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Quality Minus Junk

Predicting Wealth Generating Stocks with Quality Minus Junk

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Abstract

In this thesis, we investigate if the quality minus junk (QMJ) factor can be used to predict the stocks responsible for the excess wealth creation in the US. We find that quality has a low predictive power on next months wealth generating stocks. Our findings do suggest that investors can benefit in terms of risk-adjusted returns if they use quality to predict portfolios of wealth generating stocks and portfolios of wealth destroying stocks. A predicted QMJ factor that buys and sells these high and low portfolios does not provide any additional compensation for risk over the original QMJ factor, unless investors are willing to weight the stocks equally. We also find that quality portfolios of stocks that are considered wealth generating and wealth destroying differs in quality, and that this difference also increases over time.

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1 Introduction

The motivation for this thesis arises from the findings presented by Bessembinder (2018), where the majority of firms listed on the US stock market failed to outperform 1-month(4 week) treasury bill in generated wealth during their lifetime. Bessembinder (2018) found that only about 4% of these stocks were responsible for the entire net wealth creation in the US market from July 1926 to the end of 2016. Since there are so few stocks that are considered responsible for creating wealth in the market, we are motivated to test if they share a concentration or similarities in some known accounting measures that would allow us to separate them. A factor that is based on these accounting measures might prove useful for this manner. Since there exists a jungle of factors that proxies for a variety of different sources of risk, and for the purpose of separating firms related to creation of wealth, we find the quality minus junk (QMJ) factor to be appropriate. The QMJ factor was chosen because it involves a battery of accounting measures in assigning each firm a quality score, and its abnormal risk-adjusted return generated has yet not been fully explained.

Asness, Frazzini, and Pedersen (2013) documents that portfolios which buys quality stocks and sell junk stocks generate abnormal risk-adjusted returns, which as of yet cannot be tied to a collection of different sources of risk. What drives this abnormal risk-adjusted returns is valuable, and motivates alternative approaches for explaining this anomaly. This thesis emphasizes an alternative approach, where we test if the QMJ factor manages to separate wealth generating stocks (WGS) from other stocks. A troubling finding documented by Bessembinder (2018) motivates this. That only 42.6% of stocks listed in CRSP database have outperformed a 1-month treasury bill in wealth creation during their lifetime, while the stocks have a median lifetime of 7.5 years. If these stocks can be separated or identified by the QMJ factor the choice of stocks to include in portfolios might become more straightforward. Stock picking is especially valuable to actively managed funds that holds a small collection of stocks and as a result of this are poorly diversified.

Asness et al. (2013) also show that higher quality is associated with a higher price. Highly priced stocks are generally considered as safer and investors should from a simple capital asset pricing model, demand a lower return for lower risk. However, the risk-adjusted return generated from buying high quality portfolio has historically been higher than expected. A cause for this might be that the QMJ factor is able to separate the wealth-generating stocks.

By allocating wealth in a collection of risky stocks, it is beneficial to know which are more likely to generate wealth. Also, since the risk aversion of individual investors is likely to vary, some may choose to allocate in a combination of risk-free bonds and risky stocks. However, they should under equal believes choose to allocate between the same portfolio of risky stocks and a risk-free bond. Depending on their risk aversion, some prefer to be cautious when investing and some prefer to take an excessive amount of risk. Actively managed funds have historically underperformed diversified indices in terms of risk-adjusted returns, likely as a consequence of cherry-picking stocks based on confidence and subjective opinions, such as the Black-Litterman framework allows for (Black & Litterman, 1992). However, by allowing for this, the Black-Litterman model is internally inconsistent. If the QMJ factor manages to separate WGS from non-WGS then investors are better of in terms of diversification and risk-adjusted return by allocating their wealth in a combination of risk-free bonds and the stocks identified by the QMJ factor.

This thesis builds on a replication of the main findings of "Quality minus junk" presented by Asness, Frazzini, and Pedersen (2019). The 2019 edition of the paper is chosen above the 2013 edition because the sample in their 2019 edition is relatively newer. We extend upon their replication by using an extended definition [1] of quality components that use additional accounting information to assign a firm with a quality score. Followed, we apply the methodology presented by Bessembinder (2018) to determine the accumulated wealth created above a 1-month treasury bill. The wealth score of each firm is transformed into different indicators and used to determine if the QMJ factor manages to separate WGS from non-WGS in the US market for years 1963:06-2020:12. Hence, we aim to ascertain if the QMJ factor correctly predict these stocks, and if it is applicable for an investor real time. The issue of the thesis is as follows:

Can the QMJ factor predict WGS?

[1]The extended definition of quality also includes a firm's payout score, consistent with the alternative definition of quality presented by Asness, Frazzini, and Pedersen (2019). We also use an additional variable to account for safety-component, IVOL.

To answer the question, we construct several hypotheses to determine how WGS behaves in terms of quality. Our first hypothesis is a neutral one where we determine if it exists a relationship between quality and WGS:

H1: *Is there a relationship between Quality and excess wealth created?*

The second hypothesis tests whether WGS have different quality characteristics compared to the stocks that destroy wealth. In this hypothesis also aims to test if the difference persists over time:

H2: *Is there a difference in quality between WGS, and non-WGS, and does it persist?*

We test the hypothesis to see if a difference in quality between WGS and non-WGS exists. If this is the case then QMJ factor to predict the WGS. Their difference in persistence of quality is also measured to complement the following hypothesis.

The last hypothesis investigates if the stocks quality scores can be used to indicate a predicted probability of a stock being a WGS the following period. Investors can make predictions of which stocks that are more likely to become WGS next period and the selection of stocks to choose will become more applicable. If the relationship between a high-quality stock and WGS persists, there is a good reason to buy stocks with high-quality characteristics as this is likely to generate long-term wealth. The hypothesis is as follows

H3: *Can quality be used to predict WGS?*

This hypothesis assess the predicted probabilities and use it to predict if a stock is either a WGS or not. For evaluating the results of this predictive model, we use the confusion matrix framework. Through this, valuable information about which stocks to include in the portfolios are provided. If WGS are concentrated in the portfolios it sells, then the predictive model should, if successful, flag these stocks in advance. The hit rate of the QMJ factor is especially important. This measure indicated the percentage of correctly predicted WGS in the sample.

What follows is a section where we will present background of this thesis. A summary of the main findings of Asness, Frazzini, and Pedersen (2019) and Bessembinder (2018) will be presented. Together with the Fama French three and five factor model. After the background section, we present our replication of the QMJ paper and our contribution.

We contribute to the existing literature surrounding Quality minus junk by assessing the QMJ factor's ability to predict WGS and how successful it has been in predicting them.

2 Background

In this section, we present a short introduction of the literature this thesis motivated from. First, the findings of the quality minus junk (QMJ) paper by Asness, Frazzini, and Pedersen (2019) is presented, followed by the findings of Bessembinder (2018). The Fame French (FF) factor models is then presented, as this is used to control for certain types of risks.

2.1 Introduction to quality minus junk

This thesis extends on the QMJ paper written by Asness, Frazzini, and Pedersen (2019). They provide a framework where they show that the price of a stock should mirror its different quality characteristics, where quality is defined as characteristics that should demand a higher price (Asness, Frazzini, & Pedersen, 2019). A higher price in a security is associated with safety, profitability, growth, and payout as Asness et al. found deriving from the Gordon Growth Model[2]. Profitability component is explained in that if all else is equal that profitable firms should have a higher price. Quality is also predictable, meaning that high-quality portfolios today, will also persist and be considered high-quality years ahead.

As quality is associated with safety, stocks of high quality have lower exposure to fluctuations in the market. Buying a portfolio of high quality stocks does generate risk-adjusted returns above what one would expect after controlling for several sources of risk, while low-quality (junk) portfolios do generate significantly low risk-adjusted returns. This high abnormal risk-adjusted return gained from high-quality portfolios combined with selling junk portfolios does provide high risk-adjusted returns and is referred to as the QMJ factor. The factor's high risk-adjusted returns have still not been fully explained and Quality is also documented to have a low explanatory power on price (Asness et al., 2019).

Asness et al. (2019) argue that they cannot rule out that an unknown risk factor can explain this anomaly. The unexplained risk-adjusted return generated from the QMJ

[2] $P_0 = \frac{D1}{r-g}$, where price P_0 should be higher with higher payout $D1$, or when growth g or a lower required return r (safer stock).

factor also motivates alternative approaches. A puzzling finding that may be related to this was presented by Bessembinder (2018).

2.2 Introduction to Bessembinder

The paper presented by Bessembinder (2018) emphasizes the role of positive skewness in individual common stock returns. He documents that about 4% of the firms listed on the CRSP database have managed to outperform a 1-month treasury bill in terms of wealth created during their lifetime. A puzzling finding is that about 0.33% of the common stocks are responsible for half of the net wealth creation in the US (Bessembinder, 2018).

Bessembinder defines net wealth creation as the accumulated market value generated over a compounded 1-month treasury bill[3]. Bessembinder highlights the role of diversification and there is a value in not excluding stocks in portfolios as they might be generating wealth. There are few stocks that generate wealth, diversified portfolios are holding more stocks and of that reason are having a higher probability of holding these. This might explain why actively managed funds that hold a low collection of stocks in their portfolio, usually underperform diversified indices (Bessembinder, 2018). This is as they miss the wealth generating stocks (WGS). In poorly diversified strategies have a lower probability of including these WGS. In addition to this, poorly diversified strategies are more subject to positive skewness of individual common stocks, positive skewness is good in cases where you are able to find the extreme positive values[4]. As this is not the case for most investors this is usually considered a bad thing. The positive skewness can be reduced through diversification (Bessembinder, 2018).

Predicting stocks that will generate a high amount of wealth can provide significant positive returns, but require skills. If predicted correctly it is also difficult to determine if the investor actually is skilled or just lucky (Bessembinder (2018),pg. 36). In this thesis, we test if quality can be used to predict or in some way are able to capture stocks that will generate wealth, and if the QMJ factor has managed to correctly predict them. To adjust for different sources of risk, we use the FF models presented in the next section.

[3]Excess wealth creation can be viewed as the accumulated market value minus the compounded value one would receive from investing the same initial amount in a savings account.

[4]This a case where you would be rewarded for taking the higher risk in not diversifying.

2.3 Fama French factor models

The Fama French factors are used to control for different sources of risk. The two types of risk are firm-specific and market-specific (systematic), and together they add up to the firm's total risk. To adjust for the systematic component of risk, we use the FF factor model. While the firm specific risk is captured in residuals from this regression.Fama and French (2015) Fama French three-factor model is a extension of the CAPM from Sharpe (1964) and **?**, where they added to new risk factor to the market risk. These was the component of small cap stocks tend to outperform large cap stocks, Small Minus Big(SMB), and the value stocks outperform growth stocks, High Minus Low(HML)(Fama & French, 1993).

The FF five-factor model extends on the three-factor model, by also controlling for the uncaptured variation in profitability and investments. This model uses five sources of risk to capture the systematic component of risk, where these components are market, size, value, profitability, and investment profile. This model has empirically shown good performance where it explains 71% to 94% cross-sectional variations in expected return in size, value, profitability and investment portfolios(Fama & French, 2015).

In terms of measuring the regression intercept (alpha), the abnormal return should be 0 if all sources of risk are controlled for. However, this is not always the case and motivates controlling for additional sources of risk. The QMJ factor has shown significant alphas after controlling for the FF 3 factors plus investment, profitability, liquidity, and momentum (Asness et al., 2019). The abnormal beta-adjusted return generated from the QMJ factor might be controlled for with an unknown risk factor, but we focus on an alternative story for this thesis. The alternative story our work emphasizes is that the QMJ factor separates the WGS presented by Bessembinder. In the following section, our data is presented.

3 Data

The data used for this thesis is collected from a variety of sources. In this section we will show where what data is gathered from and, when applicable, what kind of adjustments that have been done on the data sets.

3.1 Accounting data and return data

Our main source for data was the Wharton Research Data Services (WRDS) database. All data were collected with a date and a stock identifier for each observation. The stock identifier is different from Compustat and The Center for Research in Security Prices (CRSP) , this requires the CRSP/COMPUSTAT Merged Database (CCM) for merging accounting (fundamental) data and return data. From WRDS, we collected 40 annual variables from the Compustat Fundamentals Dataset of which 30 were accounting variables. Accounting data starts in June 1950 and ends December 2020. The return data was from CRSP also gathered from the WRDS database, all containing information about what exchange the stock is listed. Monthly return data consists of both the CRSP stock data (crsp.msf) and the CRSP events data[5](crsp.mse). CRSP stock data consists of price, returns, returns without dividends, volume, shares outstanding, company id, and split adjustments for both price and shares. The events data have information about delisting events for each company. We are using month return data and event data from December 1925 to December 2020, but we are reducing this period to fit the accounting data for most of the analyzes. Collected daily return data consisted of returns and delisting returns, we have reduced this data to start in January 1950 as we do not use the data before this.

3.2 Risk free rate, market returns and Consumer Price Index

The risk-free rate and market returns are collected from the Kenneth R. French Data Library under U.S. Research Returns Data. We collect this both for daily and monthly

[5]CRSP events data consist of information about all events happening to firms listed. These events[6] are such as delisting, dividends, reorganization, merger, exchange changes, change in shares, stock split, stock buy-back, liquidation etc. As most of these are in the holding period return in CRSP stock data. We are only interested in the delisting information such as return and reason for delisting.

returns. The Fama and French (FF) risk-free rate represents a proxy for the 1-month (4 week) Treasury Bill (T-Bill) rate. The variable for market return is the excess return on the US stock market. This means the return is the value-weight return of all CRSP firms listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ). FF only use firms with a CRSP share code of 10 or 11, good shares, and price data at the beginning of the month, and a good return for last month adjusted for the risk-free rate and risk-adjusted market returns. Consumer Price Index (CPI) is a monthly variable gathered from the Federal Reserve Economic Data (FRED) database by the Research Division of the Federal Reserve Bank of St. Louis.

3.3 Sample adjustments

To replicate the papers we reduced the data gathered from the sources to match the papers as close as possible. There were some small differences between the QMJ paper and Bessembinder. The reduction of the sample size was done in the following way.

First, the data was reduced to only include securities that both have account data and return data available. For each month we only include the security (PERMNO) with the highest market equity (ME) for each company (PERMCO). sampleFrom QMJ (2013) we require that the securities are common shares with share code (SHRCD) 10 or 11, the only exchanges (EXCHCD) we include are NYSE (1), AMEX (2) and NASDAQ (3). This is different from the approach QMJ choose in 2018, where they included all securities except over-the-counter exchanges. It is still consistent with the approaches Asness, Frazzini, and Pedersen (2013)), Fama and French (1993), and Bessembinder (2018) exercise. All financial firms are included and we do not include stock that is incorporated outside the US. This gives a sample of 21586 different securities(stocks) for the period. We also add N.A. to dates missing in the return data for each PERMNO to maintain a balanced panel data.

3.4 Data adjustments

The returns are adjusted for delisted return. We do it as following[7]: In cases where delisting payment date (DLPDT) is the same or earlier than delisting date the delisting return is a partial-month return[8]. We calculate return adjusted for delisting return as $return = delisted\ return$ in these cases. When the DLPDT is after delisting date the delisting returns is the return of a security after it is delisted. We then calculate it as $return = (1 + return) \times (1 + delisted\ return) - 1$[9] to get both the return before and after the delisting on the security. If delisted returns are missing and the stocks have the delisting code 500, 520, 551-574, 580, or 584[10] the stock is given a return of -30% consistent with Shumway (1997). If a stock has -100% returns these are set to -99.999% for computational reasons, one of them when we take the log of the gross return ($log(1+ret)$) which is not possible if the return is -100%. Market equity (ME) is adjusted in cases where a company has multiple securities, we keep the security on the primary exchange and add the ME for all PERMNO to only keep one observation for a company for each month. The market return from FF is adjusted for risk-free rate; we add this back to get unadjusted market returns when calculating betting against beta (BAB) and idiosyncratic volatility (IVOL) factors for QMJ. In cases we add delisting data, the exchange code (EXCHCD) and SHRCD is missing. We replace the missing values with values of the last given EXCHCD and SHRCD for that stock. This is to make them fill the requirement from sample adjustment.

The book equity (BE) is the book value of stockholders' equity plus deferred taxes minus the book value of preferred stock. Stockholders' equity is SEQ if available; if not the sum of common equity (CEQ) and preferred stock (PSTK) is used; if this is not available we make a proxy by taking total assets (AT) minus total liabilities (LT). Deferred taxes is deferred taxes and investment tax credit (TXDITC), deferred taxes or investment tax credit depending on availability in prioritized order. Preferred stock is the preferred stock redemption value (PSTKRV), liquidating value (PSTKL) or total (PTSK). This also

[7] " CRSP Calulations of Delisting Returns adjustment ©2021 Center for Research in Security Prices (CRSP), The University of Chicago Booth School of Business."

[8] The partial-month returns do not represent values after delisting.

[9] In some cases the delisiting return is in seperate month and we get $return = delisted\ return$ in these cases too.

[10] These are the delisting codes Shumway found in his paper to have negative delisting returns. All of these codes are interrelated to performance of the firm as the reason for delisting.

depends on availability. We require the stockholders' equity to have one of the values, but for the others, we give a value of zero if all are missing. We also gathered adjusted book equity data from the Davis database. This is used supplement in cases where we are missing BE for a PERMNO, then we add it if available from Davis. Davis provides additional book equity data during the earlier years and only ranges up to 2001[11].

3.5 Survival bias

Asness et al. (2019) states that some of their results are conditional on survival. In our data, firms with a lower lifetime are not treated differently than those with a longer lifetime, thus we try to limit the survival bias to the extent it is possible. This is done to provide realistic scenarios in capturing WGS, as the median lifetime of a firm has been documented to be 7.5 years, and with a 90 percentile lifetime of 28 years (Bessembinder, 2018). Our sample does require a firm to have been listed for at least 5 years to be assigned a growth score, which conflicts with the low median lifetime reported by Bessembinder.

3.6 QMJ specifics

We have relatively few observations from Compustat annual and Davis BE during the early years (1951) relative to 1963 and forth. To avoid unnecessary omitting of variables, we determine a per case basis where there is a sub-component of a variable missing if it should receive an indication of a missing value or if the missing sub-component should be ignored. One of the variables which this concerns, is the stocks total debt (TOTD). This is composed of long-term debt (DLTT), short-term debt (DLC), minority interest (MIBT), and preferred stock (PSTK). We require only one variable to be present in order to assign a firm with a total debt[12]. Similar to Cash flow (CF), which is constructed from net income (IB) plus depreciation minus change in working capital (WC) minus capital expenditures (CAPX). For this variable, we only require net income (IB) to be

[11]The book equity provided from the Davis database is left-joined on the Compustat Book equity component. Meaning that if there already exists book equity provided through Compustat annual, then Davis Book Equity data will not be supplied. Only when N.A. values are listed in Compustat annual will the other database be used.

[12]Meaning if the stock only has its expenditures financed by short-term debt only, then $TOTD = DLC$. To filter out sub-components that are missing, we use coealesce() from SQL syntax to strip missing observations. missing observations are not replaced by 0, as this gives numerical meaning.

present in order to determine the CF of a firm, albeit these instances are few[13]. Another adjustment is that the gross domestic product (GDP) price level in dollar amount from last year (lagged one year), as their explanation lacks time script, but this is indicated in the original paper by Ohlson (1980).

What follows is our replication of the QMJ paper, by Asness, Frazzini, and Pedersen (2019) where we will show what the tables that we found interesting to test our hypotheses.

[13]If there are only not available(N.A.) values, there will be no reported CF, but if there only are net income (IB), then $CF = IB$.

4 Methodology

4.1 Variable Construction

The construction of variables and factor data are based on accounting information only available for the public with the fiscal year ending in June, following the Fama (1992) standard.[14] We create factors that proxies for different characteristics of the firm, such as the firm's safety, growth, profitability, and payout policy.

Most of the constructed variables are described in the appendix, while some measurements require specific adjustments and will be described in detail in this section. One of these is the earnings volatility (EVOL) of a stock, which is constructed as the standard deviation of monthly earnings with a five-year rolling window, conditional on no missing observations. The construction of the stock's market beta, for the BAB component, is constructed by following the pre-ranking beta estimation of Frazzini and Pedersen (2014):

$$\beta_i = \rho_{i,m} \frac{\sigma_i}{\sigma_m},$$

where the estimated volatilities, σ_i, and σ_m uses daily 1-day overlapping log gross return with a 1-year rolling window. For the correlation, we take into account the possibility of non-synchronous trading and therefore use a 3-day overlapping log gross return with a 5-year rolling window. A firm also only gets a correlation and standard deviation conditional on 750 and 120 trading days without missing observations, respectively. The monthly reported beta is the last daily beta of the month and is chosen because the rebalancing of portfolios happens at the end of each month.

Under the construction of a firm's market beta, we observed a handful of firms with extreme beta values. The methodology presented by Vasicek (1973) is therefore used to reduce the expected estimation errors. This is done by shrinking the stocks market beta β_i^{TS} towards the cross-sectional mean β^{XS}. This new market beta, β_i, is now adjusted for estimation errors and have reduced the outliers, and can be stated as follows:

[14] The Fama (1992) and french methodology forms portfolios with fiscal year ending in June.

$$\beta_i = w * \beta_i^{TS} + (1-w)\beta^{XS},$$

where w is a constant weight of 0.6 [15] and the cross-sectional mean β^{XS} is set to 1 and is chosen for simplicity.

The construction ofidiosyncratic volatility (IVOL) we are taking basis in findings of Sharpe (1964) and **?** from CAPM. IVOL is the part of total volatility of a asset's return that cannot be explained by market returns, but can be diversified away by holding a large portfolio of stocks. Idiosyncratic return is the error term from a regression after the market has explained the systematic risk. First we created the idiosyncratic return $\varepsilon_{i,t}$ as:

$$\varepsilon_{i,t} = R_{i,t} - r_{f,t} - \beta_{i,t}(R_{m,t} - r_{f,t}),$$

where $R_{i,t}$ is the return of each stock, $R_{m,t}$ is the market return, $r_{f,t}$ is the risk free rate and β_i^{TS} is the beta we created above before the shrinkage factor.

Then we used the estimated idiosyncratic return $\varepsilon_{i,t}$ to create an IVOL factor as following:

$$IVOL_{i,t} = \sum_{t=-1}^{-252} \sqrt{var(\varepsilon_{i,t})},$$

where the $IVOL_{i,t}$ for firm i in period t is the sum of standard deviation of last year (last 252 days) idiosyncratic return $\varepsilon_{i,t}$, skipping the most recent trading day.

4.2 Quality Score

Based on accounting information and return data, we assign each firm an individual quality score derived from four different components of quality. A firm of quality is a safer firm that is profitable, growing, and offers payout, similar to the alternative description of quality provided by (Asness, Frazzini, & Pedersen, 2019). We include the additional payout component based on the argument presented by Bessembinder (2018). Stocks that have created a high amount of wealth during its life can get a low stock price before filing

[15] The shrinkage factor did not have any significant impact in the "Betting against beta" 2014 paper. The weight of 0.6 is chosen in consensus with this paper. Vasicek (1973) shrink this factor based on firm-specific and time-varying factors. We consider this to be too comprehensive and use fixed parameters instead.

for delisting if they offer high payouts in form of dividends[16]. The construction of each of these quality components will further be described in detail.

The z-score assigned to each measure of these quality components are constructed in the following way. For each firm every month, we do a cross-sectional rank of variable x_i. Where this variable represents an accounting measure for a particular firm. This leaves us with a vector of ranked scores relative to other firms, $r_i = rank(x_i)$[17]. This tells us the stocks position of its accounting measure, r_i, and allows us to compare this measure relative to other stocks. However, to combine this measure with other accounting variables, we center and scale the rank, providing us with a normalized z-score (N(0,1)) for the variable.

$$z_x = \frac{r - \mu_r}{\sigma_r},$$

where r is the rank of the firm, μ_r is the mean of all ranks that period[18] and σ_r is the standard deviation of the ranks in that period[19]

Now, each accounting measure share an equal footing through being normalized. Using this recipe, we assign each firm a profitability, safety, growth, and payout score based on the average of the z-scores, Z_x, of their components. If any sub-components of quality are missing, then the z-score will be the average of the remaining ones, the same goes for the components of quality.

Profitable firms are associated with a high gross profit over asset (GPOA), return on equity (ROE), return on asset (ROA), cash flow over asset (CFOA) and gross margin (GMAR). Followed by deducting the accruals (ACC) (Asness, Frazzini, & Pedersen, 2019). Each of these components gets assigned a z-score, z_x, where the average z-scores of these variables gives us the profitability score.

$$Profitability = \frac{1}{N}(z_{gpoa} + z_{roe} + z_{roa} + z_{cfoa} + z_{gmar} + z_{acc}) \tag{4.1}$$

[16] Bessembinder (2018) argues that General Motors generated a high amount of wealth, but as a result of offering high dividend payout prior to bankruptcy had a low price.

[17] Different software or programs define the rank function differently. In r, rank() assigns N.A.'s a ranked score. To properly adjust for this, we allocate all observations with N.A.'s on the top and rank ascending. Followed by replacing the scores given to the N.A.'s with N.A. at their position in the vector.

[18] μ_r is always 0.

[19] σ_r is always 1.

The growth measure is constructed by using the same measures as profitability, but is based on the change over a five-year period[20]. We use growth in residuals to weight the choices a firm makes regarding retaining its earnings.[21]

$$Growth = \frac{1}{N}(z_{\Delta gpoa} + z_{\Delta roe} + z_{\Delta roa} + z_{\Delta cfoa} + z_{\Delta gmar} + z_{\Delta acc}) \tag{4.2}$$

Firms that are characterized as safe are firms with low β_{Market} (BAB), low leverage (low LEV), low bankruptcy risk (Ohlson's o-score and Altman's z-score), and low earnings volatility:

$$Safety = \frac{1}{N}(z_{bab} + z_{lev} + z_{o} + z_{Z} + z_{evol} + z_{ivol}) \tag{4.3}$$

Further, we measure a firm payout score (4) based on its one year change in split-adjusted shares (EISS), one year change in total debt (DISS), and its five-year change in net payout over profits:

$$Payout = \frac{1}{N}(z_{eiss} + z_{diss} + z_{npop}) \tag{4.4}$$

Combined, each firm is assigned a quality score based on these four measures of quality (5):

$$Quality = \frac{1}{N}(Profitability + Growth + Safety + Payout) \tag{4.5}$$

If there are periods where only some components of quality are available, we ignore the ones not present and calculate the average quality score from the remaining ones[22]. This quality score tells us which firms that are considered to be of higher and lower quality. In the following section, a factor that buys high and sells low quality portfolios will be introduced.

[20]We only assign a stock a growth score after being listed for five years.

[21]A firms who retain earnings but generates the same amount of income as a firms who does not will be penalized through the use of residuals. Using five-year change in profitability measures does not capture this.

[22]If a firm only has a profitability and growth score, its quality score will be the mean of these

4.3 Quality minus junk and Fama and French factors

In this section, the quality score of each stock presented earlier is used for allocation in different portfolios. It is valuable to know which stocks are more likely to be a WGS. Through the six different portfolios of quality we will present, it is likely that the concentration of WGS is different from each portfolio. We will also present how we replicated the Fama and French 5 factor model plus momentum.

The recipe we use to construct the QMJ factor is as follows. At the end of each month, common stocks from the primary exchange[23] are ranked in ascending order based on previous month's market capitalization. The median of these ranked stocks is then used to divide small and big stocks into two size portfolios, Small and Big. Where US common stocks[24] are allocated[25]. Conditional on these size portfolios, the common stocks are sorted into three different quality portfolios, high (top 30%), neutral (middle 40%), and low quality (bottom 30%). This leaves us with 6 portfolios where the value-weighted average is used to calculate the return of each portfolio. The QMJ factor is constructed from the intersection of buying the two quality portfolios and selling the two junk portfolios[26].

$$\text{QMJ} = 1/2\ (\text{Small Quality} + \text{Big Quality}) - 1/2\ (\text{Small Junk} + \text{Big Junk})$$

As shown above, the QMJ factor is formed from the average return of going long in the average of the two high value-weighted quality portfolios and going short in the average of the two low value-weighted quality portfolios. Since the QMJ factor follow the Fama and French methodology, we also replicate their 5 factors plus momentum to appropriately adjust for different sources of risk. Because of this, we do not use external factor return data available from Kenneth R. French's website, only their risk-free component provided by Ibbotson Associates Inc.

[23]Primary exchange in US is NYSE.

[24]US common stocks are the securities listed on NYSE, AMEX and NASDAQ.

[25]The number of small firms is higher than Big firms since the NYSE median is much higher than most of the common shares listed in NASDAQ and AMEX.

[26]This is the equivalent of a double sort on size/quality which follows the FF methodology. Double sorting is when you first sort based on characteristic like size and then on a second like quality/value/momentum.

Under the construction of these factors, the BE is of last year's fiscal year and reflects the public information available at the construction date[27]. BE is then divided by the firm's market equity in December last calendar year. To replicate these factors, we follow the recipe explained by Fama and French (1993) and a suggested replication provided by Chang and Liu. We replicate these factors in the following way:

We start by only including the stocks with common BE listed in the CRSP database ranging 1950:07-2020:06. Further, the construction of small and big portfolios are the same as with the QMJ factor, where quality represents a value, in the value-sorted portfolios. The FF factors are the constructed from double sort on size and value[28].

SMB double sort consists of three buy buckets and three sell buckets:

$$SMB = \begin{array}{l} 1/3 \text{ (Small Low + Small Neutral + Small High) -} \\ 1/3 \text{ (Big Low + Big Neutral + Big High)} \end{array}$$

HML double sort consist of two buy buckets and two sell bucket[29]:

$$HML = \begin{array}{l} 1/2 \text{ (Small Low + Big Low) -} \\ 1/2 \text{ (Small High + Big High)} \end{array}$$

By following this methodology we replicate factors that control for market risk (Mkt), firm size[30] (SMB), firm value HML, operating profitability, investment, and the Carhart momentum factor. This momentum factor is used in all of our replications which are presented in the following section.

[27] The BE available at the construction date of the portfolios in June is from the fiscal year available last calendar year

[28] Value portfolio are in FF methodology referred to a portfolio of a value characteristic. For the QMJ factor this is the quality variable.

[29] This is the method used on other factor in the FF factor models.

[30] Size is constructed by multiplying shares outstanding with current price, $ME = SHROUT * Price$

5 Replication

In this section, our replicated results will be presented. The tables we have chosen to replicate both verify the structural properties of our replicated quality score, and are also important later when determining quality's ability to separate WGS.

The following replications we provide shows that quality persists and that the return of quality sorted portfolios increases monotonically. For the QMJ factor, we replicate and provide the alphas after controlling for several risk factors. Combined, these form four tables with replicated results.

5.1 Persistence of quality

We choose to focus on the persistence of quality, since this property may be common among WGS. Excess wealth creation is generated by only a few percentage of stocks (Bessembinder, 2018). This table involves sorting stocks into portfolios based on their quality scores and valuating their persistence. It is also related to our later hypothesis where we test if there is a difference in persistence among WGS and non-WGS.

By using the quality score and its individual components, we replicate the results from Table 1: Persistence of quality measures, by Asness, Frazzini, and Pedersen (2019). Our replication highlight that a portfolio's quality and its components persists over time and still increases monotonically after 10 years. This predictability of quality may allow for the use of quality today to predict WGS of tomorrow. If WGS share the same quality characteristics and persists differently than non-WGS, then the predictability of quality should provide valuable information about which stocks that are more likely to be WGS.

We replicate table 1 by following Asness, Frazzini, and Pedersen (2019). At month t, NYSE decile breakpoints are created based on the Quality scores observable. US common stocks are then allocated into these portfolios based on their quality score, forming 10 quality portfolios. For n months ahead in time, we calculate the value-weighted quality-score at $t + n_{months}$ using the firms selected in the portfolio at time t. This is done for 12, 36, 60, and 120 subsequent months ahead in time for the quality score and for 120 months for its individual components. The quality score reported in table 1 is the time-series average of each portfolio's monthly value-weighted quality score, ranging 06/1975 - 12/2016. Further, the rightmost column reports the quality score of a portfolio that buys high (P10) and sells low quality (P1). The standard errors used are heteroskedasticity and autocorrelation consistent (HAC) over 5-year window, in consensus with Newey and West (1987)[31]. Statistical significance at 95% level is indicated in bold. The hypothesis tested is:

H_0: There is no significant difference in high and low quality portfolios.

H_A: There is a significant difference in high and low quality portfolios.

Our replicated results are presented in the top panel, while the original results are in the bottom panel.

[31] HAC standard error are used to control for Heteroscedasticity and autocorrelation. Heteroscedasticity indicates that variation in errorterms are not similar over time. While autocorrelation indicates that the error terms are correlated. By controlling for these, the uneven variation in error terms and its correlation are reduced. These standard errors are then used to calculate the t-stat.

Table 5.1

Table 1: Persistence of quality and its components

		P1 (Low)	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10** (High)	**H-L**	**H-L** t-stat
Panel A: Replicated results, 6/1975 - 12/2016													
Quality	t	−1.22	−0.66	−0.40	−0.18	0.02	0.23	0.45	0.69	0.99	1.56	**2.78**	14.11
Quality	t + 12M	−0.61	−0.33	−0.18	−0.04	0.09	0.28	0.46	0.65	0.89	1.35	**1.96**	10.49
Quality	t + 36M	−0.24	−0.10	−0.02	0.08	0.18	0.31	0.50	0.64	0.87	1.25	**1.49**	22.24
Quality	t + 60M	0.02	0.06	0.10	0.17	0.26	0.35	0.52	0.66	0.87	1.19	**1.17**	28.14
Quality	t + 120M	0.15	0.19	0.21	0.29	0.34	0.42	0.62	0.80	0.91	1.17	**1.02**	23.49
Profit	t + 120M	−0.09	0.08	0.14	0.21	0.32	0.46	0.58	0.73	0.99	1.42	**1.51**	31.09
Growth	t + 120M	0.03	0.06	0.03	0.08	0.04	0.07	0.13	0.24	0.40	0.61	**0.58**	21.02
Safety	t + 120M	−0.27	−0.13	0.08	0.18	0.32	0.39	0.53	0.65	0.80	0.87	**1.15**	26.85
Payout	t + 120M	0.07	0.22	0.31	0.31	0.38	0.45	0.52	0.53	0.63	0.67	**0.6**	15.11
Panel B: Original results, 6/1975 - 12/2016													
Quality	t	−1.44	−0.83	−0.53	−0.29	−0.07	0.15	0.38	0.65	0.99	1.64	**3.07**	54.21
Quality	t + 12	−0.86	−0.51	−0.33	−0.20	−0.01	0.16	0.36	0.54	0.83	1.46	**2.34**	40.31
Quality	t + 36	−0.50	−0.32	−0.23	−0.16	−0.02	0.11	0.23	0.41	0.65	1.22	**1.73**	19.33
Quality	t + 60	−0.23	−0.17	−0.14	−0.12	−0.04	0.06	0.18	0.31	0.52	1.07	**1.31**	13.96
Quality	t + 120	−0.23	−0.18	−0.14	−0.09	−0.04	0.07	0.16	0.33	0.48	0.91	**1.14**	12.96
Profit	t + 120	−0.37	−0.23	−0.12	−0.02	0.10	0.13	0.26	0.33	0.53	1.08	**1.47**	22.42
Growth	t + 120	−0.15	−0.11	−0.13	−0.11	−0.13	−0.08	−0.05	0.02	0.23	0.41	**0.56**	5.96
Safety	t + 120	−0.43	−0.27	−0.14	−0.04	0.04	0.13	0.23	0.37	0.60	0.75	**1.18**	14.38

This table reports the average quality scores ranging 6/1975 − 12/2016. At each month, NYSE firms are ranked ascending based on their quality score, where NYSE decile breakpoints are measured. Each US firm is then divided by these quality breakpoints, forming 10 value-weighted quality portfolios. The reported quality scores for each portfolio are the time-series average of the cross-sectional value-weighted mean at subsequent t and $t+$ 12, 36, 60 and 120 months ahead in time. The rightmost column reports the t-stats, where the standard errors are heteroskedasticity and autocorrelation consistent over 60 months (Newey and West 1987) and statistical significance at 5% level are indicated in bold. Panel A presents our replicated results, and Panel B presents the original results.

Our replicated results presented in Panel A shows that quality increases monotonically and persists across quality portfolios up to 10 years. From this, a portfolio of stocks that are considered high-quality today, are also considered high-quality in 1, 3, 5, and 10 years ahead in time. Our results from the portfolio (H-L) that buys high quality (P10) and sell low (P1) quality generate a similar spread relative to the original results. We find that the growth component are the least persistent, followed by payout and safety component. Our low growth portfolio (P1) has a rather high growth score after 10 years, but the spread (H-L) between high and low are still significant and similar.

Asness, Frazzini, and Pedersen (2019) assume that their results are conditional on survival. Our replicated results are also subject to this survival bias, as the firms who have survived during the reported periods are the only ones included in the sample[32] when computing quality scores.

Overall, our replicated results are similar to then original ones, and because of the significant reported results we reject the null hypothesis of no difference between high and low quality portfolios up to 10 years. We will later extend on this replication by testing if WGS and non-WGS persists differently.

Further, we follow Asness, Frazzini, and Pedersen (2019) by verifying that high- and low-quality portfolios deliver a significant positive and negative abnormal risk-adjusted return, respectively. We do this to validate our replicated quality score.

5.2 Return of quality-sorted portfolios

In this section, we aim to replicate the findings in the original paper that shows that high quality portfolios outperform low quality portfolios. Portfolios of higher quality are safer and should have a lower loading on the market factor. We aim to show that positive significant alphas are still present after controlling for the FF-3 and FF-3 plus momentum models . Our replicated table, Table 2, shows the regression results of each quality portfolio after controlling for different sources of risk. The returns are beta-adjusted by market risk (CAPM), firm size (SMB), value of the firm (HML), and momentum (UMD). The regression results reported are from FF 1-factor (CAPM), 3-factor model (Mkt, SMB

[32]If any stocks gets delisted, the value-weighted quality-score will be calculated based on the remaining ones from the initial portfolio. As a result of this, the reported quality scores are survival biased.

and HML), and the 4-factor model presented below.

$$r_i = \alpha + \beta^{MKT} MKT + \beta^{SMB} SMB + \beta^{HML} HML + \beta^{UMD} UMD + \epsilon_i$$

Where r_i is the return of portfolio, α is the regressions intercept, and β represents the portfolios loading on market, size, value and momentum. we construct table 2 in the following way. For each month, 10 deciles are constructed from 10 NYSE breakpoints based on the quality scores of the firms. Each firm is then allocated into one of these buckets based on their quality score. The portfolio's value-weighted return is then calculated based on last month's market capitalization. The column to the right reports a self-financing portfolio[33]that buys high-quality (P10) and sells low-quality (P1) portfolios. The hypothesis tested are as follows:

H_0: There is no significant difference in return between high- and low-quality firms

H_A: There is a significant difference in return between high- and low-quality firms

Statistical significant values reported are indicated in bold, and the alphas and excess return are in monthly percentage. Standard errors are heteroskedasticity and autocorrelation consistent over 5 years and information ratio and sharpe ratio are annualized. The Beta reported are the market loading for the respective portfolio. The alphas reported are the intercepts from the three different regressions. Information ratio are estimated from the 4-factor alpha divided by the standard deviation of the residuals from this regression (Asness, Frazzini, & Pedersen, 2019). Our replicated results are presented in the top panel, and the original are presented in the bottom.

[33]A self financing portfolio is a portfolio that does not have any in our out flux. This means that the portfolio can ony buy from the sales it makes. In this case it buys high quality and sells low quality portfolios. There are no additional transactions going in or out besides these.

Table 5.2

Table 2: Return of quality-sorted portfolios

	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L
Panel A: Replicated Results, 07/1957 - 12/2016											
Excess return	0.24	0.37	**0.47**	**0.45**	**0.49**	**0.56**	**0.62**	**0.55**	**0.66**	**0.67**	**0.43**
	(0.98)	(1.71)	(2.49)	(2.6)	(2.85)	(3.37)	(3.65)	(3.27)	(4.03)	(4.13)	(4.37)
CAPM alpha	**-0.41**	**-0.24**	-0.11	-0.09	-0.04	0.03	0.07	0.05	**0.14**	**0.16**	**0.57**
	(-3.78)	(-2.76)	(-1.49)	(-1.59)	(-0.65)	(0.49)	(1.44)	(0.92)	(2.92)	(2.54)	(3.99)
3-factor alpha	**-0.53**	**-0.43**	**-0.24**	**-0.19**	**-0.16**	-0.04	0.04	0.04	**0.2**	**0.3**	**0.83**
	(-5.97)	(-5.79)	(-3.49)	(-3.31)	(-2.81)	(-0.78)	(0.79)	(0.69)	(4.22)	(5.55)	(7.33)
4-factor alpha	**-0.46**	**-0.37**	**-0.16**	**-0.15**	**-0.11**	-0.03	0.03	0.03	**0.21**	**0.26**	**0.72**
	(-5.12)	(-4.89)	(-2.4)	(-2.68)	(-1.91)	(-0.59)	(0.61)	(0.62)	(4.16)	(4.68)	(6.29)
Beta	1.36	1.24	1.1	1.03	1	0.99	1	0.97	0.96	0.91	-0.45
Sharpe Ratio	0.13	0.22	0.32	0.34	0.37	0.44	0.47	0.42	0.52	0.54	0.36
Information Ratio	-0.77	-0.73	-0.36	-0.4	-0.29	-0.09	0.09	0.09	0.62	0.7	0.94
Adjusted R2	0.9	0.91	0.9	0.92	0.91	0.91	0.92	0.92	0.93	0.91	0.56
Panel B: Original results, 7/1957 - 12/2016											
Excess return	0.28	**0.43**	**0.43**	**0.51**	**0.55**	**0.53**	**0.48**	**0.62**	**0.52**	**0.70**	**0.42**
	(1.09)	(2.10)	(2.29)	(2.88)	(3.14)	(3.18)	(2.94)	(3.71)	(3.11)	(4.11)	(2.56)
CAPM alpha	**-0.44**	**-0.17**	-0.13	-0.02	0.03	0.03	-0.01	**0.12**	0.01	**0.20**	**0.64**
	(-3.72)	(-2.29)	(-1.94)	(-0.29)	(0.55)	(0.60)	(-0.19)	(2.36)	(0.28)	(3.11)	(4.26)
3-factor alpha	**-0.57**	**-0.28**	**-0.21**	-0.10	-0.03	-0.02	-0.02	**0.10**	0.05	**0.31**	**0.88**
	(-6.52)	(-4.45)	(-3.68)	(-1.89)	(-0.60)	(-0.41)	(-0.39)	(1.99)	(1.01)	(5.90)	(8.23)
4-factor alpha	**-0,59**	**-0,39**	**-0,28**	**-0,19**	-0.11	**-0,12**	-0.10	**-0,11**	0,07	**0.46**	**1.05**
	(-6.30)	(-5.90)	(-4.56)	(-3.58)	(-1.91)	(-2.41)	(-1.79)	(2.10)	(1.55)	(8.59)	(9.31)
Beta	1.28	1.16	1.10	1.06	1.04	1.00	0.97	0.97	0.97	0.92	-0.36
Sharpe Ratio	0.14	0.27	0.30	0.37	0.41	0.41	0.38	0.48	0.40	0.53	0.33
Information Ratio	-0.88	-0.83	-0.64	-0.50	-0.27	-0.34	-0.25	0.29	0.22	1.2	1.31
Adjusted R2	0.88	0.91	0.91	0.92	0.90	0.92	0.91	0.91	0.93	0.91	0.59

This table reports the average monthly excess return for 10 quality portfolios. At the end of each month, NYSE stocks are ranked and quality decile breakpoints are measured. US stocks are then allocated into their respective quality portfolio based on their quality score. The reported excess returns are the average of the monthly value-weighted return over a t-bill, based on last month's market cap. The three regressions use market (MKT), size (SMB), value (HML), and momentum (UMD) as explanatory variables and the dependent is the return of the quality portfolio. Where the first regression use market (MKT), the second regression uses market (MKT), size (SMB) and value (HML), and the last regression uses all 4 explanatory variables. The alphas reported are the intercept of the regression. Alphas and excess returns are reported in percentage and sharpe ratio and information ratios are annualized. The beta reported is the portfolio's market loading. Information ratio are estimated from the four-factor alpha divided by the standard deviation of the residuals from the regression. The rightmost column represents a self-financing portfolio that buys high quality and sells low quality. The standard errors are HAC standard errors (Newey and West, 1987) and statistical significance is indicated in bold.

Our replicated result shows that excess return increases in quality significantly from P3 to P10. This increase also appears to be almost monotonic. Important results are also present among the two high-quality portfolios, P9 and P10. There CAPM alpha is significant and positive, indicating a common structural property of the stocks included in these two portfolios. High-quality stocks are considered safer stocks, and as a result of being safe they are less exposed to fluctuations in the market. If the market is in a recession, then these high-quality portfolios will do it better during these bad times. A high safety score is incorporated through the low market beta of safety's BAB component. Our replication also shows that portfolio P9, in addition to P10, also have a significant positive alpha when controlling for the one, three, and four-factor model. While this is not present in their original results for portfolios P9. We also observe that the beta is decreasing in quality. This is a result of the sorting on quality, as safer stocks are among the higher portfolios and vice versa(Asness, Frazzini, & Pedersen, 2019).

The three and four-factor alpha replicated are similar to the original paper. We show a strong significance among the lower and higher quality portfolios. Where the low quality portfolios have underperformed, and high quality have overperformed in terms of risk-adjusted returns. Our self-financing portfolio which buys high and sells low quality does as a result of this earn significantly high risk-adjusted return. The excess return for this portfolio is also similar to the original, while obtaining similar results for the loading on market, three and four factor model. However, our loading when adding our momentum factor is slightly lower than their original results.

The replicated sharpe ratios are similar to the original results, but show some variation in the quality neutral portfolios ranging from P3 to P5. However, this measurement is consistent across the lower and higher quality portfolios.

Because of the direction and significance of the reported alphas, and the market loading decreasing monotonically in quality, our quality scores shows the expected exposure to different sources of risk. Through this table, we observe that high-quality stocks are considered safe and are less exposed to market-specific risk. And as a result of this, high-quality portfolios overperform, and low-quality portfolios underperform, even after controlling for the FF three- and four-factor models. Through this table, we have observed consistency shown in the original results and validated of the structural properties of our quality score. Further, when testing the QMJ factor's exposure to these sources of risk, we should observe similar results.

In the following section, we validate our replicated QMJ factor.

5.3 Quality minus Junk

In this section, we present our replicated QMJ factor and verify that its alphas are statistically significant and present after controlling for several risk factors. As shown in the earlier section, buying high-quality and selling low-quality generates returns that are unexplained by the FF four-factor model. A factor that buys high-quality stocks from small and big portfolios, and sells junk (low-quality) stocks from small and big portfolio does from this generate high risk adjusted returns. We validate the QMJ factor to show that its overperformance is present in our factor. This factor will because of the quality score provide useful information about the probabilities of including WGS in its portfolios. In our later hypothesis, we assess the QMJ factor's hit rate and success in predicting WGS and home run stocks.

The QMJ factor is formed from the average return of going long in the average of the two high value-weighted quality portfolios and going short in the average of the two low value-weighted quality portfolios. This construction is also done similarly for the profitability, safety, growth and payout score. We construct factors based on the components of quality using the same recipe as the factors replicated earlier, the intersection between the 6 value-weighed portfolios. A more detailed description of the portfolio formation for these are provided in appendix, section A5. These factors are named by the values they represent in our two following replicated tables.

Table 3 provides the factor loading for the return generated from the QMJ, profitability, safety, growth, and payout factors where the explanatory variables of the regression are the same as regression used in the previous section. The results of a regression between QMJ and these explanatory variables will be presented in the following table. Where the alphas reported are the regression's intercept. Both excess return and alphas are reported in percentage and sharpe ratio and information ratio are annualized. The information ratio are calculated from the four-factor alpha divided by the standard deviation of its regression's estimated residuals and statistical significance at 5 percent level are indicated in bold. Our replicated results are on the section to the left, and the original results are provided in the section to the right.

Table 5.3

Table 3: Quality minus junk: Returns

	Replicated results (7/1957 - 2016/12)					Original results (7/1957 - 2016/12)			
	QMJ	Profitability	Safety	Growth	Payout	QMJ	Profitability	Safety	Growth
Excess Return	**0.36**	**0.27**	**0.22**	**0.15**	**0.26**	**0.29**	**0.25**	**0.23**	**0.17**
	(4.6)	(3.82)	(2.51)	(2.12)	(3.28)	(3.62)	(3.69)	(2.44)	(2.46)
CAPM-alpha	**0.56**	**0.35**	**0.47**	0.12	**0.48**	**0.39**	**0.32**	**0.40**	**0.16**
	(7.82)	(4.97)	(5.78)	(1.61)	(7.45)	(5.43)	(4.75)	(5.52)	(2.28)
3-factor alpha	**0.69**	**0.53**	**0.64**	**0.37**	**0.33**	**0.51**	**0.40**	**0.52**	**0.28**
	(10.96)	(8.76)	(8.8)	(6.19)	(5.95)	(8.90)	(6.97)	(9.06)	(5.17)
4-factor alpha	**0.61**	**0.47**	**0.5**	**0.33**	**0.28**	**0.60**	**0.51**	**0.51**	**0.46**
	(9.68)	(7.75)	(7.2)	(5.4)	(4.97)	(9.95)	(8.32)	(8.39)	(8.29)
MKT	**-0.22**	**-0.14**	**-0.27**	**-0.03**	**-0.15**	**-0.2**	**-0.12**	**-0.32**	**-0.04**
	(-14.38)	(-9.64)	(-15.84)	(-2.1)	(-10.68)	(-14.35)	(-8.47)	(-22.30)	(-2.81)
SMB	**-0.23**	**-0.19**	**-0.23**	-0.04	**-0.16**	**-0.26**	**-0.22**	**-0.30**	-0.04
	(-10.05)	(-8.38)	(-8.99)	(-1.95)	(-7.85)	(-11.92)	(-10.01)	(-13.55)	(-1.76)
HML	**-0.23**	**-0.32**	**-0.28**	**-0.45**	**0.27**	**-0.37**	**-0.29**	**-0.28**	**-0.49**
	(-9.83)	(-13.81)	(-10.52)	(-19.49)	(12.73)	(-15.58)	(-12.57)	(-11.91)	(-23.09)
UMD	**0.1**	**0.06**	**0.16**	**0.05**	**0.06**	**-0.09**	**-0.10**	0.01	**-0.16**
	(6.17)	(4.23)	(8.84)	(3.12)	(4.17)	(-4.34)	(-4.87)	(0.32)	(-9.17)
Sharpe Ratio	0.6	0.49	0.32	0.28	0.43	0.47	0.48	0.32	0.32
Information Ratio	1.47	1.18	1.1	0.82	0.76	1.40	1.17	1.18	1.16
Adjusted R2	0.51	0.42	0.55	0.42	0.51	0.50	0.34	0.62	0.46

This table provides the factor loadings and excess returns for the quality minus junk (QMJ) factor and its components. The return of the QMJ factor is formed from the average return of going long in the average of the two high value-weighted quality portfolios and going short in the average of the two low value-weighted quality portfolios. this construction is similar for profitability, safety, growth and payout. The explanatory variables are market (MKT), size(SMB), value (HML), and momentum (UMD). Where the first regression (CAPM) use only the market, second regression (FF 3 factor) use MKT, SMB, and HML, and the third regression (FF 4 factor) use all 4 explanatory variables. The alphas reported are the regression's intercept. Excess return and alphas are reported in percentage and sharpe ratio and information ratio are annualized. Information ratio is the four factor-alpha divided by the standard deviation of the regression's residuals. Statistical significance at a 5% level is indicated in bold and the original results are placed next to our replicated results.

Our replication shows that after controlling for the 3 and 4-factor model, the QMJ factor generates highly significant alphas. We also observe as expected that this factor overperformed when controlling for the market loading. From the earlier results presented in Table 2, we observed that portfolios that buys high quality and sells junk generate significant alphas after controlling for the market. These alphas arise from the structural properties associated with safety, that the portfolio buys low beta stocks, and sells high beta stocks. The QMJ factor also has a negative risk-factor loading on the market, size, and value. Given that this factor buys safe stocks, a negative risk-factor loading on the market is to be expected. A negative loading on the size factor is also consistent with the QMJ factor buying highly priced stocks and selling low priced stocks. Stocks that are higher priced are also associated with bigger firms, and small firms carry are priced lower. Since the size-factor, SMB, buys small and sells Big firms, the QMJ factors attains a negative risk-factor loading on size. (Asness, Frazzini, and Pedersen (2019))

The excess returns and risk-adjusted returns from the QMJ factor are slightly higher than the original results. From the high excess return obtained from the payout factor, this is to be expected as our quality score also includes this. Because the value factor, HML, buys stocks with low price, and sells stocks with high price, the negative risk-factor loading on the value shown from the QMJ factor is to be expected. As the QMJ factor buys stocks that are, through quality, highly priced and sells stocks with a low price.

The profitability, safety, and growth factors all have a nearly identical excess return, one and three-factor alpha. However, our growth component does not have a significant alpha after controlling for market.

Altogether, our replication of the QMJ factor provides results consistent with what one would expect from this factor. This is based on the direction and significance of the risk-factor loading and the alphas presented after controlling for different sources of risk. The QMJ factor does through quality buy highly priced stocks and sell low priced stocks, thus the negative value-factor loading. Consistent with the results presented in Table 2, the QMJ factor also has a negative risk-factor loading on the market and has significantly outperformed it as a result of buying safe and selling unsafe firms. The QMJ factor also consistent with original results shows a negative risk-factor loading on size, as the size-factor buys small and sells big stocks, as smaller firms have lower prices, and larger firms are higher priced. From the consistencies shown in our one, three, four-factor alpha, and the risk factor loadings, we consider our replication of the QMJ factor as validated. However, as a robustness check, we also control for the additional risk sources by using the FF five factor and FF five factor plus momentum. The risk-factor loadings are also presented in appendix, Table A6, and indicates that the overperformance of our replicated QMJ factor are still present after additional explanatory variables. Similar results are also obtained when using components of quality as dependent variables.

$r_i = \alpha + \beta^{MKT}MKT + \beta^{SMB}SMB + \beta^{HML}HML + \beta^{CMA}CMA + \beta^{RMW}RMW + \beta^{UMD}UMD + \epsilon_i$

The risk factor loading obtained on the RMW factor is positive, as Quality are constructed from measurements of profitability, while the RMW factor buy profitable and sells unprofitable stocks. Overall, we see that the direction of the risk-factor loadings is consistent with what one should expect from a portfolio that buys quality and sells junk. The significant abnormal risk adjusted return is still unexplained, even after controlling for the 5 and 6-factor models.

As a summary of our replication, our quality score represents the properties of quality and its exposure to different sources of risk. Higher quality portfolios consistently overperform the market and low quality portfolios underperform. Adding additional explanatory variables that proxies for different sources of risk does not add to the explanation of the return of quality portfolios. A factor that buys high quality portfolios and sells low quality portfolios does benefit from both the over and under performance of these. In the next section, we will assess if the stocks quality scores can be used to predict WGS and test our hypotheses to answer if the QMJ factor manages to separate WGS in its portfolios. The role of the quality scores of each firm will also be used to assign each firm with a probability of being a WGS.

6 Wealth generating and home run stocks

Our definition of wealth-generating stocks(WGS) builds on the findings of Bessembinder (2018), where they found that about 4% of all stocks account for all net wealth-generating in the US stock market. Bessembinder, Chen, Choi, and Wei (2019) also found similar results when test this in other stock markets. Individual stock returns are positively skewed in this market, which means there is a chance of large positive return, but the average return for a stock is less than zero. Only about 47.8% of all common stocks listed on NYSE, AMEX and NASDAQ deliver higher return than the t-bill.

In this work we test if quality factor is able to predict these stocks with positive returns. The choice of keeping WGS on a return level, is that we are not interested in magnitude of wealth generate. Another important thing when defining WGS was to have stocks that consistently deliver good returns, but also make sure this is not being caused by the momentum effect[34] by Jegadeesh and Titman (1993). This is done by only using the return for the stock in time t: $Wr_t = R_t - rf_t$, where $R_t - rf_t$ is the return over the treasury bill and Wr_t is the wealth return. De Bondt and Thaler (1987) found effect of stocks having negative returns in one period to have a reversal effect[35] after this. The effect from their finding where strongest in the first month after. One last effect we need to controll for was the leverage effect[36] from Christie (1982). This can cause securities to destroy a lot of value in one period and create some value back in the next. This is controlled for by a variable we call controlled return (Cr): $Cr = ((1 + Wr_t) \times (1 + Wr_{t-1})) > 1$, where we require that the return has been positive[37] across this month and last month. This will ensure that stocks that have a higher leverage in the last period will still not be considered WGS, unless they create more value than was destroyed this period.

The last adjustment was for small stocks hard to trade and are therefore likely to have less liquidity with returns that are not market efficient because information of a small

[34] Momentum effect: short-term winners deliver higher return than short-term losers

[35] Reversal effect is related to the that markets are not efficient in short-term and tendency to overreact to news.

[36] Leverage effect is a firm's stock price declines and as a cause the firm's financial leverage increases. Debt/Equity ratio increases and the firm has higher risk.

[37] if both Wr_t and Wr_{t-1} has 0 return the security will not be considered WGS as Cr is not larger than 1. Same in cases where we destroy 50% of the stock value , but then make back 100% next. Still not considered WGS as the stock has not created any wealth.

stock gets less attention and it takes longer time for the market to adapt. A requirement for a stock to be WGS is set to have a ME over 1 million dollars. If a firm fills these requirements and has a positive wealth return in time t, they are considered WGS in that period.

$$Ws = \begin{cases} Wr_t > 0 & = WGS \\ Wr_t <= 0 & = WDS \end{cases}$$

Haugen and Baker (1996) states that higher profitability gives higher stock return. They also explain that profitable firms tends to grow fast and have a greater potential for future growth (Haugen & Baker, 1996). From Gordon Growth Model[38] we expect a higher stock price if the growth of a firm is increasing. This can explain why growth is likely to increase shareholders wealth and growing firms expected to have higher returns[39]. Also if the growth or dividends are consistent for a longer long period of time, this will cause a higher price and also return. This can be seen as the safety component of quality. Investors would like to have safety in the returns they get. As mentioned we want the WGS to reflect on consistently deliver good returns. Good returns may be captured by the quality components payout and profitability, consistency can be thought as safety

Wealth generating stocks is a quite broad term in this paper and consider most of the firms that generate positive returns, as of this reason we wanted to check for the quality's predictive power of a more narrow estimate we called home run stocks(HRS). These HRS are mentioned in the conclusion of Bessembinder (2018). He did not specify exactly what categorized a HRS, but mentioned that about 1/3 of 1% of all stocks account for over 50% of all net wealth generated in the market this is used as a foundation to create a measure for HRS.

For HRS we decided to go for firm level, because we wanted the stocks to be the best in the market the ones that are generating the most wealth. We said that the one percent that has created most wealth in time t, while also have created wealth in t-1. We define wealth generated as: $Wg_t = Wr_t * ME$, where Wg_t is the wealth for a firm on this month. HRS is considered to be the top one percent of the Wg_t values each month. Here we most likely will only have stocks with already a high ME, creating some challenge for

[38] Gordon (1959)

[39] $return = \frac{P1-P0}{P0}$, where P1 is the price this period and P0 is the price last period

the QMJ predict to test its capacity. To capture these QMJ would have to see these in the big quality bucket. Larger firms also create more wealth and its more like to have all information incorporated. This means if is quality score is right in capturing the quality of firms, it should be reflected in a high quality stocks also being a HRS.

7 Hypothesis

In this section, we aim to answer if our quality score can be used to predict WGS. The QMJ factor buys portfolios of high quality and sells portfolios of low quality. If the QMJ factor manages to predict these WGS, then investors can reliably use this factor when selecting stocks in their investment portfolio. First, we determine if there exists a relationship between a stock's quality score and the wealth. The direction of this relationship should provide valuable information about quality and wealth. If there is a negative relationship between wealth and quality, then the WGS may be allocated on the short side of QMJ portfolios. Selling WGS is not desirable as it leads to low returns. On the other hand if there is a difference between WGS and WDS, then it is possible that the QMJ factor have allocated WDS in the portfolio on the short side, and WGS on the long side. Because of this, we test if there is a difference in quality between WGS and WDS and if this difference persists. If WDS of high quality does not persist similarly to high quality WGS, Then the difference is valuable to investors. However, if there is no difference in persistence, it should be more difficult for quality to predict WGS.

In our last hypothesis, we test if quality can be used to predict WGS. The success of the QMJ factor is also assessed, as this factor buys quality portfolios. We also inspect if the QMJ factor have managed to correctly separate home run stocks, as Bessembinder documents that a third of 1% of individual common stocks are responsible for half of the excess wealth creation in the US. The QMJ factor holds diversified portfolios, and we expect that some WGS will be predicted on the portfolios it buys. However, the number of wrongly predicted WGS on the short side may very easily ruin the payoff from the good predictions.

This section is constructed as follows, first we test the relationship between Wealth and quality. Followed by this, the difference in quality between WGS and WDS are assessed. Lastly, quality is used to predict WGS and the predictive power of quality on WGS is evaluated.

7.1 Relationship between wealth and quality

In this section, we aim to answer if there exists a positive significant relationship between quality and Wealth. If there is a positive relationship, higher quality should be associated with higher wealth. By construction, wealth incorporates the firms price, which also is used as a sub-component of quality components. Because of this, we use wealth measured on return level.

Since we are interested in a relationship, we approach this econometrically by using a regression model that uses quality as the explanatory variable, and excess wealth created as the independent variable.

$Wealth_t = \alpha + \beta^{Quality} Quality_t + \epsilon$

As a robustness, we split the sample into 5 different decades. The wealth in the regression is the accumulated wealth on return level.

Table 7.1

Table 4: Relationship between wealth and quality

Sample: 01/1970-12/2020					
Decade:	**1971-1980**	**1981-1990**	**1991-2000**	**2001-2010**	**2011-2020**
Dependent variable:	Wealth	Wealth	Wealth	Wealth	Wealth
Intercept	**0.61**	**1.41**	**9.84**	0.68	**71.98**
	(5.32)	(7.48)	(8.3)	(0.46)	(18.71)
Quality	0.01	**1.45**	**8.59**	**3.89**	**67.93**
	(0.12)	(7.66)	(7.23)	(2.62)	(17.63)
Adjusted R2	0	0.0001	0.000072	0.000011	0.000743

This table provides a summary of the regression coefficients from time-series regressions between wealth and quality, $Wealth_t = \alpha + \beta^{Quality} Quality_t + \epsilon$, for each decade ranging 1970-2020. The t-stat are reported under the betas and statistical significance are indicated in bold. The used wealth is the excess wealth on return level.

The results presented shows a significant positive relationship between quality and wealth during the last 4 decades. However, the results also indicates that quality has no explanatory power on wealth. The strength of the relationship have varied slightly up 2010, but have during the last decade shown a strong positive relationship. Besides the significant direction between quality and wealth, the low explanatory power suggests that this relationship likely is a result of quality and wealth being correlated. The result presented in this table suggests that quality does not manage to explain the variation in wealth and that their relationship is a result of being correlated.

We show additional results in appendix, Table A10, where we run similar regression, but use dummies for WGS and WDS to inspect their loading of Quality and its components on the dependent variable, wealth. The results presented in that table also suggests that the direction of the relationship is a result of structural components being correlated.

Viewing the first hypothesis of the thesis in light of these results, we find that there exists a positive significant relationship between quality and wealth created. This relationship is due to similarities in construction between the dependent and explanatory variable and quality is not useful in explaining variations in wealth.

In the following section, we test the difference in quality among WGS and WDS.

7.2 Difference in quality between WGS and WDS

In this section, we aim to answer the second hypothesis of the thesis: Is there a difference in quality between WGS and WDS? We test this hypothesis to make the selection of which stocks to include when diversifying portfolios easier. If there exists a difference in quality among WGS and WDS, then this difference could help predict the stocks that are more likely to be a WGS the following month.

To test this hypothesis, we follow the methodology used in our replicated table 1. There we tested if there was a significant difference in quality between high and low quality portfolios. Some adjustments to this methodology have been done. Our definition high and low quality are the top 70th and bottom 30th percentile, Where this done to provide similarities with the value breakpoints of the FF methodology. The wealth score is based on return level and not firm level. We choose not to use accumulated wealth at firm level because large firms are then favored. Large firms with average return slightly over the treasury bill will with the use of firm level receive a higher wealth score then a small firm with much higher average return.

The reported quality score is the time series mean of the cross-sectional average quality score from today up to 10 years ahead in time. The stocks included up to ten years ahead in time are the same as selected at portfolio formation date. If any stocks are delisted, the quality score at the last month, will be the value-weighted average of the remaining stocks. Table 5 consists of three panels, where the rightmost columns show the significance of the difference in quality between high quality stock and low quality stocks for WGS and WDS. Panel C reports the results of a test of difference in mean between quality portfolios of WGS and WDS, and the persistence of difference in mean up to 10 years. The standard errors used are HAC standard errors Newey and West (1987).

Table 7.2

Table 5: Difference in quality among WGS and WDS

		P1 (Low)	**P2**	**P3** (High)	**H-L**	**H-L** t-stat
Panel A: Wealth generating stocks, 7/1963 - 12/2020						
Quality	t	-0.72	0.14	1.18	**1.9**	24.09
Quality	t + 12	-0.2	0.25	0.99	**1.19**	30.27
Quality	t + 36	0.06	0.33	0.97	**0.91**	23.77
Quality	t + 60	0.16	0.4	0.96	**0.8**	18.89
Quality	t + 120	0.39	0.58	1.01	**0.62**	17.17
Panel B: Wealth destroying stocks, 7/1963 - 12/2020						
Quality	t	-0.89	0.04	1.13	**2.02**	15.98
Quality	t + 12	-0.36	0.16	0.96	**1.32**	25.89
Quality	t + 36	-0.06	0.23	0.9	**0.96**	33.11
Quality	t + 60	0.05	0.27	0.87	**0.82**	18.17
Quality	t + 120	0.2	0.34	0.82	**0.62**	5.99
Panel C: Difference in WGS and WDS						
Quality	t	**0.17**	**0.1**	**0.05**		
		(5.67)	(8.05)	(6.49)		
Quality	t + 12	**0.16**	**0.09**	**0.03**		
		(3.31)	(5.21)	(5.61)		
Quality	t + 36	**0.12**	**0.1**	**0.07**		
		(2.4)	(4.31)	(4.66)		
Quality	t + 60	**0.11**	**0.13**	**0.09**		
		(3.3)	(4.88)	(5.74)		
Quality	t + 120	**0.19**	**0.24**	**0.19**		
		(5.82)	(6.7)	(7.23)		

Panel A, and Panel B presents the average quality scores ranging 07/1963 – 12/2020. At each month, stocks are ranked ascending based on their quality score, where 70th and 30th percentile breakpoints are measured. US common shares are then allocated into these, forming 3 quality portfolios ranging from low to high. The reported quality score for each portfolio is the time-series average of the cross-sectional value-weighted mean at subsequent t and t + 12, 36, 60, and 120 months ahead in time. The rightmost column reports the t-stats, where the standard errors are heteroskedasticity and autocorrelation consistent over a 60 month period (Newey and West 1987). Panel C reports the difference in quality between WGS and WDS. The reported portfolios are from a portfolio that buys WGS and sells WDS. The standard errors are HAC standard errors and statistical significance at a 5% level are indicated in bold.

We observe that high quality portfolios among WGS remain higher quality up to 10 years, while the high quality portfolios among WDS are less persistent. By looking at the difference in quality portfolios presented in Panel C, we observe that there is a significant difference in quality that increases monotonically over time for the neutral (P2) and high portfolios (P3). This is, however, not the case with portfolios of lower quality.

From these results, we reject the null hypothesis of no difference in quality between WGS and WDS. As a result of this, we accept at a 95% confidence level that there is a difference in quality among WGS and WDS that persists up to 10 years.

The results of this hypothesis implies that WGS and WDS are different in terms of quality and persists differently. This information is also useful in evaluating quality's ability in predicting WGS. In the following section, we will test our last hypothesis.

7.3 Quality's ability to predict WGS

From the earlier hypotheses, we find that quality and wealth have a positive relationship. Also that there is a difference in quality between WGS and WDS that increases over time. In this section, we aim to answer if quality of today can be used to predict WGS of tomorrow. To evaluate this problem, we are interested in the hit rate, meaning the percentage of correctly classified WGS among the sample of WGS. If quality provides a high hit rate, then these good predictions are extremely valuable to investors. However, how bad the bad predictions are may easily ruing this payoff.

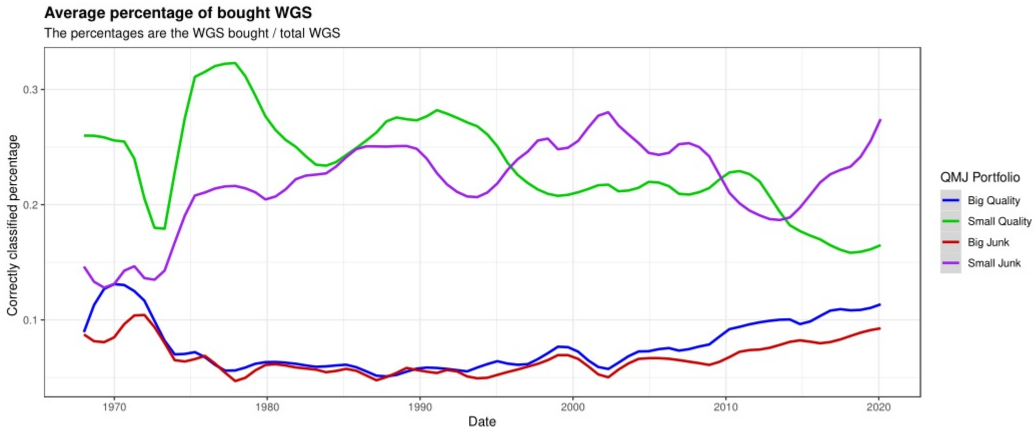
Since the outcome of a stock being a WGS or not is binary, our model is a predictive probit regression. Where WGS is the dependent variable, and our replicated quality score is the random variable. We choose to exercise the probit model above the logit model because of the distribution of our random variable, the stocks normalized quality scores.

$P(WGS|Quality) = \phi(\alpha + \beta^{Quality} Quality)$

By using the probit model, we assign each stock a probability of being a WGS. The model is estimated on the quality scores of last month, where the fitted values is used as probabilities of a stock being a WGS the next period. We split the probabilities at the mean of probailities of each month, where those with probabilities above the mean gets predicted WGS, and those below, WDS. This is done because of the data is unbalanced[40].

[40] Our data is unbalanced in terms of the few WGS relative to its sample.

As a comparison to our predictive model, we provide a plot of the hit rate gained from the QMJ factors portfolios. Where the shown percentages are the WGS bought divided by the total sample of WGS. Some WGS are also located in the quality neutral portfolios, but are not shown in this plot.



We observe that the QMJ factor have historically allocated the majority of WGS in either the small junk portfolio or the Small quality portfolios. That the QMJ factor have allocated WGS correctly on its long side is desirable. However, some periods during the later years, the majority of WGS have been allocated in the small junk. This indicates that the high payoffs earned from the small quality portfolio is likely diminished by the shorting WGS. By the use of our predictive regression, we hope to provide valuable information about which stocks that are more likely to become WGS. If this model proves reliable, then the predicted QMJ factor payoff could offer higher risk-adjusted returns.

In the following table, we show how the predicted probabilities from our probit regressions. To assess how the predicted probabilities of holding a WGS have varied through time in the QMJ factor, we take the mean of each portfolio's average monthly probability for the subsequent decades ranging 1971:2021. We also report the variation of these probabilities, as well as the highest and lowest monthly probability of holding a WGS in the following table, Table 6.

Table 7.3

Table 6: Average probability of holding a WGS in QMJ's portfolios

	Long side		Short side	
	Big Quality	Small Quality	Big Junk	Small Junk
Sample: 01/1971-12/1980				
Average probability of holding WGS:	0.0775	0.2708	0.0709	0.186
Standard Deviation:	0.0331	0.0663	0.0351	0.0412
Max:	0.1746	0.4018	0.2213	0.2652
Min:	0.0161	0.0567	0.0153	0.052
Sample: 01/1981-12/1990				
Average probability of holding WGS:	0.0577	0.2548	0.0552	0.2385
Standard Deviation:	0.0173	0.0277	0.0191	0.0327
Max:	0.1084	0.3509	0.1097	0.3285
Min:	0	0.1896	0	0.1801
Sample: 01/1991-12/2000				
Average probability of holding WGS:	0.0641	0.243	0.0582	0.2303
Standard Deviation:	0.0163	0.0347	0.0169	0.0335
Max:	0.1011	0.3257	0.1042	0.3229
Min:	0.0254	0.1852	0.0181	0.161
Sample: 01/2001-12/2010				
Average probability of holding WGS:	0.0717	0.2156	0.0612	0.2543
Standard Deviation:	0.0186	0.0194	0.0145	0.0322
Max:	0.1395	0.2685	0.0935	0.3407
Min:	0.0275	0.1641	0.0133	0.1785
Sample: 01/2011-12/2020				
Average probability of holding WGS:	0.1035	0.1832	0.0819	0.2157
Standard Deviation:	0.0213	0.0336	0.0175	0.0397
Max:	0.1628	0.2638	0.1529	0.3913
Min:	0.0408	0.1135	0.0441	0.1476

This table presents the average probability of holding a wealth-generating stock through five different decades. The portfolios are from the replicated QMJ factor and the average probability of holding a WGS in the QMJ portfolios are constructed in the following way. At each month, a probit regression between the stock being a WGS, $WGS = 1$, and the stocks observable quality score, $Quality_{t-1}$, is used to assign a probability of stock being a WGS. Where the model is a rolling probit regression with 1 month rolling window. The portfolio's average probability of holding a WGS is the time-series mean of the cross-sectional average probability of QMJ's portfolio . The reported standard deviation, max, and min are the time-series average across subsequent decades.

We observe from this table that the average probabilities of holding a WGS throughout the decades have varied and have rarely been highest on the long side. On the short side, we observe that the average probability of holding a WGS are during the later years higher. In addition to this, we observe that the small quality portfolios from the plot earlier which had the highest rate of classified WGS, now still has the highest probability of holding a WGS. It is possible that what we are observing is a size effect, as the small portfolios consistently have a higher probability of being a WGS Banz (1981).

From the results presented in this table, the fitted values from our probit regression(predicted probabilities) suggests choice of WGS consistent with the classifications already done by the original QMJ factor. How well our predictions performs are now of interest.

In the following table, Table 7, we present the classification results from our prediction model. Where the Quality score of last month is estimated on WGS of tomorrow. A brief summary of the meaning of the classification results presented in Table 7 are the true positive(TP), true negative(TN), false positive(FP), false negative(FN), Accuracy(ACC), precision and hit rate[41]. An accuracy score of about 50% indicates that the results are due to randomness. The precision is the percentage of correctly predicted WGS among true positive and true negative. While a high Hit rate indicates a high percentage of correctly classified WGS out of the sample of WGS[42]. A high hit rate indicates that the model is successful in predicting WGS.

[41] A true positive(TP) and true negative(TN) are the correctly predicted WGS and non-WGS, respectively. The false positive(FP) is a predicted WGS that was a non-WGS, and false negative(FN) means that the model predicted non-WGS but it was a WGS. Accuracy is the number of correctly estimated WGS divided by the total sample.

[42] Hit rate is derived as: TP/(TP+FN)

Table 7.4

Table 7: Classification results from predicting WGS based on last month's Quality score

Sample period: 1971/01 - 2020/12							
Sample period	TP	TN	FP	FN	Accuracy	Precision	Hit Rate
1971/01-1980/12	449	1479	788	767	0.554	0.363	0.369
1981/01-1990/12	567	2146	982	1057	0.571	0.366	0.349
1991/01-2000/12	694	2662	1397	1110	0.572	0.332	0.385
2001/01-2010/12	540	2049	1190	778	0.568	0.312	0.41
2011/01-2020/12	449	1479	930	595	0.559	0.326	0.43

This table provides the classification results of predicting next months wealth generating stocks based on quality scores of today for five different decades ranging 1971/01 - 2020/12. The model is a probit regression where next month's WGS is predicted by Quality scores of today. The results presented the following. A true positive and true negative are the correctly predicted WGS and non-WGS. While false positive is a predicted WGS that was a non-WGS, and false negative is a predicted non-WGS that was a WGS. Accuracy is the number of correctly estimated values divided by sample, and precision is the percentage of correctly predicted WGS among true positive and true negative. The Hit rate indicates the percentage of correctly classified WGS out of the sample of WGS and is derived as: TP/(TP+FN).

From the results presented in this table, we observe that there is a low accuracy of about 55% across all decades. This indicated that the results are due to randomness, and that there are no valuable information provided in our predictive model. The table also shows that quality have a hit rate ranging from about 35% to 43%. The predictions do predict some WGS as WGS. However, a high number WGS are classified wrongly. This is concerning. By following this predictive model. The model will in many cases predict a WGS as a stock that should be sold (FN). This is also reflected in the low hit rate. The majority of predictions are true negatives, indicating that most stocks that was flagged as WDS were WDS. This is a good sign, but the high amount of bad predictions (FN) are likely to reduce the payoffs. In appendix, Table A8, we show two versions of the predicted QMJ factor, one where stocks are equally weighted (EW) and one where they are value weighted (VW).

The predicted QMJ portfolios are constructed as follows. at each month, previous month's NYSE size median is used to divide firms into two portfolios, small and big. In this case, we do not do an conditional sort on quality, but a conditional sort on the predictive probabilities from our probit regression. Where the top 70th NYSE percentile and bottom 30th NYSE percentile are used as probability breakpoints. Stocks are allocated into these 6 portfolios based on their probabilities of being a WGS. Those above the 70 percentile are considered WGS and those below the 30th percentile are defined as WDS. The classification results of the QMJ factor is presented in appendix, Table A7, and shows a slightly higher hit ratio than earlier. From this it motivates to test if the predicted QMJ factor performs better than the original QMJ factor in terms of risk-adjusted returns.

Our results presented in appendix, Table A8, suggests the VW predicted QMJ factor performs much worse than the original QMJ, while the EW predicted QMJ factor have much higher performance in terms of risk-adjusted returns.

To shed some additional light on the abnormal risk adjusted returns of the original QMj factor, we also show the frequencies of home run stocks in the QMJ factor. These home run stocks makes up for many of the badly selected stocks in terms of return. Thus, it motivates to show where these stocks have been allocated historically. In the following table, table 8, we present the average number of home run stocks in each quality portfolio throughout the decades ranging 1971:2020.

Table 7.5

Table 8: Average frequency of home run stocks in QMJ portfolios. 01/1971-12/2020

Decade	Big Quality	Big Neutral	Big Junk	Small Quality	Small Neutral	Small Junk	% Bought HRS
1971-1980	14.77	14.67	6.5	0.13	0.25	0.26	40.73%
1981-1990	19.99	19.2	10.66	1.58	1.18	0.46	40.64%
1991-2000	25.72	22.92	13.58	0.12	0.37	0	41.21%
2001-2010	20.53	15.94	10.28	0.39	0.36	0.31	43.76%
2011-2020	17.4	12.26	5.95	0.13	0.05	0.07	48.88%

This table provides the number of allocated home run stocks in the 6 Quality portfolios and the percentage of bought home run stocks (HRS) by the QMJ factor across 5 decades. The reported frequencies are the time series average of bought HRS in each portfolio for each decade. The percentage of correctly bought HRS represents the allocation of HRS on the buy side of the QMJ factor divided by the total number of HRS in that month. The reported percentage is the time series average of the decade. A home run stock is defined as the top 1 percentile in terms of wealth creation. The reported percentage of bought HRS is the time-series average of the percent bought HRS of each month across the decade.

We observe that the Average frequency of bought home run stocks are clustered towards the big portfolios of the QMJ factos. Theis factor buys between 40% to 48% of these stocks, and sells relatively fewer. By holding the original QMJ factor, investors are likely to capture the few home run stocks (HRS) that makes up for the many bad stocks.

Additional results are also presented in appendix, Table A9. Where we run a similar probit model to the one we used to assess if quality could predict WGS earlier, but in this case in stead of the dependent variable being WGS, it is now HRS. HRS indicates 1 for home run stocks and 0 for those who are not. The classification results shows that the predictions have a very low hit rate and a overall lack of predictive performance.

In light of the our last hypothesis. We do not find that the quality score can be used to predict WGS. What we find is that if we look in Table A10 appendix the high-quality stocks actually destroy more wealth than low-quality in WDS. This is telling us that a investor takes a risk investing in high-quality, they can either get much higher or much lower returns. It does not explain why QMJ have high returns, but might be a piece of the puzzle. However, we find that how the weights of the predicted QMJ factor matters. By not weighting big firms more than the small ones, the equally weighted predicted QMJ factor benefits in terms of risk adjusted returns.

8 Conclusion

Through this thesis, we have contributed to the "quality minus junk" 2019 paper by assessing the predictive power of quality and the QMJ factor on stocks that generates excess wealth.

We find that quality does not manage to predict WGS. However, by sorting the probabilities of a stock being a WGS, similar to the QMJ factor, the equally-weighted predicted QMJ factor improves in terms of risk-adjusted returns. In addition to this, we show that there is a difference in quality between WGS and WDS. This difference also increases over time, as quality of WGS portfolios persists more than the quality among WDS portfolios. We also find that quality has no explanatory power on excess wealth created, but a positive relationship. The QMJ factor have historically bought the majority of WGS, but in the later years, the allocation of WGS appears to be more concentrated in the short side of the QMJ factor. A predictive regression that is estimated on last months quality score, and used to predict WGS of the following month is useful in this manner. This model can be used to form a predicted value-weighted QMJ factor. However, the predicted value weighted performs much worse in therms of risk-adjusted returns. The weights of these predicted portfolios matters. By assigning each stock equal weight, the predicted QMJ portfolio provides a higher risk-adjusted return than our replicated QMJ factor. We also show that the QMJ factor have historically managed to buy around 40% of the home run stocks, but the use of quality to predict these are unsuccessful.

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Appendix

A1 Accounting variables[43]

ACT	Current Assets - Total
AT	Assets - Total
CAPX	Capital Expenditures
CEQ	Common/Ordinary Equity - Total
CHE	Cash and Short-Term Investments
COGS	Cost of Goods Sold
DLC	Debt in Current Liabilities - Total
DLTT	Long-Term Debt - Total
DP	Depreciation and Amortization
EBIT	Earnings Before Taxes and Interest Margin
IB	Income Before Extraordinary Items
INVT	Inventories - Total
LCT	Current Liabilities - Total
LT	Liabilities - Total
MIB	Minority Interest (Balance Sheet)
MIBT	Noncontrolling Interests - Total - Balance Sheet
PI	Pretax Income
PSTK	Preferred/Preference Stock (Capital) - Total
PSTKL	Preferred Stock/Liquidating Value
PSTKRV	Preferred Stock/Redemption Value
RE	Retained Earnings
REVT	Revenue – Total
SALE	Sales/Turnover (Net)
SEQ	Stockholders' Equity - Total
TXDB	Deferred Taxes Balance Sheet)
TXDI	Income Taxes - Deferred
TXDITC	Deferred Taxes and Investment Tax Credit
TXP	Income Taxes Payable
XINT	Interest and Related Expense - Total
XSGA	"Selling, General and Administrative Expense"

Where "Total" means it has sub accounts[45] (Chen, Miao, & Shevlin, 2015).

[43]"Description of variables from ©2021 Center for Research in Security Prices (CRSP), The University of Chicago Booth School of Business."[44]

[44]"Where description of variables is missing we use this description from ©2011 Center for Research in Security Prices (CRSP), The University of Chicago Booth School of Business."

[45]Sub accounts is refering to other accounting variables. All sub accounts add up to total value of the

A2 Delisting Codes[46]

Code	Description
500	Issue stopped trading on exchange - reason unavailable.
520	Issue stopped trading current exchange - trading Over-the-Counter.
551	Delisted by current exchange - insufficient number of shareholders.
552	Delisted by current exchange - price fell below acceptable level.
560	Delisted by current exchange - insufficient capital, surplus, and/or equity.
561	Delisted by current exchange - insufficient (or non-compliance with rules of) float or assets.
570	Delisted by current exchange - company request (no reason given).
572	Delisted by current exchange - company request, liquidation.
573	Delisted by current exchange - company request, deregistration (gone private).
574	Delisted by current exchange - bankruptcy, declared insolvent.
580	Delisted by current exchange - delinquent in filing, non-payment of fees.
584	Delisted by current exchange - does not meet exchange's financial guidelines for continued listing.

variable.

[46]"Delisting Codes information from ©2021 Center for Research in Security Prices (CRSP), The University of Chicago Booth School of Business."

A3 Variables constructed

WC	$ACT - LCT - CHE + DLC + TXP$	Working capital
ΔWC	$WC_t - WC_{t-1}$	Change in working capital
CF	$NB + DPWCCAPX$	Cash flow
ME	$SHROUT * PRC$	Market equity
GP	$REVT - COGS$	Gross profit
SHROUT_ADJ	$SHROUT * CFACSHR$	Adjusted shares outstanding
TOTD	$DLTT + DLC + MIBT + PSTK$	Total debt
MWCPD	-$(DP - \Delta WC)$	Minus ΔWC plus depreciation
ADJASSET	$AT + 0.1 * (ME - BE)$	Adjusted total asset
TLTA	$\frac{DLC+DLTT}{ADJASSET}$	Total liabilities over total assets
WCTA	$\frac{ACT-LCT}{ADJASSET}$	Working capital over total assets
CLCA	$\frac{LCT}{ACT}$	Current liabilities over current assets
NITA	$\frac{IB}{AT}$	Net income over total assets
FUTL	$\frac{PI}{LT}$	Pretax income over total liabilites
CHIN	$\frac{IB_t - IB_{t-1}}{\lvert IB_t\rvert + \lvert IB_{t-1}\rvert}$	Change in net income
OENEG	$\begin{cases} 1, & \text{if } LT > AT \\ 0, & \text{otherwise} \end{cases}$	Dummy for total liabilites larger than total assets
INTWO	$\begin{cases} 1, & \text{if } \max(IB_t, IB_{t-1}) < 0 \\ 0, & \text{otherwise} \end{cases}$	Dummy for negative income last two years

A4 Quality minus junk variables

Profitability		
GPOA	$\frac{REVT-COGS}{AT}$	Gross profit over assets
ROE	$\frac{IB}{BE}$	Return on equity
ROA	$\frac{IB}{AT}$	Return on asset
CFOA	$\frac{IB+DP-\Delta WC-CAPX}{AT}$	Cash flow over assets
GMAR	$\frac{REVT-COGS}{SALE}$	Gross margin
ACC	$\frac{DP-\Delta WC}{AT}$	Low accruals
Growth		
ΔGPOA	$\frac{(GP_t-rfAT_{t-1})-(GP_{t-5}-rfAT_{t-6})}{AT_{t-5}}$	Growth in residual GPOA
ΔROE	$\frac{(IB_t-rfBE_{t-1})-(IB_{t-5}-rfBE_{t-6})}{BE_{t-5}}$	Growth in residual ROE
ΔROA	$\frac{(IB_t-rfAT_{t-1})-(IB_{t-5}-rfAT_{t-6})}{AT_{t-5}}$	Growth in residual ROA
ΔCFOA	$\frac{(CF_t-rfAT_{t-1})-(CF_{t-5}-rfAT_{t-6})}{AT_{t-5}}$	Growth in residual CFOA
ΔGMAR	$\frac{GP_t-GP_{t-5}}{SALE_{t-5}}$	Growth in gross margin
ΔACC	$\frac{MWCPD_t-MWCPD_{t-5}}{AT_{t-5}}$	Growth in accruals
Safety		
BAB	$-\beta$	Low beta
LEV	$-\frac{DLTT+DLC+MIBT+PSTK}{AT}$	Low leverage
Ohlson's O	$-(-1.32-0.407*log(\frac{ADJASSET}{CPI})+6.03*TLTA-1.43*WCTA+0.076*CLCA-1.72*OENEG-2.37*NITA-1.83*FUTL+0.285*INTWO-0.521*CHIN)$	Low bankruptcy risk
Altman's Z	$\frac{1.2\,WC+1.4\,RE+3.3\,EBIT+0.6\,ME+SALE}{AT}$	Low bankruptcy risk
EVOL	$\sqrt{\frac{1}{5}\sum_{y=1}^{5}(ROE_{t-y}-\overline{ROE}_t)^2}$	Low ROE volatility
IVOL	$-\sigma^i_{(t-1,t)}$	Low idiosyncratic volatility
Payout		
EISS	$-log(\frac{SHROUT\_ADJ_t}{SHROUT\_ADJ_{t-1}})$	Equity net issuance
DISS	$-log(\frac{TOTD_t}{TOTD_{t-1}})$	Debt net issuance
NPOP	$\frac{\sum_{y=1}^{5} IB_{t-y}-\Delta BE_{t-y}}{\sum_{y=1}^{5} RETV_{t-y}-COGS_{t-y}}$	Total net payout over profits

A5 Profitability, growth, safety and payout factors

Profitability:

PMU = 1/2 (Small Profitable + Big Profitable) - 1/2 (Small Unprofitable + Big Unprofitable)

Growth:

GMNG = 1/2 (Small Growing + Big Growing) - 1/2 (Small Not Growing + Big Not Growing)

Safety:

SMU = 1/2 (Small Safe + Big Safe) - 1/2 (Small Unsafe + Big Unsafe)

Payout:

PMR = 1/2 (Small Payout + Big Payout) - 1/2 (Small Retaining + Big Retaining)

A6 Quality minus junk, robustness, six factor returns

Table A6.1

Table A6: Quality minus junk: Robustness, six factor returns

	Replicated results (7/1963 - 2016/12)					Original results (7/1963 - 2016/12)			
	QMJ	Profitability	Safety	Growth	Payout	QMJ	Profitability	Safety	Growth
Excess Returns	**0.35**	**0.26**	**0.19**	**0.12**	**0.29**	**0.29**	**0.29**	**0.20**	**0.15**
	(4.07)	(3.46)	(2.05)	(1.71)	(3.33)	(3.30)	(3.92)	(2.04)	(2.02)
5-factor alpha	**0.44**	**0.28**	**0.47**	**0.29**	**0.14**	**0.38**	**0.29**	**0.38**	**0.30**
	(8.13)	(5.98)	(6.16)	(5.68)	(2.93)	(7.71)	(6.85)	(5.75)	(6.60)
6-factor alpha	**0.4**	**0.27**	**0.39**	**0.27**	**0.12**	**0.33**	**0.28**	**0.29**	**0.27**
	(7.5)	(5.63)	(5.26)	(5.23)	(2.54)	(6.81)	(6.54)	(4.49)	(5.85)
MKT	**-0.18**	**-0.1**	**-0.25**	**-0.04**	**-0.1**	**-0.17**	**-0.08**	**-0.28**	**-0.05**
	(-13.33)	(-8.78)	(-13.51)	(-3.05)	(-8.59)	(-14.07)	(-7.72)	(-17,60)	(-4.47)
SMB	**-0.13**	**-0.08**	**-0.17**	**0**	**-0.09**	**-0.11**	**-0.07**	**-0.19**	0.03
	(-6.9)	(-8.38)	(-6.54)	(0.07)	(-5.44)	(-6.51)	(-4.57)	(-8.89)	(1.83)
HML	**-0.25**	**-0.3**	**-0.29**	**-0.25**	**0.1**	**-0.26**	**-0.29**	**-0.19**	**-0.26**
	(-9.68)	(-13.1)	(-8.4)	(-10.06)	(4.25)	(-10.85)	(-13.80)	(-6.26)	(-11.88)
CMA	**0.12**	**0.07**	**0.04**	**-0.43**	**0.52**	-0.05	**0.09**	0.04	**-0.36**
	(3.04)	(2.06)	(0.67)	(-11.26)	(14.43)	(-1.39)	(3.04)	(0.94)	(-11.46)
RMW	**0.57**	**0.61**	**0.32**	**0.31**	**0.43**	**0.55**	**0.58**	**0.32**	**0.33**
	(18.37)	(22.25)	(7.56)	(10.41)	(15.76)	(24.07)	(28.37)	(10.67)	(15.70)
UMD	**0.06**	**0.02**	**0.14**	**0.03**	**0.03**	**0.07**	0.01	**0.13**	**0.05**
	(4.58)	(1.93)	(7.8)	(2.78)	(2.48)	(5.68)	(1.25)	(8.87)	(4.37)
Sharpe Ratio	0.56	0.47	0.28	0.23	0.45	0.45	0.54	0.28	0.28
Information Ratio	1.41	1.13	1.04	0.77	0.85	1.00	0.96	0.66	0.86
Adjusted R2	0.7	0.71	0.59	0.65	0.72	0.72	0.70	0.63	0.67

This table provides the risk-factor loadings and excess returns for quality minus junk-factor and its components. The QMJ factor is constructed as follows. At each month, NYSE firms are ranked in ascending order based on their market cap, where the median is used to divide small large firms into 2 portfolios. Conditional on each size portfolio, firms are then sorted into 3 quality portfolios, high (top 30 percentage), neutral (middle 40 percentage), and low quality (bottom 30 percentage). The return of the QMJ factor is obtained from going long in the average of two value-weighted high quality portfolios and the average of going short in the two value-weighted low quality portfolios. this construction is the same for profitability, safety, growth, and payout. The explanatory variables are market (MKT), size(SMB), value (HML),investment approach (CMA), profitability (PMU) and momentum (UMD). Where the 5-factor model includes the five first explanatory variables, and the six-factor model includes all explanatory variables. The alphas reported are the regression's intercept. Excess return and alphas are reported in percentage and sharpe ratio and information ratio are annualized. Information ratio is the four-factor alpha divided by the standard deviation of the regression's estimated residuals. Statistical significance at a 5 percent level is indicated in bold.

A7 QMJ's ability to predict WGS

Table A7.1

Table A7: QMJ's ability to predict WGS:

Sample period: 1971/01 - 2020/12

Sample period	TP	TN	FP	FN	Accuracy	Precision	Hit Rate
1971/01 - 1980/12	187	152	145	160	0.6	0.563	0.539
1981/01 - 1990/12	182	240	164	212	0.529	0.526	0.462
1991/01 - 2000/12	233	275	220	237	0.527	0.514	0.496
2001/01 - 2010/12	179	204	180	165	0.527	0.499	0.52
2011/01 - 2020/12	142	142	130	117	0.535	0.522	0.548

This table provides the classification results provided from a confusion matrix. True positive and true negative are the correctly predicted WGS and non-WGS. While false positive is a predicted WGS that was a non-WGS, and false negative is a predicted non-WGS that was a WGS. Accuracy is the number of correctly estimated values divided by sample, and precision is the percentage of correctly predicted WGS among true positive and true negative. The determination of accuracy is done at the end of the sample period, month T. The Hit rate indicates the true positive rate of classified WGS.

A8 EW and VW predicted QMJ portfolios

Table A8.1

Table A8: Regression summary of predicted QMJ portfolios, 1968/07 - 2020/12

	EW Predicted QMJ	VW Predicted QMJ	Original VW QMJ
Excess return	**1.14**	**0.35**	**0.31**
	(6.56)	(2.02)	(4.33)
1-factor alpha	**1.25**	**0.64**	**0.53**
	(6.24)	(3.37)	(8.11)
3-factor alpha	**1.24**	**0.71**	**0.61**
	(6.1)	(3.74)	(10.63)
4-factor alpha	**1.2**	**0.67**	**0.52**
	(5.85)	(3.51)	(9.19)
MKT	-0.06	-0.06	**-0.21**
	(-1.31)	(-1.35)	(-15.4)
SMB	-0.09	**-0.15**	**-0.24**
	(-1.2)	(-2.04)	(-11.11)
HML	0	**-0.22**	**-0.2**
	(0.05)	(-3.18)	(-9.31)
UMD	0.05	0.05	**0.1**
	(1.08)	(1.14)	(6.46)
Sharpe Ratio	1.02	0.32	0.52
Information Ratio	1.09	0.65	1.29
Adjusted R2	0.01	0.04	0.5

This table provides the factor loadings and excess returns for the quality minus junk (QMJ) portfolio and the predicted QMJ portfolios. For the predicted portfolios, a 1-month rolling probit model assign each stock a probability of being a WGS based on last months quality score, $P(WGS_t|Quality) = \phi(\alpha + \beta^{Quality} * Quality)$. If a stock have a predicted probability above the sample's average in the respective month, it gets predicted WGS. The two portfolios the predicted QMJ portfolio buys do only consist of predicted WGS. The two portfolios the QMJ factor sells are not treated differently than the original QMJ as quality wrongly sells a majority of WGS. The explanatory variables are market (MKT), size(SMB), value (HML), and momentum (UMD) Where the first regression (CAPM) use only the market, second regression (FF 3 factor) use MKT, SMB, and HML, and the third regression (FF 4 factor) use all 4 explanatory variables, where the momentum factor is the Carhart momentum-factor. The alphas reported are the regression's intercept and excess return and alphas are reported in percentage. The sharpe ratio and information ratio are annualized. Information ratio is the four factor-alpha divided by the standard deviation of the regression's estimated residuals. Statistical significance at a 5 percent level is indicated in bold.

A9 Use of Quality to predict home run stocks

Table A9.1

Table A9: Predicting home run stocks based on last months quality score

Total sample period: 1971/01 - 2020/12							
Sample period	TP	TN	FP	FN	Accuracy	Precision	Hit Rate
1971/01-1980/12	16	2218	22	1236	0.59	0.421	0.013
1981/01-1990/12	22	3115	30	1591	0.6	0.423	0.014
1991/01-2000/12	27	4068	36	1735	0.634	0.429	0.015
2001/01-2010/12	20	3252	27	1261	0.69	0.426	0.016
2011/01-2020/12	19	2409	17	1009	0.67	0.528	0.018

This table provides the classification results of predicting next month's home run stocks based on its quality today for five different decades ranging 1971/01 - 2020/12. The model is a probit regression where Home run stocks (HRS) of tomorrow is predicted by Quality scores of today based on the predicted probability of being a HRS. The results presented the following. A true positive and true negative are the correctly predicted HRS and non-HRS. While false positive is a predicted HRS that was a non-HRS, and false negative is a predicted non-HRS that was a WGS. Accuracy is the number of correctly estimated values divided by sample, and precision is the percentage of correctly predicted HRS among true positive and true negative. The Hit rate indicates the percentage of correctly classified HRS out of the sample of HRS, and is derived as: TP/(TP+FN).

A10 Relationship between quality characteristics and wealth among Quality sorted portfolios

Table A10.1

Table A10: Relationship between quality characteristics and wealth among WGS and WDS

Sample perdiod: 01/1951-12/2020	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth
Intercept	**-0.03**	**-0.02**	**-0.03**	**0.01**	**-0.03**	**0.004**
	(-33.287)	(-19.485)	(-27.808)	(5.406)	(-29.567)	(2.94)
$Quality * WGS$ dummy	**0.06**					
	(83.915)					
$Quality * WDS$ dummy	**-0.04**					
	(-72.532)					
$Profitability * WGS$ dummy		**0.06**				**0.072**
		(89.435)				(50.97)
$Profitability * WDS$ dummy		**-0.04**				**-0.044**
		(-63.228)				(-40.16)
$Safety * WGS$ dummy			**0.05**			**0.05**
			(67.672)			(37.35)
$Safety * WDS$ dummy			**-0.03**			**-0.039**
			(-50.227)			(-36.59)
$Growth * WGS$ dummy				**0.05**		**0.001**
				(51.132)		(0.74)
$Growth * WDS$ dummy				**-0.02**		**0.011**
				(-25.355)		(11.56)
$Payout * WGS$ dummy					**0.03**	**0.02**
					(41.286)	(17.37)
$Payout * WDS$ dummy					**-0.03**	**-0.017**
					(-55.948)	(-18.85)
Firm Age	**-0.012**	**-0.01**	**-0.011**	**-0.001**	**-0.011**	**0**
	(-26.541)	(-21.961)	(-24.098)	(-1.151)	(-24.289)	(-0.07)
One year return	**0.046**	**0.047**	**0.046**	**0.065**	**0.045**	**0.064**
	(138.423)	(140.735)	(138.283)	(143.324)	(136.475)	(142.17)
Size	**0.021**	**0.018**	**0.02**	**0.011**	**0.021**	**0.011**
	(102.533)	(86.104)	(95.557)	(39.924)	(101.101)	(39.39)
Adjusted R2	0.016	0.017	0.014	0.016	0.013	0.026

This table presents a regression summary for the sample period 01/1951-12/2020 of US common shares. The regressions are between wealth and Quality, and its characteristics: profitability, safety, growth, payout, together with additional control variables. The additional control variables are a firm's age, 1-year return, size, and dividend payout. For each quality component, dummies variables are used to indicate the loading on the dependent variable, wealth, among wealth-generating, and wealth-destroying stocks. The wealth variable represents the normalized excess wealth creation above a 1-month treasury bill. t-stat are reported under the beta coefficients and the statistical significance at a 5 percent level are indicated in bold.