Where is the risk in risk factors? Evidence from the Vietnam war to the COVID-19 pandemic.

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Abstract

During the COVID-19 pandemic (Jan 2020 - Mar 2020) all of the Fama and French (2018) factors except momentum lost money. Negative payoffs in a bad state would appear to justify the positive premia generated by these risk factors. But this is atypical – historically the value, profitability, investment and momentum factors are all *more* profitable in bear markets. The five non-market factors exhibit their own bull and bear market phases, but these do not correlate with the economic cycle. Factor profitability in bear markets arise primarily from the short side. Biased expectations corrected around earnings announcement offer only a partial explanation.

Keywords: Risk factors; COVID-19; Bear markets; Short-sales constraints; Biased expectations

JEL codes: G12; G14

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1 Introduction

The coronavirus disease 2019 (COVID-19) started spreading widely in January 2020 and became a full-blown pandemic in March of 2020. Over this time-frame the S&P 500 composite index fell by more than 20%. This dramatic drop in stock prices reflect the severe impact on the real economy caused by COVID-19. The size, value, profitability and investment factors all suffered losses in the first three months of 2020. These losses appear are consistent with risk-based motivations for the factors. If risk factors are proxies for state variables as proposed by Fama and French (1992), their low payoffs in bad states make them undesirable and thus investors require a premium to hold them. Cochrane (2009) puts it this way:

> *Other things equal, an asset that does badly in states of nature like a recession, in which the investor feels poor and is consuming little, is less desirable than an asset that does badly in states of nature like a boom in which the investor feels wealthy and is consuming a great deal. The former asset will sell for a lower price; its price will reflect a discount for its "riskiness," and this riskiness depends on a co-variance, not a variance.* (page 3)

However, factor performance during the COVID-19 pandemic is not representative of the previous 10 bear markets from the Vietnam War to the Global Financial Crisis (GFC). Of the five non-market factors in the Fama and French (2018) six-factor model *none* generate statistically lower returns during bear markets than during bull markets. The SMB size factor is the only factor with lower returns in bear markets than bull markets, but the difference is not statistically significant. Instead, in bear markets all non-market factors in the six-factor model of Fama and French (2018), aside from the size factor, generate large and significant returns on average. These bear market returns are an order of magnitude larger than in bull markets. Clearly this is difficult to reconcile with models based around risks to consumption or wealth.

When we consider all 11 bear markets individually, COVID-19 stands out because five of the six Fama and French (2018) factors generate highly significant and negative average monthly returns. During the COVID-19 period CMA incurs the smallest average monthly loss (−1.22%) and HML incurs the largest average monthly loss (−8.13%) among the non-market factors. UMD is the only profitable factor during COVID-19, with an average monthly return of 4.59%. In each of the 10 prior bear markets, profitable non-market factors outnumbered loss-making non-market factors.

It is possible that factors proxy for other systematic risks that are not strongly correlated with the state variables we consider. If this is the case factors should produce lower returns during these alternative episodes of systematic risk. To this end we use cumulative factor indices to construct factor bull and bear markets, analogous to the bull and bear phases constructed from aggregate equity market indices. The individual factors bear markets do not exhibit any commonality among themselves or with our state variables. Instead factor bear markets appear to reflect the unique circumstances of each factor at the time, instead of systematic risk across business cycles.

Non-market factors are constructed using two-way sorts on size and the sorting variable associated with the factor[1]. As such they reflect the relative performance of both long and short legs. It is possible that the underlying dynamics of the long and short legs are obscured when aggregated into factor returns. For this reason we separately examine the long and short legs of factors. In bull markets the long legs returns exceed the short leg returns for all five non-market factors, but the difference is typically small – of the order of 3 to 27 bp/month (except for UMD where the difference is 55 bp/month). In bear markets short leg returns exceed long leg returns for all non-market factors except SMB (where the returns differ by only 4 bp/month). The excess of short leg returns over long leg returns is 104 bp/m for HML, 57 bp/m for RMW, 110 bp/m for CMA and 109 bp/m for UMD, all statistically significant at the 1% level (5% for RMW). This means that the full sample premia generated

[1]The size factor is based on a two-way sort of book-to-market and size.

by HML, RMW, CMA and UMD are mostly the result of large negative returns on the short legs of these strategies during bear markets. Such a pattern of returns is more consistent with a market hedging instrument, except that hedges usually require payment of a premium rather than generating a premium.

An alternative explanation is that factors reflect behavioural biases rather than priced risk. If factor returns are the result of biased investor expectations, then we would expect earning announcements returns to be a substantial fraction of factor returns (as biases are revealed to be in error by the release of actual earnings). Following the approach of Porta et al. (1997) we construct our own versions of the factors, but with actual returns replaced by [-1,1] cumulative returns centered on earnings announcement days. In bear markets the earnings announcement returns for HML, RMW, CMA and UMD make up around between 8% and 15% of full returns while accounting for 5% of the days. On the whole the evidence suggests that biased investor expectations explains only a small part of realised factor premia.

We contribute to the literature by examining factor returns across different states. Our paper is related to Porta et al. (1997), Nagel (2005) and Golubov and Konstantinidi (2019). We show that the heightened factor profitability during bear markets primarily arise from the short side of factor hedge portfolios. These bear market factor profits could be hard to realise because short-selling are often subject to tight limits to arbitrage in bear markets. Factor profits in bear markets suggest that they might compensate for rare disaster risks as posited by Gabaix (2012) and Watcher (2013) or have negative bear betas as modelled in Lu and Murray (2019). However, disaster risk or downside risk are unlikely to explain our findings because such insurance-like features are desirable, thus factors should earn negative premia instead of the positive mean returns in our full sample.

2 Data

We use factor time-series data from Ken French's data library to generate our main results and factor returns from Lu Zhang's global-q library and the AQR insights data library for ancillary analysis[2]. Table 6 in the Appendix contains a summary description of the factors and the sorting variables used in their construction.

To construct portfolios we rely on the Compustat quarterly and annual data files, as well the CRSP monthly file. Our sample starts in July 1963 and ends March 2020. The portfolios are based on the value-weighted returns using NYSE breakpoints. We only include common domestic US stocks (CRSP share codes 10 or 11) listed on the NYSE, Amex or NASDAQ (CRSP exchange codes 1, 2 or 3). Returns are delisting adjusted. Where delisting returns are missing we follow the approach in Beaver et al. (2007) which entail replacing missing delisting returns with the average delisting return over the prior 60 months for firms with the same exchange and 2-letter delisting code. If still missing we replace missing delisting returns with -30% for NYSE stocks and with -55% otherwise, following Shumway (1997) and Shumway and Warther (1999).

To test whether factor returns during bear markets may be driven by biased expectations, we calculate stock level earnings announcement returns for each factor during both bull and bear markets. The earnings announcement returns are calculated over a [-1,1] window centered on the quarterly earnings announcement date (Compustat quarterly RDQ) and are set to zero for all days outside the window. We then recreate the SMB, HML, CMA and RMW factors using the earnings announcement returns instead of normal returns.

Our classification of bear markets prior to the COVID-19 pandemic is detailed in Table 1 and follows Table 1 of Nyberg (2013) which is based on the dating methodology introduced by Bry and Boschan (1971) and modified by Pagan and Sossounov (2003). We add an

[2] See Sections 9.2 and 9.3 in the Appendix

additional bear market for the period covering January 2020 to March 2020 to reflect the COVID-19 pandemic of 2020. This period covers the incubation, outbreak and fever periods of COVID-19 studied by Ramelli and Wagner (2020). The *Bull* and *Bear* indicator variables reflect these bull and bear markets respectively.

The bull and bear market turning points in Nyberg (2013) are constructed using the Bry and Boschan (1971) dating rule with modifications proposed by Pagan and Sossounov (2003) for detecting cycles in stock markets. The Pagan and Sossounov (2003) algorithm first recognises local peaks and troughs within a fixed window. Then it applies a set of censoring rules to determine whether these peaks and troughs qualify as bull or bear market turning points. The censoring rules include a minimum bear and bull market length (six months unless the change is more than 20% in absolute terms), minimal full cycle length (16 months) and some additional heuristics[3]. Nyberg (2013) applied the Pagan and Sossounov (2003) algorithm and manually deleted two mild bear markets in 1971 and 1994, because the drops were less than 10%.

As a robustness check, we also used the Lunde and Timmermann (2004) algorithm to identify bull and bear markets (indicated by the *BullLT* and *BearLT* indicator variables). The Lunde and Timmermann (2004) approach only specifies the trough to peak increases (15%) and deceases (15%) and does not impose any limit on durations; thus it requires fewer parameters than either the Bry and Boschan (1971) or the Pagan and Sossounov (2003) approaches.

We also use NBER business cycles (*Expansion* and *Recession*) and stock market crash months (where the monthly return is lower than -10%) as additional state variables to investigate factor returns in different states of the world. Stock market crashes (based on the market premium MKTRF) are indicated by *Crashmarket,* with *Stablemarket* representing any month that is not a *Crashmarket* month. Likewise we identify positive and negative market premium months by the *Upmarket* and *Downmarket* indicator variables, respectively.

[3]Appendix B in Pagan and Sossounov (2003) describe the steps to recognise and filter the peaks and troughs.

Table 1: Bear markets

This table summarises bear market periods. Each bear market has an associated indicator variable (Bear Market), a starting month (Start), an ending month (End), number of months (N), market return (Total Drop) during the bear market and a brief description of the bear market (Comment). The dating rule for bear markets prior to the COVID-19 pandemic follows Nyberg (2013) which is based on Bry and Boschan (1971) and Pagan and Sossounov (2003). The COVID-19 pandemic includes the first three months in 2020 (Ramelli & Wagner, 2020). Total Drop is the market excess return (MKTRF) in percentage points, from Ken French's data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The sample period runs from July 1963 to March 2020 inclusive (681 months).

Bear Market	**Start**	**End**	**N**	**Total Drop**	**Comment**
Vietnam	1966-02	1966-09	8	-18.0	Vietnam war and high interest rates
Nixon	1968-12	1970-06	19	-40.2	Nixon - Vietnam war and social dislocation
Oilshock1	1973-01	1974-09	21	-53.0	First oil price shock
Oilshock2	1977-01	1978-02	14	-14.6	Second oil price shock
Stagflation	1980-12	1982-07	20	-33.3	Volcker fights inflation
Correction83	1983-07	1984-05	11	-18.0	The correction of 1983-1984
Crash1987	1987-09	1987-11	3	-31.0	Crash of 1987 (Black Monday)
Gulfwar	1990-06	1990-10	5	-19.7	The first Gulf war
Dotcom	2000-09	2003-02	30	-47.4	Dot com bust and 9/11 terror attacks
GFC	2007-11	2009-02	16	-51.5	Global financial crises
COVID	2020-01	2020-03	3	-20.5	Covid-19 crisis

3 Factor Premia

Benchmark factors are meant to proxy for systematic risks. However, risk factors have also attracted behavioural explanations consistent with mispricing that cannot be efficiently eliminated due to limits to arbitrage. This section briefly summarises the literature motivating the five non-market factors of Fama and French (2018), along with related empirical evidence.

3.1 Size and Value

Fama and French (1993) motivate the size and value factors in their seminal paper as follows: "*one of our central themes is that if assets are priced rationally, variables that are related to* *average returns, such as size and book-to-market equity, must proxy for sensitivity to common (shared and thus undiversified) risk factors in returns.*"

The size factor originates from the size anomaly uncovered by Banz (1981) and it is the second most widely studied factor by citations (Alquist et al., 2018). The size anomaly led to the inclusion of the SMB factor in the Fama and French (1993) three-factor model. Since then academics have put forward a large number of risk-based explanations for the size premium including liquidity risk, default risk, distress risk, cash flow risk and innovation risk (for example, see Vassalou and Xing (2004), Campbell and Vuolteenaho (2004), Campbell and Vuolteenaho (2004) and Stoffman et al. (2019)). Recent papers by Alquist et al. (2018) and Hur et al. (2014) provide detailed summaries of risk-based explanations for the size premium. Alquist et al. (2018) point out that small stocks face tighter limits to arbitrage (for example, lower institutional ownership and higher trading costs), thus the size premium is consistent with both behavioural interpretations and risk-based explanations.

The value factor is by far the most studied factor by citations (Alquist et al., 2018). A recent paper by Golubov and Konstantinidi (2019) considers various risks, irrational expectations and limits to arbitrage as possible explanations for the value premium. Risk-based explanations investigated in their study include operating leverage (Novy-Marx, 2011), duration of the equity premium (Dechow et al., 2004), exposure to technology shocks (Kogan & Papanikolaou, 2014), analyst risk ratings (Lui et al., 2012), cash flow risk (Campbell & Vuolteenaho, 2004) and consumption risks (Parker & Julliard, 2005). Golubov and Konstantinidi (2019) finds evidence that cash flow risk and consumption risk are associated with the value premium. In addition, irrational expectations and limits to arbitrage explanations can also explain the value premium.

3.2 Investment and Profitability

Investment and profitability factors have been incorporated in recent factor models by Hou et al. (2015) and Fama and French (2015).

Hou et al. (2015) build on the q-theory of investment and derive relations between investment, expected profitability and expected return within an economic framework. The intuition underpinning the investment factor is that for a fixed cash flow forecast, a higher expected return (or discount rate) will result in a lower net present value of the project and thus lower investment. Conversely, lower investment reflects higher expected returns. The same model shows that future profitability is positively related to expected return.

Fama and French (2015) motivate the investment factor and profitability factor with the dividend discount model. Because the market value of equity is the present value of future earnings less future investment, profitability and investment factors are natural choices to augment the three-factor model of Fama and French (p2, Fama and French (2015)).

3.3 Momentum

Fama and French (2018) add the momentum factor to the Fama and French (2015) five-factor model to "*satisfy insistent popular demand*" (p237, Fama and French (2018)). Indeed, according to Alquist et al. (2018), momentum is the third most studied factor by citations. While researchers put forward many behavioural explanations for momentum returns (for example, see (Barberis et al., 1998; Daniel et al., 1998; Grinblatt & Han, 2005; Hong & Stein, 1999)), there are also a number of risk-based explanations (see, e.g. (Johnson, 2002; Sagi & Seasholes, 2007)).

To keep the number of factors manageable, we examine the factors of the Fama and French (2018) six-factor model in the main body of our paper (for brevity referred to simply as factors hereafter). In the Appendix we provide results relating to the factors of the Hou et al. (2020) five-factor model (see Section 9.2), as well as a number of other well known factors that are not part of the Fama and French (2018) or the Hou et al. (2020) models – see Section 9.3 in the Appendix.

4 Bear and Bull Markets

One would expect risk factors to under-perform in bad states of the world. However, we find that most (non-market) factors perform *better* in bear markets than in bull markets. Table 2 details the performance of factors (arranged in columns) under different market states (arranged in rows). Panel A reports averages of monthly factor returns in the full sample (first row) and in good and bad states, where state variables are defined in the five different ways as described in Section 2. Panel B summarises the means of factor returns for each of the 11 bear markets.

Only SMB consistently conforms to the behaviour expected of a consumption-based risk factor. SMB produces lower returns in bear markets than bull markets, while generating a positive return – a premium – over the full sample. All the other factors (HML, CMA, RMW and UMD) produce *lower* returns in bull markets than in bear markets. For HML and CMA the difference is significant at the 5% level. The pattern is the same when we use an alternative approach by Lunde and Timmermann (2004) to date bull and bear markets. SMB continues to be the only factor that generates losses in bear markets ($BearLT$) and gains in bull markets ($BullLT$). HML, RMW, CMA and UMD all generate economically higher returns in $BearLT$ months, significant at the 5% level for all but UMD.

In terms of month-by-month variation, all factors (again apart from SMB) are more profitable in *Crashmarket* months (market excess returns below -10%) than *Stablemarket* months (the other months). This is also the case when comparing *Upmarket* months (positive market excess returns) with the remaining *Downmarket* months.

NBER expansions and recessions give rise to different results than states based on the stock market. This difference occurs because business cycles and stock markets are not perfectly synchronised, since stock markets are leading indicators of the real economy (Fama, 1981; Harvey, 1989). Both SMB and HML generate slightly higher returns in expansions, while RMW and CMA continue to be more profitable in recessions (though only marginally so in the case of RMW). On the other hand, UMD generates the bulk of its premium during NBER expansions (0.73% in expansions vs 0.17% in recessions).

Panel B of Table 2 details the performance of factors in each of the 11 bear markets from the Vietnam war to the COVID-19 pandemic. As expected average monthly MKTRF returns are all significantly negative, ranging from -11.20% for the 1987 crash (*Crash1987*) to -1.08% for the second oil shock (*Oilshock2*). Overall SMB is the most consistently negative (7 of 11 bear markets). All other factors produce more positive than negative average bear market returns. For example, HML is negative in only three bear markets and positive in eight bear markets. CMA generated positive returns in 10 out of 11 bear markets; the only negative return occurred during the *COVID* bear market. Examining each bear market in turn we find that positive factor returns outnumber negative factor returns for non-market factors in all bear markets apart from *Crash87* and *COVID*. During the *COVID* bear market, SMB, HML, RMW and CMA made the largest average monthly losses in the bear market history we cover. Only UMD has performed well during the *COVID* bear market, producing a monthly profit of 4.59% on average.

Figure 1 provides a visual description of the performance of factors in bull and bear markets. By construction the MKTRF market premium (Panel A) is perfectly aligned with bear markets. The bull markets of 1991-1999 and 2010-2020 are substantially longer, and achieve much higher cumulative returns, than other bull markets. By comparison the recent *COVID* bear market (cumulative return of -20.5% over three months) seems small and short (but as events unfolds it might turn out to be longer). The SMB factor (Panel B) is initially in synchrony with bear markets, but after the mid-1970's this association breaks down. The HML value factor seems to be particularly counter-cyclical, often generating high returns in bear markets but producing mixed results in bull markets. It did particularly well during the *Dotcom* crises as lofty (decidedly non-value) internet stocks tumbled back to earth. Both CMA and RMW exhibits relative low volatility, with the exception of the *Dotcom* crisis, when they both perform well. The UMD momentum factor is fairly subdued in the early part of our sample, but does very well during the 1990's bull market. By contrast it suffers large losses in the early stages of the most recent two bull markets. UMD is the only factor to produce positive returns during *COVID*.

Table 2: Benchmark factor returns in different states

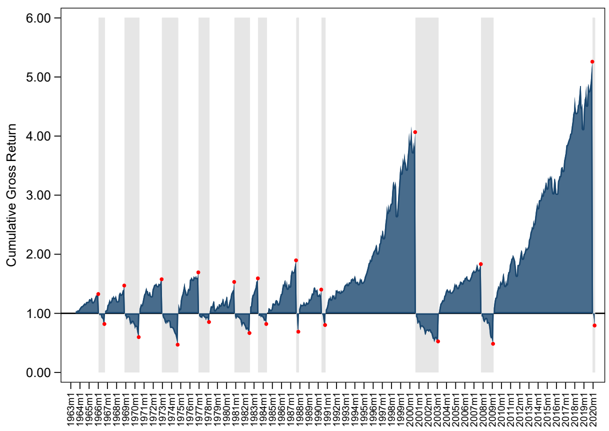
Panel A reports averages of monthly factor returns for the six factors of Fama and French (2018) (in columns) for the full sample and for different states. Returns are stated in percentage points. The number of months corresponding to each state is indicated in the first column (heading N). *Bear* and *Bull* markets are defined in Table 1. *BearLT* and *BullLT* refer to bear and bull markets dated using the approach of Lunde and Timmermann (2004). *Upmarket* and *Downmarket* refers to positive and negative market excess returns (measured by MKTRF). *Stablemarket* is any month that is not a *Crashmarket* (when monthly market excess returns are below -10%.) *Recession* and *Expansion* periods are from NBER. In addition we classify the first three months of 2020 as a recession period because the smoothed U.S. recession probability (Piger & Chauvet, 2020) jumped to a level of 25.98 on January 1, 2020, which is similar to the 24.15 level in the first month of the *GFC*. Panel B reports averages of monthly factor returns during each bear market. Significance levels are indicated by * (significant at the 10% level), ** (significant at the 5% level) and *** (significant at the 1% level) based on Newey-West HAC adjusted standard errors at a lag of 6 months.

	N	MKTRF	SMB	HML	RMW	CMA	UMD
Panel A							
Fullsample	681	0.51***	0.21*	0.27**	0.25***	0.27***	0.66***
Bull	531	1.44***	0.28**	0.05	0.16*	0.03	0.54***
Bear	150	-2.78***	-0.04	1.03***	0.57**	1.10***	1.09***
(Bull-Bear)		4.22***	0.32	-0.98**	-0.41	-1.07***	-0.54
BullLT	524	1.54***	0.41***	0.07	0.08	0.03	0.53***
BearLT	157	-2.95***	-0.47	0.91**	0.81***	1.07***	1.12***
(BullLT-BearLT)		4.49***	0.88***	-0.84**	-0.73**	-1.04***	-0.60
Upmarket	407	3.29***	0.80***	-0.16	-0.10	-0.23**	0.41
Downmarket	274	-3.62***	-0.67***	0.90***	0.77***	1.01***	1.03***
(Upmarket-Downmarket)		6.91***	1.47***	-1.06***	-0.88***	-1.25***	-0.62
Stablemarket	667	0.79***	0.29**	0.23**	0.21**	0.21***	0.63***
Crashmarket	14	-12.97***	-3.83***	1.90	2.04	3.00***	2.12
(Stablemarket-Crashmarket)		13.76***	4.12***	-1.67	-1.82	-2.79***	-1.49
Expansion	595	0.71***	0.22*	0.28**	0.24**	0.21**	0.73***
Recession	86	-0.86	0.09	0.17	0.31	0.68*	0.17
(Expansion-Recession)		1.57*	0.13	0.11	-0.06	-0.47	0.56
Panel B							
Vietnam	8	-2.41***	-0.01	-0.18	0.15	0.24	0.68
Nixon	19	-2.56***	-1.38**	0.58	0.23	1.08	0.81***
Oilshock1	21	-3.43***	-0.50	2.08***	-0.64	1.63***	2.02***
Oilshock2	14	-1.08**	2.11***	0.81	0.04	0.17	1.30***
Stagflation	20	-1.94***	0.44	1.99***	-0.28	1.20***	0.32
Correction83	11	-1.76***	-0.77***	2.85***	0.59*	1.47***	-0.93
Crash1987	3	-11.20***	-1.63*	2.55***	-0.27	1.66***	-2.77***
Gulfwar	5	-4.24***	-2.92***	0.12	0.20	1.79***	4.48***
Dotcom	30	-1.97***	1.07**	1.78*	2.30***	1.80***	0.96
GFC	16	-4.26***	0.05	-1.11	1.68***	0.12	1.79***
COVID	3	-7.21***	-4.31***	-8.13***	-1.40***	-1.22**	4.59***

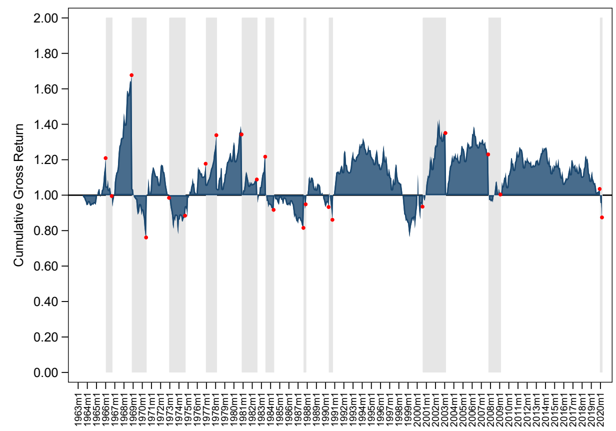
Figure 1: Cumulative benchmark factor returns

These figures depict cumulative gross returns from $1 investments in each of the Fama and French (2018) factors in each bull and bear market. Cumulative returns reset to $1 at the start of each bear and bull markets. Areas shaded in grey indicate bear markets (see Table 1). Red dots mark the cumulative gross return at the end of each bull and bear market.

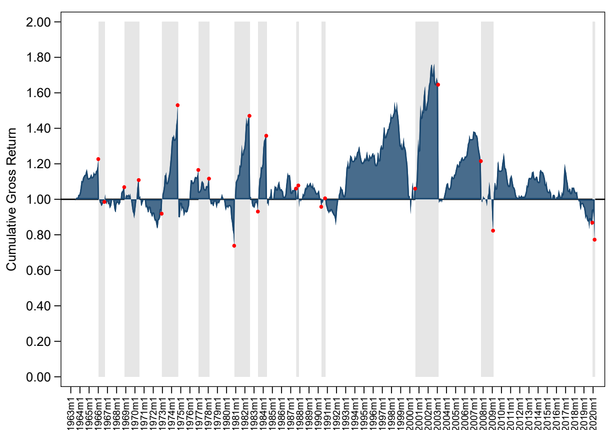
Panel A: MKTRF (Market premium factor)



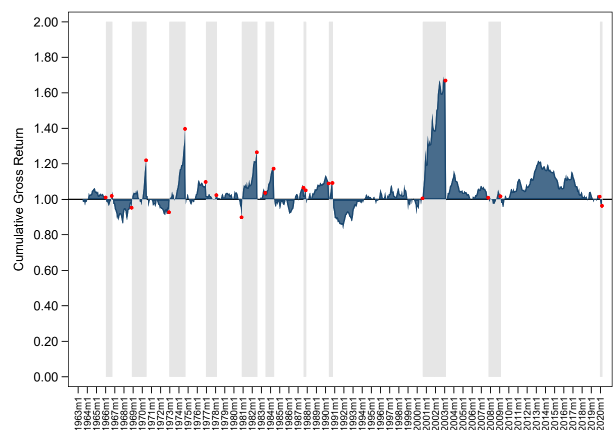
Panel B: SMB (Size factor)



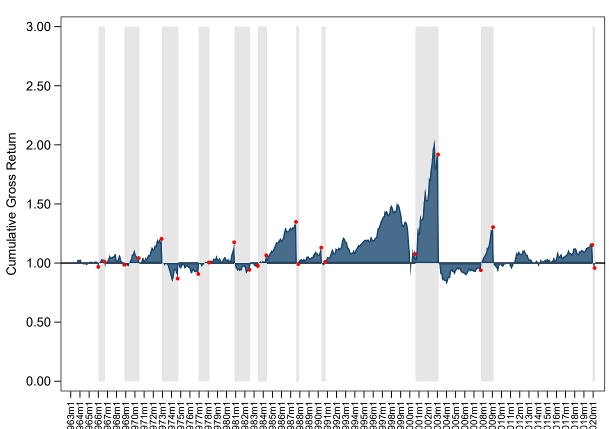
Panel C: HML (Value factor)



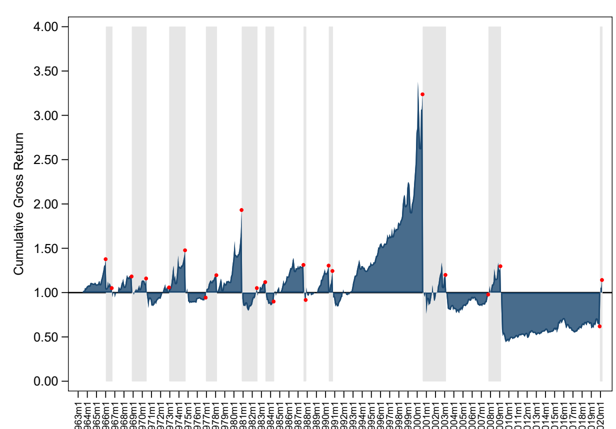
Panel D: CMA (Investment factor)



Panel E: RMW (Profitability factor)



Panel F: UMD (Momentum factor)



5 Factor Bear Markets

Positively priced risk factors are expected to produce sub-par returns during “bad” states of the world. However, in Section 4 we show that most risk factors produce *superior* returns during bear markets and to a lesser extent also in recessions – both classical “bad” states. If factors do not generate low returns during classical bad states, then when *do* they generate low returns? To investigate we apply the bear market dating approach of Lunde and Timmermann (2004) to cumulative factor returns. These *factor bear markets* indicate states when factors are generally losing money, exactly analogous to the bear markets identified by analysing the aggregate market.

Figure 2 illustrates factor bear markets visually. The shaded grey areas in Figure 2 correspond to the bear markets listed in Table 1. The bottom half of Figure 2 identifies all 11 individual bear markets, for ease of reference. NBER recessions are indicated directly above the individual bear markets. As expected NBER recessions and bear markets correspond loosely, although the turning points do not always line up. Above NBER recessions we indicate MKTRF bear markets identified using the Lunde and Timmermann (2004) approach, which corresponds closely to the bear markets in Table 1. Table 3 report correlations between indicator variables for bear markets (*Bear*), recessions (*Recession*) and factor bear markets. Recession and bear markets are positively correlated at 0.4 while the correlation between bear markets (*Bear*) and MKTRF bear markets is 0.81.

The SMB bear markets initially line up with the second and third bear markets (*Nixon* and *Oilshock1*), but thereafter produces long stretches that appear to be mostly aligned with bull markets (1984-91, 1994-99 and 2012-2020). While SMB is the only factor that performs worse during bear markets, the long losing streaks of SMB during apparently tranquil times make it hard to interpret the SMB premium as compensation for classical “bad state” risk. HML bear markets are shorter and reasonably evenly distributed over time, but only occasionally correspond with bear markets or recessions. The losing streak leading up the *Dotcom* bear market likely reflects the high returns of low book-to-market internet stocks during this time. During the *GFC* we also note a losing stretch as high book-to-market financial stocks are punished. There are only three RMW bear markets. The first bridges the two oil shocks while the latter two bookends the *Dotcom* crisis. The CMA bear markets are concentrated in the latter part of our sample, particularly after the *Dotcom* crisis and continuing unbroken for seven years starting in 2013 – the longest bull market in history. UMD bear markets are of far shorter duration than the other factor bear markets and seem to be loosely clustered around bear markets without actually aligning with them. This suggests some connection with the formation and ultimate resolution of bear markets. UMD and RMW are the two factors that do not enter factor bear markets during the *COVID* bear market (despite RMW producing negative returns during the *COVID* bear market). Large technology firms did comparatively well before and during the *COVID* bear market, which goes some way to explaining the performance of UMD and RMW.

The results in Figure 2 and Table 3 suggests that performance of factors during bear markets reflect the unique circumstances of each factor bear market instead of systematic risk across business cycles. While economic textbooks treat "bad" states as homogeneous and interchangeable, real bear markets all seem to be different in their own way.

Figure 2: Factor bear market states

The figure below plots bear market states for the factors of the Fama and French (2018) six-factor model, along with 11 individual bear markets (see Table 1). The factor bear markets are indicator variables identified by applying the approach of Lunde and Timmermann (2004) to the cumulated returns of the individual factors.

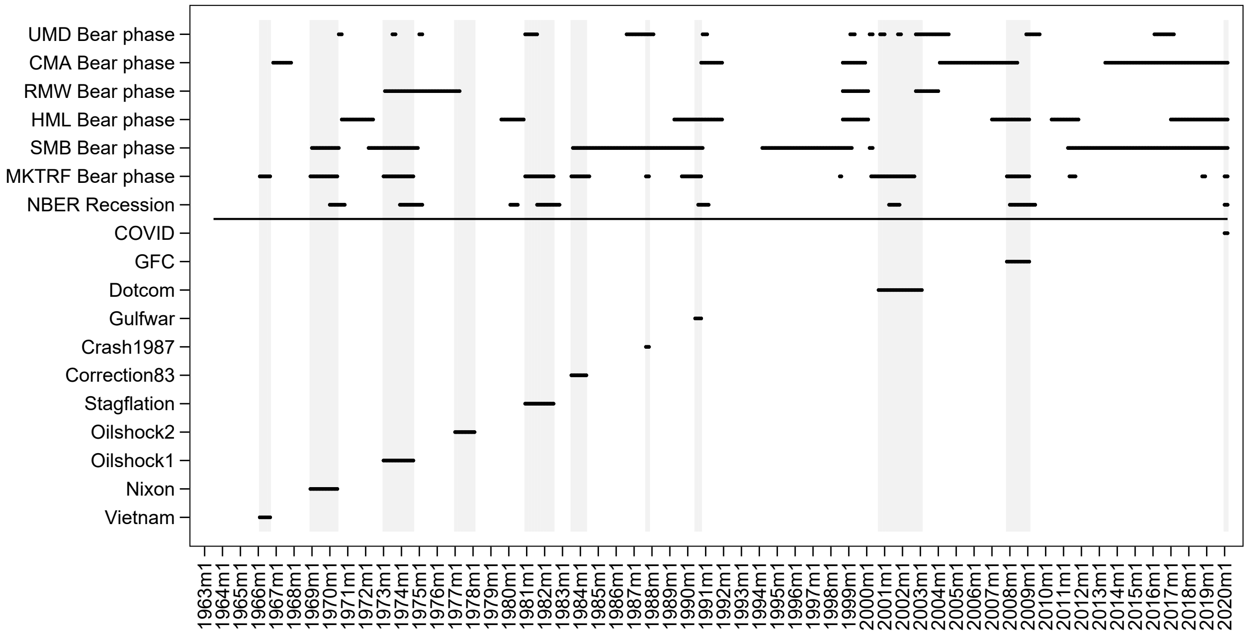


Table 3: Factor bear market indicator correlations

The table below presents time-series correlations between bear markets (Table 1), NBER recessions and factor bear market states for the factors of the Fama and French (2018) six factor model. The factor bear markets are indicator variables identified by applying the approach of Lunde and Timmermann (2004) to the cumulated returns of the individual factors.

	Bear	Recession	MKTRF bear	SMB bear	HML bear	RMW bear	CMA bear	UMD bear
Bear	1.000							
Recession	0.395***	1.000						
MKTRF bear	0.811***	0.380***	1.000					
SMB bear	-0.064*	-0.111***	0.076**	1.000				
HML bear	-0.115***	0.123***	0.009	-0.010	1.000			
RMW bear	0.110***	0.070*	0.004	-0.081**	-0.037	1.000		
CMA bear	-0.222***	-0.078**	-0.210***	0.062	0.323***	-0.065*	1.000	
UMD bear	0.075*	0.088**	0.034	-0.032	-0.103***	0.165***	0.019	1.000

6 Long and Short Portfolios

Returns from investing in the value, profitability, investment and momentum factors (HML, RMW, CMA and UMD) are highly positive and significant in bad states, on average (Table 2). In contrast, their average returns in good states are either close to zero (for HML and CMA) or less than one-third to one-half of the average returns in good states (for RMW and UMD). Among the five non-market factors, only the size factor (SMB) has a higher average monthly return in good states than in bad states. This is puzzling – four of five non-market factors are inconsistent with positive risk premia (assuming that the risk is related to bad economic states such as bear markets or recessions). Since these risk factors "pay out" during bad states, we can interpret investing in these risk factors as equivalent to buying insurance against bad states. Unlike normal insurance which require the *payment* of a regular premium, investors investors *receive* a premium for this insurance in the form of positive unconditional average returns. It is possible that these factors proxy for undesirable states not considered in our study. However, bear markets (*Bear*), drops in stock index levels (*Downmarket*), stock market crashes (*Crashmarket*) and recessions are usually regarded as bad states where consumption drops so that investors particularly value higher returns in these states. Another potential explanation for this apparent inconsistency could be limits to arbitrage, particularly short sales. Shorting stocks can be costly in normal times and even more so during in bad times. If the short legs of factor strategies account for the bulk of factor returns, it may be difficult for an investor to actually realise the full factor strategy return. This is what we find.

We repeat the analyses in Panel A of Table 2 with the long and short legs of each non-market factor. Table 4 reports the results. Both long and short legs are profitable in good states and loss-making in bad states for all factors, following overall market movements. For example, monthly returns to the long leg of SMB (SMB_L) average 2.04% in bull markets (*Bull*) and -2.20% in bear markets (*Bear*). This remains the case when we use alternative definitions of states. In good states the long and short legs of factor portfolios tend to have similar average returns. In contrast, in bad states short legs drop more than the long legs. For example, in the *Bear* state the HML short leg (HML_S) produces -2.74% while the long leg (HML_L) produces -1.70%. The difference of 1.03% accounts for the bear market return of HML (Panel A of Table 2). Thus the short leg contributes disproportionately to the the overall profit of the HML strategy during bear markets. Similarly, in bear markets RMW, CMA and UMD also generate somewhere between two-thirds to almost all of their monthly profits from shorting stocks. The only exception is the SMB size factor. SMB consistently lose more money from its long leg than its short leg during bear markets (*Bear*, *BearLT*, *Downmarket* and *Crashmarket*). Similar to our findings in Section 4, the overall magnitude of the difference between short and long legs is lower in NBER recessions, but the overall pattern of short legs disproportionately contributing to factor returns during bad states remain intact.

Table 4: Long and short leg returns in different states

This table reports means of monthly returns to portfolios on the long legs (suffix _L) and short legs (suffix _S) of five benchmark factors in different states. These portfolio returns are constructed from the 2 by 3 portfolio returns for each factor as sourced from Ken French's data library. Refer to Table 2 for the definitions of states. Significance levels are indicated by * (significant at the 10% level), ** (significant at the 5% level) and *** (significant at the 1% level) based on Newey-West HAC adjusted standard errors at a lag of 6 months.

	N	SMB_L	SMB_S	HML_L	HML_S	RMW_L	RMW_S	CMA_L	CMA_S	UMD_L	UMD_S
Fullsample	681	1.11***	0.90***	1.15***	0.88***	1.09***	0.84***	1.13***	0.87***	1.30***	0.64**
Bull	531	2.04***	1.77***	1.95***	1.90***	2.00***	1.84***	1.97***	1.94***	2.25***	1.70***
Bear	150	-2.20***	-2.16***	-1.70***	-2.74***	-2.13***	-2.70***	-1.82***	-2.92***	-2.04***	-3.13***
(Bull-Bear)		4.25***	3.93***	3.66***	4.64***	4.13***	4.54***	3.79***	4.86***	4.29***	4.83***
BullLT	524	2.27***	1.86***	2.12***	2.05***	2.13***	2.05***	2.13***	2.10***	2.41***	1.89***
BearLT	157	-2.76***	-2.29***	-2.10***	-3.01***	-2.38***	-3.20***	-2.20***	-3.27***	-2.39***	-3.52***
(BullLT-BearLT)		5.02***	4.14***	4.22***	5.06***	4.51***	5.24***	4.33***	5.37***	4.80***	5.40***
Upmarket	407	4.39***	3.59***	4.00***	4.16***	4.06***	4.16***	4.04***	4.27***	4.43***	4.01***
Downmarket	274	-3.77***	-3.10***	-3.09***	-3.99***	-3.33***	-4.10***	-3.18***	-4.19***	-3.34***	-4.37***
(Upmarket-Downmarket)		8.16***	6.70***	7.09***	8.15***	7.39***	8.26***	7.21***	8.46***	7.77***	8.39***
Stablemarket	667	1.46***	1.17***	1.45***	1.22***	1.40***	1.18***	1.43***	1.22***	1.63***	0.99***
Crashmarket	14	-15.73***	-11.90***	-13.24***	-15.15***	-13.68***	-15.72***	-13.01***	-16.01***	-14.08***	-16.21***
(Stablemarket-Crashmarket)		17.19***	13.07***	14.69***	16.37***	15.08***	16.91***	14.44***	17.23***	15.71***	17.20***
Expansion	595	1.30***	1.08***	1.34***	1.06***	1.27***	1.03***	1.29***	1.08***	1.52***	0.78***
Recession	86	-0.23	-0.32	-0.18	-0.35	-0.20	-0.50	0.08	-0.60	-0.18	-0.36
(Expansion-Recession)		1.53	1.40*	1.52	1.41	1.47	1.53	1.20	1.68	1.70*	1.14

7 Biased Expectations

In the presence of limits to arbitrage biased expectations (corrected by subsequent events) can also lead to return predictability. Earnings announcements are often regarded as important events that correct biased expectations (for example, see Engelberg et al. (2018) and Porta et al. (1997)). We calculate factor returns using stock-level returns around earnings announcement dates to test whether factor profits in bad states are associated with biased expectations.

In the spirit of Porta et al. (1997), we generate earnings announcement returns for each factor, which we then compare with normal factor returns in different states of the market. Earnings announcement returns for each stock are cumulative returns over the three-day window surrounding the earnings announcement date. We replace a constituent stock's monthly return with its three-day cumulated returns surrounding an earnings announcement date if this three-day window falls in the calendar month. If the constituent stock does not have an earnings announcement in a given month we set the monthly earnings announcement return to zero. We then construct factor returns following the methodology of Fama and French (2018)[4]. Table 5 report the factors returns and earnings announcement returns (indicated by the suffix _rea).

Table 5 shows that the value and momentum factors (HML and UMD) generate significant returns around earnings announcement dates over the full sample. HML_rea and UMD_rea in Table 5 are 0.04 and 0.07 percentage points and significant at 5% and 1% levels respectively. The average earning announcement return of HML is 15% of the average HML factor return and that of UMD is 11% of its average factor return.

The value, profitability and momentum factors (HML, RMW and UMD) usually generate significant returns around earnings announcement dates in the four bad market states (*Bear*,

[4]Our replicated factors (SMB, HML, RMW, CMA and UMD) using conventional returns all have correlations above 0.97 with the factors obtained from Ken French's data library.

BearLT, *Downmarket* and *Crashmarket*). UMD earnings announcement returns are significant in all four bad states, while RMW is significant in all except *Downmarket*. HML earnings announcement returns are significant in two bad states (*Downmarkets* and *BearLT*). The magnitude of earnings announcement returns is around 10% of full returns but reflect only 5% of trading days[5], suggesting that factors earn twice as much on earnings announcement days in bear markets than on other days in bear markets. These results suggest that profits of RMW and UMD in bad states may be partially attributed to the correction of biased expectations.

By contrast there is little to suggest that CMA earnings announcement returns are different from other days, both in the full sample and during bad market states. SMB earning announcement returns are close to zero in the full sample, and around 8% of normal returns during bad markets. On the whole biased expectations does not seem to offer an explanation for these two factors.

[5]There are 3 earnings announcement days per quarter and around 62 trading days per quarter. This means $3/62 = 4.8\%$ of days are included in earnings announcement returns.

Table 5: Factor earnings announcement returns in different states

This table reports monthly averages of factor earnings announcement returns (indicated by _rea) in different states along side with the means of monthly returns of replicated factors. In order to identify constituent stocks in factor portfolios, we have replicated all five non-market factors following Fama and French (2018) and the correlations between our factors and those from Ken French library are all above 0.97. Refer Table 2 for the definitions of states. Significance levels are indicated by * (significant at the 10% level), ** (significant at the 5% level) and *** (significant at the 1% level) based on Newey-West HAC adjusted standard errors at a lag of 6 months.

	N	SMB	SMB_rea	HML	HML_rea	RMW	RMW_rea	CMA	CMA_rea	UMD	UMD_rea
Fullsample	681	0.21*	0.01	0.27**	0.04**	0.25***	0.02	0.27***	0.02	0.66***	0.07***
Bull	531	0.28**	0.02	0.05	0.02	0.16*	-0.00	0.03	0.01	0.54***	0.05**
Bear	150	-0.04	-0.02	1.03***	0.09	0.57**	0.08**	1.10***	0.04	1.09***	0.13***
(Bull-Bear)		0.32	0.04	-0.98**	-0.06	-0.41	-0.09*	-1.07***	-0.03	-0.54	-0.08*
BullLT	524	0.41***	0.02*	0.07	0.02	0.08	0.00	0.03	0.01	0.53***	0.05**
BearLT	157	-0.47	-0.04	0.91**	0.11*	0.81***	0.08*	1.07***	0.04	1.12***	0.13***
(BullLT-BearLT)		0.88***	0.06**	-0.84**	-0.09	-0.73**	-0.08*	-1.04***	-0.03	-0.60	-0.08*
Upmarket	407	0.80***	0.04***	-0.16	0.01	-0.10	0.01	-0.23**	0.00	0.41	0.04*
Downmarket	274	-0.67***	-0.04**	0.90***	0.07*	0.77***	0.03	1.01***	0.04*	1.03***	0.11***
(Upmarket-Downmarket)		1.47***	0.09***	-1.06***	-0.06	-0.88***	-0.03	-1.25***	-0.04	-0.62	-0.07*
Stablemarket	667	0.29**	0.02	0.23**	0.04**	0.21**	0.01	0.21***	0.02	0.63***	0.06***
Crashmarket	14	-3.83***	-0.34**	1.90	-0.04	2.04	0.33**	3.00***	-0.01	2.12	0.42*
(Stablemarket-Crashmarket)		4.12***	0.36**	-1.67	0.08	-1.82	-0.32*	-2.79***	0.03	-1.49	-0.36
Expansion	595	0.22*	0.00	0.28**	0.04***	0.24**	0.01	0.21**	0.02	0.73***	0.07***
Recession	86	0.09	0.07	0.17	-0.02	0.31	0.10*	0.68*	-0.01	0.17	0.08
(Expansion-Recession)		0.13	-0.06	0.11	0.07	-0.06	-0.09	-0.47	0.03	0.56	-0.02

8 Conclusion

We investigate risk, limits to arbitrage and biased expectations as explanations for large returns produced by factors during bear markets from the Vietnam War to the COVID-19 pandemic. We find that all non-market factors (except SMB) generate substantially higher average monthly returns in bear markets than in bull markets. Such bear market profitability can not be readily explained by consumption based risk because high payoffs in bad states should be associated with negative risk premia. This inconsistency with risk-based explanations might be related to limits to arbitrage since the bear market profitability of factors primarily comes from the short side.

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9 Appendix

9.1 Factor time-series description

Table 6: Factor time-series

The table below details factor time series used in this paper. Panel A contains the factors sourced from Ken French's data library, Panel B contains factors sourced from Lu Zhang's data library and Panel C contains data sourced from the AQR data library. All series are monthly returns. Data source URL's are provided at the bottom of the table.

Panel A: From Ken French's data library

Factor	Description	Sorted on
RF	Risk free rate (t-bills)	n/a
MKTRF	Market return less risk free rate	n/a
SMB	Small - minus - Big size factor	size = #shares x share price
HML	High - minus - Low book-to-market value factor	book2market = book value / market value, and size
RMW	Robust - minus - Weak profitability factor	profitability = net income / book value, and size
CMA	Conservative - minus - Aggressive investment factor	investment = change in assets / lagged assets, and size
UMD	Up - minus - Down momentum factor	momentum = past t-2 to t-12 month cumulative returns
STREV	Short term reversal factor	prior month return
LTREV	Long term reversal factor	historical returns = returns from t-60 to t-13

Panel B: From Lu Zhang's data library

Factor	Description	Sorted on
MKT	Market return less risk free rate	n/a
ME	Market Equity size factor	#shares x share price
I2A	Investment to Asset factor	i2a = annual change in assets / total assets
ROE	Return On Equity factor	roe = net income / book value (using most recent monthly data)
EG	Expected Growth factor	expected growth from cross-Sectional predictive regressions

Panel C: From AQR's data library

Factor	Description	Sorted on
HMLdevil	High - minus - Low book-to-market value factor	book2market = book value / market value (*calculated monthly*)
BAB	Betting Against Beta factor	beta (with leverage overlay), see Frazzini and Pedersen (2014)
QMJ	Quality - minus - Junk factor	quality measure, see Asness et al. (2017)

Sources:

Ken French's data library: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
Lu Zhang's data library: http://global-q.org/factors.html
AQR's data library: https://www.aqr.com/Insights/Datasets

9.2 Hou et al. (2020) factor results

Table 7: Hou et al. (2020) benchmark factor returns in different states

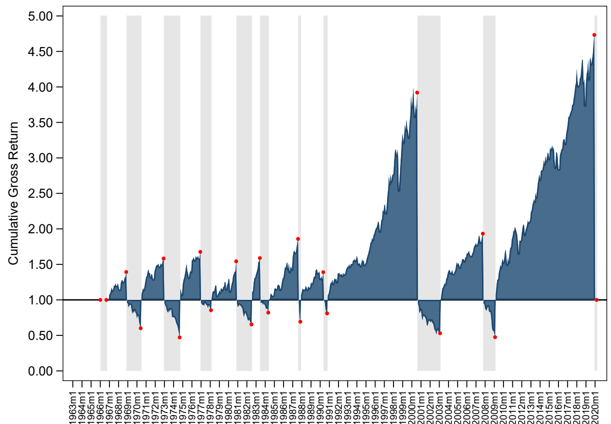
Panel A reports averages of monthly factor returns for the five factors of Hou et al. (2020) (in columns) for the full sample and for different states. Returns are stated in percentage points. The number of months corresponding to each state is indicated in the first column (heading N). *Bear* and *Bull* markets are defined in Table 1. *BearLT* and *BullLT* refer to bear and bull markets dated using the approach of Lunde and Timmermann (2004). *Upmarket* and *Downmarket* refers to positive and negative market excess returns (measured by MKTRF). *Stablemarket* is any month that is not a *Crashmarket* (when monthly market excess returns are below -10%.) *Recession* and *Expansion* periods are from NBER. In addition we classify the first three months of 2020 as a recession period because the smoothed U.S. recession probability (Piger & Chauvet, 2020) jumped to a level of 25.98 on January 1, 2020, which is similar to the 24.15 level in the first month of the *GFC*. Panel B reports averages of monthly factor returns during each bear market. Significance levels are indicated by * (significant at the 10% level), ** (significant at the 5% level) and *** (significant at the 1% level) based on Newey-West HAC adjusted standard errors at a lag of 6 months.

	N	MKT	ME	I2A	ROE	EG
Panel A						
Fullsample	681	0.53***	0.27**	0.36***	0.54***	0.81***
Bull	531	1.44***	0.30**	0.13*	0.46***	0.58***
Bear	150	-2.71***	0.17	1.18***	0.83***	1.64***
(Bull-Bear)		4.15***	0.14	-1.05***	-0.37	-1.06***
BullLT	524	1.56***	0.43***	0.14*	0.39***	0.53***
BearLT	157	-2.90***	-0.26	1.12***	1.04***	1.76***
(BullLT-BearLT)		4.46***	0.69**	-0.99***	-0.65**	-1.22***
Upmarket	407	3.35***	0.86***	-0.09	0.24	0.26**
Downmarket	274	-3.66***	-0.59***	1.04***	0.98***	1.64***
(Upmarket-Downmarket)		7.01***	1.44***	-1.13***	-0.73***	-1.38***
Stablemarket	667	0.82***	0.35***	0.31***	0.51***	0.75***
Crashmarket	14	-13.03***	-3.32**	3.05***	2.00*	3.81***
(Stablemarket-Crashmarket)		13.85***	3.67***	-2.74***	-1.49	-3.06***
Expansion	595	0.71***	0.26*	0.30***	0.56***	0.74***
Recession	86	-0.66	0.39	0.76**	0.41	1.33***
(Expansion-Recession)		1.37*	-0.13	-0.46	0.15	-0.59**
Panel B						
Vietnam	8	0.00	0.00	0.00	0.00	0.00
Nixon	19	-2.54***	-1.05**	1.30*	0.86**	1.73***
Oilshock1	21	-3.42***	-0.16	1.41***	0.34	2.12***
Oilshock2	14	-1.08**	2.17***	0.34**	0.68**	1.31***
Stagflation	20	-2.03***	0.75	1.33***	0.26	1.43***
Correction83	11	-1.75***	-0.98***	1.27***	0.25	1.49***
Crash1987	3	-11.09***	-1.15	1.95***	0.15	1.75***
Gulfwar	5	-4.06***	-2.72***	2.16***	1.08***	1.37***
Dotcom	30	-1.94***	1.00*	1.65***	1.37*	1.63***
GFC	16	-4.36***	-0.07	-0.09	1.67***	1.64***
COVID	3	0.00	0.00	0.00	0.00	0.00

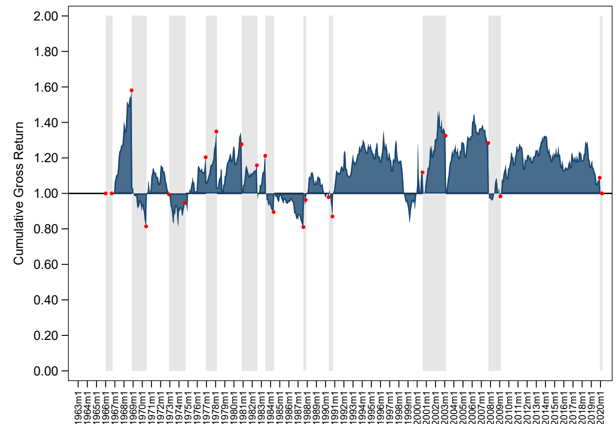
Figure 3: Hou et al. (2020) cumulative benchmark factor returns

These figures depict cumulative gross returns from $1 investments in each of the Hou et al. (2020) factors in each bull and bear market. Cumulative returns reset to $1 at the start of each bear and bull markets. Areas shaded in grey indicate bear markets (see Table 1). Red dots mark the cumulative gross return at the end of each bull and bear market.

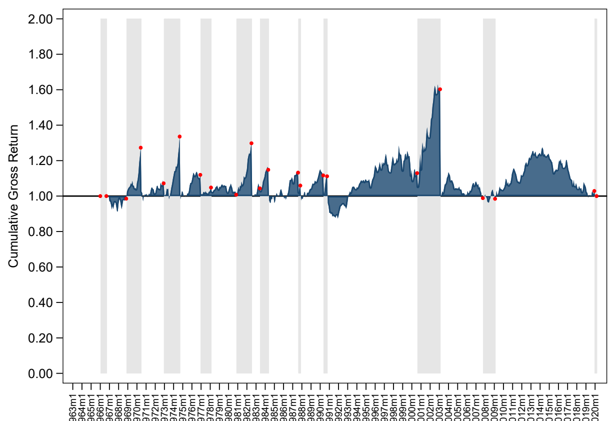
Panel A: MKT (Market premium factor)



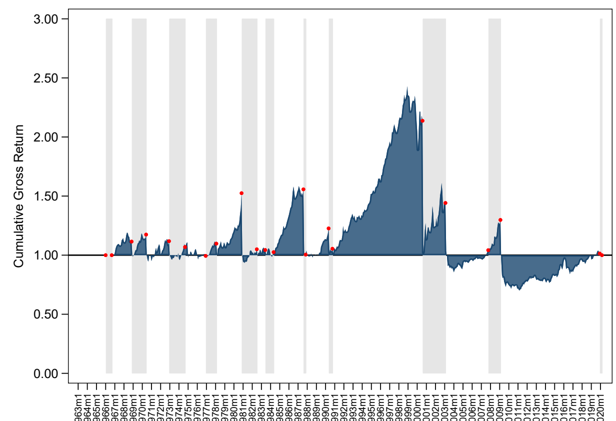
Panel B: ME (Size factor)



Panel C: I2A (Investment factor)



Panel D: ROE (Profitability factor)



Panel E: EG (Expected Growth factor)

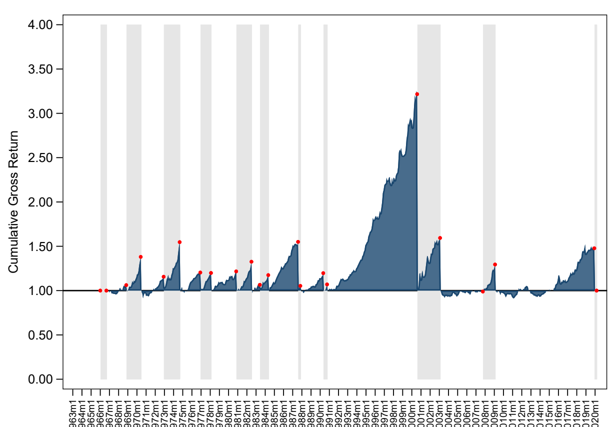


Figure 4: Hou et al. (2020) factor bear market states

The figure below plots bear market states for the factors of Hou et al. (2020) five-factor model, along with 11 individual bear markets (see Table 1). The factor bear markets are indicator variables identified by applying the approach of Lunde and Timmermann (2004) to the cumulated returns of the individual factors.

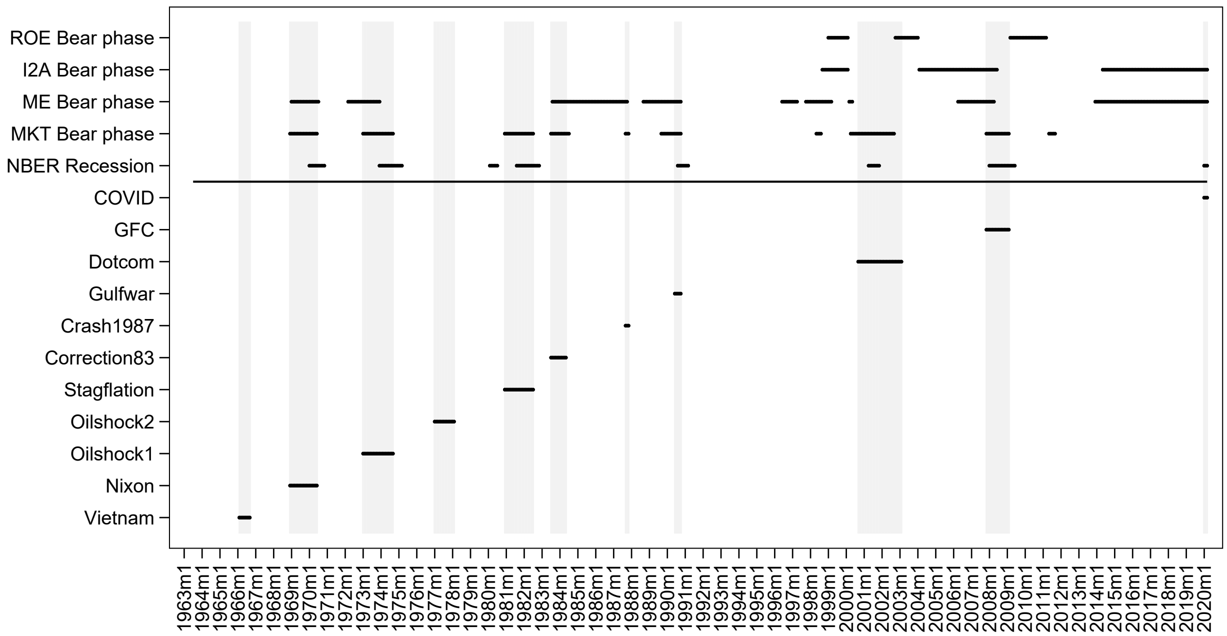


Table 8: Hou et al. (2020) factor bear market indicator correlations

The table below presents time-series correlations between bear markets (Table 1), NBER recessions and factor bear market states for the factors of the Hou et al. (2020) five-factor model. The factor bear markets are indicator variables identified by applying the approach of Lunde and Timmermann (2004) to the cumulated returns of the individual factors.

	Bear	Recession	MKT bear	ME bear	I2A bear	ROE bear
Bear	1.000					
Recession	0.395***	1.000				
MKT bear	0.762***	0.375***	1.000			
ME bear	0.005	-0.126***	0.123***	1.000		
I2A bear	-0.177***	-0.097**	-0.196***	0.380***	1.000	
ROE bear	-0.093**	-0.048	-0.154***	-0.193***	0.034	1.000

9.3 Other factor results

Table 9: Other factor returns in different states

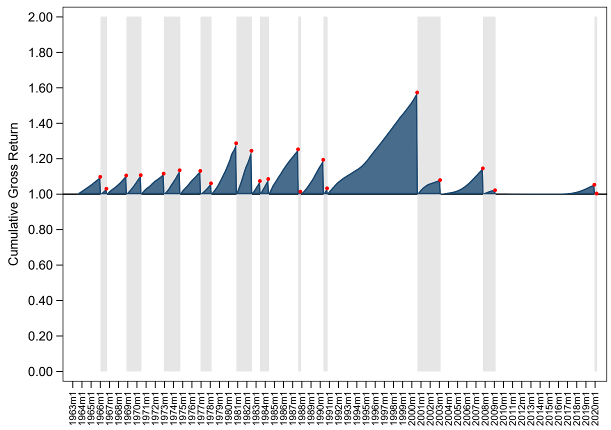
Panel A reports averages of monthly factor returns for a variety of other common factors (in columns) for the full sample and for different states. Returns are stated in percentage points. The number of months corresponding to each state is indicated in the first column (heading N). *Bear* and *Bull* markets are defined in Table 1. *BearLT* and *BullLT* refer to bear and bull markets dated using the approach of Lunde and Timmermann (2004). *Upmarket* and *Downmarket* refers to positive and negative market excess returns (measured by MKTRF). *Stablemarket* is any month that is not a *Crashmarket* (when monthly market excess returns are below -10%.) *Recession* and *Expansion* periods are from NBER. In addition we classify the first three months of 2020 as a recession period because the smoothed U.S. recession probability (Piger & Chauvet, 2020) jumped to a level of 25.98 on January 1, 2020, which is similar to the 24.15 level in the first month of the *GFC*. Panel B reports averages of monthly factor returns during each bear market. Significance levels are indicated by * (significant at the 10% level), ** (significant at the 5% level) and *** (significant at the 1% level) based on Newey-West HAC adjusted standard errors at a lag of 6 months.

	N	RF	STREV	LTREV	HMLdevil	BAB	QMJ
Panel A							
Fullsample	681	0.38***	0.48***	0.18	0.22	0.39***	0.80***
Bull	531	0.34***	0.52***	-0.01	0.04	0.15	0.84***
Bear	150	0.51***	0.32	0.86***	0.88**	1.25***	0.66
(Bull-Bear)		-0.17***	0.20	-0.86***	-0.84*	-1.10***	0.18
BullLT	524	0.33***	0.61***	0.08	0.12	0.03	0.86***
BearLT	157	0.52***	0.02	0.53*	0.59	1.58***	0.61
(BullLT-BearLT)		-0.19***	0.60*	-0.44	-0.47	-1.55***	0.24
Upmarket	407	0.35***	0.91***	0.17	-0.09	-0.38***	0.55***
Downmarket	274	0.42***	-0.17	0.20	0.69***	1.53***	1.17***
(Upmarket-Downmarket)		-0.07***	1.09***	-0.02	-0.79**	-1.90***	-0.62*
Stablemarket	667	0.38***	0.54***	0.17	0.20	0.29***	0.83***
Crashmarket	14	0.48***	-2.69*	0.99	1.60	5.05***	-0.61
(Stablemarket-Crashmarket)		-0.10	3.24**	-0.82	-1.40	-4.76***	1.44
Expansion	595	0.36***	0.45***	0.09	0.17	0.33***	0.91***
Recession	86	0.52***	0.66	0.81**	0.60	0.80**	0.00
(Expansion-Recession)		-0.17**	-0.20	-0.71*	-0.43	-0.47	0.91*
Panel B							
Vietnam	8	0.38***	0.58	0.53**	0.08	0.24	-0.69***
Nixon	19	0.54***	0.14	1.39	0.51	1.59***	0.39
Oilshock1	21	0.60***	1.00**	1.17**	1.96***	0.24	-0.67**
Oilshock2	14	0.43***	0.63***	0.62*	0.74	-0.05	1.27***
Stagflation	20	1.10***	0.15	2.05***	1.97***	0.61***	1.80***
Correction83	11	0.75***	1.12***	0.59**	2.96***	0.97***	1.26***
Crash1987	3	0.47***	-0.38***	-1.02	3.47***	1.43***	-2.76**
Gulfwar	5	0.65***	-2.57***	-0.92***	-1.24***	2.83***	-0.86
Dotcom	30	0.26***	1.21	1.42***	1.63	2.03***	3.35***
GFC	16	0.14***	-0.96	-0.15	-1.83**	2.72***	-2.23***
COVID	3	0.12***	-3.81**	-5.08***	-8.66***	1.63	-3.03*

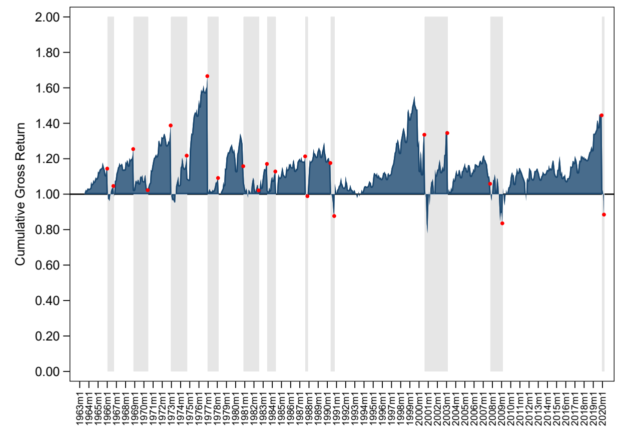
Figure 5: Cumulative benchmark factor returns – other factors

These figures depict cumulative gross returns from \$1 investments in a variety of other common factors in each bull and bear market. Cumulative returns reset to \$1 at the start of each bear and bull markets. Areas shaded in grey indicate bear markets (see Table 1). Red dots mark the cumulative gross return at the end of each bull and bear market.

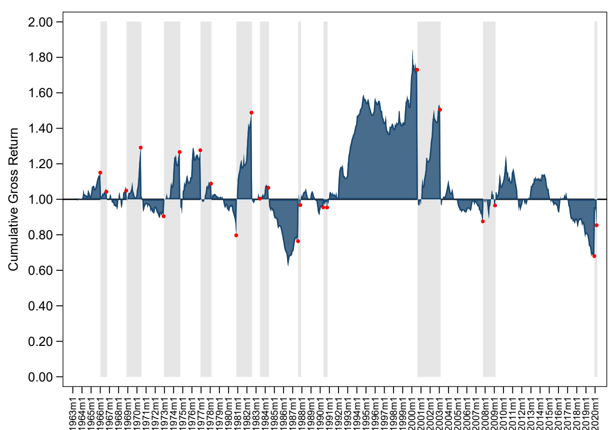
Panel A: RF (Risk free rate)



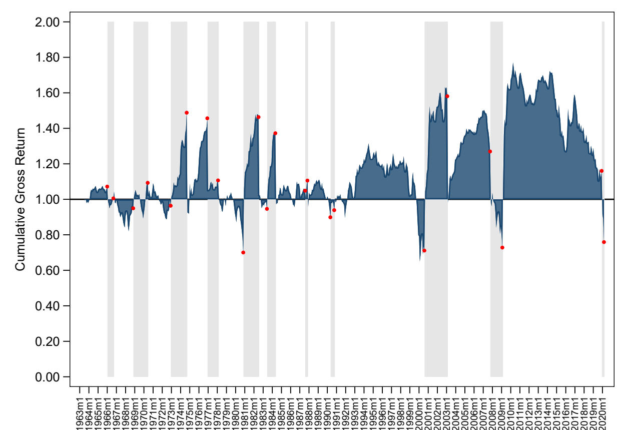
Panel B: STREV (Short term reversal factor)



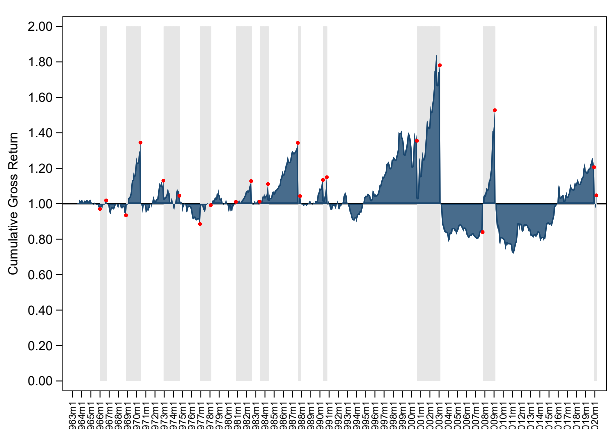
Panel C: LTREV (Long term reversal factor)



Panel D: HMLdevil (Monthly value factor)



Panel E: BAB (Betting against Beta factor)



Panel F: QMF (Quality minus Junk factor)

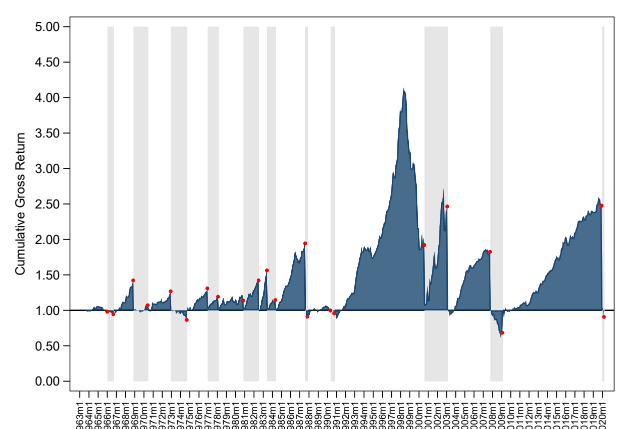


Figure 6: Other factor bear market states

The figure below plots bear market states for other common factors, along with 11 individual bear markets (see Table 1). The factor bear markets are indicator variables identified by applying the approach of Lunde and Timmermann (2004) to the cumulated returns of the individual factors.

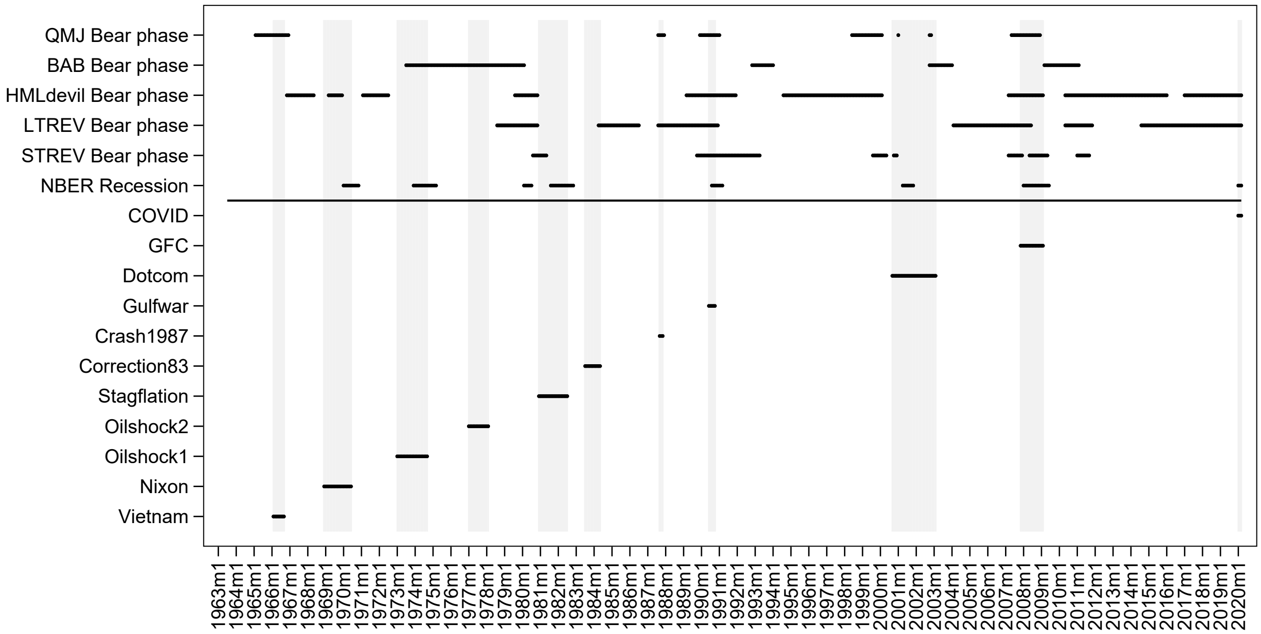


Table 10: Other factor bear market indicator correlations

The table below presents time-series correlations between bear markets (Table 1), NBER recessions and factor bear market states for other common factors. The factor bear markets are indicator variables identified by applying the approach of Lunde and Timmermann (2004) to the cumulated returns of the individual factors.

	Bear	Recession	STREV bear	LTREV bear	HMLdevil bear	BAB bear	QMJ bear
Bear	1.000						
Recession	0.395***	1.000					
STREV bear	0.045	0.109***	1.000				
LTREV bear	-0.232***	-0.092**	0.052	1.000			
HMLdevil bear	-0.223***	-0.057	0.206***	0.168***	1.000		
BAB bear	0.038	0.044	-0.088**	-0.139***	-0.310***	1.000	
QMJ bear	0.150***	0.095**	0.310***	0.019	0.175***	-0.167***	1.000