The Best Strategies for the Worst Crises

MICHAEL COOK, EDWARD HOYLE, MATTHEW SARGAISON, DAN TAYLOR, and OTTO VAN HEMERT[1]

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ABSTRACT

Hedging equity portfolios against the risk of large drawdowns is notoriously difficult and expensive. Holding, and continuously rolling, at-the-money put options on the S&P 500 is a very costly, if reliable, strategy to protect against market sell-offs. Holding 'safe-haven' US Treasury bonds, while providing a positive and predictable long-term yield, is generally an unreliable crisis-hedge strategy, since the post-2000 negative bond-equity correlation is a historical rarity. Long gold and long credit protection portfolios appear to sit between puts and bonds in terms of both cost and reliability.

In contrast to these passive investments, we investigate two dynamic strategies that appear to have generated positive performance in both the long-run but also particularly during historical crises: futures time-series momentum and quality stock factors. Futures momentum has parallels with long option straddle strategies, allowing it to benefit during extended equity sell-offs. The quality stock strategy takes long positions in highest-quality and short positions in lowest-quality company stocks, benefitting from a 'flight-to-quality' effect during crises. These two dynamic strategies historically have uncorrelated return profiles, making them complementary crisis risk hedges. We examine both strategies and discuss how different variations may have performed in crises, as well as normal times, over the years 1985 to 2016.

Keywords: trend following, quality, momentum, crisis hedge, crisis alpha, futures, equities

JEL codes: E32, E44, G11, G12, G14

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[1] All authors are affiliated with Man Group. Dan Taylor is at Man Numeric; the others at Man AHL. The authors would like to thank Giuliana Bordigoni, Richard Bounds, Tom Bowles, Paul Chambers, Yoav Git, Nick Granger, Carl Hamill, Campbell Harvey, Keith Haydon, Lawrence Kissko, Russell Korgaonkar, Anthony Ledford, Charles Liu, Andrea Mondelci, Jay Rajamony, Sandy Rattray, Graham Robertson, and Drake Siard for valuable comments. Please direct correspondence to: ovanhemert@ahl.com.

1. Introduction

Investors typically hold a large allocation to equities, which makes strategies that have the potential to do well during equity market sell-offs valuable diversifiers. In this paper, we examine active and passive strategies that hold potential to perform positively during the worst crises. We focus on liquid strategies with intuitively-sound features, such as long volatility or an overweight to less risky securities. The performance of the strategies is analyzed from a historical perspective, looking at seven instances between 1985 and 2016 where the S&P 500 fell by more than 15%.

Section 2 begins with an examination of two types of passive strategies. First, approaches that benefit directly from a falling market. A strategy that buys, and then rolls, one-month, at-the-money S&P 500 put options performs well in each of the seven crises. However, it is very costly during the 'normal' times, which constitute 86% of our sample, and as such seems too expensive to be a viable crisis hedge. A strategy that goes long credit protection (short credit risk) also benefits during each of the seven crises, but in a more uneven manner, benefiting particularly during the 2007-2009 Financial Crisis, which was a credit crisis. On the other hand, the short credit risk strategy is less costly during normal times than the put strategy.

Next, we consider so-called 'safe-haven' investments. A strategy that holds long positions in 10-year US Treasuries performed well in the post-2000 equity crises, but was less effective during previous crises. This is consistent with the negative bond-equity correlation witnessed post-2000, which on further analysis appears atypical from the longer historical perspective. As we move beyond the extreme monetary easing that has characterized the post-Financial Crisis period, it is possible that the bond-equity correlation may revert to the previous norm, rendering a long bond strategy a potentially unreliable crisis hedge. A long gold strategy generally performs better during crisis periods than at normal times, consistent with its reputation as a safe-haven security. However, its appeal as a crisis hedge is potentially diminished by the fact that its long-run return, measured over the 1985-2016 period, is close to zero and that it carries substantial idiosyncratic risk unrelated to equity markets.

We then turn our attention to dynamic strategies. Certain dynamic strategies – such as shorting currency carry or taking long positions in on-the-run Treasury bonds against short positions in off-the-run bonds – may perform well during crisis periods, but are expensive in the long-term. Because of the costs involved in managing any active strategy, we choose to focus only on those that are, at the least, positive in expectation before costs.

In Section 3, we consider futures time-series momentum strategies, which historically have been shown to provide "crisis alpha" potential.[2] Hamill, Rattray, and Van Hemert (2016) argued that this is because trend followers add to winning positions (ride winners) and reduce losing positions (cut losers), much like a dynamic replication of an option straddle strategy. We show that such strategies performed well over the seven equity crises. We also explore various methods to limit the exposure to equities, with a view to enhancing the crisis performance potential. We find that simply not allowing long equity

[2] See for example Kaminski (2011) and Hamill, Rattray, and Van Hemert (2016).

positions worked as well as more complicated approaches, such as capping the beta of the strategy to the equity market at zero. We argue that this is because estimation is challenging when imposing beta restrictions, given that betas vary through time, and possibly abruptly so when entering a crisis.

In Section 4, we consider long-short US equity strategies. A review of the factors proposed in the academic literature suggests that those that take long positions in high-quality and short positions in low-quality companies are most promising as crisis hedges, since they can potentially benefit from flights to quality when panic hits markets. The definition of a quality business is, of course, open to debate. However, broadly speaking, such companies will be profitable, growing, have safer balance sheets, and run investor-friendly policies in areas such as payout ratios. We examine a host of quality metrics, and examine improvements that may be made to strategies from employing more sophisticated portfolio construction techniques than are typically found in the academic literature.

Finally, in Section 5 we show that futures time-series momentum strategies and quality long-short equity strategies are not only conceptually different, but also have historically uncorrelated returns, meaning that they can act as complementary crisis-hedge components within a portfolio. We demonstrate the efficacy of the dynamic hedges through some portfolio simulations.

2. Crisis performance of passive investments

We begin by identifying the seven worst equity crises in the 32-year period from 1985 to 2016. Next, we consider a number of passive, buy-and-hold, strategies including ones that hold futures contracts which are rolled according to some pre-defined schedule. The first analysis is of strategies that should logically benefit from falling firm valuations, such as a long put option and a short credit investment, and explore how they perform during these crises. This is followed by a discussion how a long safe-haven (bond or gold) position fares during equity crises, which includes an analysis of the bond-equity correlation since 1900 and the gold-equity correlation post Bretton Woods.

2.1 Crisis definition

Figure 1 shows the cumulative total return of the S&P 500 (top line) using daily data from 1985 to 2016.[3] A log scale is used, such that a straight line would correspond to a constant rate of return, aiding the comparison of the severity of drawdown periods at different points in time. In this paper we focus on the seven periods in which the S&P 500 lost more than 15% from its peak, with the corresponding peak-to-trough periods shown in grey in Figure 1.

[3] For 1988-2016 daily total returns are available from Bloomberg. Prior to 1988, we use data on daily index percent changes (excluding dividends) and monthly total returns (including dividends), and we proxy the daily total return as the daily index percentage change plus the monthly dividend return spread equally over the days of the month.

Figure 1: Passive investment total return over time (1985-2016)

We show the cumulative return of the S&P 500 (funded and in excess of cash), as well as the excess return of long puts (one-month, at-the-money S&P 500 puts), short credit risk (duration-matched US Treasuries over US investment grade corporate bonds), long bonds (US 10-year Treasuries), and long gold (futures). We highlight in grey the seven worst drawdowns for the S&P 500. The data run from 1985 to 2016.

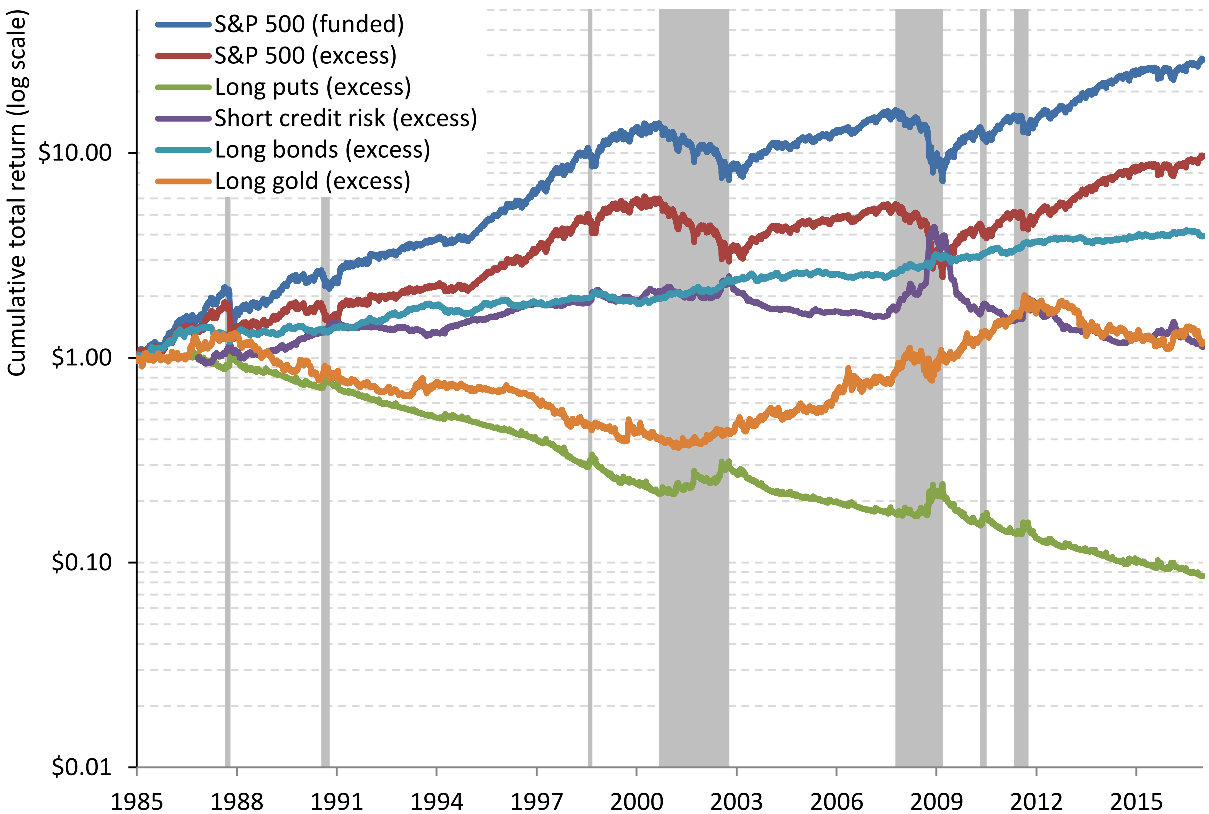


Table 1 lists the seven crises, giving the peak and trough dates, lengths of the drawdowns, and whether the peak was an all-time high or a local high. The bursting of the tech bubble and the Financial Crisis were the most severe crises, with the S&P 500 losing about half of its value. The drawdown around 1987's Black Monday was also severe, with a -32.9% return in less than two months. The remaining equity sell-offs are associated with the first Gulf war, the Asian financial crisis (and also the ruble devaluation and LTCM collapse) and two episodes of the euro area sovereign debt crisis.

Table 1: Passive investment performance in crisis periods (1985-2016)

We report the total return of the S&P 500 and various passive strategies during the seven worst drawdowns for the S&P 500 and the annualized (geometric) return during crisis, normal, and all periods. Volatility is the annualized standard deviation of 5-day overlapping returns. The row 'Peak = HWM' indicates whether the index was at an all-time high before the drawdown began. The data run from 1985 to 2016.

	Black Monday	Gulf war	Asian crisis	Tech burst	Financial crisis	Euro crisis I	Euro crisis II	Crisis (14%)	Normal (86%)	All (100%)	All (100%)
Peak day	25-Aug-87	16-Jul-90	17-Jul-98	01-Sep-00	09-Oct-07	23-Apr-10	29-Apr-11				
Trough day	19-Oct-87	11-Oct-90	31-Aug-98	09-Oct-02	09-Mar-09	02-Jul-10	03-Oct-11				
Weekdays count	39	63	31	548	369	50	111				
Peak = HWM?	Yes	Yes	Yes	Yes	Yes	No	No				
Strategy				**Total return**					**Annualized return**		**St. dev.**
S&P 500 (funded)	-32.9%	-19.2%	-19.2%	-47.4%	-55.2%	-15.6%	-18.6%	-43.5%	24.5%	11.0%	16.7%
S&P 500 (excess)	-33.5%	-20.7%	-19.7%	-51.0%	-56.3%	-15.7%	-18.6%	-45.1%	20.2%	7.3%	16.7%
Long puts (excess)	38.0%	12.4%	15.5%	44.7%	40.5%	15.8%	13.4%	40.2%	-13.7%	-7.7%	11.4%
Short credit risk (excess)	9.2%	7.5%	12.0%	16.9%	127.3%	11.6%	26.0%	41.0%	-5.2%	0.4%	10.0%
Long bonds (excess)	-8.3%	-2.7%	3.0%	24.2%	20.4%	5.7%	10.1%	10.7%	3.4%	4.4%	6.5%
Long gold (excess)	4.4%	5.5%	-6.9%	7.5%	18.9%	4.6%	6.3%	8.4%	-0.7%	0.5%	16.1%

Based on this definition, 14% of days since 1985 are crisis days and 86% are normal days. The annualized S&P 500 return during crisis and normal periods is -43.5% and 24.5%, respectively, and it is 11.0% overall. Both the total return and annualized return take into account the effect of compounding.[4] The second row in Table 1 reports the S&P 500 return above that of one-month T-bills, which can be compared with the strategy excess returns we discuss in what follows.

2.2 Hedging with short firm-value strategies: long puts and short credit risk

A long equity strategy generally benefits when the total asset value of firms increases. A natural class of hedging strategies to consider is the set of strategies that benefit from decreases in firm value. This follows the line of reasoning in Merton (1974), where a firm's stock and corporate bonds are considered options on the total firm value. In this subsection we consider passive hedging strategies belonging to this class: a long put option strategy and a short credit risk strategy.

A rolling long put option strategy is perhaps the most direct crisis hedge since it explicitly protects against the risk of a sudden, severe equity market drawdown. Various other equity derivatives may also be usefully considered for crisis hedges; most notably variance and volatility swaps, due to the inverse relationship between equity returns and equity volatility. Although only traded over-the-counter, these swaps can be liquid and can also be entered on a forward-starting basis (see, for example, Demerterfi, Derman, Kamal and Zou (1999)). However, as these are all somewhat related, we have focused only on the most straightforward option-based strategy for this analysis.

To evaluate how a long put investment performs during the seven crises we identified, as well as in normal times, we look at the CBOE S&P500 PutWrite Index, for which we have daily returns starting in 1986. The index tracks the performance of selling one-month at-the-money S&P 500 put options each month and holding them until expiry, at which point new options are sold. Positions are sized such that the options are fully collateralized at all times. Then even if the S&P 500 goes to zero the obligation towards the put option buyer can be honored. Since we are interested in the returns of buying puts, rather than selling puts, we use the negative of the index's returns, but with an adjustment for cash. We do not include transaction costs or fees.

Figure 1 and Table 1 show that the long put strategy performs well in all seven crises. However, the performance is not evenly spread over the crisis period, but appears earned in short periods of time, like October 2008, when the equity sell-off suddenly accelerated. Once a crisis has begun, it can be observed that subsequent rolls of the options become more expensive as implied volatility rises, increasing the cost of the hedge. This effect then requires accelerated price movement to produce the same hedge return.

Indeed, the main concern with this strategy is its long-term overall cost. During the whole sample (crisis and normal), its annualized excess return was -7.7%. An equal-weighted combination of a long S&P 500

[4] This means that we take into account that a +10% return followed by a -10% return actually means a loss of -1% (computed as 1.1x0.9-1). The annualized return is computed as $(1+\text{geometric mean})^{\text{days per year}}$.

investment and the long put strategy has a negative excess return in each of the seven crises, as well as a negative overall excess return.[5]

Long credit protection strategies have generally benefited during crises as the spreads between corporate and Treasury bond yields widen. It is generally more difficult, in the case of credit strategies, to accurately simulate historical returns going back to 1985, as many reliable indices only became actively monitored significantly later. We use the BofA Merrill Lynch US Corp Master Total Return index, which tracks the performance of US investment grade corporate bonds. Index returns in excess of duration-matched Treasury bonds are available from 1997. Our passive investment uses the negative of these returns. For earlier years, using a rolling one-year window, we measured the beta of the index to US 10-year Treasury futures. The strategy takes a beta-adjusted long position in Treasury futures and a short position in the credit index. One lot of cash returns is added to produce an excess strategy. As a final step, we scaled the returns ex-post to achieve a volatility of 10% across the whole sample. This is based on what we feel is the reasonable assumption that leverage can be applied, without capital borrowing requirements, as these instruments are generally traded on margin.[6]

From a practical point of view, while it may be hard to short a large amount of corporate bonds (particularly during a crisis), a very similar strategy can be created using credit default swaps using synthetic index securities, like CDX.[7] One consideration, which we do not attempt to address here, is that during a major crisis there may be other risks that affect any credit strategy, such as the reliability of mark-to-market pricing and heightened counterparty risk.

Similar to the put strategy, the credit strategy appears to have had negative returns on average outside of crisis periods. Crisis period returns are on a similar scale to the put strategy. The 2007-2009 Financial Crisis – which was primarily a credit crisis – was a particularly profitable episode for the strategy (127% return). Unfortunately, the subsequent drawdown was equally as large and as swift. Over the whole sample, the credit strategy generated a small positive return. The positive return of the strategy over the sample period is somewhat surprising to us, since the strategy is short the credit risk premium which has positive expected return (see, for example, Luu and Yu (2011)). It is noted, however, that Figure 1 shows the strategy has been on a downward drift since 2000.

Comparing the long put option and short credit risk strategies, long puts should intuitively be more reliable, because it is more directly linked to the equity value it aims to hedge. However it appears to

[5] Various approaches could be taken to mitigate the strategy's costs, but their benefits need to be carefully weighed against any loss of hedge efficacy, which is beyond the scope of this paper. First, one can generate income by selling out-the-money options, such as through put spreads or collars. Second, one can purchase protection where it is cheapest, by analyzing the cost across strikes, across tenors or across markets. Third one could employ a timing approach: buying more protection at times of stress, and buying less when conditions are loose. This might involve measuring market conditions, e.g., along the lines of the Chicago Fed's National Financial Conditions Index. Alternatively, one could forecast realized volatility directly using a statistical model (for example, Shepherd and Sheppard (2010)), and then increase protection ahead of expected volatility spikes and the associated increased probability of market falls.

[6] Before scaling, the volatility of the strategy was 2.7%.

[7] Because historical data is limited, we have not used credit default swap or CDX for our empirical analysis.

come at a higher cost in terms of negative long-term returns. In other words, we have a tradeoff between reliability and cost of the hedge.

2.3 Hedging with safe-haven assets: long bonds and long gold

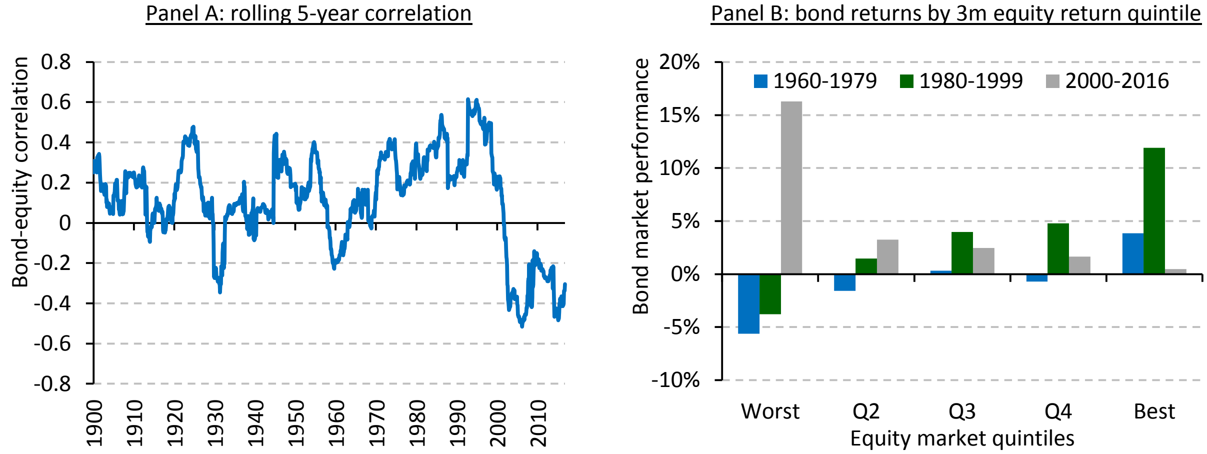
Government bonds and gold are often described as 'safe-haven' assets. A long bond position is sometimes viewed as a crisis hedge, possibly based upon the perception that the government bonds of advanced economies are safe-haven securities. We show the performance of a long 10-year US Treasury investment in Figure 1 and Table 1. Returns are based on 10-year Treasury futures contracts.[8]

In the period 1985-2016, bonds performed well, helped by the compression in 10-year yields, from double digit levels in the mid-80s, to below 2% in 2016. The annualized return over cash for crisis periods is 10.7%, which exceeds the still positive value of 3.4% for normal periods. However, it is only during the crises after 2000 that bonds performed well. During the earlier crises, the performance of bonds was mixed, and over the Black Monday crisis period, the bond return was -8.3%.

It is a reflection of the recent shift into negative territory of bond-equity correlations that the recent performance of bonds during crisis periods exceeds that of earlier times. That is to say, since 2000, when stock prices have fallen, Treasuries have rallied. To explore further the long-term evidence for this, we looked at monthly returns from Global Financial Data for the US equity index and Treasury bond returns. Figure 2 (panel A) shows the rolling five-year bond-equity correlation. We see that, although post-2000 the correlation was negative, it was positive for most of the 100 years before that. This is in line with academic studies that argue that common fundamental factors would typically imply a positive bond-equity correlation (see, for example, Baele, Bekaert and Inghelbrecht (2010)). Funnell (2017) provides a similar long-term perspective of the bond-equity relationship for the UK.

Figure 2: Time varying co-movement between equity and bond returns (funded)

In panel A, we plot the rolling 5-year correlation between monthly US equities and US Treasury bond returns from 1900 to 2016. In panel B, we plot the annualized bond returns by 3-month equity quintiles and for different sub-periods. The data are from Global Financial Data.



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[8] Throughout this paper, a futures return is based on the near contract, rolled into the next contract shortly before the expiration date.

One approach to analyzing this effect is to take the period 1960-1979, divide it into three-month periods, and then sort these into quintiles based on the equity return. Quintile one is for the periods with the worst equity returns, quintile five is for the periods with the best equity returns. Figure 2 (panel B), plots the annualized average bond return for the five quintiles. Consistent with the positive bond-equity correlation before 2000, a long bond position cannot be shown to provide a crisis hedge before 2000. In fact, bond returns are negative in quintile one (the worst periods for equities) for both the 1960-1979 and 1980-1999 periods. Fixed income assets can typically make up significant portions of traditional portfolio allocations, for reasons of their generally reliable fixed stream of income. However, there appears to be no strong evidence over the long term that they can be relied upon to hedge concurrent equity exposures.

Gold has long been viewed as the original safe-haven asset, a source of absolute value in an uncertain world, whose price rises with increased risk aversion in markets. It does not provide a dividend, but, as a real asset, it can help offer protection to certain sources of inflation. Gold is typically priced in US dollars (and all subsequent analysis follows this convention), and so its price is partly driven by fluctuations in foreign exchange rates. This then links gold to US monetary policy. For example, a hawkish shift in policy may lead to a rise in the dollar (on a trade-weighted basis) and a subsequent fall in the gold price. A related scenario under which gold may benefit is a significant loss of confidence in fiat currencies, a tail risk in the true sense of the expression. However, gold is also subject to significant idiosyncratic risk, for example, miners' strikes and political instability in mining regions, which may make gold an unreliable hedge in many circumstances.

We use gold futures for the excess returns shown in Table 1. Gold shows positive returns in six of the seven crisis periods, with an annualized crisis return of 8.4%. Outside of crisis periods, gold returns were negative on average, leading to a whole-sample performance that is marginally better than flat.

In Appendix A, we take a longer view of gold, like we did with bonds in Figure 2, and find that from 1972 (after Bretton Woods) to 1984 the gold-equity correlation is slightly positive. From 1985 gold has performed well during the worst equity market environments. In sum, gold has mostly shown promising return characteristics during the worst equity crises, but with some exceptions and with considerable exposure to gold-specific supply and demand shifts.

3. Futures time-series momentum

This section examines the performance of futures time-series momentum strategies during crisis and normal times. We explore various restrictions on the equity exposure, with a view to enhancing the crisis performance. The performance is reported gross of transaction costs.[9]

[9] We estimate that the combined transaction and slippage costs of implementing the 3-month momentum strategy would be 0.6-0.8% per annum. This estimate is based on execution analysis of live trades at Man over a 25 year history.

3.1 A straightforward momentum strategy

We define a simple futures time-series momentum signal as the compounded return over the past N days, scaled by volatility:

$$mom_{t-1}^{k}(N)=\frac{\left(1+R_{t-1}^{k}\right)\times\ldots\times\left(1+R_{t-N}^{k}\right)-1}{\sigma_{t-1}^{k}\times\sqrt{N}}, \qquad [1]$$

where R_{t-i}^{k} is the daily return of security *k* at time *t-i*, σ_{t-1}^{k} is the standard deviation of the past 100 daily returns for security *k*, observed at time *t-1*, which is multiplied by $\sqrt{N}$ to achieve an approximate unit standard deviation for the signal.[10]

For the purpose of analysis, we consider 1-, 3-, and 12-month momentum strategies to capture short-, medium-, and long-term momentum trading. That is, the N in Equation [1] is set to 22, 65, and 261 days respectively.

We divide the momentum score by the standard deviation of security returns to calculate a risk-adjusted market target allocation. The strategy performance is then given by multiplying the market target allocations by a gearing factor and the next period's return, and then summing across securities:

$$Performance_{t}(N)=\sum\nolimits_{k} Gearing_{t-1}^{k}\frac{mom_{t-1}^{k}(N)}{\sigma_{t-1}^{k}}R_{t}^{k}\ . \qquad [2]$$

The gearing factor is chosen such that we target an annualized volatility of 10% and allocate risk to six groups as follows: 25% currencies, 25% equity indices, 25% fixed income, and 8.3% to each of agricultural products, energies, and metals. Within each group, markets are allocated equal risk. Gearing factors are calculated at the group-level using an expanding window.

3.2 Restricting the equity exposure

In order to prevent the strategy from actually increasing overall portfolio equity beta, we follow Hamill, Rattray, and Van Hemert (2016, henceforth HRV) and consider an extension of the strategy, whereby positions in each equity market are capped at zero (only zero or short equity positions are acceptable). HRV rescale the position-capped strategy return series to achieve the same realized volatility as the unconstrained strategy and, as such, effectively redistribute some of the equity risk allocation to the other asset classes. In addition, we look at construction methods that restrict beta to the equity market. In all, we consider the following momentum strategies:

- **Unconstrained.** As defined in Equation [1] with no further limits to the equity exposure.
- **EQ position cap.** Positions in equities are capped at zero (as in HRV).

[10] We further restrict the signal value to between -2 and 2, to prevent putting too much weight on outliers. We omit this step from the formula for ease of exposition.

- **EQ beta cap.** The beta of the equity portfolio to the S&P 500 is capped at zero. If this condition is not met, then all equity positions with a positive beta are proportionally reduced so that the new equity portfolio has a beta of zero. Thus, the strategy may take some long equity index positions as long as they are offset by an equal or greater beta-equivalent short position in other indices. The portfolio beta is determined as the sum of portfolio weights times the security betas, where the latter is based on five-day returns over a rolling one-year window.[11]
- **ALL beta cap.** Similar to EQ beta cap, but now the beta of the entire portfolio (equity and non-equity), to the S&P 500, is capped at zero.

We scale the returns of each strategy (ex-post) to 10% annualized volatility to allow for fair comparison.

We also considered a version where first the beta of the equity portfolio and then the beta of the entire portfolio is capped at zero. This restriction is stronger than just capping the beta of either the equity or entire portfolio alone. The results in this case are very similar to the results for capping the beta of the entire portfolio, and so are omitted.

3.3. Securities included

We study the empirical performance of the different strategies using the 50 liquid futures and forwards listed in Table 2. While we evaluate strategy returns from 1985 onwards only, where possible we use data from 1980 to compute risk estimates. Prior to its introduction in 1999, the euro (EUR/USD) is replaced with the Deutsche Mark.

Table 2: Data for futures time-series momentum analysis

This table lists the 50 futures and forward markets used for evaluating the times-series momentum strategies.

Name	Exchange	Start date	Name	Exchange	Start date	Name	Exchange	Start date
COMMODITIES - AGRICULTURALS			**CURRENCIES (AGAINST USD)**			**FIXED INCOME - BONDS**		
Corn	CBOT	Jan-80	Australian dollar	OTC forward	Jan-80	2-year Germany	Eurex	Mar-97
Soybeans	CBOT	Jan-80	Canadian dollar	OTC forward	Jan-80	5-year Germany	Eurex	Oct-91
Wheat	CBOT	Jan-80	Euro (D-Mark)	OTC forward	Jan-80	10-year Germany	Eurex	Jun-83
Cocoa	ICE - US	Jan-80	Norwegian krone	OTC forward	Dec-88	10-year Japan	TSE	Mar-83
Coffee	ICE - US	Jan-80	New Zealand dollar	OTC forward	Dec-88	10-year UK	LIFFE	Nov-82
Sugar	ICE - US	Jan-80	Swiss franc	OTC forward	Jan-80	30-year US	CBOT	Jan-80
			Swedish krona	OTC forward	Dec-88	2-year US	CBOT	Jul-05
COMMODITIES - ENERGIES			British pound	OTC forward	Jan-80	5-year US	CBOT	Oct-91
Crude oil - Brent	ICE - Europe	Jun-88	Japanese yen	OTC forward	Jan-80	10-year US	CBOT	May-82
Crude oil - WTI	NYMEX	Oct-83						
Heating oil	NYMEX	Jan-80	**EQUITIES**			**FIXED INCOME - INTEREST RATE**		
Natural gas	NYMEX	Apr-90	CAC 40	Euronext	Nov-88	Eurodollar	CME	Feb-82
Gas oil	ICE - Europe	Apr-81	DAX	Eurex	Nov-90	Euribor	LIFFE	Apr-89
Gasoline	NYMEX	Dec-84	Nasdaq	CME	Apr-96	Short sterling	LIFFE	Nov-82
			Russell	ICE - US	Sep-00			
COMMODITIES - METALS			S&P 500	CME	Apr-82			
Aluminium	LME	Jan-80	EuroSTOXX	Eurex	Jun-00			
Copper	COMEX	Jan-80	FTSE	LIFFE	May-84			
Gold	COMEX	Jan-80	Hang Seng	HKFE	Jan-87			
Lead	LME	Jun-89	KOSPI	KSE	Sep-00			
Nickel	LME	Jan-80	Nikkei	SGX	Mar-87			
Silver	COMEX	Jan-80						
Zinc	LME	Jan-80						

[11] The results are similar for half-year and two-year windows.

3.4 Performance of futures time-series momentum strategies

For the various strategies considered, Table 3 reports the total return during the various equity crisis periods, the annualized return during crisis, normal, and all periods, and the annualized Sharpe ratio (SR), correlation to the S&P 500, and the annualized information ratio (IR) with respect to the S&P 500. The "other statistics" are based on five-day overlapping returns. The SR is determined as the ratio of the mean and the standard deviation of the strategy return. For the IR, we regressed the strategy returns onto S&P 500 returns (excess of T-bills). The IR is then computed as the ratio of the alpha (intercept) and the standard deviation of the regression error.[12] In both cases we apply an annualization factor:

$$SR = \frac{\mu\left(R_t^{strategy}\right)}{\sigma\left(R_t^{strategy}\right)} \times \sqrt{261/5},$$
$$IR = \frac{\alpha}{\sigma(\varepsilon)} \times \sqrt{261/5}, \text{ where } R_t^{strategy} = \alpha + \beta R_t^{S\&P} + \varepsilon_t. \qquad [3]$$

Table 3: Futures time-series momentum performance in crisis periods (1985-2016)

We report the total return of various strategies during the seven worst drawdowns for the S&P 500 since 1985, the annualized (geometric) return during crisis, normal, and all periods, and the annualized Sharpe ratio, correlation to the S&P 500, and information ratio to the S&P 500. All strategies are scaled to 10% annualized volatility (ex-post). The data run from 1985 to 2016.

Strategy		Total return crisis periods							Annualized return			Other statistics		
		Black Monday	Gulf war	Asian crisis	Tech burst	Financial crisis	Euro crisis I	Euro crisis II	Crisis (14%)	Normal (86%)	All (100%)	SR	Corr. to S&P500	IR to S&P500
1m MOM	Unconstrained	5.6%	19.3%	9.0%	31.3%	28.6%	2.7%	4.9%	21.8%	6.5%	8.6%	0.88	-0.19	1.00
1m MOM	EQ position cap	9.5%	22.8%	12.5%	37.4%	34.3%	4.8%	8.4%	28.2%	3.5%	6.8%	0.70	-0.35	0.95
1m MOM	EQ beta cap	6.8%	20.6%	12.3%	36.2%	32.8%	4.2%	7.9%	26.2%	3.6%	6.6%	0.69	-0.32	0.90
1m MOM	ALL beta cap	7.2%	21.7%	13.2%	34.0%	29.8%	4.7%	8.4%	26.0%	1.3%	4.5%	0.49	-0.37	0.73
3m MOM	Unconstrained	10.3%	10.5%	9.3%	50.7%	32.6%	0.5%	10.9%	26.4%	6.4%	9.1%	0.93	-0.13	1.00
3m MOM	EQ position cap	15.4%	18.7%	14.4%	61.3%	41.4%	4.7%	13.7%	36.6%	4.0%	8.2%	0.84	-0.36	1.10
3m MOM	EQ beta cap	10.0%	15.6%	12.5%	60.3%	40.9%	4.3%	13.5%	33.6%	4.1%	7.9%	0.82	-0.30	1.02
3m MOM	ALL beta cap	13.0%	15.4%	12.7%	66.1%	44.0%	3.5%	18.3%	37.0%	2.0%	6.4%	0.67	-0.36	0.92
12m MOM	Unconstrained	0.4%	12.2%	7.7%	52.3%	17.3%	-4.0%	-4.1%	16.1%	11.5%	12.1%	1.19	0.04	1.18
12m MOM	EQ position cap	8.3%	18.7%	16.2%	71.7%	23.7%	2.1%	0.2%	28.9%	8.9%	11.6%	1.15	-0.24	1.31
12m MOM	EQ beta cap	8.4%	15.3%	14.6%	70.7%	23.0%	2.2%	-0.1%	27.4%	9.4%	11.8%	1.17	-0.22	1.31
12m MOM	ALL beta cap	-0.9%	16.3%	13.1%	78.8%	23.1%	3.7%	2.0%	27.1%	6.9%	9.6%	0.97	-0.23	1.12

The 1- and 3-month unconstrained strategies have tended to perform well during crises, consistent with HRV, who argue that faster trend strategies are particularly good at providing potential crisis alpha. On the other hand, the 12-month unconstrained strategy has negative returns during the two most recent crises.

The EQ position cap strategy performs better during crises. In the cases of 3- and 12-month momentum, this comes at the modest cost of a 0.9% and 0.5% lower overall performance (per annum) respectively, compared to the unconstrained strategy. The information ratio of the 3- and 12-month EQ position cap strategies are higher than for the unconstrained strategy.

The EQ beta cap strategy has a slightly worse crisis performance for all three momentum speeds compared to the EQ position cap strategy, while the overall performance is similar.

[12] This ratio is also sometimes referred to as the appraisal ratio.

The ALL beta cap strategy performs similarly to the EQ beta cap strategy during crises, but has noticeably poorer overall performance. The unfavorable cost-benefit tradeoff in restricting the entire portfolio perhaps matches intuition. One might expect the correlation between a non-equity security and the S&P 500 to vary more through time than the correlation between an equity security and the S&P 500. Higher variation is coupled with higher estimation error, which effectively introduces noise into the calculation of trading positions, leading to weaker performance.

In Table 4, we report the return (not annualized) of 3-month momentum strategies for different equity quintiles based on 5-, 22-, 65-, and 261-day windows. These statistics were derived without reference to our equity crisis periods, and so offer additional insight into the strategies' performance when equity markets fall. While the capped strategies perform comparably well in the worst equity quintile, in the best equity market quintile, unsurprisingly, the ALL beta cap strategy underperforms considerably.

Table 4: Average return 3-month futures times-series momentum for different equity quintiles (1985-2016)

We report the average return of the S&P 500 and various 3-month futures times-series momentum strategies by S&P 500 return quintiles. The momentum strategies are scaled to 10% annualized volatility (ex-post). The data run from 1985 to 2016.

5-day equity quintiles		Worst	Q2	Q3	Q4	Best	ALL
S&P500 (excess)		-3.02%	-0.70%	0.30%	1.19%	3.06%	0.16%
3m MOM	Unconstrained	0.31%	0.02%	0.17%	0.28%	0.11%	0.18%
3m MOM	EQ position cap	0.80%	0.18%	0.11%	0.02%	-0.30%	0.16%
3m MOM	EQ beta cap	0.71%	0.16%	0.12%	0.04%	-0.26%	0.16%
3m MOM	ALL beta cap	0.80%	0.18%	0.09%	-0.02%	-0.40%	0.13%

22-day equity quintiles		Worst	Q2	Q3	Q4	Best	ALL
S&P500 (excess)		-5.73%	-0.98%	1.08%	2.89%	6.24%	0.70%
3m MOM	Unconstrained	1.39%	0.18%	0.66%	0.73%	0.94%	0.78%
3m MOM	EQ position cap	2.42%	0.57%	0.48%	0.17%	-0.07%	0.71%
3m MOM	EQ beta cap	2.09%	0.52%	0.53%	0.25%	0.04%	0.69%
3m MOM	ALL beta cap	2.30%	0.43%	0.43%	0.02%	-0.36%	0.57%

65-day equity quintiles		Worst	Q2	Q3	Q4	Best	ALL
S&P500 (excess)		-8.93%	-0.49%	2.64%	5.63%	11.26%	2.02%
3m MOM	Unconstrained	4.11%	0.65%	1.26%	1.85%	3.68%	2.31%
3m MOM	EQ position cap	6.03%	1.04%	0.94%	0.98%	1.56%	2.11%
3m MOM	EQ beta cap	5.28%	0.98%	1.03%	1.10%	1.75%	2.03%
3m MOM	ALL beta cap	5.60%	0.92%	0.76%	0.71%	0.34%	1.67%

261-day equity quintiles		Worst	Q2	Q3	Q4	Best	ALL
S&P500 (excess)		-17.17%	3.51%	10.02%	17.26%	27.92%	8.31%
3m MOM	Unconstrained	14.88%	6.47%	7.42%	8.92%	10.61%	9.66%
3m MOM	EQ position cap	18.90%	5.84%	6.64%	7.19%	5.33%	8.78%
3m MOM	EQ beta cap	16.63%	5.63%	6.58%	7.28%	5.84%	8.39%
3m MOM	ALL beta cap	16.54%	5.26%	5.37%	5.54%	2.09%	6.96%

Summarizing, medium-term time-series momentum strategies have performed well during recent crisis periods, as well as over our whole sample. Restricting long equity exposures seems to increase the crisis performance potential of these strategies, with only a modest cost in terms of whole-sample performance.

4. Quality stocks

In this section we explore the crisis behavior of long-short US equity strategies, with a particular emphasis on strategies that use quality metrics to determine positions. Performance is reported gross of transaction costs.[13]

[13] We estimate that the combined transaction, slippage, and financing costs of implementing the composite quality strategies amounts to around 1.0-2.0% per annum. This estimate is based on the live trading experience at Man. As with futures, sophisticated execution and implementation rules can further reduce the cost.

4.1 Motivation to look at quality stocks

Asness, Frazzini, and Pedersen (2013, henceforth AFP) argue that while quality stocks logically deserve a higher price-to-book ratio, in reality they do not always exhibit such a premium. In particular, towards the end of equity bull markets, quality stocks have often looked underpriced. Then, when the market has a drawdown, these stocks have outperformed, benefitting from the so-called flight-to-quality effect.

Using the Gordon growth model, AFP derive the following formula for the price-to-book (P/B) ratio:[14]

$$\frac{P}{B} = \frac{\text{Profitability} * \text{PayoutRatio}}{\text{Required Return} - \text{Growth}}. \quad [4]$$

Each of the four components on the right-hand side of Equation [4] is a quality metric that can be measured in several ways, such as:

1. Profitability: profits (gross profits, earnings, cash flows) scaled by an accounting value (book equity, book assets, sales)
2. Growth: trailing five-year growth of a profitability measure
3. Safety (required return): safer companies command lower required returns; return-based measures include market beta and volatility and fundamental-based measures include low leverage, low volatility of profitability and low credit risk
4. Payout: the fraction of profits paid out to shareholders, which can be seen as a measure of the "shareholder friendliness" of management

In the academic literature, many of these metrics have been documented to predict cross-sectional stock returns and have been written about extensively.

4.2 Evidence from academic factor analysis

We start our analysis by using publicly available daily returns to evaluate the performance of factors documented in the academic literature. In Table 5, we present results for the Fama and French (2015) five-factor model (the first five factors), as well as factor returns based on AFP and affiliated researchers (the last three factors).[15] Only US stocks are considered in all cases.

Quality and profitability (in itself a component of quality) stand out in terms of their crisis performance. It is important to note that these factors are constructed in a dollar-neutral way, which is common practice in the literature. In the case of the quality factor, however, this leads to a negative correlation of -0.49 to the S&P 500, based on five-day overlapping returns. This raises the question of whether the positive crisis performance is simply explained by the negative equity exposure. Subsections 4.3 and 4.4 present evidence that suggests this is not the case.

[14] In the Gordon growth model, *price = dividend / (required return – growth)*. Using *profitability = profit/B* and *payout ratio = dividend/profit*, and then rearranging terms yields Equation 4.

[15] Daily returns are available from: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html and https://www.aqr.com/library/data-sets.

Table 5: Equity factors performance in crisis periods (1985-2016)

We report the total return of various long-short US equity strategies with publicly available return data during the seven worst drawdowns for the S&P 500, the annualized (geometric) return during crisis, normal, and all periods, and the annualized Sharpe ratio, correlation to the S&P 500, and information ratio to the S&P 500. Strategies are scaled to a dollar long-short. The data run from 1985 to 2016.

Factor	Total return							Annualized return			Other statistics		
	Black Monday	Gulf war	Asian crisis	Tech burst	Financial crisis	Euro crisis I	Euro crisis II	Crisis (14%)	Normal (86%)	All (100%)	SR	Corr. to S&P500	IR to S&P500
Market (NYSE, AMEX, NASDAQ)	-30.1%	-22.2%	-21.3%	-51.8%	-55.8%	-16.1%	-20.3%	-45.3%	20.3%	7.3%	0.51	0.99	-0.01
Size	9.5%	-11.0%	-8.6%	29.4%	-5.5%	-3.8%	-10.1%	-1.3%	0.4%	0.1%	0.06	-0.03	0.07
Value	4.4%	7.3%	5.6%	72.0%	-23.2%	-8.9%	-7.7%	6.0%	2.4%	2.9%	0.35	-0.11	0.41
Profitability (Robust - Weak)	-2.3%	-1.0%	5.2%	123.4%	31.5%	2.2%	13.3%	30.7%	0.4%	4.3%	0.59	-0.27	0.75
Investment (Conservative - Aggressive)	4.0%	12.3%	9.8%	61.2%	0.2%	-1.9%	-4.7%	15.3%	1.3%	3.2%	0.50	-0.35	0.73
Momentum	-7.9%	10.0%	2.3%	39.3%	35.7%	-5.4%	1.3%	14.5%	4.8%	6.2%	0.50	-0.14	0.58
Quality (Quality - Junk)	1.5%	7.7%	9.1%	101.9%	67.3%	7.6%	24.1%	43.7%	-0.1%	5.3%	0.64	-0.49	1.02
Low risk (Bet-against-Beta)	3.1%	-1.3%	-0.1%	115.3%	-32.0%	3.8%	5.3%	11.1%	8.6%	8.9%	0.81	-0.37	1.08

Also noteworthy for its return during crises is the stock momentum factor, which in this case is traded at the stock level and in a cross-sectional (dollar-neutral) fashion, and so differs from the futures time-series momentum discussed in Section 2. However, some of the intuition behind futures trend-following providing crisis alpha (see HRV) may carry over to stock momentum. For example, stock momentum may pick up sector trends that reflect the broader macro movements, which are also picked up by futures trend-following. The investment factor, which goes long the stock of conservative companies with low growth in book assets, whilst shorting aggressive, high-asset-growth companies, performs about as well as the stock momentum factor during crises.

In contrast, the value factor has been much less effective as a crisis hedge than the quality and profitability factors. In general, a profitability factor is the ratio of two accounting values, for example the ratio of net income to the book value of equity, and as such the positioning is unaffected by the short-term gyrations of the equity market. A value factor is the ratio of an accounting value and a market value, for example the ratio of net income to the market value of equity. Hence a value metric will change more favorably for stocks that underperform the market, causing the factor to increase its exposure to such stocks.

4.3 Individual quality factor performance

In this section, we evaluate various quality metrics. Table 6 lists all the signals we consider, which form a subset of AFP's signals, as we omit Ohlson's O and Altman's Z (which are more highly parameterized than the others and so more open to claims of over-fitting), and instead focus on return- and leverage-based safety measures.[16]

[16] Also, AFP use CRSP/XpressFeed Global data, while we use their Worldscope analogues. The accounting data is extracted from the Worldscope fundamental dataset, where we use annual, semi-annual and quarterly data where available. We generate comparable numbers by constructing trailing 12-month averages for each frequency, per variable.

Table 6: Quality factor definitions

We list the various quality factors used in our strategies.

Category	Name	Description
Profitability	Cash flow over assets	(net income + depreciation - change working capital - capital expenditures) / total assets
Profitability	Gross margin	(revenue - cost of goods sold) / net sales
Profitability	Gross profits over assets	(revenue - cost of goods sold) / total assets
Profitability	Low accruals	(depreciation - change working capital) / total assets
Profitability	Return on assets	Net income / total assets
Profitability	Return on equity	Net income / book equity
Payout	Net debt issuance	-log(total debt current / total debt one year ago)
Payout	Net equity issuance	-log(outstanding number of shares current / outstanding number of shares one year ago)
Payout	Total net payouts over profits	Total net payouts / profits
Growth	Cash flow over assets (5y change)	Five-year change corresponding profitability metric, i.e. ($CashFlow_t$ - $CashFlow_{t-5}$) / $TotalAssets_{t-5}$
Growth	Gross margin (5y change)	Five-year change corresponding profitability metric
Growth	Gross profits over assets (5y change)	Five-year change corresponding profitability metric
Growth	Low accruals (5y change)	Five-year change corresponding profitability metric
Growth	Return on assets (5y change)	Five-year change corresponding profitability metric
Growth	Return on equity (5y change)	Five-year change corresponding profitability metric
Safety	Low beta	Minus realized beta to S&P 500 Index based on weekly returns over a rolling three-year window
Safety	Low idiosyncratic volatilty	Minus standard deviation of the daily market-adjusted returns over the past year
Safety	Low leverage	Total debt / total assets

At each date, the raw signal value, *s*, is ranked cross-sectionally, *r(s)=rank(s)*, and then a cross-sectional *z*-score is determined, $z(r)=(r-\mu_r)/\sigma_r$, where μ_r is the cross-sectional mean and σ_r is the cross-sectional standard deviation. The key purpose of this ranking step is to reduce the impact of outliers. This robustness step can be a relevant precaution when working with accounting data. Denoting the signal coming out of this first step time at *t* for stock *i* as $Sig_{t,i}$, we form a beta-neutral portfolio by defining a neutral signal as:

$$Sig_{t,i}^{Neutral} = \begin{cases} \dfrac{Sig_{t,i}}{BetaLong} \text{ for positive } Sig_{t,i} \\ \dfrac{Sig_{t,i}}{BetaShort} \text{ for negative } Sig_{t,i} \end{cases},$$
$$BetaLong = \sum_j Sig_{t,j} * \beta_{t,j} \text{ for all positive } Sig_{t,j}, \qquad [5]$$
$$BetaShort = -\sum_j Sig_{t,j} * \beta_{t,j} \text{ for all negative } Sig_{t,j}.$$

The beta is computed with respect to the S&P 500 using five-day overlapping returns over the past three years. Strategy returns are obtained by multiplying the final signal values, lagged by a day, with stock returns:

$$Performance_t = \sum_i Sig_{t-1,i}^{Neutral} * R_{t,i}. \qquad [6]$$

In a final step, we scale strategy returns (ex-post) such that the full-sample realized volatility is 10%, merely to aid comparison across variations and with the futures time-series momentum strategies.

We evaluate the performance of the different quality factors in a universe of mid- and large-cap US stocks. Each month we define a market cap threshold: those stocks that exceed it are defined as large-cap, and those that do not are mid-cap. This threshold is set equal to $2bn at the end of 2016, and for earlier dates is suitably deflated.[17] As an example, the threshold in 1986 was about $200m. This results in a universe with low turnover, with the number of constituents ranging between 951 and 1,611 over the sample.

Table 7 reports the crisis- and normal-period performance for the different quality factors. As a result of data availability, some factors have returns missing for the first two crises. For most factors, the annualized crisis return is higher than the return during normal periods, suggesting a crisis-hedge property. A first notable exception, however, is the set of growth factors, where in three out of six cases the crisis performance is worse than the normal performance, and moreover the overall performance is around zero for all six growth factors.

Table 7: Quality factor performance, beta-neutral (1986-2016)

We report the total return for various quality factors during the seven worst drawdowns for the S&P 500, the annualized (geometric) return during crisis, normal, and all periods, and the annualized Sharpe ratio, correlation to the S&P 500, and information ratio to the S&P 500. Portfolios are constructed to be beta-neutral. Signal values are scored globally and we use no stock-level volatility scaling. All strategies are scaled to 10% annualized volatility (ex-post). The data run from 1986 to 2016.

Category	Name	Total return							Annualized return			Other statistics		
		Black Monday	Gulf war	Asian crisis	Tech burst	Financial crisis	Euro crisis I	Euro crisis II	Crisis (14%)	Normal (86%)	All (100%)	SR	Corr. to S&P500	IR to S&P500
Profitability	Cash flow over assets		14.3%	8.0%	152.3%	10.9%	1.4%	3.5%	32.0%	3.0%	7.9%	0.69	-0.14	0.76
Profitability	Gross margin	5.1%	2.7%	8.9%	-28.1%	13.9%	5.1%	5.2%	1.3%	2.5%	2.3%	0.27	0.02	0.25
Profitability	Gross profits over assets	0.6%	-4.3%	6.6%	167.2%	16.1%	-1.0%	3.3%	29.0%	1.3%	4.9%	0.47	-0.19	0.57
Profitability	Low accruals		-6.0%	4.5%	79.5%	0.7%	0.0%	-2.1%	12.7%	1.6%	3.7%	0.38	-0.11	0.43
Profitability	Return on assets	0.2%	8.9%	6.8%	158.1%	25.3%	2.7%	3.4%	34.9%	-1.0%	3.5%	0.35	-0.17	0.44
Profitability	Return on equity	1.8%	1.6%	7.6%	189.2%	10.2%	2.4%	3.9%	33.2%	1.1%	5.2%	0.47	-0.15	0.55
Payout	Net debt issuance	0.2%	6.8%	16.3%	139.5%	23.9%	-1.3%	3.1%	33.0%	7.0%	10.4%	1.00	-0.18	1.11
Payout	Net equity issuance	-3.4%	4.1%	8.9%	210.7%	6.5%	0.3%	3.0%	32.9%	2.8%	6.7%	0.60	-0.18	0.71
Payout	Total net payouts over profits		13.4%	11.2%	65.1%	9.5%	4.4%	-2.9%	19.8%	-0.6%	2.4%	0.26	0.01	0.26
Growth	Cash flow over assets (5y change)			0.2%	46.9%	6.4%	1.7%	2.7%	11.2%	-0.8%	1.2%	0.16	-0.04	0.18
Growth	Gross margin (5y change)		-5.3%	-6.0%	-44.0%	5.1%	3.4%	2.3%	-11.9%	0.9%	-1.2%	-0.05	0.12	-0.11
Growth	Gross profits over assets (5y change)		-5.2%	-5.6%	-36.4%	10.8%	1.7%	1.3%	-8.9%	-0.4%	-1.9%	-0.11	0.07	-0.14
Growth	Low accruals (5y change)			-3.1%	-36.6%	2.2%	0.7%	-0.1%	-9.4%	-0.1%	-2.2%	-0.14	0.07	-0.17
Growth	Return on assets (5y change)		3.0%	-3.4%	14.1%	15.0%	3.9%	2.4%	7.4%	-1.9%	-0.7%	-0.01	-0.01	0.00
Growth	Return on equity (5y change)		-5.3%	-5.0%	23.9%	14.1%	4.4%	5.1%	7.5%	-1.3%	-0.1%	0.05	0.01	0.04
Safety	Low beta	-7.7%	-5.6%	-8.3%	95.5%	-19.5%	1.1%	3.6%	6.1%	10.9%	10.6%	0.91	0.23	0.82
Safety	Low idiosyncratic volatility	-0.3%	12.6%	10.2%	131.9%	4.3%	1.5%	5.6%	28.6%	1.5%	5.2%	0.47	-0.19	0.58
Safety	Low leverage	-2.8%	5.7%	-2.7%	57.8%	-15.4%	1.9%	0.7%	7.0%	0.0%	1.0%	0.14	-0.04	0.16

A second exception is the low beta factor. A beta-neutral implementation of the low beta factor in effect means leveraging the long positions in low beta stocks. This tends to lead to better overall performance, but worse crisis performance due to the fact that strategies with embedded leverage underperform when funding constraints tighten (Frazzini and Pedersen (2014)), which often occurs at times of market stress (such as in the Financial Crisis). In contrast, a beta-neutral, low idiosyncratic volatility strategy does not involve as much leveraging of the long positions, and indeed still historically performs well during crises.

In Appendix B, Table 12, we report results for dollar-neutral versions of the strategies, which can be constructed by setting all beta estimates to unity in Equation [5]. Constructing the strategies in this way can lead to negative correlations with the S&P 500. The low beta factor provides an extreme example with a correlation of -0.73. Dollar-neutral implementations are commonplace in academia (and used by AFP also), but leave open the possibility that a good crisis performance can be attributed to the negative

[17] The deflation factor is proportional to the total return index of the S&P 500 (see Figure 1).

equity exposure, rather than performance being a "positive convex" function of the equity market return. We are mostly interested in positive convexity, with a factor performing well during equity bear markets, without performing badly during equity bull markets.

4.4 Composite quality factor performance (various constructions)

Table 8 presents the performance of composite factors for different portfolio construction choices. Composites are determined at each point in time, by averaging the (ranked and z-scored) score of a stock across multiple factors, and then re-ranking and *z*-scoring these averages across stocks. We consider three deviations from the most basic dollar-neutral implementation typically used in academia (including AFP), as well as a version where all three changes are implemented at the same time:

- Dollar-neutral, as used by AFP and in Table 12 in Appendix B.
- A: beta-neutral, as in the previous subsection and Table 7.
- B: sector-neutral, ranking and z-scoring within each sector, rather than globally, where we use the GICS level 2 classifications, which results in 24 sectors.
- C: stock-vol scaling, divide the ranked and z-scored signal by the volatility of the security to transform it into a risk-adjusted signal.[18]
- A+B+C, combining all portfolio construction choices A, B, and C

Overall we see that profitability, payout, safety, and a grand composite of the four quality composites, denoted "quality all", performed well during crises, and have IRs between 0.44 and 1.14. Only the growth composite stands out as performing poorly during both crisis and normal periods. Based on IR, all three deviations from the basic dollar-neutral portfolio construction method add value, and the stock-level volatility scaling (C) leads to the best performance in most cases over the time periods tested.[19]

In Appendix B, Table 13, we report the output of a regression of the different quality composites on the market, size, value, and momentum factors. The main result is that quality composites capture anomalies beyond these control factors. Also noteworthy is that, except for growth, all composites have a negative beta to the size factor.[20] Profitability and growth have a negative beta to the value factor, while payout and safety have a positive beta to value. The exposure to the stock momentum factor is small in all cases.

[18] Here, the volatility is estimated as the rolling 50-day standard deviation of daily returns. This step is common practice in managed futures trading. Indeed this step is included in Equation [2] of Section 3, and it is important because volatility varies significantly across futures markets; e.g., natural gas can be very volatile, while government bond futures rarely are. Although volatility is unlikely to vary across stocks as much as it does across futures markets, we view this as a beneficial step.

[19] We also considered additional variations: a constant volatility or variance target at the portfolio level, following the recent paper of Moreira and Muir (2016). The volatility target in particular added value, but it led to large fluctuations in the gross dollar exposure, as well as high leverage at times of low volatility.

[20] The relationship between quality and different size metrics is discussed by Asness et al. (2015).

Table 8: Quality performance, composites, various constructions (1986-2016)

We report the total return for various quality composites during the seven worst drawdowns for the S&P 500, the annualized (geometric) return during crisis, normal, and all periods, and the annualized Sharpe ratio, correlation to the S&P 500, and information ratio to the S&P 500. We consider a dollar-neutral version (which is not sector neutral and without stock-level volatility scaling), three versions with one change compared to the dollar-neutral version, and a version with all three changes made simultaneously. All strategies are scaled to 10% annualized volatility (ex-post). The data run from 1986 to 2016.

Category	Construction	Total return							Annualized return			Other statistics		
		Black Monday	Gulf war	Asian crisis	Tech burst	Financial crisis	Euro crisis I	Euro crisis II	Crisis (14%)	Normal (86%)	All (100%)	SR	Corr. to S&P500	IR to S&P500
Profitability	Dollar-neutral	-1.8%	-2.4%	3.5%	202.9%	39.7%	12.2%	12.6%	43.3%	0.7%	6.0%	0.56	-0.26	0.72
Profitability	A: Beta-neutral	2.8%	3.5%	11.2%	219.9%	26.2%	3.0%	4.1%	42.2%	1.4%	6.5%	0.57	-0.19	0.69
Profitability	B: Sector neutral	-2.3%	-2.4%	3.7%	216.2%	38.5%	11.7%	13.6%	44.5%	0.9%	6.3%	0.58	-0.27	0.75
Profitability	C: Stock vol scaling	-1.5%	-2.3%	5.5%	136.6%	30.2%	6.9%	14.3%	33.6%	4.3%	8.1%	0.73	0.03	0.71
Profitability	A+B+C	2.8%	4.5%	12.0%	200.9%	36.6%	2.9%	8.2%	44.5%	2.1%	7.4%	0.65	-0.16	0.74
Payout	Dollar-neutral	0.1%	7.3%	10.6%	224.5%	24.0%	8.2%	5.8%	44.3%	0.5%	5.9%	0.55	-0.38	0.81
Payout	A: Beta-neutral	-3.3%	9.8%	14.5%	267.1%	16.0%	1.5%	1.4%	43.4%	4.2%	9.1%	0.79	-0.18	0.89
Payout	B: Sector neutral	0.3%	7.3%	10.8%	226.6%	24.9%	8.1%	5.8%	44.8%	0.8%	6.2%	0.58	-0.38	0.84
Payout	C: Stock vol scaling	-2.0%	2.7%	5.6%	187.2%	10.8%	2.6%	1.4%	31.2%	10.0%	12.8%	1.09	0.08	1.06
Payout	A+B+C	-3.9%	10.3%	17.7%	274.9%	22.0%	1.4%	2.4%	46.8%	5.6%	10.7%	0.91	-0.15	1.00
Growth	Dollar-neutral		-7.1%	-10.4%	-9.5%	9.4%	11.7%	10.7%	0.4%	0.4%	0.5%	0.10	0.17	0.02
Growth	A: Beta-neutral		-3.4%	-6.4%	-18.4%	13.7%	3.6%	3.1%	-2.3%	-0.7%	-1.1%	-0.04	0.05	-0.06
Growth	B: Sector neutral		-7.5%	-10.1%	-11.2%	8.3%	11.5%	10.8%	-0.3%	0.6%	0.5%	0.10	0.18	0.01
Growth	C: Stock vol scaling		-8.4%	-7.8%	-5.8%	35.6%	6.9%	11.7%	5.6%	-2.9%	-1.9%	-0.12	0.00	-0.11
Growth	A+B+C		-6.0%	-10.0%	-22.1%	16.9%	2.5%	4.8%	-4.0%	-0.5%	-1.2%	-0.05	0.06	-0.07
Safety	Dollar-neutral	5.6%	10.6%	10.1%	104.5%	13.5%	8.8%	15.2%	32.9%	-5.0%	-0.2%	0.03	-0.62	0.44
Safety	A: Beta-neutral	-4.2%	5.8%	1.0%	123.9%	-10.9%	2.1%	5.1%	18.4%	5.4%	7.2%	0.64	-0.02	0.64
Safety	B: Sector neutral	5.7%	11.2%	10.4%	101.9%	14.1%	8.7%	15.2%	32.9%	-5.0%	-0.2%	0.03	-0.62	0.44
Safety	C: Stock vol scaling	-1.8%	8.7%	4.3%	87.5%	-14.1%	2.9%	9.3%	16.4%	7.0%	8.3%	0.73	-0.09	0.78
Safety	A+B+C	-3.2%	8.5%	3.6%	112.2%	-10.3%	1.9%	5.6%	18.9%	6.4%	8.1%	0.71	0.01	0.70
Quality ALL	Dollar-neutral	5.0%	8.6%	9.6%	178.6%	30.9%	11.9%	17.8%	47.2%	-2.5%	3.5%	0.35	-0.55	0.75
Quality ALL	A: Beta-neutral	-4.1%	8.7%	8.2%	231.6%	11.8%	2.9%	5.7%	38.7%	5.8%	10.1%	0.83	-0.12	0.90
Quality ALL	B: Sector neutral	4.8%	7.7%	9.2%	184.1%	29.2%	11.8%	17.7%	46.9%	-2.3%	3.6%	0.36	-0.54	0.76
Quality ALL	C: Stock vol scaling	-3.3%	7.0%	5.9%	177.4%	15.4%	5.8%	17.0%	37.3%	10.1%	13.7%	1.12	-0.04	1.14
Quality ALL	A+B+C	-3.6%	9.0%	9.3%	236.0%	15.6%	3.0%	8.9%	41.5%	7.8%	12.2%	0.99	-0.07	1.03

In Table 9 we report the return (not annualized) of quality composites for different equity quintiles based on 5-, 22-, 65-, and 261-day windows, as we did in Section 3 for the futures time-series momentum strategies. The quintile analysis does not depend on our choice of crisis periods, and as such provides an alternative view of the crisis hedge property. Profitability, payout, safety, and quality all perform best in the worst equity quintile in each of the four horizons.

Table 9: Average return quality composites for different equity quintiles (1986-2016)

We report the average return of the S&P 500 and various quality composites by S&P 500 return quintiles. All strategies are scaled to 10% annualized volatility (ex-post). The data run from 1986 to 2016.

5-day equity quintiles

		Worst	Q2	Q3	Q4	Best	ALL
S&P500 (excess)		-3.02%	-0.70%	0.30%	1.19%	3.06%	0.16%
Profitability	A+B+C	0.58%	0.11%	0.05%	0.01%	0.01%	0.15%
Payout	A+B+C	0.68%	0.25%	0.15%	-0.02%	-0.01%	0.21%
Growth	A+B+C	-0.17%	-0.06%	0.00%	0.10%	0.08%	-0.01%
Safety	A+B+C	0.23%	0.19%	0.18%	0.07%	0.16%	0.16%
Quality ALL	A+B+C	0.51%	0.24%	0.20%	0.08%	0.14%	0.23%

22-day equity quintiles

		Worst	Q2	Q3	Q4	Best	ALL
S&P500 (excess)		-5.73%	-0.98%	1.08%	2.89%	6.24%	0.70%
Profitability	A+B+C	2.27%	0.34%	0.18%	0.33%	0.28%	0.68%
Payout	A+B+C	2.52%	0.89%	0.50%	0.31%	0.46%	0.94%
Growth	A+B+C	-0.15%	-0.26%	-0.22%	0.27%	0.19%	-0.04%
Safety	A+B+C	1.02%	0.72%	0.81%	0.57%	0.56%	0.74%
Quality ALL	A+B+C	2.21%	0.85%	0.75%	0.71%	0.76%	1.06%

65-day equity quintiles

		Worst	Q2	Q3	Q4	Best	ALL
S&P500 (excess)		-8.93%	-0.49%	2.64%	5.63%	11.26%	2.02%
Profitability	A+B+C	6.70%	1.70%	0.62%	0.84%	0.34%	2.04%
Payout	A+B+C	6.97%	3.12%	1.70%	1.30%	0.79%	2.78%
Growth	A+B+C	1.01%	0.10%	-0.74%	0.10%	0.09%	0.11%
Safety	A+B+C	3.04%	2.77%	2.00%	1.67%	1.71%	2.24%
Quality ALL	A+B+C	6.37%	3.46%	2.16%	2.04%	1.84%	3.18%

261-day equity quintiles

		Worst	Q2	Q3	Q4	Best	ALL
S&P500 (excess)		-17.17%	3.51%	10.02%	17.26%	27.92%	8.31%
Profitability	A+B+C	29.06%	7.56%	1.89%	4.09%	1.99%	8.92%
Payout	A+B+C	34.84%	6.56%	5.48%	7.22%	7.68%	12.36%
Growth	A+B+C	-1.00%	3.96%	-0.48%	-0.68%	-2.17%	0.04%
Safety	A+B+C	16.47%	4.92%	9.08%	7.14%	10.99%	9.72%
Quality ALL	A+B+C	32.20%	8.71%	8.16%	9.03%	12.01%	14.02%

5. Concluding remarks

A strategy that continually holds put options on the S&P 500 is a prohibitively expensive crisis hedge in our view. A strategy that passively holds US 10-year Treasuries is historically an unreliable crisis hedge, since the post-2000 negative bond-equity correlation is historically atypical. Long gold and short credit risk sit in between puts and bonds in terms of both cost and reliability according to our research.

For these reasons, in this paper we have evaluated a number of dynamic strategies for their potential to perform well during the worst equity market drawdowns, whilst also not being too expensive in other periods.

Two conceptually different classes of strategies emerge as credible candidates in our view. First, futures time-series momentum strategies, which performed well during each of the seven most severe equity market crises since 1985. Restricting these strategies from taking long equity positions further enhances their historical crisis properties at only a modest cost to overall performance.

Second, strategies that take long and short positions in single stocks, using quality metrics to rank companies cross-sectionally, have also performed well when equity markets have sold off, in what one could call a flight to quality effect. We evaluated a host of different quality metrics, and investigated the potential benefit of employing various portfolio construction methods (incorporating features such as beta-neutrality, sector-neutrality and stock-level volatility scaling).

In Table 10, we present correlations between a selected subset of the strategies considered in the paper (based on five-day overlapping returns). The futures time-series momentum strategies (1-, 3-, and 12-month momentum with equity positions capped at zero) demonstrate negligible correlation with any of the quality stock strategies (profitability, payout, growth, safety, and the grand quality composite). According to the research we would therefore expect the two strategies to help complement each other, potentially providing crisis hedge properties with added diversification benefit.[21]

To investigate the potential effectiveness of dynamic strategies in providing returns during crisis periods, we simulated portfolios with varying allocations to the S&P 500, 3-month momentum with no long equity positions, and the quality composite factor strategy. First, we deduct transaction costs from the momentum and quality strategies. We assumed the midpoints of our earlier estimates: so 0.7% per annum for momentum and 1.5% per annum for quality. Second, we scale up returns (after costs) of the hedge strategies so that they achieve 15% volatility when combined. This higher volatility is closer to the long-run historical volatility of equities. Based on the authors' experience, the combined hedge portfolio can be implemented at this leverage without any additional funding.

The simulated portfolios allocate some proportion of assets to the combined hedge portfolio, and the remaining assets to the S&P 500. Hence, a hedge proportion of 30% implies a 70% allocation to the S&P 500 and a 30% allocation to the hedge portfolio. Statistics for these portfolios are shown in Table

[21] The low correlation between futures time-series momentum and quality stocks also obtains when considering just crisis or just normal periods.

11. Although a 50% allocation to the hedge strategy is required to achieve a positive return over the crisis periods in our simulations, a smaller 10% allocation improves the return in each of the seven historical crisis periods, resulting in an 8 percentage point improvement in the annualized crisis return (from -43.5% to -35.8%).

Table 10: Correlation between strategies considered in Sections 2, 3, and 4 (1986-2016)

We report the correlations between the five-day overlapping returns of various strategies considered. From Section 2: S&P 500 (excess), long puts (one-month, at-the-money S&P 500 puts), short credit risk (duration-matched US Treasuries over US investment grade corporate bonds), long bonds (US 10-year Treasuries), and long gold (futures). From Section 3: 1-, 3-, and 12-month futures time-series momentum with equity positions capped at zero. From Section 4: the different quality stock composites, beta-neutral (A), sector-neutral (B), and with stock-level volatility scaling (C). The data run from 1986 to 2016.

	S&P 500	Long puts	Short credit risk	Long bonds	Long gold	1m MOM: EQ pos. cap	3m MOM: EQ pos. cap	12m MOM: EQ pos. cap	Profitability: A+B+C	Payout: A+B+C	Growth: A+B+C	Safety: A+B+C	Quality ALL: A+B+C
S&P 500		-0.86	-0.34	-0.04	-0.03	-0.35	-0.36	-0.24	-0.16	-0.15	0.06	0.01	-0.07
Long puts	-0.86		0.35	0.11	0.05	0.42	0.39	0.24	0.17	0.12	-0.04	-0.04	0.06
Short credit risk	-0.34	0.35		0.17	0.04	0.24	0.23	0.17	0.17	0.11	0.00	-0.02	0.07
Long bonds	-0.04	0.11	0.17		0.03	0.12	0.20	0.30	0.08	0.03	-0.03	0.18	0.16
Long gold	-0.03	0.05	0.04	0.03		0.04	0.09	0.12	-0.08	-0.04	0.08	-0.03	-0.04
1m MOM: EQ pos. cap	-0.35	0.42	0.24	0.12	0.04		0.73	0.47	0.04	0.09	-0.07	0.00	0.02
3m MOM: EQ pos. cap	-0.36	0.39	0.23	0.20	0.09	0.73		0.69	0.05	0.10	-0.07	0.03	0.05
12m MOM: EQ pos. cap	-0.24	0.24	0.17	0.30	0.12	0.47	0.69		0.01	0.04	0.00	0.07	0.07
Profitability: A+B+C	-0.16	0.17	0.17	0.08	-0.08	0.04	0.05	0.01		0.57	0.18	0.24	0.71
Payout: A+B+C	-0.15	0.12	0.11	0.03	-0.04	0.09	0.10	0.04	0.57		-0.47	0.63	0.82
Growth: A+B+C	0.06	-0.04	0.00	-0.03	0.08	-0.07	-0.07	0.00	0.18	-0.47		-0.61	-0.28
Safety: A+B+C	0.01	-0.04	-0.02	0.18	-0.03	0.00	0.03	0.07	0.24	0.63	-0.61		0.83
Quality ALL: A+B+C	-0.07	0.06	0.07	0.16	-0.04	0.02	0.05	0.07	0.71	0.82	-0.28	0.83	

Table 11: Effectiveness of dynamic hedges

We simulated portfolios with varying allocations to the S&P 500, 3-month momentum with no long equity positions, and the quality composite factor strategy. Transaction costs for the dynamic strategies are included. A hedge proportion of 30% implies a 70% allocation to the S&P 500 and a 30% allocation to the hedge portfolio. We report the total return during the seven worst drawdowns for the S&P 500, the annualized (geometric) return during crisis, normal, and all periods, and the annualized Sharpe ratio, correlation to the S&P 500, and information ratio to the S&P 500. The data run from 1986 to 2016.

Portfolio	Total return							Annualized return			Other statistics			
Hedge Proportion	Black Monday	Gulf war	Asian crisis	Tech burst	Financial crisis	Euro crisis I	Euro crisis II	Crisis (14%)	Normal (86%)	All (100%)	SR	Corr. to S&P500	IR to S&P500	Vol
0%	-32.9%	-19.2%	-19.2%	-47.4%	-55.2%	-15.6%	-18.6%	-43.5%	24.5%	11.0%	0.71	1.000	0.00	16.7%
10%	-29.1%	-15.1%	-15.6%	-33.0%	-48.5%	-13.5%	-15.2%	-35.8%	23.8%	12.6%	0.89	0.995	1.81	14.7%
20%	-25.1%	-10.9%	-11.9%	-15.0%	-40.9%	-11.4%	-11.6%	-27.1%	23.1%	14.1%	1.10	0.975	1.81	12.9%
30%	-20.9%	-6.4%	-8.0%	7.6%	-32.5%	-9.2%	-7.9%	-17.3%	22.4%	15.6%	1.34	0.926	1.81	11.3%
40%	-16.7%	-1.8%	-3.9%	35.8%	-23.0%	-7.0%	-4.2%	-6.5%	21.6%	17.1%	1.61	0.828	1.81	10.2%
50%	-12.3%	3.1%	0.2%	70.8%	-12.4%	-4.8%	-0.3%	5.6%	20.8%	18.5%	1.83	0.664	1.81	9.6%
60%	-7.7%	8.1%	4.6%	114.2%	-0.7%	-2.5%	3.7%	19.0%	19.9%	19.8%	1.94	0.445	1.81	9.6%
70%	-3.0%	13.4%	9.1%	167.8%	12.3%	-0.2%	7.7%	34.0%	19.0%	21.1%	1.92	0.212	1.81	10.3%
80%	1.8%	18.9%	13.8%	233.8%	26.6%	2.1%	11.9%	50.5%	18.1%	22.3%	1.82	0.007	1.81	11.5%
90%	6.8%	24.6%	18.7%	314.8%	42.4%	4.5%	16.1%	68.8%	17.1%	23.5%	1.68	-0.154	1.81	13.1%
100%	11.9%	30.6%	23.7%	413.9%	59.7%	6.9%	20.5%	89.0%	16.1%	24.6%	1.55	-0.275	1.81	15.0%

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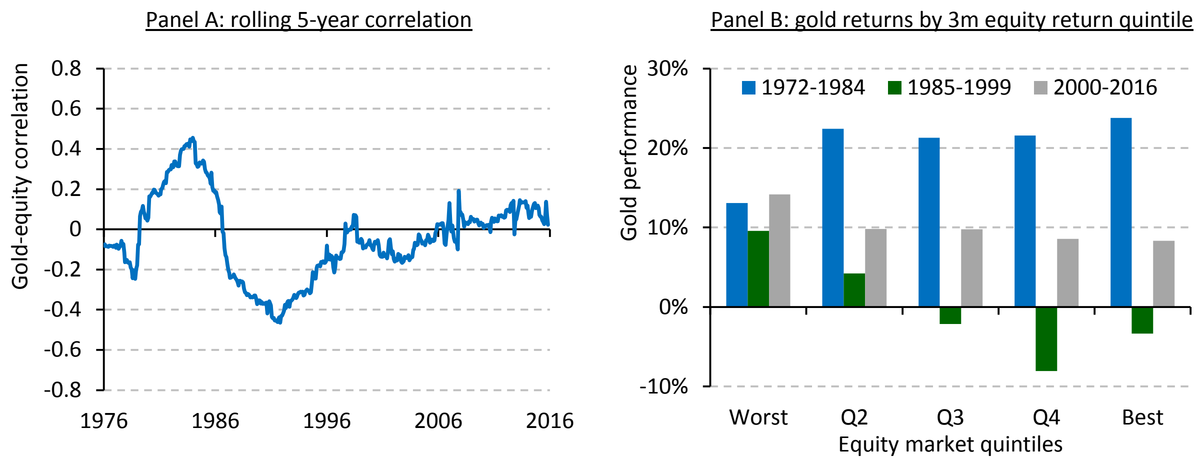
Appendix A: longer view of gold

In this appendix we take a longer view of gold. Unfortunately, the analysis of gold prices prior to 1972 is complicated by the Bretton Woods system, which tied major currencies to gold. In Figure 3 we show the five-year rolling correlation of monthly gold spot returns with US equities. Between 1976 and 1985 gold was moderately positively correlated with equities. In the subsequent 10 years, the correlation was moderately negative, and since the mid-1990s has been close to zero. We split the period 1972-2016 into three subsamples and, for each subsample, calculated the mean return of gold by three-month equity quintile. Pre-1985, the returns of gold were strong, and appear largely indifferent to equity returns. The positive equity correlation is perhaps evident in the relatively weaker performance of gold during the worst three-month periods for equities. In the period 1985 to 1999, when the gold-equity correlation was mostly negative, we see gold performing relatively well during the worst equity quintile.

This outperformance during difficult periods for equities was carried into the 2000s, but without the negative returns during best equity months.

Figure 3: Time varying co-movement between equity and gold returns (funded)

In panel A, we plot the rolling 5-year correlation between monthly US equities and gold spot returns from 1977 to 2016. In panel B, we plot the annualized gold returns by 3-month equity quintiles and for three sub-samples of 1972-2016. The gold data are from Bloomberg, the equity data are from Global Financial Data.



Appendix B: additional results for quality stocks

Table 12 report the quality factor performance based on a dollar-neutral portfolio construction, rather than the beta-neutral portfolio construction used in Table 7.

Table 12: Quality factor performance, dollar-neutral (1986-2016)

We report the total return for various quality factors during the seven worst drawdowns for the S&P 500, the annualized (geometric) return during crisis, normal, and all periods, and the annualized Sharpe ratio, correlation to the S&P 500, and information ratio to the S&P 500. Portfolios are constructed to be dollar-neutral. Signal values are scored globally and we use no stock-level volatility scaling. All strategies are scaled to 10% annualized volatility (ex-post). The data run from 1986 to 2016.

Category	Name	Total return							Annualized return			Other statistics		
		Black Monday	Gulf war	Asian crisis	Tech burst	Financial crisis	Euro crisis I	Euro crisis II	Crisis (14%)	Normal (86%)	All (100%)	SR	Corr. to S&P500	IR to S&P500
Profitability	Cash flow over assets		0.4%	5.2%	239.9%	25.2%	9.6%	14.8%	45.3%	-1.6%	4.8%	0.44	-0.41	0.70
Profitability	Gross margin	0.9%	0.8%	3.6%	-30.1%	36.1%	12.7%	13.9%	5.6%	0.8%	1.5%	0.19	-0.04	0.21
Profitability	Gross profits over assets	-2.6%	-5.7%	-1.2%	125.3%	21.5%	2.9%	11.2%	25.3%	2.8%	5.8%	0.57	-0.12	0.63
Profitability	Low accruals		0.1%	3.9%	109.4%	4.6%	-5.1%	-11.4%	15.1%	2.2%	4.6%	0.45	-0.09	0.49
Profitability	Return on assets	-3.2%	0.5%	3.2%	152.9%	33.8%	11.8%	10.6%	36.3%	-1.8%	3.0%	0.31	-0.26	0.46
Profitability	Return on equity	-0.9%	-2.3%	1.2%	198.0%	16.4%	10.8%	10.1%	35.9%	0.0%	4.5%	0.43	-0.24	0.57
Payout	Net debt issuance	3.1%	9.8%	11.2%	102.5%	30.7%	-7.3%	-4.9%	26.2%	8.4%	10.8%	1.03	-0.12	1.10
Payout	Net equity issuance	-0.8%	2.5%	8.0%	165.9%	14.0%	5.9%	10.4%	34.1%	0.2%	4.5%	0.44	-0.36	0.67
Payout	Total net payouts over profits		7.7%	4.7%	70.6%	11.7%	15.8%	-1.2%	21.4%	-4.3%	-1.0%	-0.04	-0.23	0.07
Growth	Cash flow over assets (5y change)			-0.6%	55.7%	1.3%	15.2%	21.5%	18.5%	-1.0%	2.3%	0.24	-0.14	0.31
Growth	Gross margin (5y change)		-6.6%	-9.5%	-37.8%	1.2%	9.1%	8.1%	-9.6%	1.8%	0.1%	0.06	0.28	-0.07
Growth	Gross profits over assets (5y change)		-6.2%	-8.7%	-34.5%	5.5%	6.6%	7.3%	-8.1%	1.3%	-0.1%	0.05	0.30	-0.10
Growth	Low accruals (5y change)			-3.2%	-46.3%	17.2%	3.8%	0.8%	-9.2%	-1.3%	-3.6%	-0.25	0.22	-0.37
Growth	Return on assets (5y change)		-4.4%	-7.2%	19.9%	9.6%	13.0%	9.6%	8.3%	-1.2%	0.1%	0.06	0.02	0.05
Growth	Return on equity (5y change)		-8.0%	-9.5%	26.2%	11.3%	15.5%	15.1%	10.0%	-0.7%	0.9%	0.14	0.04	0.12
Safety	Low beta	8.2%	10.0%	8.9%	90.0%	16.1%	10.6%	19.5%	33.2%	-5.7%	-0.9%	-0.03	-0.74	0.48
Safety	Low idiosyncratic volatilty	3.4%	10.6%	11.8%	114.9%	22.0%	7.3%	12.7%	35.2%	-4.2%	0.7%	0.12	-0.55	0.46
Safety	Low leverage	0.0%	4.3%	3.3%	77.7%	-16.5%	-0.4%	-0.2%	10.5%	-2.3%	-0.5%	0.01	-0.22	0.12

In Table 13 we show the output of the following regression, performed using five-day returns, and as before defining the information ratio as the regression alpha divided by the standard deviation of the error.

$$R_t^{strategy} = \alpha + \beta^{Market} R_t^{Market} + \beta^{Size} R_t^{Size} + \beta^{Value} R_t^{Value} + \beta^{Mom} R_t^{Mom} + \varepsilon_t,$$
$$IR = \frac{\alpha}{\sigma(\varepsilon)} \times \sqrt{261/5}. \qquad [7]$$

As dependent variables we use the different quality composites reported on in Table 8, and as independent variables we use the market, size, value, and momentum factors used before in Table 5.

Table 13: Quality four-factor regression analysis, composites, various constructions (1986-2016)

We report the output of running the regression given in Equation [8] for various quality composites. T-statistics are based on Newey-West corrected errors (25 lags). We consider a dollar-neutral version (which is not sector neutral and without stock-level volatility scaling), three versions with one change compared to the dollar-neutral version, and a version with all three changes made simultaneously. All strategies are scaled to 10% annualized volatility (ex-post). The data run from 1986 to 2016.

Category	Construction	IR	Alpha (ann.)		Market factor		Size factor		Value factor		Mom. factor	
		Estimate	Estimate	[t-stat]	Estimate	[t-stat]	Estimate	[t-stat]	Estimate	[t-stat]	Estimate	[t-stat]
Profitability	Dollar-neutral	0.85	8.5%	[4.21]	-0.21	[-8.98]	-0.37	[-3.83]	-0.23	[-3.45]	0.09	[1.95]
Profitability	A: Beta-neutral	0.73	8.2%	[3.61]	-0.16	[-5.25]	-0.35	[-3.14]	-0.05	[-0.62]	0.06	[1.12]
Profitability	B: Sector neutral	0.86	8.7%	[4.23]	-0.21	[-8.94]	-0.37	[-3.87]	-0.19	[-2.72]	0.10	[2.02]
Profitability	C: Stock vol scaling	0.91	9.7%	[4.31]	-0.01	[-0.48]	-0.36	[-3.44]	-0.32	[-5.59]	0.02	[0.35]
Profitability	A+B+C	0.84	9.4%	[4.07]	-0.14	[-4.65]	-0.36	[-3.30]	-0.14	[-2.08]	0.04	[0.75]
Payout	Dollar-neutral	0.81	7.1%	[4.19]	-0.26	[-9.33]	-0.41	[-5.00]	0.39	[5.51]	0.06	[1.24]
Payout	A: Beta-neutral	0.89	8.8%	[4.54]	-0.13	[-4.05]	-0.43	[-4.28]	0.49	[6.15]	0.05	[0.88]
Payout	B: Sector neutral	0.83	7.3%	[4.34]	-0.26	[-9.40]	-0.40	[-5.02]	0.40	[5.70]	0.07	[1.35]
Payout	C: Stock vol scaling	1.12	11.4%	[5.66]	0.05	[2.04]	-0.45	[-3.95]	0.36	[5.11]	-0.01	[-0.27]
Payout	A+B+C	1.03	10.4%	[5.17]	-0.11	[-3.32]	-0.43	[-4.14]	0.45	[5.91]	0.02	[0.38]
Growth	Dollar-neutral	0.25	1.9%	[1.27]	0.12	[4.21]	0.01	[0.40]	-0.68	[-19.59]	0.06	[2.09]
Growth	A: Beta-neutral	0.07	0.6%	[0.40]	0.04	[1.64]	0.12	[5.12]	-0.66	[-16.54]	0.09	[2.34]
Growth	B: Sector neutral	0.26	2.0%	[1.35]	0.12	[4.53]	0.02	[0.70]	-0.69	[-20.45]	0.06	[1.91]
Growth	C: Stock vol scaling	0.07	0.6%	[0.34]	-0.01	[-0.29]	0.08	[3.12]	-0.67	[-19.60]	0.04	[1.19]
Growth	A+B+C	0.07	0.6%	[0.37]	0.04	[1.61]	0.21	[6.57]	-0.66	[-15.00]	0.06	[1.61]
Safety	Dollar-neutral	0.33	2.2%	[1.74]	-0.40	[-19.92]	-0.37	[-6.98]	0.34	[7.77]	0.09	[2.91]
Safety	A: Beta-neutral	0.50	5.1%	[2.58]	0.01	[0.31]	-0.37	[-4.28]	0.58	[7.87]	0.11	[1.99]
Safety	B: Sector neutral	0.32	2.1%	[1.70]	-0.40	[-20.16]	-0.36	[-7.24]	0.34	[8.07]	0.10	[3.19]
Safety	C: Stock vol scaling	0.67	6.8%	[3.45]	-0.04	[-1.47]	-0.41	[-5.64]	0.49	[8.84]	0.11	[2.81]
Safety	A+B+C	0.55	5.7%	[2.86]	0.03	[1.01]	-0.37	[-4.63]	0.57	[8.44]	0.11	[2.36]
Quality ALL	Dollar-neutral	0.81	6.3%	[4.07]	-0.38	[-18.67]	-0.46	[-5.61]	0.17	[2.81]	0.10	[2.29]
Quality ALL	A: Beta-neutral	0.87	9.4%	[4.29]	-0.09	[-2.73]	-0.48	[-4.05]	0.35	[4.14]	0.11	[1.76]
Quality ALL	B: Sector neutral	0.80	6.3%	[4.06]	-0.38	[-18.47]	-0.45	[-5.78]	0.18	[3.04]	0.11	[2.63]
Quality ALL	C: Stock vol scaling	1.20	12.8%	[5.70]	-0.03	[-1.25]	-0.56	[-4.81]	0.20	[2.92]	0.09	[1.78]
Quality ALL	A+B+C	1.01	10.9%	[4.94]	-0.05	[-1.53]	-0.49	[-4.20]	0.35	[4.37]	0.12	[1.93]