular, the mechanisms that have lifted Retail market participation are transitory in nature. Stimulus checks cannot continue indefinitely, and Retail trading commissions seem unlikely to turn negative. Thus, unless a collective epiphany of investors corrects some well-documented behavioral biases, it is hard to envision a scenario where Junk stocks sustain as the correct direction to invest along the Quality dimension.

Disclaimer

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Appendix

Table A1. Spanning Regressions

Time series regressions of monthly, domestic long-short factor returns (in %s) on all factors except itself; t-statistics shown in brackets.

	Response Factor (Left Hand Side of Return Regressions)					
Explanatory Coefficients	**Market RMRF**	**Size SMB**	**Value HML**	**Quality QMJ**	**Mom UMD**	**Lottery FMAX**
Alpha (Monthly)	0.77	0.39	0.63	0.39	0.91	0.18
	[5.45]	[4.12]	[8.00]	[7.39]	[7.94]	[1.71]
Market	—	-0.05	-0.07	-0.09	-0.13	0.19
	—	[-1.85]	[-3.15]	[-6.71]	[-4.25]	[6.99]
Size	-0.11	—	0.03	-0.11	0.00	0.30
	[-1.85]	—	[0.91]	[-5.31]	[0.09]	[7.13]
Value	-0.21	0.04	—	-0.35	-0.96	-0.76
	[-3.15]	[0.91]	—	[-16.75]	[-23.20]	[-18.64]
Quality	-0.66	-0.35	-0.82	—	-0.36	-1.16
	[-6.71]	[-5.31]	[-16.75]	—	[-4.25]	[-18.62]
Momentum	-0.19	0.00	-0.46	-0.07	—	-0.22
	[-4.25]	[0.09]	[-23.20]	[-4.25]	—	[-6.68]
Lottery	0.35	0.23	-0.44	-0.29	-0.28	—
	[6.99]	[7.13]	[-18.64]	[-18.62]	[-6.68]	—

Source: AQR Data Library (all factors except FMAX), Turan G. Bali Data Library (FMAX factor), and WEDGE Capital Management.
Data covers only the periods where monthly returns are available for all factors: July 1963 to December 2020.