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A RETURN BASED MEASURE OF FIRM QUALITY

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ABSTRACT

We show that superior performance relative to peers during stressful times identifies higher quality firms as measured by conventional historical financial statement based measures as well as default probability measures. Quality measured this way is persistent, but different from price momentum. Further, a managed portfolio that takes a long position in top quintile (Stable) firms and a short position in bottom quintile (Vulnerable) firms earns superior risk adjusted returns in excess of the risk-free rate. The portfolio has an annualized Fama and French three-factor alpha of 5.2% (t=5.04) and a five-factor alpha of 3.3% (t=3.38)

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A rising tide lifts all boats. Only when the tide goes out do you discover who has been swimming naked.

– *Warren Buffet*

1 Introduction

Firm quality plays an important role in asset pricing and asset management. Several successful long term investors like Graham[1] and Buffett have emphasized the importance of investing in high quality companies at reasonable prices.[2] While there is no agreed upon definition of quality, one would expect high quality firms in better businesses, ceteris paribus, to be well governed, having higher profitability, and requiring fewer resources.

Identifying higher quality firms based on the above mentioned characteristics requires information available in firms financial statements for constructing firms' profitability and resource-use measures. Novy-Marx (2013) advocates using the ratio of gross profits to assets employed as the measure of profitability. Fama and French (2015) augment their widely used three factor model with two additional quality related factors: a profitability factor referred to as robust-minus-weak, RWM; and an investment factor referred to as conservative-minus-aggressive, CMA. The RWM factor is based on the ratio of operating profitability to total assets (OP); and the CMA factor is based on asset growth (INV), which can be interpreted as a measure of resources used by firms for exploiting future profitable opportunities. Chen and Zhang (2010) construct two quality related factors: one based on profitability, and the other based on asset growth rate. In contrast to Fama and French (2015), profitability is measured by return-on-equity, ROE; and asset growth rate by the ratio of investments to total assets, I/A. Piotroski (2000) constructs a quality measure referred

[1] See Graham (1965)

[2] According to Charlie Munger, Vice Chairman of Berkshire Hathaway, a company which according to Frazzini et al. (2013) ranks #1 among all stocks and mutual funds with 30 or more years of history, and 4th among 1,994 mutual funds and 62 among 9035 firms with at least a 10 year history, during 1976-2011, the bulk of the billions in Berkshire Hathaway has come from the better businesses. See 'Poor Charlie's Almanac', 2005, p204.

to as the Piotroski score from information in financial statements to identify higher quality firms among firms trading at low share prices relative to book value. Asness et al. (2019) construct an aggregated quality score based on firms' profitability, growth, and safety rankings.

We propose a measure of firm quality that does not require information from firms financial statements. Following the folk wisdom that quality shines during difficult times, we measure a firms quality based on its stock price performance relative to peers during *stressful times*. In particular, we use the Fama-French 12 industry classifications (FF12) to identify firms' peer groups, and use the month with the lowest return during a year as proxy for the *stressful time*. For each industry group, we first identify the worst month in a given year. To avoid size bias, we group stocks into big and small. Stocks are sorted by worst month returns within each size group separately. We term stocks with worst month returns in the top 20% percentile as Stressful time Stable (SS) firms and those with returns in the bottom 20% percentile as Stressful time Vulnerable (SV) firms.

We find that SS firms are of higher quality, when quality is measured using information in financial statements and market prices as in the literature, even though we did not use any information from financial statements for classifying firms as SS or SV. We find that SS firms are more profitable – higher gross profits to assets ratios, higher operating profitability, and higher return on equity when compared to SV firms. SS firms also have lower asset growth rate than SV firms, i.e., SS are more conservative ceteris paribus requiring less resources. Further, SS firms are safer with lower average default probabilities as given by Ohlson O-score in Ohlson (1980), and of higher quality as measured by Piotroski F-score.[3].

We also compare SS and SV firms based on their exposure to systematic and idiosyncratic risks. SS firms are safer.[4] Furthermore, SS firms have less co-skewness and less co-kurtosis, i.e., they are less sensitive to extreme market downturns. Finally, SS firms continue to be of higher quality

[3] See Piotroski (2000).

[4] We measure systematic risk by market beta and idiosyncratic risk by the volatility of the residual in the Fama-French 3 factor model in Fama and French (1993). See Appendix 8.2 for details.

according to financial statements based quality measures, and safer according to market based risk measures for several years following the year in which we identified them as being Stressful time Stable (SS).

We find that the portfolio of stocks of firms in the SS category significantly outperforms the portfolio of stocks in the SV category during the worst month in the following year. The relative performance spread between the SS and SV portfolios of stocks is relatively stable over time across all industry groups. The average worst month return difference between SS and SV portfolios is about 4% per month. The persistent superior performance of SS firms relative to SV firms during the worst months in a year is consistent with the findings in Lempérière et al. (2017) and Asness et al. (2019) that stocks of higher quality firms have lower tail risk.

The natural questions that arise are whether the higher quality SS firms we identify are the same as past winners with positive momentum, or low historical beta firms with low systematic risk exposures. To answer these questions we first consider two sorting methods for identifying stocks with positive momentum: past-year cumulative returns and partial cumulative returns excluding the worst month. We find that past winners do have a higher return on average than past losers during the worst month in the following year. However, the difference becomes insignificant when the worst month was excluded when measuring past year cumulative returns for identifying past winners and losers. This suggests that it is the worst month performance that helps in identifying firm quality. We then consider firms identified as safe based on sorting on their traditional market betas as well as their downside betas. Firms with high past low market betas as well as low downside betas perform better during the worst month in the following year. However, both high and low beta firms have similar financial statement based quality measures, i.e., they are of similar quality. The same is true for high and low downside beta firms[5].

[5] A similar observation can also be found in Novy-Marx and Velikov (2018).

Asness et al. (2019) document that high quality firms had higher risk adjusted returns on average. Therefore, if SS firms are of high quality, then SS firms should also have higher historical average risk adjusted returns, when quality related risk factors are not used for computing risk adjusted returns. We find that over the 52-year from 1967:01 to 2018:12, the Fama and French (1993) three factor (FF3) alpha for SS is 0.15% per month (t-statistics 3.24) while that for SV is -0.29% per month (t-statistics -4.21). When we augment the FF3 model with the momentum factor to construct a four factor model (FF4) for risk adjustment, the alpha of the SS portfolio alpha comes down to 0.10%, but remains significant (t-statistics 2.16). However, the alpha of SV becomes insignificant. The SS portfolio returns load positively on the quality related factors in Fama and French (2015), Chen and Zhang (2010), and Asness et al. (2019). We interpret this as the SS portfolio earning a quality premium. The alphas are not significant when we use quality related factors in addition to the market for controlling for exposure to systematic risk.

Given our finding that stressful time relative performance is highly persistent, we should expect the long SS and short SV (SMV) portfolio to perform better than other commonly used factor portfolios during the collection of worst month in a year. Our findings are consistent with this expectation. During the 52 market worst months the SMV portfolio gained 2.67% per month on average during the 52 worst months. In comparison, the average worst months returns for the two quality related factors of Fama and French, RMW and ROE, are 0.93% and 1.10% per month respectively. The 'quality-minus-junk' factor QMJ has a comparable worst month return of 2.41% per month, with a slightly higher standard deviation (2.97 versus 2.53). During the continuing COVID-19 Pandemic, the stock market suffered the worst loss in March 2020 with the S&P500 index losing more than 16%. The SMV portfolio gained about 10 percent during that month.

The rest of the paper is organized as follows. In Section 2 we describe the data and the methods we use to identify stressful time stable (SS) and vulnerable (SV) firms. In Section 3 we examine firm-level characteristics of the SS and SV firms. In Section 4 we compare the characteristics of the returns on portfolios constructed based on worst month return performance, and portfolios constructed based on traditional price momentum and historical betas. In Section 5 we provide a comprehensive analysis of the return dynamics of managed portfolios of SS and SV firms' stocks. We discuss the performance of the SMV portfolio during the COVID-19 crisis in Section 6 and conclude in Section 7.

2 Data and Methodology

2.1 Data

We focus on the US stock market. Our universe consists of all individual stocks traded on the NYSE, NYSE MKT, NASDAQ, and Arca. Our data sample period is from 1967:01 to 2018:12, when both individual stock market data, firm level financial data, and market-wide pervasive risk factors data are all available.[6] We collect individual stock and firm level data and the market level risk factor data from several sources.

Individual Stock Market Data We obtain monthly and daily stock returns (RET), number of shares outstanding (SHROUT), and exchange codes (EXCHCD) for all available publicly traded common stocks (with share codes 10 and 11) from the Center for Research in Security Prices (CRSP) for the period 1967:01 to 2018:12. We require that a stock has a valid share prices number of shares outstanding with at least 3-year price history. For delisted stocks, we use delisting return (DLRET) as the last month return and we adjust the missing delisting returns following the procedure in Shumway (1997) and Bali et al. (2016). We collect the monthly value-weighted (VWRETD) and

[6]The CRSP/Compustat Merged Fundamentals Annual data is available from 1950:01. Fama-French 5-factor data is available from 1964:01. As suggested by Banz and Breen (1986), it is common practice in the literature to omit the first few years of accounting data from COMPUSTAT, since they are likely to be backfilled. The Q-factor data for HXZQ-model is available from 1967:01.

equal-weighted (EWRETD) aggregate market portfolio return from CRSP. We use PERMNO as the unique identifier for individual stocks.

Firm Level Financial Statements Data The annual firm level financial data are from the CRSP-COMPUSTAT merged database from 1967 to 2018. The firm level financial data are matched with stock data by using the PERMNO-PERMCO link table. We use the SIC codes in CRSP as industry identifiers, and for firms with missing SIC codes in CRSP we use the ones from COMPUSTAT. We assign firms to one of the Fama-French 12 industries based on SIC codes. We refer the reader to the French Data Library available on Professor French's website for the map between SIC codes and industries.

Market Wide Factors Data Monthly returns data for the Fama-French 12 Industry portfolios (FF12) and benchmark market wide factors, i.e. one-month treasury-bill rate (RF), Fama-French 3-factosr (MktRF, SMB and HML), Cachart momentum factor (UMD), and the two additional factors in the Fama-French 5-factor model (RMW and CMA) are downloaded from the French Data Library available on the website.[7] Monthly returns data on the Quality-minus-Junk (QMJ) factor andthe Betting Against Beta (BAB) factor for the US market are collected from the AQR website.[8] We thank Lu Zhang for providing us the up-to-date monthly data for the Q-factor model in Hou et al. (2019).

2.2 Methodology

Industry Classification In order to compare firms' performance in stressful time with their peers in the same industry, we need to first specify the industries. Among various available industry classifications, we use the widely accepted Fama-French industry classifications based on firms'

[7] Website: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.
[8] Website: `https://www.aqr.com/Insights/Datasets`.

Standard Industry Classification codes (SIC). In the Fama-French online data library, firms are grouped into from 5 to 49 industries. Since our purpose is to compare firms' performance in stressful time with their peers in the same industry, we need the industry classification to be sufficiently granular for defining peer groups of firms with sufficient precision, and at the same time sufficiently coarse so that there are enough number of firms within each industries. Given this tradeoff, we decided on the Fama-French-12 industry categories (FF12) as our benchmark industry groups. The Fama-French-12 industry groups are: Consumer NonDurables (NoDur), Consumer Durables (Durbl), Manufacturing (Manuf), Oil, Gas, and Coal Extraction and Products (Enrgy), Chemicals and Allied Products (Chems), Business Equipment (BusEq), Telephone and Television Transmission (Telcm), Utilities (Utils), Wholesale, Retail, and Some Services (Shops), Healthcare, Medical Equipment (Hlth), Finance (Money), and Others (Other). The Fama-French 12 industry categories are based on SIC codes which are available from both COMPUSTAT fundamental file and CRSP security file on WRDS. It is well-known that in some firms their SIC codes in CRSP and COMPUSTAT may be different.[9]

Table 1 lists the number of firms in each of the Fama and French 12 industries based on SIC codes from COMPUSTAT and SIC codes from CRSP for 2018, along with the number of firms that have the same classification in both COMPUSTAT and CRSP. Among all 3604 firms, 72.56% have consistent industry classification based on SIC codes from COMPUSTAT and CRSP. In fact, except for the residual group 'Other', the industry classification based on CRSP SIC codes is generally consistent with that based on COMPUSTAT SIC codes across all industry groups. One of the reasons for the inconsistency in 'Other' group is the COMPUSTAT and CRSP allocate different SIC code to conglomerates. For example, Warren Buffett's Berkshire Hathaway is classified as 'Financial' industry according to SIC code from CRSP (6371) while the SIC code from COMPUSTAT is 9997

[9] see Guenther and Rosman (1994) for a detailed discussion.

(conglomerate), which falls into 'Other' industry, though Berkshire Hathaway is widely considered as a financial company. In order to avoid this inconsistency, we rely on SIC codes from CRSP for the industry classification and our empirical results are robust to use SIC codes from COMPUSTAT.

Table 1: Industry Composition based on COMPUSTAT and CRSP SIC in 2018

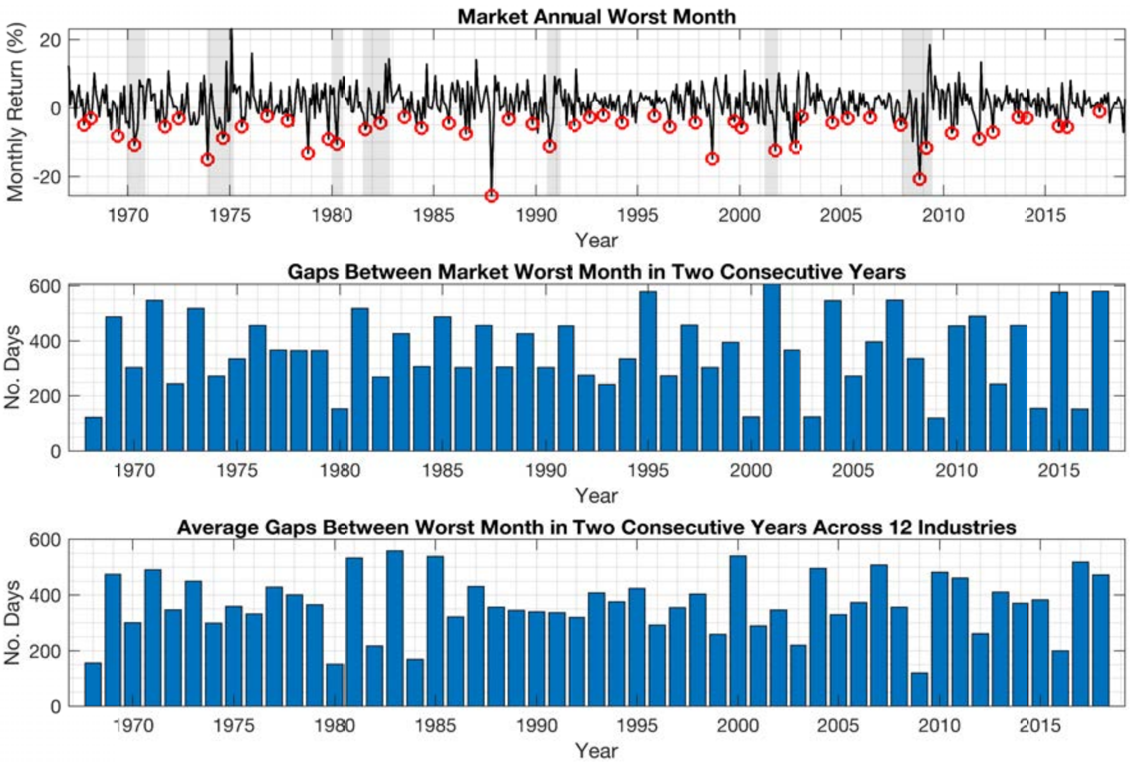
Industry	COMPUSTAT	CRSP	Both
NoDur	139	141	111
Durbl	82	65	50
Manuf	299	264	221
Enrgy	141	133	120
Chems	81	74	57
BusEq	543	411	353
Telcm	80	77	60
Utils	81	77	72
Shops	282	292	222
Hlth	597	289	273
Money	671	567	530
Other	608	1214	546
Total	3604	3604	2615

Stressful Times We define *stressful time* for an industry as that time interval among successive time intervals within a given time period during which the industry stock index portfolio has the worst return. For operational convenience we define a time period as a calendar year and the time interval as a month. Therefore, there is one *stressful* month within each calendar year. More generally, *stressful times* occur regularly once within each successive time period. Note that the stressful times are different from 'crashes', like the ones that occurred during the Dotcom period, the financial crisis, and the current COVID-19 pandemic. Unlike stressful times, crashes are rare and happen infrequently.

While there is one worst (stressful) month in each calendar year, the length of time between two successive worst months are random. The top panel in 1 plots the monthly return of the equal-weighted market portfolio of all stocks in the CRSP database (EWRET on CRSP[10]) from 1967:01 to 2018:12, where the red circles represent the worst month in each year and the grey shades

[10]We use the equal-weighted portfolio rather than the value-weighted portfolio to avoid the performance of the portfolio being being driven by a few big firms.

Figure 1: Market Annual Worst Month



highlight the NBER recessionary time periods. The middle panel in Figure 1 plots the number of days between the worst (stressful) months in two successive calendar years for the equal-weighted market portfolio of all stocks in the CRSP database during 1967:01 to 2018:12. The lower panel in Figure 1 gives the average number of days between two consecutive worst months for the 12 industry stock industry portfolios. As can be seen, successive worst months are reasonably well separated in time, with an average gap of around 200 days, although the gap tends to shrink during recessions.

Stressful Time Relative Performance We proceed to introduce our method for ranking firms according to their relative performance over stressful times. For each industry group, at the end of each calendar year, we identify the month with the worst return on the corresponding industry stock index portfolio. We then sort stocks within each industry into two groups – Big and Small – based on their market capitalization (mcap) in the worst month for that industry. We use the median market capitalization for stocks listed in the NYSE as the break point. To avoid using newly listed or short-lived stocks, we require stocks to have at least 3-year price history at the time of classification. Within each size group, we sort stocks by their worst month return. Stocks in the top quintile (20%) are labeled *Stressful time Stable* (SS) and stocks in the bottom quintile are labeled *Stressful time Vulnerable* (SV). We repeat the procedure each year and filter out stocks that moved from the top (bottom) quintile in the previous year to the bottom (top) quintile in the current year.

Our method is different from the momentum strategy in many aspects. Unlike relative price momentum strategies that rank stocks based on their returns over a given period of time in the past, we rank stocks based on their returns during the worst month, i.e., our focus is on tail risk. Further stable and vulnerable firms are identified within each industry separately. That said, we can readily modify our approach and broaden the peer group of a firm to all stocks, and define the worst month based on the return on the equal-weighted portfolio of all stocks. Since market-wide worst performance in a year is often driven by a few industries, the market-wide Stressful time Stable and Vulnerable portfolios will be less diversified across industries.

Figure 2: Market Shares of Stressful Time Stable and Vulnerable Stocks in 2008 by Industry

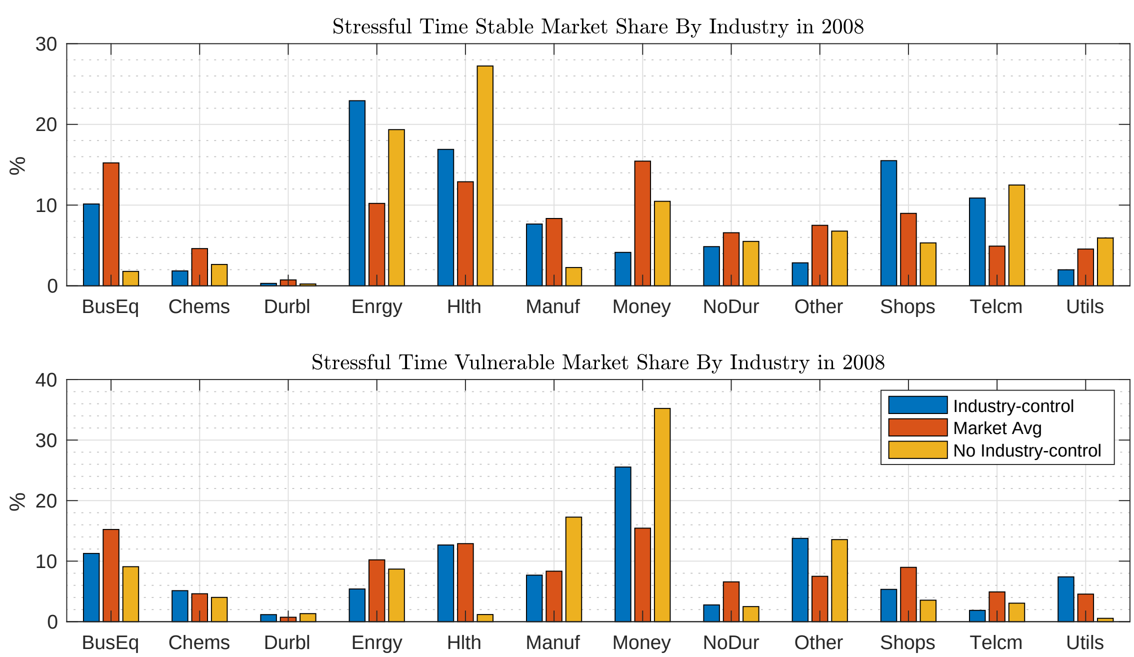
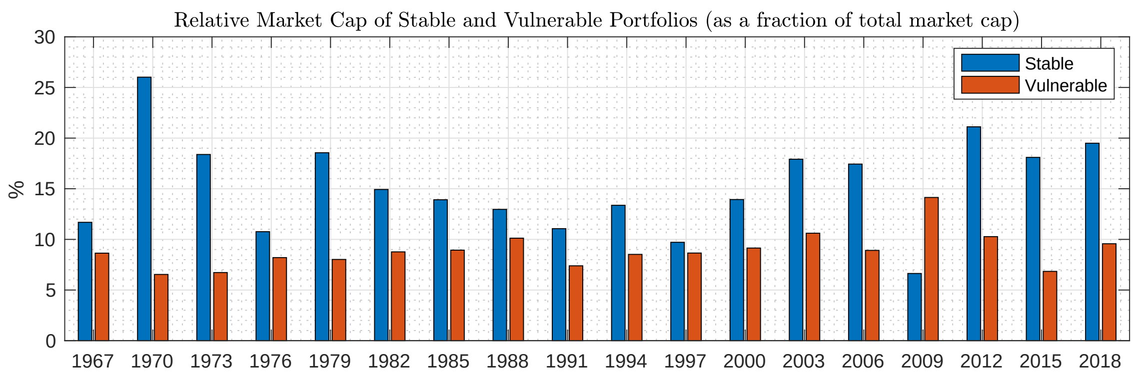


Figure 2 compares the market shares for each industry for the stressful time stable and stressful time vulnerable groups together with that for the market on average, formed with and without industry control in 2008. We note that during the 2008-2009 financial crisis, with industry control the percentage of financial firms in the stressful time vulnerable portfolio is slightly higher than that for the market average. However, without industry control, the majority of the worst month losers in 2008 consists of financial firms.

Figure 3: Relative Market Capitalization of Stressful time Stable and Vulnerable Stocks



In addition, we control for size within each industry in the ranking procedure to minimize size bias since big firms are normally more resistant to market downturns than small firms. Figure 3 compares the relative market capitalization of firms in stressful time stable and vulnerable portfolios from 1967 to 2018. We calculate the relative market capitalization for each portfolio as a percentage of the total market capitalization in a given year. As can be seen, there are more big firms in the stressful time stable portfolio, with an average market capitalization of around 20% of the total market. The average market capitalization of stressful time vulnerable firms is around 10% of the total market capitalization. Nevertheless, the relative market capitalization for stressful stable and vulnerable portfolios are comparable in the sense that neither of them are dominated by small firms.

3 A Return Based Measure of Firm Quality

In this section, we demonstrate that firms that perform better relative to their peers during stressful time continue to do so in the future. They have stronger and better financial statements based quality measures. Further they are less risky based on conventional measures of risk.

3.1 Persistence of Stressful Time Relative Performance

As documented in the literature, firm quality is persistent.[11] If stressful time relative performance is sufficient to separate high and low quality firms, stressful time stable firms should continue to outperform their stressful time vulnerable firms in the future as well. To examine the persistence of the stressful time relative performance, we therefore compare the performance of the past-year SS and SV firms in worst month of the following year.

Table 2: Performance of Stressful Time Stable and Vulnerable Stocks During Next Year

Industry	R_{SS}	R_{SV}	R_{Ind}	R_{Mkt}	R_{SMV}	t-stat
NoDur	-6.17	-8.95	-7.50	-6.48	2.77	5.87
Durbl	-8.17	-12.12	-9.94	-6.31	3.94	3.75
Manuf	-7.20	-10.43	-8.98	-6.47	3.23	5.08
Enrgy	-9.42	-13.94	-11.77	-4.67	4.51	4.24
Chems	-6.44	-9.96	-8.89	-6.48	3.51	3.90
BusEq	-9.13	-12.52	-10.86	-6.34	3.39	7.05
Telcm	-7.45	-11.26	-9.78	-6.51	3.80	3.26
Utils	-3.89	-5.15	-4.85	-4.72	1.26	2.01
Shops	-7.34	-10.81	-8.83	-6.16	3.47	8.36
Hlth	-8.60	-10.48	-10.31	-5.94	1.88	2.44
Money	-5.06	-9.26	-6.50	-6.45	4.19	7.62
Other	-7.53	-11.36	-9.09	-6.35	3.83	5.97

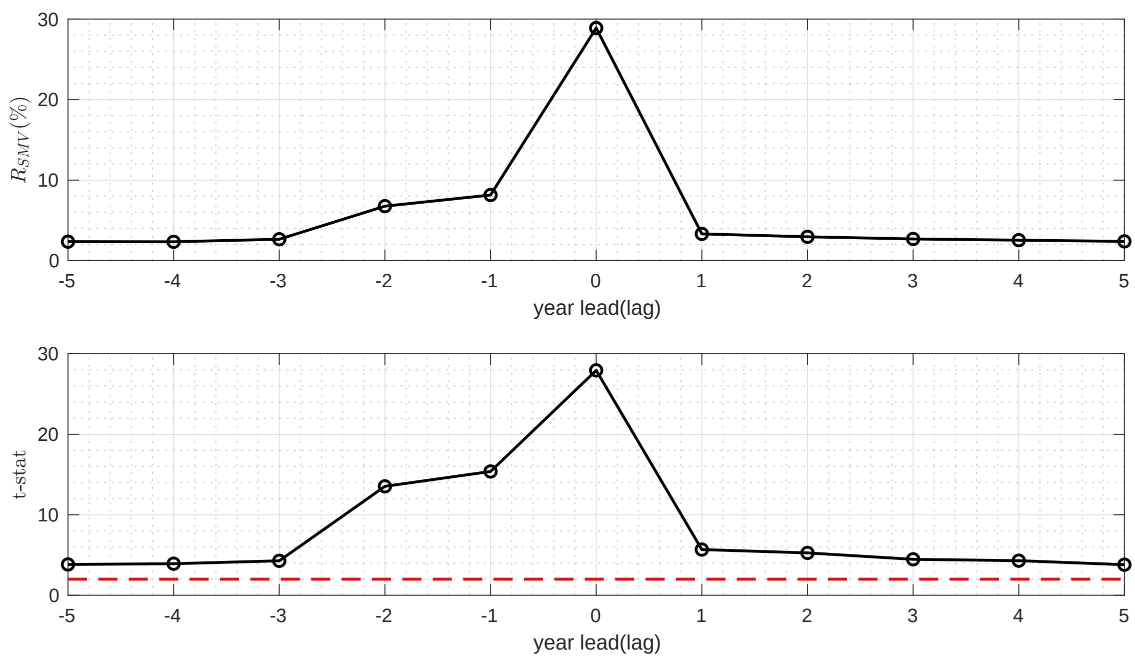
Notes: Table reports the average monthly returns for past-year stressful time stable (SS, R_{SS}) and vulnerable (SV, R_{SV}) portfolios in next year's worst month, respectively. R_{Ind} and R_{Mkt} are the corresponding equal-weighted industry and market portfolio monthly returns. $R_{\text{SMV}} = R_{\text{SS}} - R_{\text{SV}}$ represents the monthly return spread of the R_{SS} and R_{SV}. The last column reports the t-statistics for $H_0 : \mathbb{E}[R_{\text{SMV}}] = 0$. The sample period is 1967 to 2018.

Table 2 reports the time-series average of the worst month returns (% per month) for the equal-weighted past-year SS and SV portfolios for each industry in the worst month of the following

[11] Two of the notable papers are, Novy-Marx (2013) and Asness et al. (2019).

year. As a benchmark, we also report the average worst month returns for the equal-weighted industry portfolio along with that from the equal-weighted aggregated market index. In the last two columns, we calculate the equal-weighted average return spread between the past-year SS and SV and the t-statistics ($\mathbb{E}[R_{SMV}]$ is different from zero). Across all industries, the past-year SS loses less in the next-year worst month compare to the industry average while the SV performs worse than the industry average as well as the aggregated market portfolio. The average return spread between the past-year SS and SV is around 3.5% and is significantly different from zero across time. The positively significant SS-SV return spread suggests that the past-year SS maintains the outperformance over SV in the next-year worst month.

Figure 4: Stressful Time Average Return Spread for Stable and Vulnerable Firms



We further examine the persistence of the worst month return spread between SS and SV for longer horizon. In particularly, we calculate the worst month return spread between SS and SV over a 10-year lead-lag period, i.e. 5-year before and 5-year after the identification year. The hard-lines in Figure 4 plot the return spread (upper panel) and the corresponding t-statistics (lower panel). Not surprisingly, the return spread is largest at the identification year, with the highest t-statistic.

The return-spread drops significantly immediate after the identification year. Since we rely on the past-two year Stressful Time Stable and loser identifications to filter out any conflict assignments, the return-spreads are slightly higher. Other than that, the lead-lag worst month return spread between the winner and loser is around 3.5% (with a t-statistics around 5) and significantly positive before and after the identification year in a 10-year horizon .

Table 3: Empirical Transition Probability Matrix for Stressful Time Relative Performance

State	Vulnerable	Low	Medium	High	Stable
Vulnerable	50.66	11.22	9.86	9.26	10.19
Low	11.23	48.81	11.33	10.89	10.83
Medium	10.06	11.33	48.87	11.75	11.19
High	9.33	10.73	11.67	49.37	11.71
Stable	10.03	10.52	10.88	11.50	48.84

Notes: Table reports the empirical transition matrix for the stressful time relative performance ranking across all industry groups. The sample period is 1967 to 2018.

Finally, Table 3 reports the empirical transition probability matrix for the stressful time relative ranking from 1967 to 2018 across all industry group. Firms are grouped into five categories at the end of each year based on their relative performance in the worst month within each industry, where vulnerable and stable represent the bottom and top quintile (20%), respectively. As it shows, the stressful time relative performance states are relatively stable, where the transition probability for vulnerable state is around 50% and that for the stable state is around 48%.

3.2 Characteristics of Stressful Time Stable and Vulnerable Firms

In this subsection, we compare various firm level quality related characteristics for firms in SS and SV categories. Given that there is no universally agreed upon definition of quality, we focus on some of balance sheet, profitability, and risk measures of quality that have been widely used in the literature.

Following Novy-Marx (2013), Fama and French (2015), and Hou et al. (2015), we consider gross profitability (GPOA), operating profitability (OP), and return-on-equity (ROE) as profitability indicators and total asset growth (IV) as the investment measure. In terms of safety, we rely on the Ohlson O-score as a measure of default risk. Furthermore, we use the Piotroski F-score as our aggregated quality score measure. Finally, we consider several market return based risk measures, including including systematic risk (proxied by market beta), idiosyncratic volatility (based on the residuals from Fama-French 3-factor model), and higher order co-moments (e.g. co-skewness and co-kurtosis).[12]

At the end of each year, we calculate the financial statements based characteristics for each firm in SS and SV with one-year lagged annual financial data from COMPUSTAT. The market based risk measures are estimated from daily returns over the past one year. In the following analysis, for each measure, we report the cross-sectional average estimates for all firms in SS and SV categories, together with the average from the market[13].

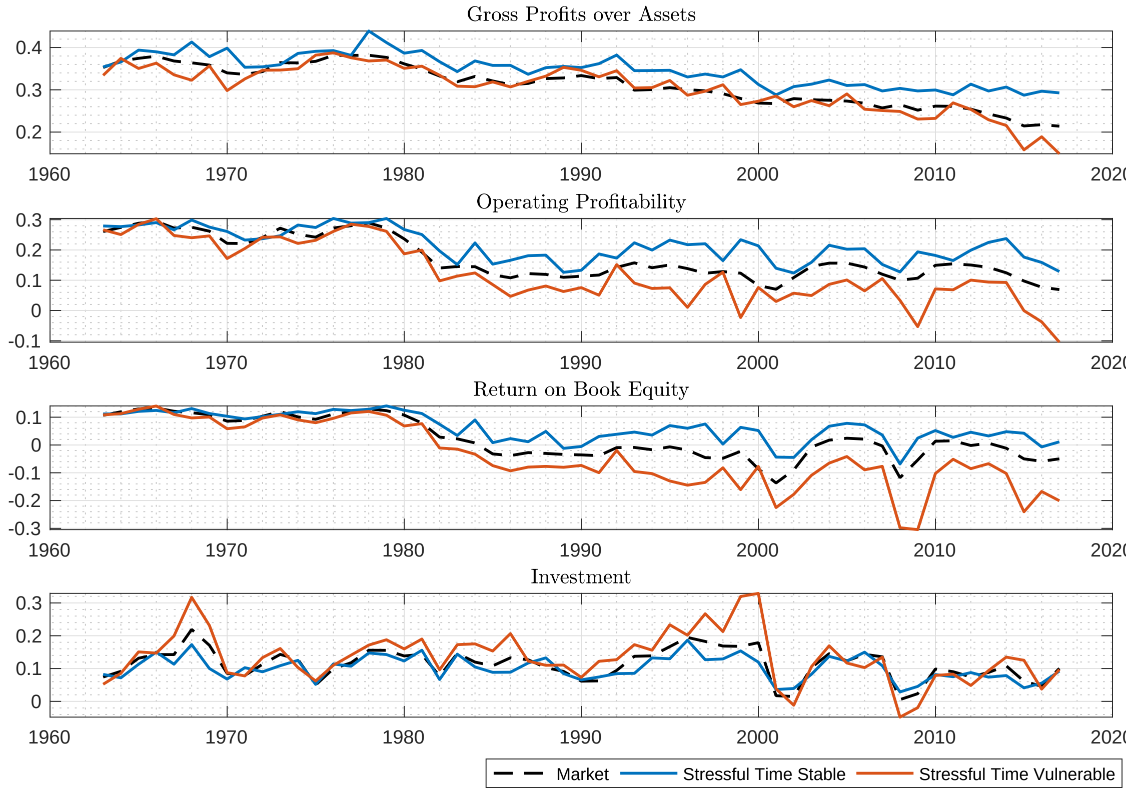
Profitability and Investment Figure 5 plots the time-series of the average profitability and investment ratios for SS firms (blue hard-line) and SV firms (red hard-line), together with the market-wide average (black dashed-line). Firms in SS have higher gross profits, operating profitability and return-to-equity ratios than the market average while the firms in SV underperform the market average. The spreads between the profitability ratios of SS and SV are non-trivial and persistent over the whole sample period, indicating firms in SS are consistently more profitable than those in SV. However, the patterns for investment is less significant. Indeed, for most of the time, firms in SS have a lower total asset growth rate than those in SV, however, the spread is relatively small and the firms in SS occasionally have a higher investment ratio than those in SV. One explanation is that growth rate of total asset is a very noisy measure of investment, as the change of total asset can be affected by several activities, such as mergers and acquisitions, which

[12]The details of definitions and formulas for the fundamental based quality related characteristics and market based risk measures are provided in Appendix 8.1 and 8.2.

[13]We report the cross-sectional average for each ratio rather than the value-weighted aggregated ratio as our purpose here is to compare the firm level characteristics rather than portfolio level.

typically involve changes of total assets.

Figure 5: Profitability and Investment Ratios for Stressful Time Stable and Loser

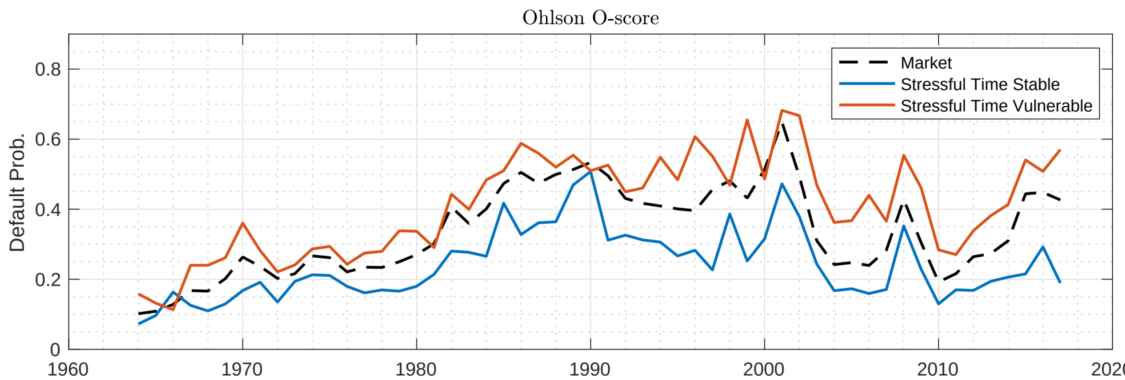


Safety Altman Z-score and Ohlson O-score are among the commonly used indicators of default (credit) risk in empirical accounting literature. The Altman Z-score was first proposed to measure the financial health for manufacturing firms based on 66 companies. We use the Ohlson O-score which is considered more suitable for firms in different industries and over the periods of time in our study.[14] As can be seen from Figure 6, except at the beginning of the sample, firms in SS group display a consistent lower default risk than the market average and those in SV. Overtime, the average default probability for the market is around 33%, while that for SS and SV is around 25% and 45% separately. The spread between SS and SV is remarkable wider during the crisis periods,

[14] Begley et al. (1996) find the Ohlson's O-score displays overall stronger and more consistent performance and is a preferred model as an indicator of financial distress comparing with Altman Z-score. Grice and Ingram (2001) find Altman's original model is not as useful for predicting bankruptcy in recent periods as it was for periods when it was developed and the model is bias for predicting bankruptcy of non-manufacturing firms.

e.g. late 1980s, early 2000s, and 2008-09. In particular, during the most recent volatile periods (at the end of 2018), the average default probability for firms in SV is more than 80% while that for firms in SS is only 20%.

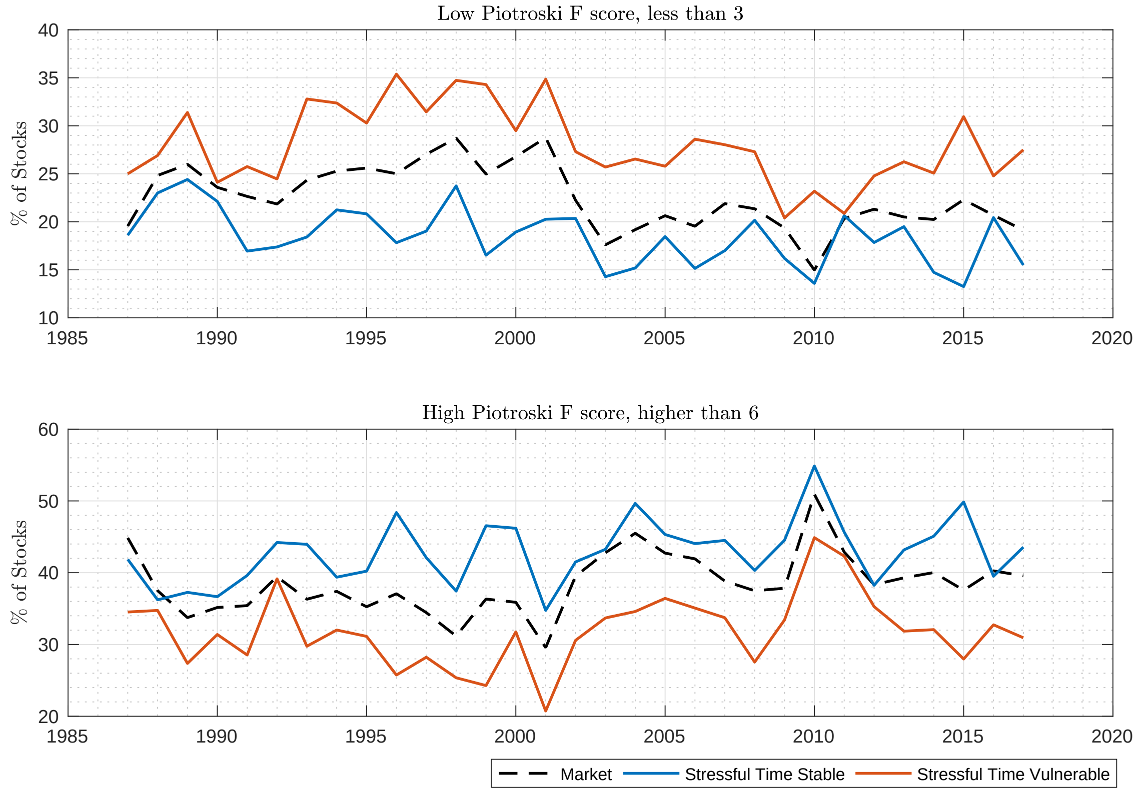
Figure 6: Stressful Time Stable and Loser Ohlson O-score



Aggregate Quality Score We use the intuitive and widely used *Piotroski F-score* proposed by Piotroski (2000). The F-score is an aggregate measure of a firm's quality obtained by summing nine binary scores, including profitability, efficiency, safety, and growth. The aggregate Piotroski F-score ranges from 0 to 9, where 0 represents the lowest quality ranking and 9 is the highest. In Figure 7, we plot the time-series of the percentage of firms with a Piotroski F-score lower than 3 (low quality) and higher than 6 (high quality) in SS and SV separately.[15] As a benchmark, we also reports the percentage of 'low quality' and 'high quality' firms in the whole market (black dashed-line). Throughout the whole sample period, SS category has a higher percentage of high quality firms (around 45% on average) than the SV category (around 25% on average) and the market (around 35% on average). Similarly, the SV category has a much higher percentage of firms with a Piotroski F-score less than 3 (around 30% on average) than the SS category (around 15% on average) and the market benchmark (around 20%).

[15]Due to low data availability in earlier time periods in our sample, the time-series for the Piotroski F-score is from 1985 to 2018.

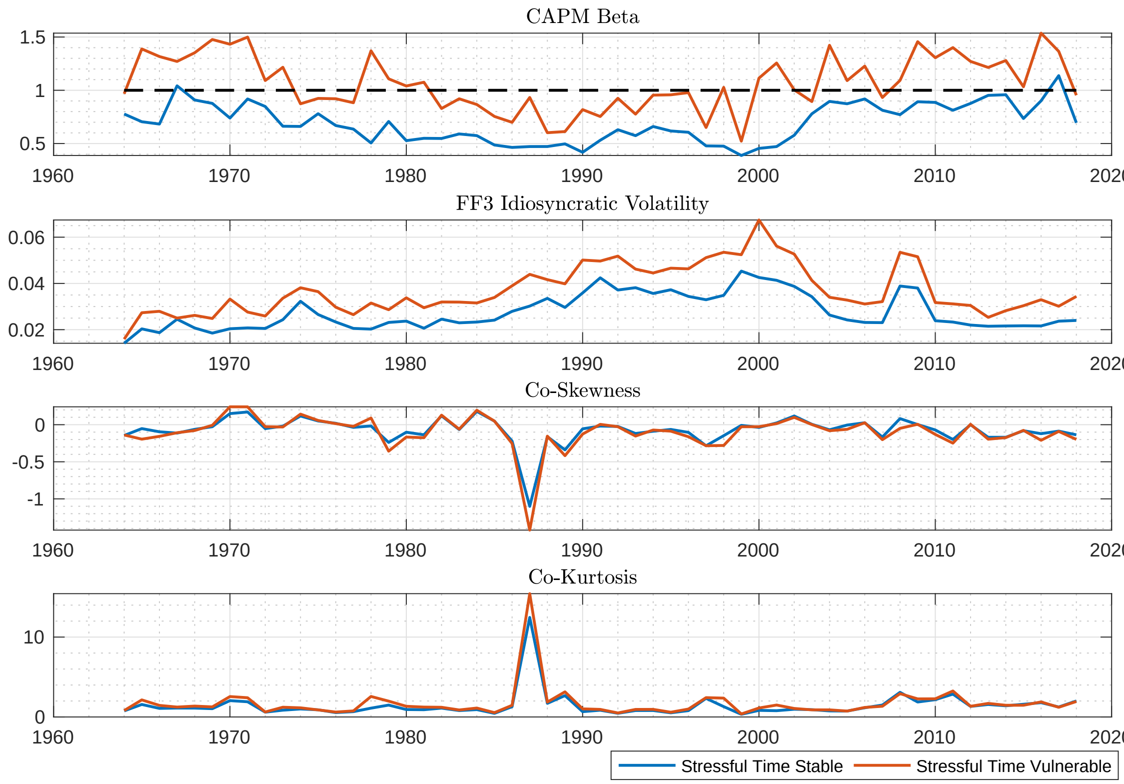
Figure 7: Stressful Time Stable and Loser Piotroski F-score



Return based Risk Measures Figure 8 presents the time-series of various return based risk measures for firms in SS and SV separately. The average market beta for firms in SS is almost always below one through the entire sample, while that of firms in SV is mostly higher than 1, indicating firms in SS have lower systematic risk exposures than those in SV.[16] Moreover, firms in SV also have higher idiosyncratic volatility (based on the Fama-French 3-factor model) than those in SS and the spread is non-trivial and consistent across time. Turning to the higher-order co-moment risk measures, the average co-skewness of SV firms is more negative than SS firms, suggesting that firms in SV are more sensitive to market downside risk. Similarly, SV firms also exhibit higher co-kurtosis.

[16]While SS firms have lower betas than SV firms on average, SS firms have higher quality scores on average as well. In contrast, as we show later, high beta and low beta firms have about the same financial statements based quality scores.

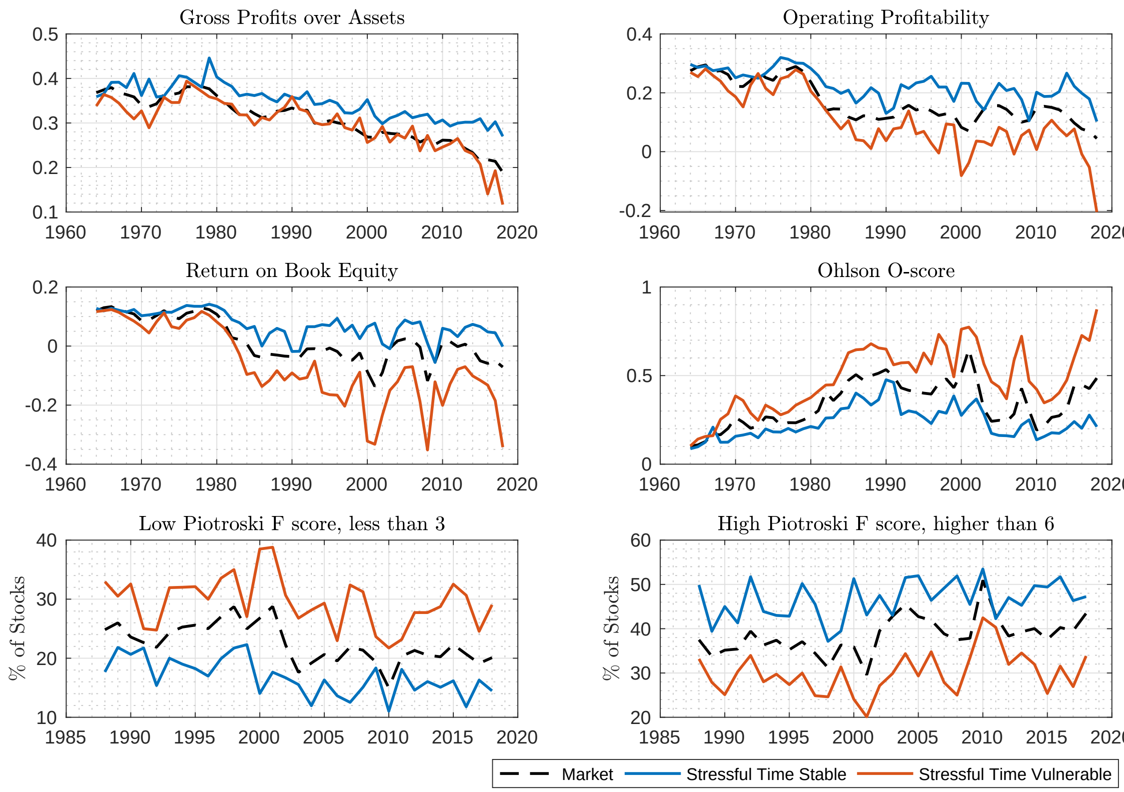
Figure 8: Stressful Time Stable and Loser Market-based Risk Measures



Persistence So far, we have demonstrated that at the time of identification, firms in SS are of high quality while those in SV are of low quality. As observed by Novy-Marx (2018), quality is highly persistent, in other words, higher quality firms will continue to be of higher quality in the future. Figure 9 plots the quality measures for SS and SV one year after they have been classified as SS or SV. It can be seen that firms in SS continue to show higher profitability, lower default risk, and high aggregated quality score, while those in SV continue to have worse measures than the market average. These persistent patterns confirm that relative performance during stressful times is a valid measure of firm quality. By sorting stocks based on their returns in the worst month, we are able to separate stocks of higher quality without directly observing any of the various quality related characteristics.

To summarize, we find that sorting on stressful time relative performance identifies firms' quality along various dimensions. Stressful time stable firms have higher aggregate quality scores, are more

Figure 9: Stressful Time Stable and Loser Quality Measure: Next Year



profitability and more conservative in their investments, and have lower default risk. Moreover, stressful time stable firms have lower exposure to systematic and idiosyncratic risks and are affected less by extreme market movements.

4 Stressful Time Performance, Momentum, and Beta

The natural questions that arise are whether the higher quality SS firms we identify are the same as past winners with positive momentum, or low historical beta firms with low systematic risk exposures. To answer this question, in this section we consider two alternative sorting strategies: (1) momentum based sorting: identify winners/losers based on past returns; (2) market beta based sorting: identify high/low risk firms based on historical betas. We then focus on comparing the stressful time performance and fundamental based quality measures between the alternative sorting portfolios and the ones identified based on stressful time relative performance.

4.1 Momentum and Beta Sorted Portfolios

At the end of each year, we calculate the following four characteristics for each firm:

A.1 Past-year holding return: the cumulative monthly return over past 12 months;

A.2 Past-year cumulative return excluding the worst month return;

A.3 Market beta from past 3-year monthly data;

A.4 Market downside beta from past 3-year monthly data;

The market beta β and downside beta β^- are calculated following Bawa and Lindenberg (1977) and Ang et al. (2006),

$$\beta_i = \frac{\text{cov}(r_i, r_m)}{\text{var}(r_m)}, \quad \text{and} \quad \beta_i^- = \frac{\text{cov}(r_i, r_m | r_m < \mu_m)}{\text{var}(r_m | r_m < \mu_m)},$$

where r_i (r_m) represents the stock i's (the market's) excess return and μ_m is the average market excess return.

To be consistent with the stressful time relative performance ranking procedure in Section 2.2, we control for both industry and size in forming the alternative momentum and beta sorted portfolios. We require firms have at least three-year stock price history. At the end of each year, calculate the four characteristics A.1 - A.4 for each firm. For each industry group, we first sort stocks into big and small by their market capitalization and use the median market capitalization of NYSE stocks as break-point. Within each size group, we then sort stocks into five quintiles (from low to high) based on one of the characteristics A.1 - A.4. Table 4 summarizes how the four characteristic sorted portfolios are formed.

These four alternative return-based sorting characteristics are based on their wide use in the empirical asset pricing literature. Procedure A.1 replicates the momentum portfolio construction

Table 4: Sorting on Past Returns and Betas

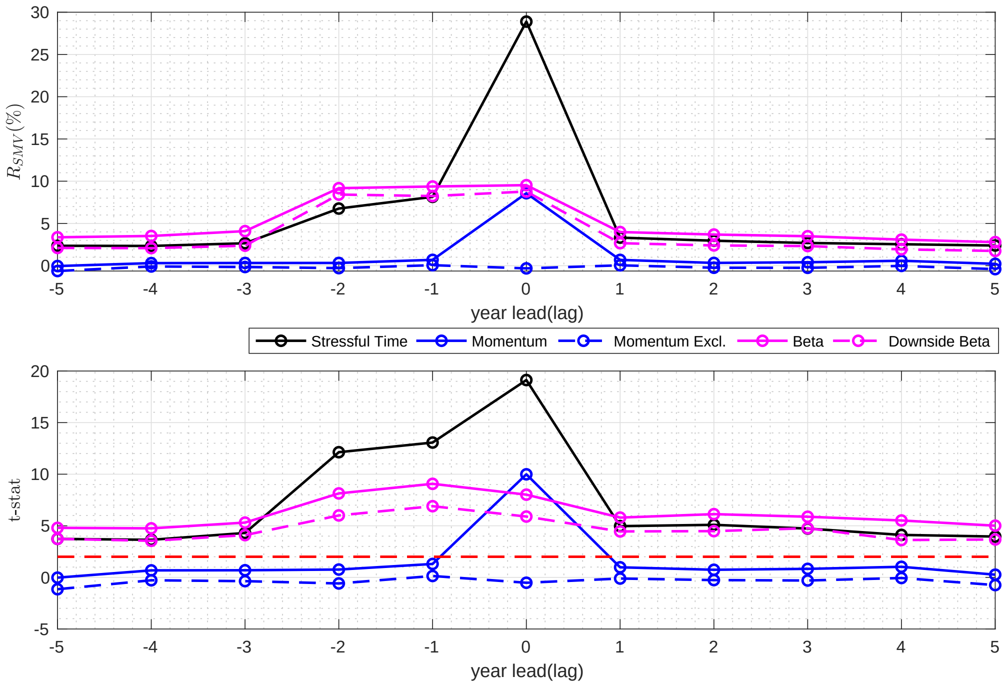
Sorting Var.	A.1	A.2	A.3	A.4
Q1. Bottom 20%	Past Winner	Past Winner Excl.	Low Beta	Low Down Beta
Q5. Top 20%	Past Loser	Past Loser Excl.	High Beta	High Down Beta

method in Jegadeesh and Titman (1993) with industry and size control. By excluding the worst month return in calculating the past-year cumulative return, Procedure A.2 allows us to explicitly investigate the role of the worst month return in momentum sorted portfolios. Procedure A.3 is based on the "betting-against-beta" investing strategy in Frazzini and Pedersen (2014) and Asness et al. (2014). Finally, Procedure A.4 follows Ang et al. (2006).

4.2 Stressful Time Performance Comparison

We first compare the stressful time performance of the four alternative return-based portfolios with the stressful time portfolios with a lead-lag analysis as in 3.1. Figure 10 plots the average worst month return spreads (upper) and the corresponding Newey-West t-statistics (lower) between Q5 and Q1 from the stressful time and A.1 to A.4 ranking in a 10-year lead-lag window. First, it can be seen clearly that the average worst month return spread for the stressful time stable-minus-vulnerable (SMV) is the most significant and consistent. The average worst month return spreads for both momentum-based sorting strategies are barely significant over the 10-year lead-lag period. This further confirms that stressful time relative performance contains different information than past performance. Turning to the beta-based sorting strategies, the average worst month return spreads for both market beta and market downside beta are significantly positive and comparable to SMV at both leads and lags. This suggests that stressful time relative performance captures the tail risk relevant information in firms' betas and downside betas.

Figure 10: Average Worst Month Return Spread (Q5 - Q1)



4.3 Quality Measures Comparison

In this subsection we compare the various financial statements based quality measures of the top and bottom quintile firms in the four alternative ranking procedures with those of SS and SV firms. For each quality characteristics, we plot the time-series of sample average of the top (Q5) and bottom (Q1) groups, along with the average of the whole market. The summary statistics for the spread between the top and bottom quintiles (Q5 - Q1) for each of the characteristics are reported. In order to test whether the separation between Q5 and Q1 from stressful time relative performance ranking is stronger than the alternative sorting procedures, we report the difference between Q5 - Q1 from stressful time relative performance ranking procedures and the alternative ones in row 'SMV - X', along with the associated t-statistics.

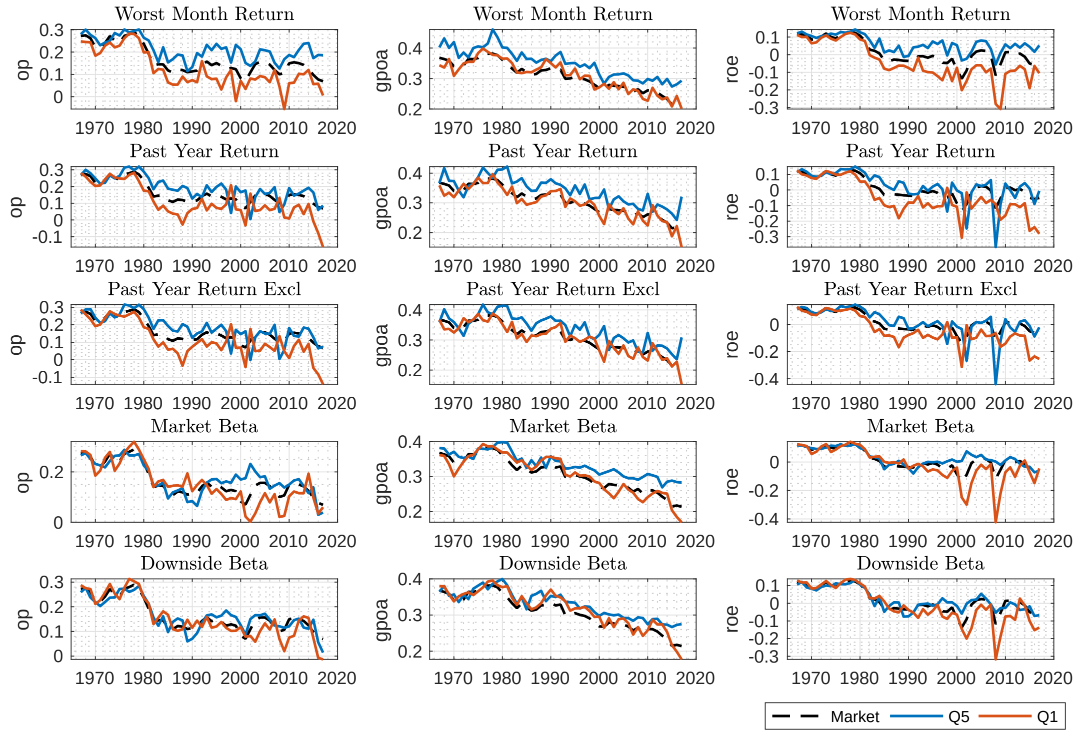
Profitability Figure 11 and Table 5 compare the measures of profitability of the four alternative ranking strategies with those based on stressful time relative performance. In general, all of the four alternative ranking strategies are able to separate profitable and unprofitable firms, though with occasionally crossing. Across all three profitability measures, the momentum-based portfolios show better separations between profitable and unprofitable firms than the beta-based strategies. Beta-based portfolios provide weaker separation of high and low profitability firms when compared to sorts based on stressful time performance. Surprisingly, the difference between Q5 - Q1 spreads from portfolios sorted by past-year holding returns (momentum) are not significantly different from the ones from stressful time relative performance. However, after taking out the 'worst month', stressful time relative performance does show stronger separations, which suggests it is the worst month that help to separate more profitable firms from less profitable ones.

Table 5: Profitability Measures: Alternative Sorted Portfolios Q5 - Q1

Panel A: Operating Profitability to Equity					
Q5 - Q1	Stressful Time	Momentum	Mom. Exl.	Beta	Down Beta
Min	0.005	-0.166	-0.178	-0.114	-0.088
Max	0.252	0.248	0.237	0.229	0.107
Mean	0.091	0.082	0.070	0.021	0.011
t-statistics	11.706	7.111	5.947	2.365	1.767
SMV - X		0.009	0.021	0.070	0.080
t-statistics		0.898	1.911	6.987	11.059
Panel B: Gross Profits					
Q5 - Q1	Stressful Time	Momentum	Mom. Exl.	Beta	Down Beta
Min	0.000	-0.045	-0.058	-0.031	-0.021
Max	0.110	0.169	0.155	0.113	0.097
Mean	0.042	0.040	0.032	0.027	0.012
t-statistics	12.724	7.758	6.260	6.447	3.935
SMV - X		0.001	0.009	0.014	0.029
t-statistics		0.273	1.636	3.461	7.021
Panel C: Return on Book Equity					
Q5 - Q1	Stressful Time	Momentum	Mom. Exl.	Beta	Down Beta
Min	0.000	-0.274	-0.374	-0.054	-0.065
Max	0.318	0.286	0.279	0.426	0.264
Mean	0.103	0.077	0.061	0.047	0.033
t-statistics	10.291	5.227	4.032	3.520	3.586
SMV - X		0.026	0.041	0.055	0.070
t-statistics		1.717	2.487	4.613	8.281

Notes: The sample period is 1967 to 2018.

Figure 11: Profitability Measures



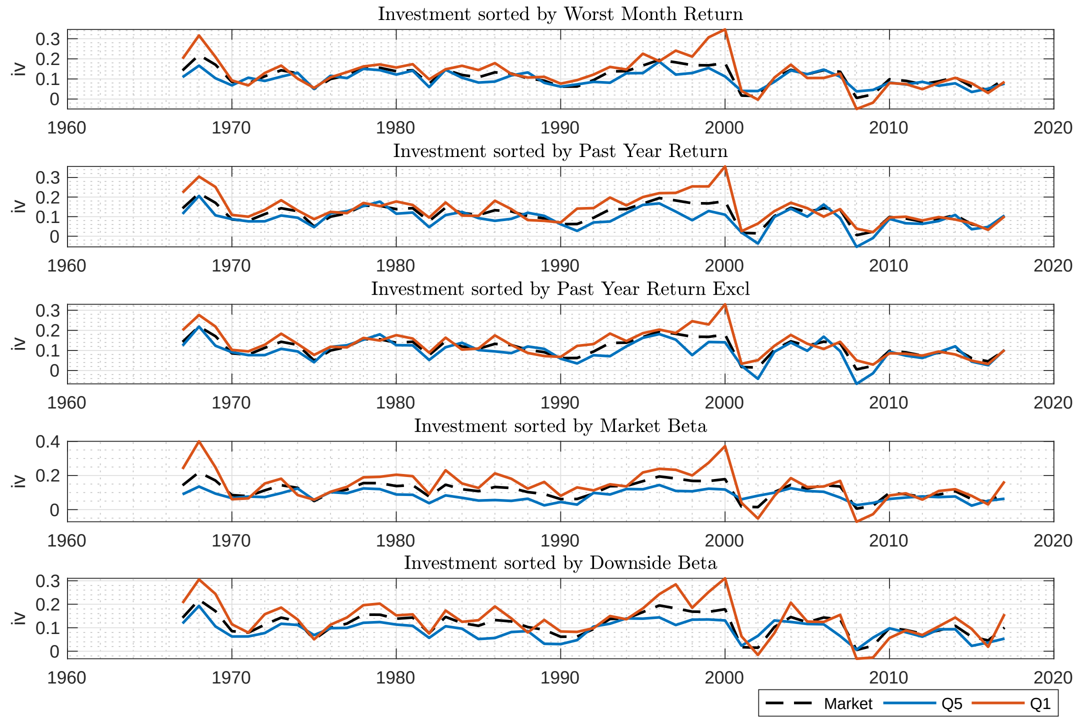
Investment Figure 12 and Table 6 compares the total asset growth ratio between Q5 and Q1 from different ranking procedures. Since high quality firms tend to have lower investment ratio, the Q5 - Q1 spread should be negative. In contrast to profitability measures, momentum and market (downside) beta based ranking procedures result stronger separations of investment than the stressful time relative performance strategies.

Table 6: Investment Measures: Alternative Sorted Portfolios Q5 - Q1

Q5 - Q1	Stressful Time	Momentum	Mom. Exl.	Beta	Down Beta
Min	-0.233	-0.246	-0.189	-0.265	-0.179
Max	0.087	0.061	0.061	0.133	0.084
Mean	-0.029	-0.046	-0.034	-0.060	-0.044
t-statistics	-3.643	-5.847	-5.026	-5.627	-5.575
SMV - X		0.017	0.005	0.031	0.015
t-statistics		2.441	0.672	4.849	2.637

Notes: The sample period is 1967 to 2018.

Figure 12: Investment Measure



Safety Figures 13 and Table 7 provide a comparison of the Olson O-scores (with the exponential transformation) of firms in Q5 and Q1 for the different sorting procedures. As can be seen from the figures, the separation along the O-score dimension is stronger for stressful time relative performance based sorting.

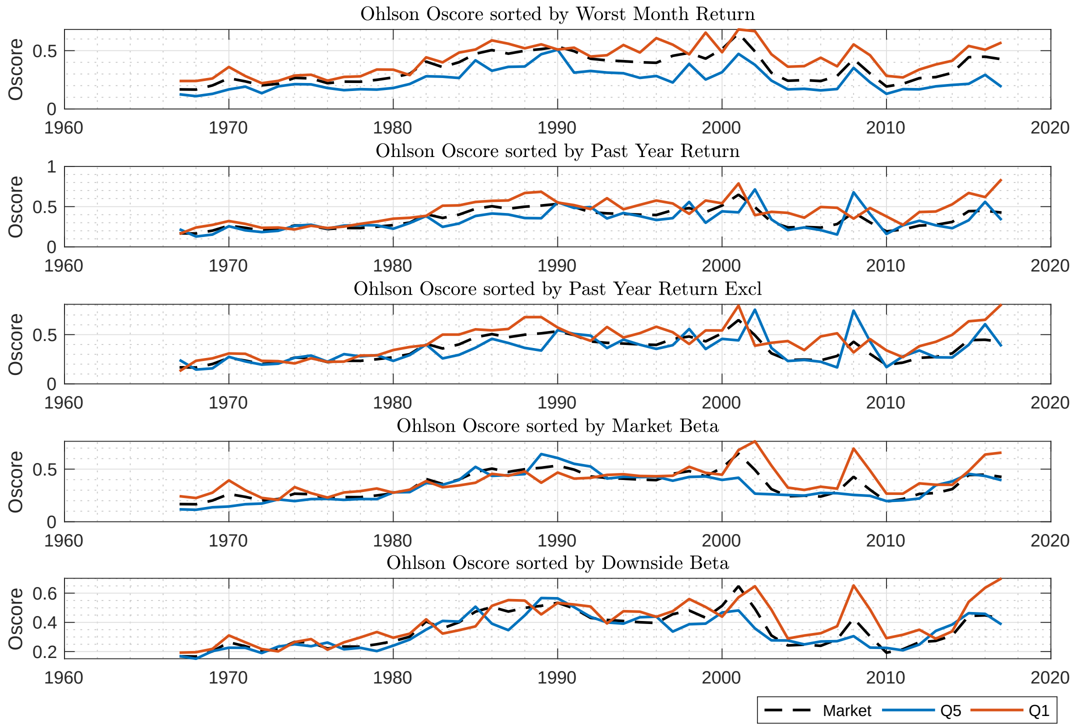
Table 7: Safety Measures: Alternative Sorted Portfolios Q5 - Q1

Q5 - Q1	Stressful Time	Momentum	Mom. Exl.	Beta	Down Beta
Min	-0.402	-0.506	-0.426	-0.497	-0.347
Max	-0.002	0.327	0.424	0.272	0.135
Mean	-0.175	-0.115	-0.087	-0.067	-0.067
t-statistics	-14.585	-5.205	-3.871	-3.570	-4.679
SMV - X		-0.060	-0.088	-0.108	-0.108
t-statistics		-2.904	-3.938	-5.681	-7.968

Notes: The sample period is 1967 to 2018.

Aggregate Quality Figures 14 and Table 8 provide a comparison of the Piotrosky F-scores of firms in Q5 and Q1 for the different sorting procedures. As can be seen from the figures, the

Figure 13: Safety Measure



separation along the Piotrosky F-scores dimension is stronger for stressful time relative performance based sorting.

Table 8: Aggregated Quality Measures: Alternative Sorted Portfolios Q5 - Q1

Panel A: Low F Score Percentage

Q5 - Q1	Stressful Time	Momentum	Mom. Exl.	Beta	Down Beta
Min	-0.184	-0.194	-0.179	-0.202	-0.144
Max	0.015	0.115	0.154	0.041	0.045
Mean	-0.087	-0.087	-0.070	-0.050	-0.032
t-statistics	-10.339	-6.995	-5.475	-5.123	-4.017
Stress - X		0.000	-0.016	-0.037	-0.054
t-statistics		0.009	-1.187	-3.007	-4.964

Panel B: High F Score Percentage

Q5 - Q1	Stressful Time	Momentum	Mom. Exl.	Beta	Down Beta
Min	0.004	-0.182	-0.251	-0.049	-0.072
Max	0.243	0.219	0.202	0.265	0.198
Mean	0.106	0.100	0.086	0.056	0.033
t-statistics	10.353	6.616	5.327	4.420	3.286
Stress - X		0.005	0.020	0.049	0.072
t-statistics		0.312	1.042	3.400	5.986

Notes: The sample period is 1986 to 2018.

To summarize, we find that sorting on firms' relative performance in stressful times helps sepa-

Figure 14: Aggregated Quality Measure

rate higher quality firms from lower quality firms better than sorting based on past returns, market beta, and market downside beta.

5 Portfolios Based on Stressful Time Performance

Folk wisdom is that investing in higher quality stocks leads to long run higher returns and lower risk. Asness et al. (2019) finds that higher quality portfolios higher risk adjusted returns. Therefore, if stressful time performance does indeed separate high quality and low quality firms, then it would be reasonable to expect managed portfolios SS firms firms to load positively on market wide quality related factors used in the literature, and have similar risk adjusted returns. On the other hand, SV firms should earn lower risk adjusted returns and load negatively on quality related factors.

At the beginning of each year, we form value-weighted portfolio of SS (SV) firms where firms were assigned to SS (SV) category in the previous year as described in in Section 2.2. The portfolios are rebalanced slightly each month so that they remain value weighted. For each industry, we have four value-weighted portfolios: big stressful time stable (BSS), small stressful time stable (SSS), big stressful time vulnerable (BSV), and small stressful time vulnerable (SSV). We calculate the monthly return for each group by averaging across all industry, i.e., our SS and SV portfolios are obtained by equally weighting the corresponding small and large industry portfolios.

We first examine the monthly returns in excess of the risk free rate [17] for SS and SV portfolios. Table 9 provides the summary statistics for the monthly excess returns for SS and SV portfolios against the aggregate stock market (MktRF from Fama-French data library). As expected, the SS portfolio consistently earns higher excess return than the market while the SV portfolio underperform the market portfolio. As shown in Table 9, SS earns a much higher average excess returns than the market portfolio (0.73% versus 0.52% per month) with the same risk exposure (almost the same standard deviation of 4.48). In contrast, portfolio based on SV has the same average excess return as the market portfolio but with a much higher standard deviation (6.31 versus 4.48). The annualized Sharpe ratio for the market portfolio is 0.42, while that of the SS and SV portfolios are 0.55 and 0.31 respectively.

Table 9: Summary Statistics

Monthly Excess Return %	P2.5	P25	P50	P75	P97.5	Mean	STD	SR
Market	-9.24	-2.11	0.86	3.49	8.40	0.52	4.48	0.12
Stressful Stable (SS)	-8.34	-1.74	0.88	3.71	8.26	0.73	4.48	0.16
Stressful Vulnerable (SV)	-12.39	-3.17	0.64	4.38	12.13	0.54	6.31	0.09

Notes: Table reports the summary statistics for the excess monthly returns of the market, SS, and SV portfolios. The sample period is 1967 to 2018.

5.1 Risk-adjusted Returns

Next we examine the risk-adjusted returns of the SS and SV portfolios. We start with the traditional CAPM with market factor (Mkt), Fama-French 3-factor (FF3) model with size (SMB) and value

[17] We use the R_f from Fama and French Data Library for the risk free rate.

(HML) factors, and the Fama-French-Carhart 4-factor (FFC4) with momentum factor (MOM). We then consider the more recent factor models that have quality related factors – the Fama-French 5-factor model by Fama and French (2015), the HXZQ-factor model by citehou2015digesting, and the FF3Q model in Asness et al. (2019).

Table 10: Stressful Time Stable Portfolio

	CAPM	FF3	FFC4	FF5	HXZQ	FF3Q
α	0.24	0.15	0.10	0.02	-0.00	-0.00
	(4.09)	(3.24)	(2.16)	(0.56)	(-0.01)	(-0.19)
Mkt	0.94	0.91	0.92	0.94	0.93	0.96
	(70.78)	(83.12)	(84.40)	(91.11)	(84.40)	(81.70)
SMB/ME		0.30	0.30	0.35	0.33	0.36
		(19.40)	(19.91)	(24.56)	(21.68)	(22.98)
HML		0.13	0.16	0.05		0.17
		(8.38)	(9.59)	(2.78)		(11.16)
MOM			0.05			
			(5.33)			
CMA/IA				0.17	0.21	
				(5.87)	(8.59)	
RMW/ROE				0.25	0.16	
				(12.37)	(8.73)	
QMJ						0.24
						(9.72)

Notes: Table reports the time-series regression results for the monthly return of the stressful time stable portfolio (SS) over the sample period from 1967 to 2018. The associate t-statistics are in parenthesis.

We report the alphas for each of the factor models based on time-series regression of the monthly excess returns on the SS and SV portfolios on the risk factors in Table 10. The SS portfolio has a significant monthly CAPM alpha of 0.24% per month with the market beta of 0.94. The alpha drops to 0.15% per month when the FF3 model is used for risk adjustment, but remains significant. Since there are more small firms in general, SS loads positively on SMB. By construction, SS also loads positively on the momentum factor MOM. However, the MOM coefficient is only 0.05 and the FFC4 alpha of 0.10% per month is significant. As expected, SS loads positively on quality factors. In particular, SS loads heavily on the investment factor (CMA) with a coefficient 0.17 and the profitability factor (RMW) with a coefficient 0.25 per month. The FF5 alpha is almost zero (0.02% per month) and insignificant (t-statistics = 0.56). Similarly, SS loads significantly on the investment (I/A) and profitability (ROE) factors in the HXZQ-factor model and the HXZQ-alpha is insignificant.[18] In FF3Q, we augment the FF3 model with the aggregate quality factor, QMJ, in Asness et al. (2019). SS portfolio has a coefficient of 0.24 for QMJ which is highly significant with an associated t-statistic of 9.72. The loadings for Mkt, SMB and HML are almost the same as the corresponding loadings in the FF3 model. Not surprisingly, the FF3Q alpha is not much different from zero. These findings are consistent with our hypothesis that the SS portfolio will have a positive alpha unless quality related factors are included in the factor models.

Table 11: Stressful Time Vulnerable Portfolio

	CAPM	FF3	FFC4	FF5	HXZQ	FF3Q
α	-0.13	-0.29	-0.09	-0.26	-0.07	-0.07
	(-1.40)	(-4.21)	(-1.55)	(-3.65)	(-1.04)	(-1.09)
Mkt	1.29	1.22	1.17	1.21	1.20	1.14
	(59.33)	(75.12)	(85.79)	(69.92)	(74.75)	(64.00)
SMB/ME		0.57	0.57	0.56	0.46	0.48
		(24.91)	(29.78)	(23.18)	(20.67)	(20.20)
HML		0.19	0.10	0.22		0.13
		(7.81)	(5.15)	(6.63)		(5.81)
MOM			-0.23			
			(-16.84)			
CMA/IA				-0.06	0.11	
				(-1.30)	(3.10)	
RMW/ROE				-0.04	-0.31	
				(-1.41)	(-11.48)	
QMJ						-0.32
						(-8.66)

Notes: Table reports the time-series regression results for the monthly return of the stressful time vulnerable portfolio (SV) over the sample period from 1967 to 2018. The associate t-statistics are in parenthesis.

Table 11 presents the results for the monthly excess returns on the SV portfolio. The SV portfolio has a monthly negative CAPM alpha, that is not significantly different from zero, and a FF3 model alpha that is significantly negative, -0.29% per month. As the portion of small firms in SV is even higher than that in SS, the SMB coefficients are positively significant and much larger than those for the SS portfolio. Not surprisingly, SV loads heavily on momentum factor with a significantly

[18]Notice that the loadings on investment factor in HXZQ is higher than that in FF5 as HXZQ drops the value factor (HML), which may be redundant. This is in consistent with the findings in Fama and French (2015), that with the addition of the two quality related factors, profitability and investment, the value factor (HML) becomes redundant.

negative coefficient of -0.23. The FFC4 alpha, though negative is not significant. Note that SV has significantly positive loadings on investment and significantly negative loadings on profitability in HXZQ-model, and a significantly negative loading on the quality factor (QMJ). All these findings are consistent with what we would expect, given our view that SV is a portfolio of low quality stocks. Next we proceed to examine the risk-adjusted abnormal returns on the long-short SMV portfolio. In addition to the risk factor models in Tables 10 and 11, we also consider the FF3 model augmented with the betting-against-beta factor (BAB), i.e., the FF3B model.

Table 12: Stressful Time Stable minus Vulnerable Portfolio

	CAPM	FF3	FFC4	FF5	HXZQ	FF3Q	FF3B
α	0.38	0.44	0.19	0.28	0.07	0.06	0.23
	(4.16)	(5.04)	(2.56)	(3.28)	(0.89)	(0.80)	(2.81)
Mkt	-0.35	-0.31	-0.25	-0.26	-0.26	-0.17	-0.30
	(-17.27)	(-15.10)	(-14.64)	(-12.64)	(-14.26)	(-8.13)	(-16.31)
SMB/ME		-0.27	-0.26	-0.20	-0.12	-0.11	-0.27
		(-9.33)	(-10.93)	(-6.97)	(-4.93)	(-4.12)	(-10.34)
HML		-0.05	0.05	-0.16		0.03	-0.16
		(-1.71)	(1.93)	(-4.09)		(1.33)	(-5.32)
MOM			0.28				
			(16.52)				
CMA/IA				0.24	0.10		
				(3.96)	(2.43)		
RMW/ROE				0.29	0.47		
				(7.27)	(15.12)		
QMJ						0.56	
						(12.63)	
BAB							0.26
							(10.68)

Notes: Table reports the time-series regression results for the monthly return of the stressful time stable minus vulnerable portfolio (SMV) over the sample period from 1967 to 2018. The associate t-statistics are in parenthesis.

Table 12 reports the time-series regression results. The SMV portfolio earns significantly positive abnormal returns with the traditional risk-adjusted factor models, e.g. CAPM, FF3, and FFC4. As expected, SMV has significantly negative coefficients on the market, size, and value factors. Further, SMV loads positively on the quality factors, RMW and CMA in FF5 and IA and ROE in HXZQ and QMJ in FF3Q. While the FF5 alpha is significant, the HXZQ and FF3Q alphas are insignifantly differentfrom zero, indicating that the quality premium in SMV is due to exposure to the quality factors IA, ROE, and QMJ. Also note that the loading on HML becomes insignificant, suggesting HML becomes redundant after controlling for QMJ. Finally, while the SMV loads positively on the betting-against-beta factor (BAB), the FF3B factor model alpha is positive and significant.

To summarize, we find that the portfolio of firms that perform better in stressful times relative to peers (SS) earns positive risk adjusted abnormal returns on average when risk adjustment is done using traditional factor models. The portfolio of stressful times poor performing firms (SV) has a negative alpha when conventional factor models are used for risk adjustment. However, there is no abnormal risk adjusted returns when traditional factor models are augmented with quality related factors identified in the literature. This is what one should expect if stressful time relative performance is a measure of firm quality.

Table 13: FF3 Regression Results for SMV & Risk Factors

Panel A : FF3 + SMV	UMD	RMW	ROE	PMU	QMJ
α	0.39	0.25	0.48	0.28	0.50
	(2.79)	(3.07)	(5.88)	(6.75)	(7.86)
Mkt	0.13	0.00	0.07	-0.03	-0.13
	(3.62)	(0.28)	(3.34)	(-2.77)	(-7.56)
SMB	0.26	-0.16	-0.13	-0.04	-0.17
	(5.35)	(-5.80)	(-4.76)	(-2.80)	(-7.78)
HML	-0.30	0.02	-0.15	-0.09	-0.14
	(-6.16)	(0.89)	(-5.24)	(-6.15)	(-6.40)
SMV	1.05	0.24	0.52	0.15	0.36
	(16.52)	(6.58)	(14.27)	(8.14)	(12.63)
Panel B : FF3 + Risk Factors			SMV		
α	0.19	0.34	0.10	0.20	0.06
	(2.56)	(4.00)	(1.32)	(2.23)	(0.80)
Mkt	-0.25	-0.29	-0.26	-0.25	-0.17
	(-14.64)	(-14.52)	(-14.83)	(-11.97)	(-8.13)
SMB	-0.26	-0.21	-0.14	-0.23	-0.11
	(-10.93)	(-7.04)	(-5.22)	(-7.75)	(-4.12)
HML	0.05	-0.05	0.03	0.02	0.03
	(1.93)	(-1.88)	(1.10)	(0.73)	(1.33)
UMD/RMW/ROE/PMU/QMJ	0.28	0.26	0.47	0.67	0.56
	(16.52)	(6.58)	(14.27)	(8.14)	(12.63)

Notes: Table reports the time-series regression results for the monthly return of stressful time stable minus vulnerable portfolio (SMV) and other quality related risk factor mimicking portfolios over the sample period from 1967 to 2018. The associate t-statistics are in parenthesis.

5.2 Tail Risk Exposure

In this subsection we compare the tail risk in the SMV portfolio return, which can be viewed as a 'quality factor' with the tail risk in the various market wide risk factors and quality related factors in the literature.

For that purpose, we use the worst month in a given year for the value-weighted market portfolio (MktRF) and compare the returns on the factor portfolios in the various factor models we examined Section 5.1, and the return on the SMV portfolio. Table 14 reports the correlation of worst month returns of SMV with other risk factors. Note that SMV is signficantly positively correlated with the quality factors – 0.68 with QMJ, 0.60 with ROE, and 0.59 with RMW – as we expected. However, the correlations with size (SMB), momentum (MOM) and betting-against-beta (BAB) factors are lower.

Table 14: Correlations for Monthly Portfolio Returns in Market Worst Month

	MktRF	SMB	HML	MOM	RMW	CMA	QMJ	BAB	IA	ROE	SMV
MktRF	1.00	0.44	-0.19	0.04	-0.23	-0.32	-0.49	0.38	-0.32	-0.15	-0.47
SMB		1.00	0.11	0.29	-0.08	0.10	-0.34	0.57	0.02	-0.05	-0.18
HML			1.00	0.01	0.24	0.78	0.12	0.49	0.79	0.11	0.36
MOM				1.00	0.09	0.08	0.08	0.30	0.05	0.32	0.36
RMW					1.00	0.15	0.81	0.35	0.15	0.82	0.59
CMA						1.00	0.22	0.37	0.96	0.11	0.45
QMJ							1.00	0.10	0.21	0.79	0.68
BAB								1.00	0.32	0.30	0.18
IA									1.00	0.09	0.47
ROE										1.00	0.60
SMV											1.00

Notes: Table reports the correlations of the monthly returns between the stressful time stable minus vulnerable portfolio (SMV) and the other risk factors over the sample period from 1967 to 2018.

The summary statistics for SMV and various risk factors are reported in Table 15. On average, SS loses less than the market portfolio during the worst months while SV has a much fatter left tail, with the 2.5% quantile be -26.86%. Turning to the risk factor mimicking portfolios, SMB, MOM, and BAB are among the ones with the lowest worst month returns and fatter left tails. The average worst month return for SMB is even -1.62% per month, indicating small firms perform poorly over stressful time. The quality factors are more robust over the worst months, among which QMJ has the highest average return of 2.41% with the standard deviation being 2.97. However, SMV beats QMJ with a higher average return of 2.67% and a smaller standard deviation of 2.53. The SMV portfolio performs better than QMJ in all inter-quantiles.

Table 15: Summary Statistics for Monthly Portfolio Returns in Market Worst Month

	2.5%	25%	Median	75%	97.5%	Mean	STD
MktRF	-18.43	-9.80	-5.81	-3.86	-1.18	-6.81	4.41
SS	-18.43	-8.34	-4.71	-3.31	-0.99	-6.45	4.88
SV	-26.86	-12.30	-7.39	-4.60	-0.57	-9.13	5.97
SMB	-8.48	-3.44	-1.06	0.27	3.63	-1.62	3.05
HML	-3.77	-1.04	1.38	3.73	11.62	1.59	3.51
MOM	-8.63	-1.70	0.56	1.95	9.77	0.63	4.14
RMW	-4.34	-0.26	0.68	2.09	9.86	0.93	2.99
CMA	-2.32	-0.32	1.28	2.69	8.72	1.52	2.63
QMJ	-2.76	0.55	2.12	3.76	9.43	2.41	2.97
BAB	-6.57	-0.95	0.48	2.39	13.87	0.80	4.25
IA	-2.24	-0.16	1.25	2.77	7.82	1.57	2.43
ROE	-3.17	-0.68	0.87	2.57	6.79	1.10	2.54
SMV	-1.20	1.13	2.23	3.42	10.08	2.67	2.53

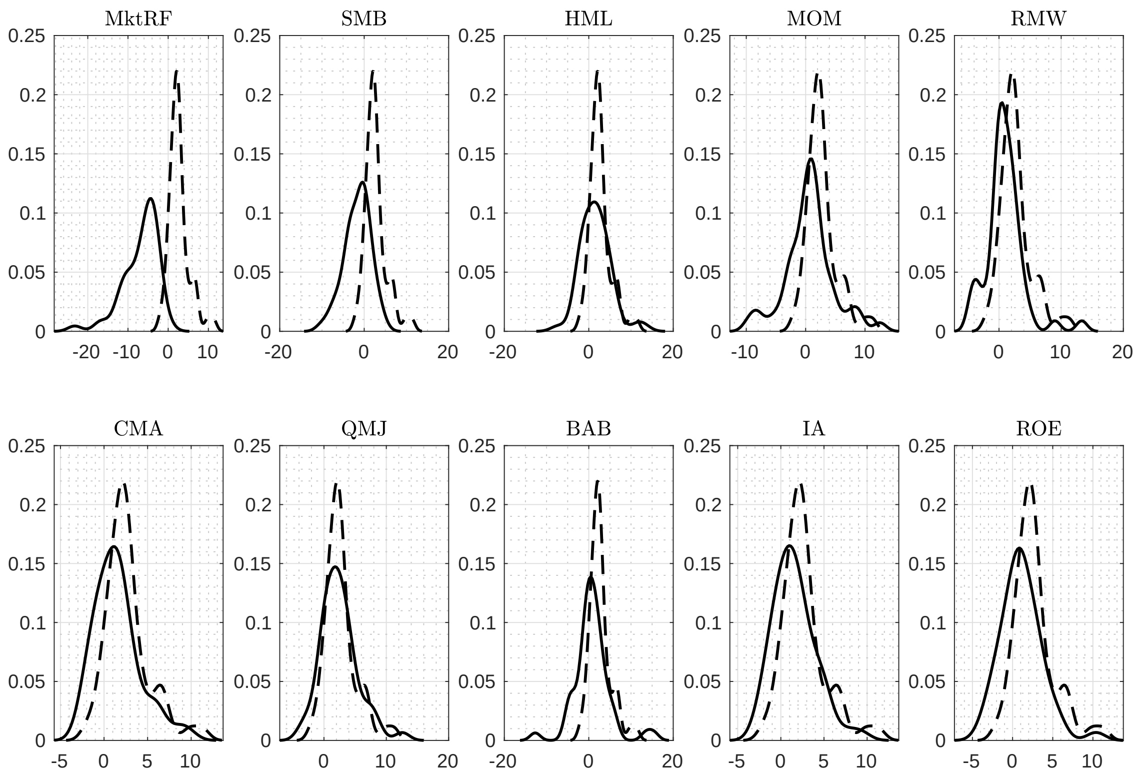
Notes: Table reports the summary statistics for the monthly returns of the stressful time stable (SS), vulnerable (SV), stable minus vulnerable portfolios, and other risk factors in the annual worst month of the market. The sample period is from 1967 to 2018.

Figure 15 plots the distribution densities of the worst month returns for each risk factor mimicking portfolio (black hard line) against that of the long-short worst month portfolio SMV (black dashed line). Across all pairs, SMV has a more concentrated distribution with a thinner left tail, suggesting the SMV has lower exposure to tail risk relative to the profitability and quality factors. Consistent with the evidence in the summary statistics table, SMB, MOM, and BAB exhibit fatter left tails. The quality based factors are less left skewed in general, indicating quality stocks are more robust to downside risk.

6 Update 2020: The COVID-19 Pandemic

In this subsection we examine the performance of the various industry level SMV portfolios during the worst of the first five months of 2020. We use the year 2019 to identify the stressful time stable

Figure 15: Worst Month Excess Return Distributions



and vulnerable firms/stocks. The monthly stock return data are sourced from Bloomberg. During the first 5 months of 2020, the US stock market has saw its worst performance in in 2020 March with the S&P 500 Index has falling by 13.99%.

Table 16: 2019 Stressful Time Vulnerable & Stable Stocks Performance in 2020 March

	Value Weighted				Equal Weighted			
Industry	Industry	Vulnerable	Stable	SMV	Industry	Vulnerable	Stable	SMV
NoDur	-11.43%	-17.81%	-12.88%	4.93%	-18.36%	-17.36%	-7.96%	9.41%
Durbl	-22.70%	-24.55%	-14.01%	10.54%	-27.38%	-41.01%	-16.41%	24.61%
Manuf	-19.89%	-23.39%	-11.34%	12.05%	-24.58%	-32.20%	-21.96%	10.24%
Enrgy	-34.61%	-59.84%	-23.01%	36.83%	-47.46%	-56.57%	-21.49%	35.09%
Chems	-10.77%	-27.22%	-3.81%	23.41%	-21.77%	-25.41%	-21.13%	4.28%
BusEq	-9.85%	-8.23%	-13.15%	-4.92%	-18.04%	-17.89%	-16.37%	1.51%
Telcm	-13.39%	-33.04%	-4.16%	28.89%	-23.54%	-28.25%	-14.14%	14.11%
Utils	-12.99%	-11.16%	-16.66%	-5.51%	-10.36%	-14.89%	-22.41%	-7.52%
Shops	-7.68%	-14.48%	-12.02%	2.46%	-25.70%	-31.05%	-26.84%	4.21%
Hlth	-5.31%	-4.47%	-8.03%	-3.56%	-17.28%	-3.62%	13.68%	17.29%
Money	-20.05%	-24.17%	-10.51%	13.67%	-23.54%	-29.10%	-21.12%	7.99%
Average	-15.50%	-21.97%	-12.11%	9.86%	-23.80%	-26.71%	-16.60%	10.11%

Notes: Table reports the value and equal weighted average monthly returns for the stressful time stable (SS), vulnerable (SV), and stable minus vulnerable (SMV) portfolios for each FF12 industry groups in 2020 March, together with the industry average. The stocks in SS and SV are identified based on the worst month return in 2019.

Table 16 compares the value and equal weighted monthly returns for the stressful time vulnerable (SV), stable firms (SS), and the long Stable and short Vulnerable (SMV) portfolio, for each of the industry groups during March 2020. The corresponding monthly returns for the Fama-French 12 Industry Portfolios are used as a benchmark (column Industry). As can be seen, on the one hand, for both value- and equal-weighted portfolios, the stressful time vulnerable firms suffer larger losses than the corresponding industry benchmarks. In contrast, stressful time stable firms maintain perform better than the corresponding vulnerable firms in their industry, as well as the industry benchmarks. As a results, the long-short SMV portfolio earned a positive return across most industry groups during March 2020. There are three exceptions in the case of value-weighted portfolios: Business Equipment, Utility, and Health, where the vulnerable firms slightly outperform the stable firms. For the equal-weighted portfolios, the only exception is the Utility industry. Overall, on average, the value weighted and the equally weighted industry SMV portfolios earned large positive monthly returns of 9.86% and 10.11%, respectively.

Table 17: 2019 Stressful Time Vulnerable & Stable Stocks Performance in 2020 March

Factor	Discription	Return
Mkt	Market minus Risk Free Rate	-13.39%
SMB	Small minus Big	-8.45%
HML	High minus Low	-14.12%
RMW	Robust minus Weak	-1.33%
CMA	Conservative minus Aggressive	1.22%
UMD	Momentum	8.47%
REV	Short-term Reversal	-11.87%
QMJ	Quality minus Junk	7.32%
BAB	Betting Against Beta	-9.62%
SMV(VW)	Stable minus Vulnerable (value-weighted)	9.86%
SMV(EW)	Stable minus Vulnerable (equal-weighted)	10.11%

Notes: Table reports the monthly returns for the market , the value and equal weighted stressful time stable minus vulnerable (SMV) portfolios, and the major risk factors in 2020 March.

We proceed to compare the performance of SMV with the other long-short hedged risk factor mimicking portfolios in 2020 March in Table 17. As can be seen, the traditional Size and Value factors (SMB and HML) had large losses, which suggests small firms and value firms were more vulnerable than large and growth firms during the COVID-19 Pandemic. Momentum (UMD) and

Quality-minus-junk (QMJ) generate significant positive returns, comparable to SMV. Interestingly, betting-against-beta (BAB) portfolio lost heavily during the pandemic, confirming our earlier observation that while both SMV and BAB have lower market betas, they behave differently during stressful times. Finally, the Fama-French profitability (RMW) and investment (CMA) factors returns during the pandemic were not much different from zero.

7 Conclusion

In this paper, we propose a return-based method to identify high quality stocks. Our method is based on the street wisdom that quality shines under stress, i.e., higher quality firms perform better than other firm during stressful times. At the end of each calendar year, we identify stressful time stable (SS) and vulnerable (SV) firms by sorting firms in each industry group based on the month with the worst return for their industry. Even though we did not use any other information than returns, we find that SS firms are of higher quality as indicated by their higher profitability, more conservative investment policy, higher Piotroski F-Score, lower credit risk, lower market beta, and lower idiosyncratic volatility, than SV firms.

We construct managed portfolios of stressful time stable firms (SS) and vulnerable firms (SV) and examine their correlations with quality related market wide risk factors studied in the literature, their risk adjusted returns, and their tail risk. The SS loads positively while SV loads negatively on the quality factors and the long SS and short SV portfolio has properties similar to the 'quality-minus-junk' factor (QMJ). The long SS and short SV portfolio (SMV) has a significantly positive risk adjusted return(alpha) when risk adjustment is made using the standard CAPM, Fama and French three factor model (FF3), and the FF3 augmented by the momentum factor. When alpha becomes insignificant when FF3 is augmented with quality related QMJ factor. The alpha is also insignificant with the Chen and Zhang (2010) model that has two quality related factors. These findings are consistent with the those in the literature documenting a quality premium in stock returns.

Finally, we update the analysis with data of the first 5 months in 2020, when the global market were hit by the COVID-19 Pandemic. We compare the performance of 2019 stressful time vulnerable (SV) and stable (SS) stocks in each industry during March 2020, the worst of the first 5 months in 2020. Similar to the quality-minus-junk and the momentum factor portfolios, the stressful time hedged portfolio (SMV) earned a significant positive return. In contrast the Size, Value, and betting-against-beta portfolios suffered large losses. We conclude that the stressful time vulnerable and stable firms identified by the methodology we propose in this paper is robust, and provides a return based alternative measure of firm quality.

8 Appendix

8.1 Fundamental Based Quality Measures

At the end of each year, we calculate the fundamental based quality measures for each firm with one-year lagged financial data from annual fundamental file on COMPUSTAT.

Profitability and Investment Measures We calculate the profitability and investment measures in Novy-Marx (2013), Fama and French (2015), and Hou et al. (2015) by:

1. Gross profits (revenue less cost of goos sold) over total assets:

$$\mathrm{GPOA} = \frac{(\mathrm{REVT} - \mathrm{COGS})}{\mathrm{AT}} \tag{1}$$

2. Operating Profitability to Equity:

$$\mathrm{OP} = \frac{\mathrm{REVT} - \mathrm{COGS} - \mathrm{XSGA} - \mathrm{XINT}}{\mathrm{BE}}. \tag{2}$$

   where the book equity (BE) is calculated by:

$$\mathrm{BE} = \mathrm{SEQ} + \mathrm{TXDB} + \mathrm{ITCB} - \mathrm{BVPS}, \quad \mathrm{BVPS} = \{\mathrm{PSTKRV}, \mathrm{PSTKL}, \mathrm{PSTK}\}.$$

3. Return on book equity:

$$\mathrm{ROE} = \frac{\mathrm{IB}}{\mathrm{BE}}. \tag{3}$$

   where IB is income before income before extraordinary items.

4. Investment:

$$\mathrm{IV} = \frac{\mathrm{AT} - \mathrm{AT}_{-1}}{\mathrm{AT}_{-1}}. \tag{4}$$

Ohlson O-score At the end of each year, we calculate the Ohlson O-score using CPI data with 2009 as base year:

$$
\begin{aligned}
O = & -1.32 - 0.407 \log\left(\frac{\mathrm{AT}_{adj}}{\mathrm{CPI}}\right) + 6.03 \frac{(\mathrm{DLC} + \mathrm{DLTT})}{\mathrm{AT}_{adj}} - 1.43 \frac{(\mathrm{ACT} - \mathrm{LCT})}{\mathrm{AT}_{adj}} \\
& + 0.076 \frac{\mathrm{LCT}}{\mathrm{ACT}} - 1.72 \times \mathbf{1}_{\{\mathrm{LT} > \mathrm{AT}\}} - 2.37 \frac{\mathrm{IB}}{\mathrm{AT}} - 1.83 \frac{\mathrm{PI}}{\mathrm{LT}} \\
& + 0.285 \times \mathbf{1}_{\{\max(\mathrm{IB}_y, \mathrm{IB}_{y-1})\} < 0} - 0.521 \frac{(\mathrm{IB} - \mathrm{IB}_{-1})}{|\mathrm{IB}| + |\mathrm{IB}_{-1}|},
\end{aligned} \tag{5}
$$

where $\mathrm{AT}_{adj} = \mathrm{AT} + 0.1(\mathrm{ME} - \mathrm{BE})$ is the adjusted total assets. The probability of default in 2-year period is given by the exponential transformation of the Ohlson O-score:

$$
P_{\mathrm{default}} = \frac{\exp(O)}{1 + \exp(O)}. \tag{6}
$$

Piotroski F-score Piotroski F-score is an aggregated signal measure of firm's quality by summing nine binary scores:

$$
\begin{aligned}
\text{F-score} = & \mathbf{1}_{\mathrm{ROA}>0} + \mathbf{1}_{\mathrm{CFOA}>0} + \mathbf{1}_{\Delta\mathrm{ROA}>0} + \mathbf{1}_{\mathrm{ACC}<0} + \mathbf{1}_{\Delta\mathrm{LEV}<0} \\
& + \mathbf{1}_{\Delta\mathrm{LIQ}>0} + \mathbf{1}_{\mathrm{EQO}<0} + \mathbf{1}_{\Delta\mathrm{GMAR}>0} + \mathbf{1}_{\Delta\mathrm{TURN}>0}
\end{aligned} \tag{7}
$$

As in Piotroski (2000), the 9 binary variables can be grouped into two categories and are defined as follows:

1. Profitability Measures:

   (a) Cash flow from operating activity over total assets:

   $$
   \mathrm{CFOA} = \frac{\mathrm{OANCF}}{\mathrm{AT}} \tag{8}
   $$

   (b) Return (income before extraordinary items) to total assets:

   $$
   \mathrm{ROA} = \frac{\mathrm{IB}}{\mathrm{AT}} \tag{9}
   $$

(c) Accrual:

$$\text{ACC} = \text{ROA} - \text{CFOA} \tag{10}$$

2. Efficiency Measures

(a) Gross margin (gross profits over sales):

$$\text{GMAR} = \frac{(\text{REVT} - \text{COGS})}{\text{SALE}} \tag{11}$$

(b) Asset turnover (sale over total assets):

$$\text{TURN} = \frac{\text{SALE}}{\text{AT}} \tag{12}$$

(c) Leverage (total long-term debt over total assets):

$$\text{LEV} = \frac{\text{DLTT}}{\text{AT}} \tag{13}$$

(d) Current ratio (current assets over current liability):

$$\text{LIQ} = \frac{\text{ACT}}{\text{LCT}} \tag{14}$$

(e) New issuance (changes in common shares outstanding):

$$\text{EQO} = \text{CSHO} - \text{CSHO}_{-1} \tag{15}$$

8.2 Market Based Risk Measures

At the end of each year, we calculate the following market-based risk measures for each stock using daily return data over the past one year:

1. Market β from CAPM:

$$R_{i,t} - R_{f,t} = \alpha_i^{CAPM} + \beta_i^{CAPM} R_t^{\text{MktRf}} + \epsilon_{i,t}^{CAPM}. \tag{16}$$

2. Idiosyncratic volatility (Ang et al. (2006)):

$$\mathrm{IVOL}_{i,y} = \sqrt{\frac{\sum_{t=1}^{n} \epsilon_{i,t}^2}{n-4}}, \tag{17}$$

where $\epsilon_{i,t}$ is the residuals from the Fama-French 3-factor model:

$$R_{i,t} - R_{f,t} = \alpha_i^{FF3} + \beta_i^{FF3} R^{\mathrm{MktRf}} + \beta_i^{Size} R_t^{\mathrm{SMB}} + \beta_i^{Value} R_t^{\mathrm{HML}} + \epsilon_{i,t}^{FF3}. \tag{18}$$

3. Co-skewness and co-kurtosis as in Ang et al. (2006):

$$\mathrm{CSK}_{i,y} = \frac{\frac{1}{n}\sum_{t=1}^{n}(R_{i,t} - \overline{R}_i)(R_{i,t}^{\mathrm{MktRf}} - \overline{R^{\mathrm{MktRf}}})^2}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(R_{i,t} - \overline{R}_i)^2}\left[\frac{1}{n}\sum_{t=1}^{n}(\mathrm{MktRf}_{i,t} - \overline{R^{\mathrm{MktRf}}})^2\right]}, \tag{19}$$

$$\mathrm{CKT}_{i,y} = \frac{\frac{1}{n}\sum_{t=1}^{n}(R_{i,t} - \overline{R}_i)(R_{i,t}^{\mathrm{MktRf}} - \overline{R^{\mathrm{MktRf}}})^3}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(R_{i,t} - \overline{R}_i)^2}\left[\frac{1}{n}\sum_{t=1}^{n}(R_{i,t}^{\mathrm{MktRf}} - \overline{R^{\mathrm{MktRf}}})^2\right]^{3/2}}. \tag{20}$$

8.3 Top 3 Stressful Time Stable and Loser by Industry in 2019

Table 18: 2019 Top 3 Stressful Time Vulnerable & Stable Stock

		Stressful Time Vulnerable			Stressful Time Stable		
Industry	VW Ind.	Ticker	Name	Return in 202003	Ticker	Name	Return in 202003
NoDur	-11.43%	MAT	Mattel Inc	-25.3%	HSY	Hershey Co	-8.0%
		DXYN	Dixie Group Inc	-31.6%	BRID	Bridgford Foods Corp	32.0%
		ICON	Iconix Brand Group Inc	-42.2%	MKC	Mccormick & Co Inc	-3.4%
Durbl	-22.70%	THO	Thor Industries Inc	-44.1%	NC	Nacco Industries Inc	-32.1%
		TEN	Tenneco Inc De	-60.7%	GNTX	Gentex Corp	-17.0%
		SUP	Superior Industries Intl Inc	-53.8%	CTHR	Charles & Colvard Ltd	-22.2%
Manuf	-19.89%	BC	Brunswick Corp	-33.5%	BLL	Ball Corp	-8.2%
		GT	Goodyear Tire & Rubber Co	-39.9%	ATRO	Astronics Corp	-54.7%
		KMT	Kennametal Inc	-33.0%	SCX	Starrett L S Co	-28.9%
Enrgy	-34.61%	HAL	Halliburton Company	-58.5%	WDFC	Wd 40 Co	16.4%
		CHK	Chesapeake Energy Corp	-37.2%	CVX	Chevron Corp New	-22.4%
		WLL	Whiting Petroleum Corp New	-63.8%	PNRG	Primeenergy Resources Corp	-43.5%
Chems	-10.77%	LXU	L S B Industries Inc	7.7%	PG	Procter & Gamble Co	-2.9%
		FOE	Ferro Corp	-19.4%	KMB	Kimberly Clark Corp	-1.7%
		MOS	Mosaic Company New	-36.2%	IFF	International Flavors & Frag Inc	-14.2%
BusEq	-9.85%	SWKS	Skyworks Solutions Inc	-10.8%	RTN	Raytheon Co	-30.4%
		SANM	Sanmina Corp	3.8%	ECL	Ecolab Inc	-13.4%
		KLAC	K L A Corp	-6.5%	TRNS	Transcat Inc	-8.3%
Telcm	-13.39%	NTN	N T N Buzztime Inc	-28.5%	VZ	Verizon Communications Inc	-0.8%
		SBGI	Sinclair Broadcast Group Inc	-29.9%	ATNI	A T N International Inc	9.2%
		VIAC	Viacomcbs Inc	-42.1%	IAC	Iac Interactivecorp	-12.1%
Utils	-12.99%	CNP	Centerpoint Energy Inc	-32.9%	OKE	Oneok Inc New	-67.3%
		PEG	Public Service Enterprise Gp Inc	-11.5%	PCG	P G & E Corp	-42.0%
		UGI	U G I Corp New	-25.1%	D	Dominion Energy Inc	-7.7%
Shops	-7.68%	ARW	Arrow Electronics Inc	-22.7%	MCD	Mcdonalds Corp	-14.8%
		AVT	Avnet Inc	-17.5%	WSO	Watsco Inc	2.5%
		JCP	Penney J C Co Inc	-47.8%	OBCI	Ocean Bio Chem Inc	-3.0%
Hlth	-5.31%	BCRX	Biocryst Pharmaceuticals Inc	-33.3%	MLAB	Mesa Laboratories Inc	-5.5%
		CVM	Cel Sci Corp	5.2%	PFE	Pfizer Inc	-2.3%
		STAA	Staar Surgical Co	2.8%	UG	United Guardian Inc	-1.7%
Money	-20.05%	CAR	Avis Budget Group Inc	-57.1%	CINF	Cincinnati Financial Corp	-18.4%
		MS	Morgan Stanley Dean Witter & Co	-24.5%	PGR	Progressive Corp Oh	0.9%
		FBP	First Bancorp P R	-33.0%	WRB	Berkley W R Corp	-22.1%

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