Abnormal gold, hedge fund and bond performance during bad times

Master thesis finance

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Abstract

In this study, an important question for financial market investors is investigated, namely which assets obtain an abnormal return during bad times. Bad times are defined as months in the dataset, which have a market excess return that falls in the lowest quartile of the sample. The assets discussed in this study are gold, hedge funds and bonds. The excess returns of these assets are regressed on an asset-specific multifactor model, including a dummy variable which takes the value of 1 when an investor finds herself in good times and 0 otherwise, in order to find the abnormal return during bad times for these assets. The findings of this study reveal that both treasury and corporate bonds are very good investments during bad times, providing both positive abnormal returns during bad times of 0.43% and 0.55% per month respectively along with a relatively good excess return during these bad times. These findings are also robust for different bad time definitions and models with time variation in the explanatory variables. For the other assets discussed in this study, no or relatively little evidence was found to support the claim that these assets are a good investment against bad times for financial market investors.

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1. Introduction

Over the past decades, numerous studies have looked at the performance of stocks, bonds and other asset classes. Most of these researches, however, focused on finding out how excess returns of these particular assets are explained, like Fama and French (1992) or how these returns performed compared to certain benchmarks, like Capocci and Hübner (2004). Surprisingly few studies, on the other hand, looked at the performance of these assets during different times of the economic cycle. The topic of the performance of certain assets during difficult economic times has often been neglected, which is weird since investors are generally risk averse, as is shown in several studies like the one from Sortino and Van Der Meer (1991) and therefore knowing which assets perform well during bad times seems like something valuable which investors would want to know. On top of that, most of the studies conducted on finding the performance of asset classes during different stages of the economic cycle, do this for only 1 asset class. An example of such a research is the paper of Cao et al. (2014), who look at the time conditioned performance of hedge funds or the study of Gormsen and Greenwood (2017), who only look at stocks. Thus far, there are very few papers which look at multiple asset classes at the same time and try to find which of these asset classes obtains an abnormal return during 'bad times'. This study aims to do just that and the main question this study will try to answer is therefore; which asset classes obtain an abnormal return during bad times?

Like mentioned before, there are very few papers as of yet which have looked at this topic, but there are ample studies which have looked at the performance of one singular asset class, like hedge/mutual funds, commodities or stocks, during different economic times. These studies will provide useful literature for possible models and a benchmark for what the results of this study might look like for a certain asset class. However, most of the studies conducted on the time dependant performance of an asset class, use various definitions of bad times and widely different models to define and find the performance of the asset class they are interested in. This study will combine a unique bad times definition with an asset specific factor model for each asset class in order to find whether an asset class obtains an abnormal return during bad times. Additionally, this study uses data up to the first quarter of 2020. A lot of papers which look at assets that are also discussed in this study use data up until 2011 or earlier. Using almost an extra decade of data for asset classes like hedge and mutual funds, which often only have data available from 1994 onwards, could lead to new insights and results on these asset classes. For example, the studies on hedge funds which use data up to 2011, only have the dot-com bubble and great financial crisis as periods which are regarded as truly bad times in their sample. Because this research uses data up to 2020, it can also look at the performance of these asset classes during other months in which the stock market dropped significantly. An example for such months is the cryptocurrency crash at the end of 2018, when the S&P 500 index dropped by more than 20% in the last quarter. Therefore, the combination of the up to date data with a unique and relevant bad times definition and a sound factor model, emphasizes the relevance, importance and uniqueness of this study within this field.

The main asset classes which this study will look at include gold, several hedge and mutual fund strategies and bonds. The reason as to why these assets specifically are looked at is based on Gormsen and Greenwood (2017). They argue that the best assets for an investor to hold during difficult economic times combines both a relatively good excess return during difficult times with an alpha during difficult times. Gold has proven, by for example Baur and Lucey (2010), to have on average positive excess returns during bad times. For the selection of the particular hedge fund strategies, I used a combination of available literature, as well as my own analysis to come up with the 3 most relevant styles. Firstly, based on the findings of Gormsen and Greenwood (2017), this study looks at a portfolio of hedge funds which invests solely in small value firms. Additionally, this study looks at the performance of the dedicated short bias and managed futures hedge fund strategy. The reason as to why these two specific hedge fund styles are looked at is based on their positive average excess returns during 'bad times', as is shown by Baele et al. (2020), Cao et al. (2014) and table 9 in the appendix. If this relatively good excess return during bad times can be combined with an abnormal return during these bad times, these funds could be a very interesting investment for investors who seek protection against bad times. Finally, bonds have shown to be negatively or very weakly correlated with stocks over the past decades. This makes them a good diversifying asset, but also shows their potential as an asset to invest in when the stock market turns sour. This asset will therefore be discussed as the third and final asset class in this study.

Because the literature thus far was unable to find a good universal definition of bad times and many different definitions of bad times have been used in studies throughout time, there will be a robustness check on the main regression results for different definitions of bad times. On top of that, the main regression of this study uses constant betas. Due to the fact that previous research like Lewellen and Nagel (2006) or Cao et al. (2014) has shown that betas of certain risk factors can vary over time and because I found that this might also be the case for the data used in this study, an additional robustness check is performed using a model that contains time-varying betas. In this check, I look if the abnormal return found in the main regression result stays approximately the same when using a model which accounts for possible time variation in betas.

2. Literature and hypotheses

2.1 Identifying bad times

The first issue discussed is the classification of the months within the dataset in good and bad times. There are ample studies in the finance spectrum which make a distinction in their data between good and bad times. However, the definitions of good and bad times used in these papers is vast and differs dramatically between them. There are two main overarching indicators (economic and financial) these studies use to make this time distinction, but these overarching indicators also have various ways to divide their data in good and bad times.

One of the main ways papers differentiate between good and bad states is to look at economic indicators. Tomz and Wright (2007), for instance, use the real GDP in the local currency of the country they were investigating as a proxy to see if the economy was in a good or bad state. Ruhm and Black (2002) use the unemployment rate as a measure for the economic conditions, whereas Zeichmeister and Zizumbo-Colunga (2013) defined economic bad times more on an individual consumer level. They looked at household income and defined an economic bad time as the time when the average household income of a region decreased over the past two years. This measure is, however, quite spurious, because a drop in the income of a region could be independent of the state of the economy in a country. The most popular economic method which is often used in papers, is to look at the business cycle conditions, like Lakonishok et al. (1994) and Petkova and Zhang (2005). Papers which use this method, often use the National Bureau of Economic Research (NBER) business cycle indicator. They classify a month or quarter as a bad time when this month or quarter is labelled as either a recession or depression by the NBER. However, this measure has some shortcomings as is mentioned by Huang et al. (2014). They point out that certain months, like May and June in 2009, are defined as recession months by the NBER, even though the bull market started in March 2009. Additionally, the definition of a recession by the NBER can be a bit strict. There are months outside the contraction periods in which there are corrections in the financial market. These are, however, not classified as recession months/quarters by the NBER. The NBER measure is therefore often seen as incomplete when identifying bad states of the economy.

The other main way papers often use to differentiate between good and bad times, is by means of a financial indicator. Petkova and Zhang (2005) and Hammami (2011), for example, use the market risk premium to define the state of the economy. Schwert (1989) and Hamilton and Lin (1996) show that using the volatility of the stock market is also an option to classify certain time periods in good and bad times. They show that economic recessions are the single largest factor that cause volatility in stock returns, accounting for 60% of the variance in stock returns. Another popular financial measure that is used in research is the bull and bear market measure. Bry and Boschan (1971) were the first to come up with a model which identified turning points of bull and bear markets. This model was later modified by Pagan and Sossounov (2003), who developed an algorithm which looks at more ‘censoring rules’, like a minimum bull and bear market length of six months or a minimum full cycle length of 16 months. These additional rules help define possible turning points with more precision and gives a better understanding of which months should be classified as bad times and which as good times. When using bull and bear markets as an indicator for good and bad times, bad times are classified as times when the market is labelled as a bear market, while good times are seen as times when the market is classified as a bull market.

Baele et al. (2020) define bad times using yet another financial measure. In their paper, a bad time is characterised by 3 things; (1) a large positive bond return accompanied by a large negative equity return, (2) negative high frequency correlations between bond and stock returns and (3) elevated market stress, observable by high equity market volatility. However, probably the most used financial measure in the recent literature, for instance by Huang et al. (2014) and Cao et al. (2014), is the 200-day moving average. With this measure the close of the S&P 500 price index on the last trading day of the month is compared with its 200-day moving average. When the value at the end of the month is less than (greater than or equal to) the moving average, they classify the month as a bad time (good time). In the research of Huang et al. (2014), this measure classifies 32% of the months as bad times, compared to the 14% with the NBER measure. The moving average result is consistent with Perez-Quiros and Timmermann (2000) and Henkel et al. (2011) who identify about 30% of periods as bad times with sophisticated Bayesian learning approaches and according to Paul A. Samuelson’s quip that “Wall Street indexes predicted nine of the last five recessions!”, there are more bad times or market crashes in the financial market than the real sector.

Gormsen and Greenwood (2017) combine the economic NBER measure with a financial measure. Their financial measure is based on the S&P500 index. According to them, a financial bad time is a quarter in which either the quarterly or the yearly US stock market excess return is in the bottom quintile of their sample, which runs from 1963-2013. By controlling for both shorter term quarterly as well as yearly excess returns, they ensure that bad quarters are periods of large drawdowns. Specifically, if the market drops dramatically in one quarter, and neither recovers nor worsens in the following quarter, then this following quarter is likely to be defined as a financial bad time despite having neither high nor low returns itself. A month is defined as a bad time when it is classified as both an economic and a financial bad time in their data. Letting the definition of a bad time depend on both an economic as well as a financial measure, ensures that the quarters which you end up with are seen as a period in which the market performs poorly, by almost every investor.

As shown, there are ample definitions of bad times in the literature. Considering all the previous research along with its pros and cons, the definition of bad times used in this research will be a different one than the definitions used in most of the other studies. Because I want to predominantly focus on bad times which are observed as bad times by financial market investors and not by for instance consumers, I focus my definition of bad times purely on the movement of the stock market. A month will therefore be classified as a bad time when the excess return of the market during that month falls in the lowest quartile of the dataset. Using this definition to classify months as good and bad times, I hope to find whether some asset classes obtain an abnormal return during times which are identified as truly bad times by almost all stock market investors. However, I will perform a robustness check on my results using the bad times definitions of Gormsen and Greenwood (2017), Pagan and Sossounov (2003) and Lakonishok et al. (1994), to check whether my main regression results are still the same when I use a different method to classify the months in my dataset as good or bad times.

2.2 Gold

The price of gold has risen substantially in the past months, surpassing $2000 per troy ounce on the 4th of august 2020. A lot of the times, a negative market return is accompanied by a rise in the gold price. This makes gold an interesting asset to consider for an investor who wants protection against difficult times. A lot of studies have, because of this reason, looked at the performance of gold during difficult economic times. The main question they asked themselves was whether gold is a good investment when the economy turns sour and thus whether gold can be seen as a safe haven. According to Baur and Lucey (2010), an asset can be considered a safe haven when it is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil. Not all the studies on the performance of gold came to the same conclusion when classifying gold as either a safe haven asset or not. On the one hand you have Erb and Harvey (2013) along with Ghazali et al. (2013) and others, who argue that gold cannot be seen as a safe haven. Erb and Harvey (2013) found in their rather simple analysis that in 17% of the times, a negative stock market return was accompanied by a negative gold return. In their opinion, this large of a percentage shows that gold can’t be seen as a reliable safe haven asset. Baur and Lucey (2010) on the other hand found similar results, but looked a bit further. They also found that gold doesn't always provide a positive return when the stock market goes down. But on top of that, they found evidence in their regression that shows that gold can be interpreted as a safe haven when there is a severe market disruption. This safe haven quality of gold does, however, last on average only 15 days after the first large negative market shock, in their sample. An investor that holds gold for more than 15 days after the first large negative shock, will experience losses on their gold position. These findings amplify the usefulness of gold in a portfolio that seeks to protect itself against times when the stock market performs incredibly poor.

However, in this research I am not particularly interested in the (excess) returns of gold when an investor finds herself in bad times, but whether gold can obtain an abnormal return during bad times. In the literature, there are not many factor models which explain the returns of gold and consequently provide an abnormal return for this asset. Most researches with a factor model for gold use gold stock excess returns as the dependant variable in their regression. In this research, the return of gold is calculated using the monthly return of the gold bullion index and not via gold stocks. The reason for the use of the Bullion index as a proxy for gold returns is because this study tries to find the abnormal return of the commodity gold. In order to achieve this, the excess return of gold has to be the dependent variable and this is best displayed by the bullion index. When using gold stocks on the other hand, the returns could be influenced by idiosyncratic risk, which the regression cannot account for. Additionally, most gold stocks don't track the real gold price perfectly.

One of the best factor models for explaining returns of gold, which is available in the current literature, is the one from Baur and Lucey (2010). They prove that both the contemporaneous as well as the lagged stock market return during difficult times affects the gold return. The fact that the lagged stock market return during extremely bad times affects the gold return is consistent with the safe haven property of gold, because investors tend to buy more gold when the lagged stock market return is extremely negative, therefore increasing the demand for gold and thus increasing the price and return. However, this lagged effect has only been proven to be significant for daily data and, as mentioned before, the safe haven property of gold only lasts, on average, 15 days. I expect, because of this, that adding a lag of the market will be less useful for my regression, because of the use of monthly data in this study. On top of that, Baur and Lucey (2010) find evidence that the lagged excess gold return during bad times, displays a significant relationship with the excess gold return.

In my analysis, the excess gold returns will be regressed on the excess market return, a 1-month lag of the excess market return and a 1-month lag of the excess gold return, just like Baur and Lucey (2010). On top of that, a dummy will be added that indicates whether an investor finds herself in a good or a bad time. With this regression I hope to find out whether gold obtains an abnormal return during bad times. Because Baur and Lucey only found (weak) statistical evidence for gold as a safe haven, which lasted only for approximately 15 days and because this study uses monthly data, my hypothesis is based on the results of Coudert & Raymond-Feingold (2011), who use an extension of the model of Baur and Lucey (2010) with monthly data and find no significant alpha. My hypothesis for gold is therefore that it will have no statistically significant abnormal return during bad times. I do, on the contrary, expect gold to have positive excess returns during bad times and a market beta of approximately 0.

2.3 Mutual and hedge funds

Several studies and news articles have shown that, on average, hedge funds consistently earn lower excess returns than for instance the S&P 500. Dichev and Yu (2011) even show that the real alpha which hedge funds provide for their investors is close to 0 and that their dollar-weighted average returns in absolute terms, after fees, are just marginally higher than the risk free rate. For mutual funds, the findings are more or less the same. Fama and French (2010) for example find in their data of which they claim to be relatively free of biases, that mutual funds underperform the CAPM three-factor and four-factor benchmarks by about the costs of the expense ratios. Even though this asset class doesn't seem to perform exceptionally well compared to the market, it is still a popular investment vehicle due to the different styles of funds and the unique diversification opportunities it brings to an investors' portfolio. This study will look at the strategies which are associated with relatively good performance during times when the economy is down. In this context, good performance is first associated with relatively high excess returns. The reason for this definition of good performance is because of the fact that this study is interested in assets which provide both a relatively high excess return, as well as an abnormal return during bad times. According to Gormsen and Greenwood (2017), an asset which generates both a relatively high excess return and an abnormal return during bad times, is the optimal asset an investor can hold during bad times.

The first fund strategy which this paper will look at, will be based on the findings of Gormsen and Greenwood (2017). They find that stocks which are in the highest 30th percentile of book-to-market and profitability combined with a market value below the median, provide the best portfolio for an investor to hold during bad times. A portfolio containing stocks with these characteristics returned both a significant good and bad times alpha, as well as a positive excess return during both good and bad times. Based on these results, small value funds will be looked at as the first fund style. The hypothesis is that these funds should show approximately the same results as the findings of Gormsen and Greenwood (2017), since they invest in more or less the same securities. Because I was unable to find a database with multiple funds which invest in the three characteristics mentioned above (small, value and profitability), the performance will probably be worse than the performance found by Gormsen and Greenwood (2017). On top of that, Gormsen and Greenwood (2017) don't account for any factors like value or size in their regression models, which might explain the extremely positive and significant alphas they found for the stocks which classified as small, value and profitable. This research, on the other hand, uses the Carhart four factor model, which might cause the alphas to become lower or even insignificant compared to the significant findings of Gormsen and Greenwood (2017).

The second fund strategy which will be looked at in this paper is the dedicated short bias strategy. The main objective of this strategy is to capture returns when the market performs (very) poor. Its average returns during bad times are therefore very positive, as can be seen in table 9. A handful of studies have already looked at this strategy and found more or less the same results. Both Connolly and Hutchinson (2011), Cao et al. (2014) as well as Frydenberg et al. (2017) found that the dedicated short bias strategy provided very positive excess returns during months which they defined as bad times. On top of that, Connolly and Hutchinson (2011) and Cao et al. (2014) both found an abnormal return which was significantly positive when looking at their whole sample, but Cao et al. (2014) didn't find an alpha significantly different from 0 during bad times, whereas Connolly and Hutchinson (2011) did. The different findings could be due to the two very different factor models they used between the studies. Connolly and Hutchinson (2011) used the 7-factor model as designed by Fung and Hsieh (2004), whereas Cao et al. (2014) used the Carhart four factor model. This study will also use the Carhart model, which is why it is expected that the findings of this study will be more in line with the findings of Cao et al. (2014). However, the extra decade of data along with the different bad times definition used in this study could definitely cause the results to differ between this study and the others done on this fund style. Nonetheless, the hypothesis for this strategy is that no abnormal return will be found during bad times, just as in the study of Cao et al. (2014).

The third and final strategy discussed in this paper is the managed futures hedge fund strategy. Just like the dedicated short bias strategy, most papers find approximately the same results. Baele et al. (2020), Frydenberg et al. (2017) and Cao et al. (2014) all find that the managed futures strategy obtains positive excess returns during days/months which they define as ‘bad times’. Cao et al. (2014) also find, using an 8-factor model, that this strategy achieves a significantly positive alpha during both good and bad times, as well as over the whole sample. The study of Frydenberg et al. (2017) actually finds the opposite. They find no evidence to support the claim that this strategy produces an abnormal return when looking at the data in their entire sample. On top of that they find that the market beta is time-varying, quickly turning negative at the end or just after a crisis period. Since this study uses the same managed futures data as Frydenberg et al. (2017), I expect that the results will be more or less the same. However, since this study uses a different factor model, which is almost the same as Cao et al. (2014), it would be interesting to see if the results are more in line with the findings of Cao et al. (2014).

2.4 Bonds

The third main asset class discussed in this paper is bonds. This study will try to find if government or corporate bonds achieve an abnormal return during bad times. Thus far, there is little literature available which looks to find if bonds generate an abnormal return and no literature which looks at the abnormal return of bonds during bad times. Most research done on this topic looks at corporate bonds. The most common factor model used to find whether these bonds have an abnormal return, is the five-factor model developed by Fama and French (1993). The first three factors in this model are the standard Fama-French factors: Market, small minus big (SMB) and high minus low (HML). The two other factors which they use in this regression are the term structure and the default risk premium. The term structure and default risk premium factors are also used in almost every factor model of bonds, like the one from Elton et al. (1995) or Chen et al. (1986). The term structure is defined as the difference between long- and short-term government bond returns. Elton et al. (1995) and Bessembinder et al. (2008), show that the main objective of this variable is to explain the relation between bond returns and interest rates. The default risk premium is defined by Fama and French (1993) and Elton et al. (1995) as the difference between a high yield corporate bond index return and a government bond index return. Almost every study which uses default risk premium as a variable in their factor models, like Fama and French (1993) and Elton et al. (1995), uses return series to compute this variable and thus not the yields of these bonds. This study will therefore also compute the default risk premium with the use of return series. Fama and French (1993) show in their daily dataset that investment grade bond portfolios obtain no abnormal return and that the term structure and default factor are the only significant factors. Bessembinder et al. (2008) share this conclusion for their monthly dataset. Elton et al. (1995) replaces the SMB and HML factors by a factor which represents the unexpected change in the gross domestic product and a factor which resembles the unexpected change in the consumer price index. With this new factor model, they come to more or less the same conclusions as Fama and French (1993), but Gutierrez et al. (2007) show that excluding the two macroeconomic factors of Elton et al. (1995) (GDP and CPI) doesn't affect the goodness of fit. Since all these studies have found that investment grade bonds capture no abnormal return, it will be interesting to see if this also holds for good and bad times. It could be that the abnormal return is significantly positive in bad times and negative in good times, causing the contemporaneous effect to be 0. However, my hypothesis will be that corporate bonds will have no abnormal return which is significantly different from 0 during bad times.

For government bonds, the most used models to test their performance aren't any different than the ones used for corporate bonds. The main factor model used to test for abnormal returns of government bonds is also the model developed by Fama and French (1993). In their research they find a positive monthly abnormal return of government bond portfolios with a 1-5 and 6-10 year maturity of 0.09% and 0.11% respectively. On top of that, their regression shows that all their variables are significantly different from 0 at the 1% level, apart for the SMB and HML factor. This makes sense since these variables don't seem to have any significant relation to the excess returns of government bonds. On the contrary to the results of Fama and French (1993), Bessembinder et al. (2008) find no significant abnormal return for government bonds in their monthly dataset using both the factor model of Fama and French and the one from Elton et al. (1995). These different findings are probably due to the different bond dataset and time period used between the studies. The hypothesis for treasury bonds will be more in line with the results of Bessembinder et al. (2008), because this study also uses more recent and monthly data. This means that it is not expected that government bonds will produce an abnormal return during bad times.

3. Research method

3.1 Empirical model

The main basic multifactor regression which will be performed for each individual asset class will be the following;

$$R_{i,t}^{e} = \alpha_i^b + \Delta_i 1_t^g + \beta_i(Mkt_t - Rf_t) + f_t'\theta_i + \varepsilon_{i,t}$$

Where the dependant variable, $R_{i,t}^{e}$, is the excess return of the particular asset of interest. α_i^b shows the abnormal return of the dependant variable during bad times and this is the coefficient this study is most interested in. Furthermore, the dependant variable is regressed on a dummy, 1_t^g, which is equal to 1 once an investor finds herself in months which are defined as good times months in the dataset and 0 otherwise. The Δ_i term represents the difference in abnormal return during bad and good times. When adding this term to the α_i^b term, you will find an approximation of the abnormal return during good times. On top of that there is a market factor β_i, which represents the exposure of the dependant variable to the movement of the market and there are other relevant factors. The other relevant factors are shown via f_t' in this regression. Where f_t' is the vector of the selected factors' excess returns which are used to explain the independent variable and θ_i is the risk exposure/loading of the factors to the corresponding asset. The factors used to find whether an asset captures an abnormal return during bad times will vary between the assets and will, predominantly, be based on the literature.

I hope to find that the errors are independent and identically distributed, meaning that they have no serial correlation and are homoscedastic. Especially the homoskedasticity assumption is unlikely to hold in my models, so robust standard errors will be used when the p-value of the Breusch-Pagan test is lower than the 5% level. On top of that I assume that the error term has a population mean of 0 and that all the independent variables of a model are uncorrelated with the error term. As explained before, the main objective of this study is to find asset classes which have a significantly positive abnormal return during bad times. This means that α_i^b has to be both greater than, and statistically different from 0. The factors used for the various asset classes, will be very different. For Gold, the market factor, a 1 month lag of the market factor and a 1 month lag of the gold excess return will be used as factors, since previous research has found no other factors which are useful in explaining the excess gold returns (as is also shown in the literature section). Applying this, I got to the following regression for Gold;

$$R_{gold,t}^{e} = \alpha_i^b + \Delta_i 1_t^g + \beta_i(Mkt_t - Rf_t) + \gamma_i(Mkt_{t-1} - Rf_{t-1})1_t^b + \delta_i(R_{gold,t-1}^{e})1_t^b + \varepsilon_{i,t}$$

Where $R^e_{gold,t}$ is the excess return of gold at time t and α_i^b shows the abnormal return of gold during bad times. Δ_i represents the difference in abnormal return of gold during bad and good times, which implies that the abnormal return during good times is the sum of α_i^b and Δ_i. β_i shows the market exposure of gold and γ_i and δ_i show the exposure of the gold excess return to the 1-month lagged market excess return and the 1-month lagged gold excess return respectively. These variables are multiplied by the dummy, 1_t^b, which is equal to 1 when an investor finds herself in bad times and equal to 0 whenever an investor finds herself in good times.

For hedge and mutual funds, more factors will be used. First off, the 4 factors as described by Carhart (1997) will be used for every hedge fund strategy discussed in this study. This means that every hedge and mutual fund strategy will have the 3 basic Fama French factors, namely the market, SMB and HML factor, as well as a momentum factor. The reason for the use of the 4 factor model instead of, for instance, the Fama French 3 factor model, is the fact that previous studies like Baele et al. (2020), Cao et al. (2014) and Carhart (1997) have shown that this model can explain returns of hedge and mutual funds extremely well. Fung and Hsieh (2001) and Cao et al. (2014) show that managed futures funds also have a significant exposure to currency, commodity and bond trend following factors. This strategy will therefore have an additional three factors added to its regression. The regression performed on the 3 Strategies examined in this study, will look the following;

Small value and Dedicated short bias fund regression:

$$R^e_{Fund\ strategy,t} = \alpha_i^b + \Delta_i 1_t^g + \beta_i(Mkt_t - Rf_t) + s_i SMB + h_i HML + m_i MOM + \varepsilon_{i,t}$$

Managed futures hedge fund regression:

$$R^e_{MF,t} = \alpha_i^b + \Delta_i 1_t^g + \beta_i(Mkt_t - Rf_t) + s_i SMB + h_i HML + m_i MOM + c_i TFCURR \\ + g_i TFCOMM \varepsilon_{i,t} + b_i TFBOND + \varepsilon_{i,t}$$

Here, the dependant variable is the excess return of the particular fund strategy I look at. α_i^b is the abnormal return that the strategy of interest produces during bad times. Δ_i is multiplied by a dummy, 1_t^g, which is equal to 1 once an investor finds herself in good times according to the dataset and equal to 0 when an investor finds herself in bad times. Δ_i is therefore an estimation of the difference in abnormal return during bad and good times and $\alpha_i^b + \Delta_i$ is an approximation of the abnormal return of the strategy during good times. The first three factors; β_i, s_i and h_i, are the Fama French factors and show the exposure of the fund towards the market, small size firms and high value firms respectively. These factors are computed in the same way as Fama and French (1992). Furthermore, there is the momentum factor, m_i, which is short in low momentum stocks and long in high momentum stocks[1]. The last three factors from the managed futures regression are the Fung and Hsieh (2001) lookback straddles. These factors represent the maximum pay-out a trend following strategy can obtain by using a lookback straddle strategy, according to Fung and Hsieh (2001)[2].

For bonds, most research on factors is based on funds which invest (partially) in bonds. In this study, the S&P US treasury bond index and the BofA corporate bond index will be looked at and thus not any bond funds. Factor models like the one from Bessembinder et al. (2008) among ample others, which include an SMB, HML or other factors that are primarily related to the market, show little significance in regressions explaining treasury bond returns. The most prominent factor model to regress treasury bond index excess returns on other factors is the one from Elton et al. (1995). This model has 3 main factors. The first factor is the standard market factor used in, for example, the Fama French 3 factor model. This factor accounts for the general economic conditions according to Elton et al. (1995). Furthermore, you have the term structure variable, which is the difference between long- and short-term government bond returns. Elton et al. (1995) and Bessembinder et al. (2008), show that the main objective of this variable is to explain the relation between bond returns and interest rates. The third and final variable is the default risk premium variable. This is the difference between a high yield corporate bond index and a government bond index, matching maturities such that the difference between the two variables is due to default risk and not term structure risk. In the regression performed in this research, a dummy indicating whether an investor finds herself in either good or bad times will be added. The regression is not optimal, as is also mentioned by Bessembinder et al. (2008), but it is one of the best models available in the current literature to find abnormal bond returns. The main regression performed for the bond asset class will look the following;

$$R_{bond,t}^{e} = \alpha_i^b + \Delta_i 1_t^g + \beta_i(Mkt_t - Rf_t) + d_i DRP + t_i TERM + \varepsilon_{i,t}$$

Where $R_{bond,t}^{e}$ is the excess returns of the bond index. α_i^b represents the abnormal return during bad times and Δ_i shows the difference in abnormal return between bad and good times. Adding these two variables together results in the abnormal return of the relevant bond index

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[1] For the complete computation of this factor, visit the data library of Kenneth French; https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html

[2] Data on Fung and Hsieh trend following factors is obtained from David A. Hsieh's data library; https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

during good times. $(Mkt_t - Rf_t)$ measures the market risk premium at time t and β_i represents the exposure of the respective bond index of interest towards the market. When looking for the abnormal return of corporate bonds, an extra regression using the Fama and French SMB and HML factors will be done, to check whether these factors have some explanatory value or if they are very insignificant like in the research of Fama and French (1993). d_i measures how sensitive the dependant variable is to changes in the default risk premium. t_i shows the sensitivity of the dependant variable to changes in the interest rate between maturities.

3.2 Data collection and description

Table 1
Abbreviations and description of asset classes and risk factors used in this study

This table gives a description of the main asset classes and risk factors used in this study, along with their abbreviations.

Main asset classes

Description	Abbreviation
Gold Bullion $/troy ounce index excess return	Gold
LIPPER small cap value funds index excess return	SmV
Credit Suisse dedicated short bias hedge funds portfolio	DSB
Credit Suisse managed futures hedge funds portfolio	MF
S&P US treasury bond index excess return	TBond
ICE BofA US corporate bond index excess return	CBond

Risk factors

Description	Abbreviation
1-month risk free US treasury bill rate	Rf
Market excess return	Mkt-Rf
Fama-French size factor	SMB
Fama-French value factor	HML
Carhart momentum factor	MOM
Fung-Hsieh currency lookback straddle excess return	TFCURR
Fung-Hsieh commodity lookback straddle excess return	TFCOMM
Fung-Hsieh bond lookback straddle excess return	TFBOND
US long-term government bond rate - 1 month T-bill rate (FF 1992)	TERM
S&P 5-10 year HY index return – S&P 5-10 year treasury index return	DRP

The asset class data is collected from several sources. First off, the data on the gold asset class. The returns of gold are computed with the use of the Gold Bullion index. The data on this index is obtained via DataStream. The returns are computed by using the following formula;

$$R_{gold,t} = \frac{Gold_t - Gold_{t-1}}{Gold_{t-1}} * 100\%$$

Where $Gold_t$ represents the Gold Bullion index level at time t and $Gold_{t-1}$ is the Gold Bullion index level at time t-1.

For the hedge fund asset class, I would have liked to use the LIPPER TASS hedge fund data, since this database is used the most in research on hedge funds. Unfortunately, this data was largely unavailable to me, meaning that only the small value hedge fund style strategy uses data from the LIPPER database. The data represents the average return of hedge funds which are classified as small value funds within the LIPPER database. The LIPPER small value hedge fund data is obtained via DataStream. For the dedicated short bias and managed future strategy, I used data from the Credit Suisse database. This database is used in several studies on hedge funds performance like Frydenberg et al. (2017) and contains data on more than 9000 funds. It divides these funds into 10 fund style subcategories. Each subcategory represents at least 85% of the AUM in the representative index universe. All the indices are value weighted and rebalanced monthly. Additionally, the data is relatively free of survivorship bias. This is due to the fact that the index does not remove funds in the process of liquidation, and therefore captures all of the potential negative performance before a fund ceases to operate. Summary statistics of all the different hedge funds types from the Credit Suisse database are given in table 9. The data on these hedge funds is retrieved from the Credit Suisse website[3].

The third and final asset class, bonds, looks at government and corporate bonds. Returns on both bond categories are calculated the same way as the return on gold;

$$R_{bond,t} = \frac{Bond_t - Bond_{t-1}}{Bond_{t-1}} * 100\%$$

Where $Bond_t$ is the index level of a particular bond index at time t and $Bond_{t-1}$ is the level of the same index at time t-1. The data on treasury bonds in retrieved from DataStream and represents an S&P 500 index of treasury bonds. The index invests in treasury bonds with multiple maturities and is therefore a good approximation as a general treasury bond index. The data on the corporate bond index is retrieved from the website of the Federal Reserve Economic Data (FRED)[4]. This index is from the Bank of America and tracks the performance of US investment grade rated corporate debt which is publicly issued. For an investment grade bond

[3] All the Credit Suisse hedge fund data is retrieved from; https://lab.credit-suisse.com/

[4] Website FRED; https://fred.stlouisfed.org/

to be included in this index, it has to have a maturity of at least 1 year, a fixed coupon schedule and a minimum amount outstanding of $250 million.

The data on risk factors is collected from several different sources. First off, the Fama-French three factor data among with the Carhart momentum factor and the risk free rate, are all retrieved from the data library of Kenneth French[5]. The market factor is the excess return of a value weighted CRSP index which includes stocks from NYSE, AMEX and NASDAQ that have a share code of 10 or 11. The risk free rate is the 1-month treasury bill rate and the SMB and HML factors are computed the same way as Fama and French (1992)[5]. For the momentum factor, the returns are calculated by deducting 2 portfolios of stocks which were in the lowest 30th percentile of returns in the prior 2-12 months, from 2 portfolios of stocks which were in the highest 70th percentile of returns in the prior 2-12 months. Furthermore, there are three trend-following risk factors which are used in the managed futures regression. The first factor is the currency lookback straddle excess return, which represents the optimal excess returns of the currency straddle strategy ex post. The other trend-following factor is the commodity lookback straddle. This factor represents the optimal excess returns of the commodity straddle strategy ex post, as explained by Fung and Hsieh (2001). The third factor is the bond trend-following factor, which represents the bond straddle strategy that obtained the highest excess returns ex post. These trend following strategies achieve above average returns when the market is distressed, which explains their usefulness in explaining the returns of the managed futures strategy. Fung and Hsieh (2001) show that these factors are only useful for about 5-10% of the funds in their data, which is also approximately the amount of managed futures funds in their database. The data on these strategies is retrieved from the hedge fund data library of David A. Hsieh and is computed in the same way as in Fung and Hsieh (2001).

Furthermore, there are the bond specific factors. The term structure is computed in the same way as Fama and French (1993) and Elton et. al (1995) did, meaning that the 10-year (long-term) government bond yield is deducted by the 1-month treasury bill rate. The default risk premium variable is also calculated using the methodology as Fama and French (1993) and Elton et al. (1995). They both use a return series of a high yield index and a treasury bond index with corresponding maturities. The default risk premium variable is thereafter calculated by deducting the return on the treasury bond index from the return on the high yield index. In this study, the ICE BofA US 5-10 Year High Yield index is used as the high yield return proxy. For the treasury bond return proxy, the S&P 5-10 Year treasury index is used. Note that the

[5] Data and methodology used to compute the SMB and HML factors can be found via the following link; https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

maturities of the two indices are the same to ensure that there is not some sort of term premium in this variable and thus that this variable gives the best approximation of the default risk premium. The data on the 10-year long term government bond and the high yield index is retrieved from the FRED website, the data on the 1-month treasury bill rate is from Kenneth French' data library and the S&P 5-10 year treasury index is obtained from DataStream.

3.3 Summary statistics

From the summary statistics of the main regression factors displayed in table 2, several things can be observed. Firstly, bad times can be seen as really bad times when looking at the annualized market excess return, which is -57.8% and good times can be seen as really good times, with an annualized market excess return of more than 33%. These results are in line with my expectations, since I use the excess market returns as the key variable to divide the months in my dataset in good and bad times and the market returns are highly correlated with the market excess returns. The use of the excess market returns to divide the sample in good and bad times helps to explain two other noteworthy things in table 2. First off, it helps to explain why the standard deviation of the market is lower in both good and bad times than the standard deviation of the market in the entire sample. Because the market excess return is used to divide the sample between good and bad times, the datapoints during good (bad) times are predominantly positive (negative) and skewed towards 0 with relatively little outliers, causing the standard deviation to be relatively low compared to the standard deviation of the entire dataset, which contains both datapoints which are very negative as well as very positive. Secondly, the use of the market excess returns to divide the sample in good and bad times explains why the market returns are negatively skewed during bad times. Most of the observations during bad times are small negative market returns, causing the return distribution to be more distributed to the right.

The summary statistics results for the SMB, HML and momentum factors are more or less in line with the findings of previous studies. However, it is quite surprising that both the SMB and MOM factors obtain their lowest returns during good times. There could be several explanations as to why this happens, such as a sudden month of very positive returns for the short side of the portfolio which is used to create the factor.

Table 2
Summary statistics of the factors used in the regression models of this study

This table presents the summary statistics of the independent variables used in this study for both good and bad times, as well as the whole sample. The mean represents the average annualized return of an asset and sd is the standard deviation, displayed in an annualized percentage. The min. and max. are abbreviations for the minimum and maximum value of a factor respectively and are displayed as annualized percentages.

	Factors	Number of months	Mean (%)	Sd (%)	Min.	Max.	Skewness	Kurtosis
	Rf	468	4.5	0.9	0	16.8	0.55	3.4
	Mkt	468	33.4	10.3	-28.8	193.2	0.88	4.8
	SMB	468	6.9	10.3	-202.8	260.4	0.81	11.2
	HML	468	0.3	9.3	-118.8	103.2	-0.09	4.8
Good times	MOM	468	5.2	15.0	-412.8	220.8	-1.67	15.5
	TFCURR	243	-29.7	67.9	-381.6	1197.6	1.75	7.8
	TFCOMM	243	-12.1	48.8	-296.4	904.8	1.34	6.6
	TFBOND	243	-37.4	51.2	-319.2	1256.4	2.22	14.0
	DRP	281	11.4	8.7	-168.4	151.0	-0.32	10.3
	TERM	468	1.78	0.4	-3.6	6.2	-0.27	3.1
	Rf	156	4.9	1.0	0	15.6	0.63	3.4
	Mkt	156	-57.8	11.3	-278.4	-22.8	-2.03	9.2
	SMB	156	-15.6	10.2	-118.8	87.6	0.12	3.2
	HML	156	11.8	12.2	-169.2	154.8	-0.31	5.7
Bad times	MOM	156	15.2	14.3	-115.2	150.0	0.02	3.6
	TFCURR	72	64.7	70.0	-297.6	830.4	1.18	4.5
	TFCOMM	72	30.1	56.3	-241.2	777.6	1.28	4.8
	TFBOND	72	77.6	71.9	-286.8	826.8	0.99	3.4
	DRP	82	10.0	13.8	-203.6	190.0	-0.54	9.7
	TERM	156	1.53	0.4	-2.88	4.99	-0.36	2.9
	Rf	624	4.6	1.0	0	16.8	0.59	3.4
	Mkt	624	10.6	15.7	-278.4	193.2	-0.56	4.8
	SMB	624	1.3	10.6	-202.8	260.4	0.56	8.7
	HML	624	3.2	10.2	-169.2	154.8	-0.07	5.4
Entire dataset	MOM	624	7.7	14.9	-412.8	220.8	-1.29	13.0
	TFCURR	315	-8.1	69.2	-381.6	1197.6	1.56	6.7
	TFCOMM	315	-2.4	50.8	-296.4	904.8	1.34	6.1
	TFBOND	315	-11.1	58.3	-391.2	1256.4	1.83	8.8
	DRP	363	6.53	10.4	-203.6	190.0	-0.78	11.6
	TERM	624	1.72	0.4	-3.7	6.2	-0.32	3.1

The Fung and Hsieh straddle strategies results for the entire sample are relatively comparable to the results of Fung and Hsieh (2001). However, using almost two decades of extra data caused the average annualized mean return for all the strategies to turn negative in my sample. On top of that, it can be seen that these strategies provide an exceptional bad times excess return, which is as expected, since these strategies are specifically made to do this by Fung and Hsieh. These strategies only give a very positive return when the market goes up or down by a significant amount. This is also the reason why the straddle strategies give such a high return during bad times and not during good times. During the bad months in the sample, these strategies return a lot, but during the good months within the sample, the very good return of the straddle strategies during the extremely positive market shocks is accompanied by a relatively large amount of months when these straddles don't pay off and thus give a negative return. This causes the trend following factors mean returns to become negative during good times.

The summary statistics on the default risk premium are slightly higher than the values found in other studies. Fama and French (1993), only found an average annual default risk premium of 0.24% in their sample, compared to the 6.5% found in the sample used in this study. The difference in the DRP between the studies could be due to the different time periods or the difference in return indices used to compute the DRP. However, it is unlikely that these reasons fully explain the difference in findings of the DRP between this study and the study of Fama and French (1993). Therefore, some caution should be taken when interpreting the DRP results. The results for the TERM factor are more or less in line with the findings of Fama and French (1993). The results of Fama and French (1993) are slightly lower, but this can be explained by the different long term bond index used in this study compared to the one from Fama and French (1993), along with the additional 30 years of data used in this study. However, it is remarkable that there is little difference in returns of the DRP and TERM factors between good and bad times. As Fama and French (1989) and Chen (1991) point out that the values of these factors should vary over time. Intuitively, the DRP should be higher during bad times than good times, since the risk of default usually rises during bad times and consequently, the DRP should also rise. Chen (1991) also argues that the TERM factor should be higher around bad times than good times. These time variations don't seem to hold for the dataset used in this study. This could indicate that these variables are computed incorrectly or that these assumptions don't hold for the good and bad times definition used in this study. Furthermore, the skewness and kurtosis of the other factors seems to be in line with the results of previous studies. Finally, the minimum and maximum annualized return of some factors is very large, but this is due to the fact that the most extreme monthly returns are transferred to an annualized return. When you look at these minimum and maximum returns on a monthly basis, they are comparable to the findings of other studies.

Table 3
Summary statistics of the asset classes discussed in this study

This table presents the summary statistics of the asset classes examined in this research. The time period shows the start and end date of the data of a particular asset. The mean represents the average annualized return of an asset and sd is the standard deviation, displayed in an annualized percentage. SR is the annualized Sharpe ratio and min. and max. are abbreviations for minimum and maximum respectively and are displayed in annualized percentages.

	Factors	Time period	Number of months	Mean (%)	Sd (%)	SR	Min.	Max.	Skewness	Kurtosis
	Gold	1968/03-2020/03	468	3.7	20.1	0.18	-272.4	447.6	1.1	9.0
	SmV	1989/01-2020/03	290	13.8	17.1	0.81	-199.2	277.2	-0.2	5.7
Good times	DSB	1994/01-2017/01	212	-27.2	11.6	-2.34	-135.6	70.8	-0.0	2.6
	MF	1994/01-2020/03	243	1.8	10.8	0.17	-117.6	108.0	-0.1	3.0
	TBonds	1990/01-2020/03	281	1.2	3.3	0.36	-43.2	36.0	-0.0	4.0
	CBonds	1973/01-2020/03	428	5.6	5.9	0.95	-98.4	128.4	0.8	10.5
	Gold	1968/03-2020/03	156	7.8	21.3	0.37	-160.8	364.8	1.3	7.9
	SmV	1989/01-2020/03	84	-0.14	17.8	-0.01	-187.2	174.0	-0.4	4.0
Bad times	DSB	1994/01-2017/01	65	58.4	14.5	4.02	-74.4	267.6	0.8	6.6
	MF	1994/01-2020/03	72	5.5	12.7	0.43	-92.4	114.0	0.2	2.6
	TBonds	1990/01-2020/03	82	5.2	4.5	1.16	-31.2	54.0	-0.0	3.2
	CBonds	1973/01-2020/03	138	-4.8	7.0	-0.69	-114.0	62.4	-1.2	7.0
	Gold	1968/03-2020/03	624	4.7	20.4	0.23	-272.4	447.6	1.2	8.7
	SmV	1989/01-2020/03	374	10.7	17.3	0.62	-199.2	277.2	-0.2	5.3
Entire	DSB	1994/01-2017/01	277	-7.1	16.2	-0.44	-135.6	267.6	0.7	4.4
dataset	MF	1994/01-2020/03	315	2.6	11.3	0.23	-117.6	114.0	0.0	2.9
	TBonds	1990/01-2020/03	363	2.1	3.6	0.58	-43.2	54.0	0.1	3.9
	CBonds	1973/01-2020/03	566	3.0	6.3	0.48	-114.0	128.4	-0.0	9.7

From the results in table 3 can be observed that nearly all assets obtain a positive excess return during both good and bad times. This is as expected since the assets used in this study were chosen on the basis that they achieved a relatively good excess returns during bad times. The reason as to why I did this was because Gormsen and Greenwood (2017) found that the optimal asset to hold during bad times was an asset which combines an alpha during bad times with a relatively good excess return during bad times. Gold has an average excess return of approximately 5% with a standard deviation of around 20% within the sample, which is comparable to the results found by Baur and Lucey (2010) and Erb and Harvey (2013). My summary statistic results for the small value funds are quite comparable to the results Gormsen and Greenwood (2017) found for small value stocks. The small value funds give an annualized excess return over the whole sample of nearly 11%, just about outperforming the market and just like the small value stocks in the sample of Gormsen and Greenwood (2017), the small value funds achieve an excess return of approximately 0 in bad times. These results give a good first indication that these funds might be an attractive asset to hold if an investor wants to protect herself against bad times. For the dedicated short bias strategy, the excess returns and standard deviation are in line with my hypothesis and the findings of earlier studies, namely a very negative annualized excess return during good times and a very positive excess return during bad times. The Credit Suisse hedge fund database stopped collecting data on dedicated short bias funds at the start of 2017 due to a lack of funds which could be classified as dedicated short bias funds. Looking at the results for the managed futures strategy, the same can be said. Earlier research like the one from Baele et al. (2020), has shown that the average annual return of this strategy is around 5% during bad times. The managed futures numbers are also in line with for example Frydenberg et al. (2017), who use the same managed futures dataset as this study. This means that the managed futures strategy has a positive excess return during both good and bad times, as well as an annualized standard deviation of around 12%, a skewness of approximately 0 and a kurtosis of about 3.

When looking at the return of the bond indices used in this study, my hypothesis in the earlier part seem to come true. Corporate bonds have both a higher excess return and standard deviation over the whole sample than treasury bonds. However, the corporate bonds perform worse than expected during bad times, achieving an average return of -4.8%, while the return on treasury bonds improves drastically compared to the returns of this asset during good times. These events might, for a part, cause one another, meaning that bond investors switch from corporate to government bonds during bad times, causing the return of treasury bonds to increase during bad times, while the returns of corporate bonds decrease. Another reason for the relatively good return of treasury bonds during bad times could be that investors like a safe investment when the market drops. Treasury bonds are usually seen by investors as this safe investment. However, finding the exact reason which explains why corporate bond returns are low during bad times is a potential topic for another study. Another remarkable finding of table 3 is that the biggest negative return of all the assets discussed, except corporate bonds, actually occurs during good times. The expectation was to find this for the dedicated short bias strategy and for treasury bonds, but not for the other assets. I can't find a reasonable explanation for this result, apart from the fact that there just might have been a large negative surprise regarding the specific asset during good times. Furthermore, the skewness is surprisingly low for most assets, but the kurtosis results are in line with other studies, meaning that the sample data has heavier tails than data which is normally distributed. Finally, just as with the explanatory factors in table 2, the minimum and maximum annualized return of some asset classes are extremely big, but this is due to the fact that one extreme monthly return is computed to an annualized return. When you look at these minimum and maximum returns on a monthly basis, they are comparable to the findings of other studies.

4. Empirical results

4.1 Main regression results

4.1.1 Gold

In table 4 the main regression results for gold are displayed. As hypothesized, no evidence for an abnormal return which is statistically different from 0 is found for bad times and there is no statistical difference between good and bad times abnormal return for gold. The confidence intervals of these variables are also quite extensive, affirming their insignificance and ensuring that no useful inference can be made on these variables. Like mentioned in the literature section, no paper has looked specifically whether gold obtains an abnormal return during difficult times. However, both Baur and Lucey (2010), as well as Coudert and Raymond-Feingold (2011), find a negative alpha coefficient for gold. Both of their models, however, focus on finding out whether gold can be seen as a hedge or a safe haven asset, which might influence their abnormal return results. Almost all studies on gold find a market exposure of approximately 0, as was also the hypothesis made in this study. The result displayed in table 4 is in line with this hypothesis, failing to find evidence that supports that the market beta of gold is statistically different from 0. Both the γ and δ, which represent the exposure to the lagged market excess return and the lagged gold excess return during bad times respectively, don't provide any evidence that these variables effect the gold price. This partially contradicts the findings of Baur and Lucey (2010), who find that these variables are only significant when they represent the lowest 5% of the observations of the respective variable in the dataset. In this dataset, the lowest quartile of market returns within the sample is used as a dummy for these variables, therefore probably causing the results to turn insignificant. On top of that, Baur and Lucey (2010) found the lagged effects only in a dataset containing daily data and not monthly. This could be another explanation for the different findings between this study and Baur and

Lucey (2010). Nonetheless, the δ coefficient is still positive, suggesting that there is a positive relation between the excess gold return during bad times and the excess gold return. The goodness of fit of the regression model is also really low, indicating that gold still has a lot of idiosyncratic risk based on these factors.

Table 4
Gold main regression results

This table presents the estimation results for the multifactor gold model;

$$R^e_{gold,t} = \alpha^b_i + \Delta_i 1^g_t + \beta_i(Mkt_t - Rf_t) + \gamma_i(Mkt_{t-1} - Rf_{t-1})1^b_t + \delta_i R^e_{gold,t-1}1^b_t + \varepsilon_{i,t}$$

Where $R^e_{gold,t}$ is the excess return of the gold bullion index at time t, α^b_i is the abnormal return of gold during bad times, Δ_i is the coefficient that shows the difference between the good and bad times abnormal return of gold and 1^g_t is a dummy which is equal to 1 when an investor finds herself in good times and 0 when an investor finds herself in bad times. β_i and γ_i, represent the exposure to the market risk premium (MRP) and the 1-month lag of the market risk premium respectively. δ_i is the term that shows the exposure towards the 1-month lag of the excess gold return. 1^g_t is a dummy which is equal to 0 when an investor finds herself in good times and 1 when an investor finds herself in bad times. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively, according to heteroskedastic robust t-statistics.

Coefficient	Estimate	Confidence interval
α^b	0.74	[-1.02 2.51]
Δ	-0.25	[-2.55 1.66]
β	-0.07	[-0.27 0.12]
γ	0.09	[-0.26 0.44]
δ	0.20	[-0.06 0.46]
R^2	1%	

4.1.2 Hedge & Mutual funds

Small value funds

The regression with the LIPPER small value funds portfolio excess return as dependant variable, returned a monthly abnormal return of 0.09% during bad times. This abnormal return is not significantly different from 0 and its 95% confidence interval ranges from values lower and greater than -1% and 1% respectively. The Δ coefficient for the small value funds is greater than 1% per month, suggesting that the abnormal return of small value funds is greater during good times than the abnormal return during bad times. However, this number is also not significantly different from 0, which means there is no sound evidence to support the claim that small value funds obtain a significant abnormal return during good and bad times. These findings contradict the results of Gormsen and Greenwood (2017), who find that stocks which are classified as small, value and profitable stocks obtain an abnormal return during both good and bad times. Note, however, that they don't account for any explanatory factors apart the market factor which could be a reason why they find abnormal returns in their study. Other reasons for the different findings between this study and the one from Gormsen and Greenwood (2017) could be the different bad times definition, the different time period or the different data used between this study and the one from Gormsen and Greenwood (2017). The market beta is approximately 0 and thus in line with my hypothesis and previous research. Both the SMB and HML factors are, as expected, statistically larger than 0, indicating that these funds are more heavily invested in small and high value firms. These results amplify the validity of the LIPPER index database as the data for small value funds. The goodness of fit of this strategy is relatively low at 7%, meaning that there is still a lot of idiosyncratic risk which is not explained by this model. Adding other factors could improve the goodness of fit of this model and maybe turn the abnormal return significant, but these factors are yet to be found in the literature.

Dedicated short bias

Like mentioned before, the dedicated short bias strategy is renowned for its exceptional performance in difficult times. This is because it can be seen as being short the market for a large part, so when the market performs poorly, it should be expected that this strategy yields good returns. However, if it also provides an abnormal return during bad times, it would be even more of an attractive asset to hold when an investor wants to optimally protect herself against bad times. From table 5 can be seen that this study has found no evidence that dedicated short bias funds capture an alpha during bad times. The 95% confidence interval of the bad times abnormal return clearly shows that it could be both pretty negative (-0.5% per month) or really positive (1% per month). The Δ of the dedicated short bias strategy is also insignificant and doesn’t help in finding out whether the abnormal return during good times is positive or negative. These findings on abnormal returns for dedicated short bias funds are in line with the findings of Frydenberg et al. (2017), who use the same Credit Suisse hedge fund data and find no significant abnormal return during either good or bad times. Cao et al. (2014) on the other hand, find weak statistical evidence that dedicated short bias funds do achieve an abnormal return of 0.43% per month. The different findings between this and Frydenberg et al. (2017) studies and the study from Cao et al. (2014) is therefore probably largely due to the difference in data used. In line with my hypothesis and other studies like Frydenberg et al. (2017) and Cao et al. (2014), the market beta is significantly negative at -0.77. This amplifies the magnitude of the short positions these funds usually find themselves in. The significantly negative SMB loading of -0.32 is also in line with the results of both Frydenberg et al. (2017) and Cao et al. (2014) who find values of -0.32 and -0.36 for the SMB loading respectively. This negative loading implies that the dedicated short bias funds have a greater exposure to relatively large firms compared to relatively small firms. The HML and momentum variables are both insignificant, which seems plausible since this strategy doesn't tend to invest more in value firms than growth or vice versa. The r-squared at 73% is relatively high and comparable to earlier studies done on this strategy. The high r-squared value also underlines the explanatory power of the multifactor model used in this study over the dedicated short bias funds.

Managed futures

The results from the managed futures regression are in line with my hypothesis and the study of Frydenberg et al. (2017), that this strategy doesn't return an abnormal return during bad times. However, they don't align with the findings in the study of Cao et al. (2014). The managed futures regression returns a positive abnormal return during bad times of 0.35% per month, along with a negative Δ of 0.28% per month, but these results have very wide confidence intervals and are therefore not significantly different from 0. Frydenberg et al. (2017), also fail to find any evidence to support the claim that managed futures funds capture any abnormal return during bad times. Cao et al. (2014), however, did find evidence to support the claim that managed futures funds obtain a significantly positive abnormal return during both bad and good times. It was expected that the results found in this study would be more in line with the results of Frydenberg et al. (2017) than the results of Cao et al. (2014), since this study uses the same dataset as well as approximately the same sample time period as Frydenberg et al. (2017). The market beta is significantly above 0 for the 10% level, but still quite low at 0.13, which is in line with the expectations. Frydenberg et al. (2017) show that the market beta of managed futures funds changes a lot over time, switching from positive to negative, or the other way around, multiple times throughout their sample. Because of this, a market beta coefficient slightly greater than 0 seems to be a good approximation for managed futures funds. The statistically significant positive momentum factor of 0.13 is in line with the findings of both Frydenberg et al. (2017) and Cao et al. (2014). However, they both underline that this factor is also time varying and predominantly helps explain the returns of managed futures funds during times which are defined as good times by them. The loadings of the trend following factors are slightly lower than the values found in the research of Fung and Hsieh (2001) and Cao et al. (2014). These different loadings of the trend following factors could be due to the different managed futures data or the longer sample of hedge fund data used in this study. However, the currency and bond trend following factor coefficients are still greater than 0, suggesting that there is a significantly positive relationship between the relevant trend following factors and the managed futures excess return. This means that the managed futures funds' excess return is usually positive when the optimal straddle strategies' return is positive. The goodness of fit is also relatively low at 16%, but this is in line with other studies like the one from Frydenberg et al. (2017), who find that the managed futures strategy has the lowest r-squared of all the hedge fund strategies they looked at, at 16%.

Table 5

Hedge/mutual funds main regression results

This table shows the main multifactor regression results for the three main hedge fund strategies discussed in this study. The regression performed for each asset class looks the following;

$$R_{i,t}^{e} = \alpha_i^b + \Delta_i 1_t^g + \beta_i(Mkt_t - Rf_t) + f_t'\Theta_i + \varepsilon_{i,t}$$

Where $R_{i,t}^{e}$ is the excess return of asset i, α_i^brepresents the abnormal return of an asset during bad times, Δ_i shows the difference in abnormal return between bad and good times, 1_t^g is a dummy variable equal to 1 if the month is defined as a good month and 0 otherwise. β_i represents the market exposure, f_t' is a vector of a relevant factor' excess return and Θ_i represents the exposure of this factor towards the asset of interest' excess return. The relevant factors for hedge funds are s_i, which measures the exposure of the asset towards small stocks, h_i, which shows the exposure of the asset towards value stocks, m_i, which represents the exposure of the asset towards momentum stocks, c_i, which shows the exposure of the asset towards the Fung Hsieh currency trend following factor, g_i, which shows the exposure of the asset towards the Fung Hsieh commodity trend following factor and lastly, b_i, which shows the exposure of the asset towards the Fung Hsieh bond trend following factor. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively, according to heteroskedastic robust t-statistics.

Coefficient	Estimate	Confidence interval	Coefficient	Estimate	Confidence interval	Coefficient	Estimate	Confidence interval
	Small value			**Dedicated short bias**			**Managed futures**	
α^b	0.09	[-1.30 1.47]	α^b	0.28	[-0.53 1.09]	α^b	0.35	[-0.66 1.37]
Δ	1.06	[-0.64 2.76]	Δ	-0.48	[-1.52 0.56]	Δ	-0.28	[-1.63 1.07]
β	-0.02	[-0.25 0.20]	β	-0.77***	[-0.91 -0.63]	β	0.13*	[-0.02 0.27]
s	0.27***	[0.11 0.42]	s	-0.32***	[-0.45 -0.19]	s	-0.07	[-0.19 0.05]
h	0.30**	[0.06 0.54]	h	0.10	[-0.02 0.21]	h	0.08	[-0.06 0.21]
m	-0.07	[-0.26 0.11]	m	0.02	[-0.04 1.09]	m	0.13***	[0.06 0.21]
						c	0.04***	[0.02 0.06]
						g	0.02	[-0.00 0.04]
						b	0.03**	[0.00 0.11]
R^2	7%		R^2	73%		R^2	16%	

4.1.3 Bonds

Like mentioned before, 2 different bond categories are looked at in this study: treasury and corporate. For treasury bonds two different regressions were done, as is shown in table 6. The first regression model represents the results for the model of Elton et al. (1995). In this regression, a positive abnormal return during bad times of 0.32% per month was found. This result is statistically different from 0 at the 5% level. The delta is negative, but not greater than the alpha coefficient, suggesting that even though the abnormal return of treasury bonds is lower during good times than bad times, it could still be positive during good times. The beta of the treasury bond regression is somewhat in line with the hypothesis. It was expected to be approximately 0, but the regression results in table 6 actually show that the market beta is significantly greater than 0 at the 10% level, but still relatively low at 0.04. From its 95% confidence interval can be derived that the market beta is still very likely to take a value of around 0. However, the positive market beta contradicts the market beta found by Fama and French (1993), who find a negative beta for all treasury bonds, regardless of their maturity. The shift from a negative to a positive market beta for treasury bonds between the studies could be caused by the increased stock-bond correlations in the time period after the research of Fama and French (1993), which caused the stocks and bonds to become (weakly) positively correlated, which subsequently could cause the beta of treasury bonds to become positive. The default risk premium coefficient is -0.24 and statistically significant at the 1% level. This contradicts the findings of Fama and French (1993) and Elton et al. (1995), who find a positive default risk premium for all types of bonds. Additionally, they find that this coefficient increases going from treasury to corporate bonds. The negative coefficient suggests that the return on treasury bonds drops when the default risk premium rises. Due to the fact that the time period used in this study ranges from the beginning of 1990 to the beginning of 2020, a negative default risk premium could be plausible. Since interest rates dropped significantly after the great financial crisis, investors might be more inclined to switch their investment in treasury bonds towards high yield or corporate bonds when the default risk premium rises. Note that this is speculative, but it could explain the different findings in the default risk premium coefficient between this study and others. The term structure coefficient is approximately the same as the study of Fama and French (1993), but insignificant. I was unable to find an explanation to explain the insignificance of this variable. The computation of the variable is the same between this study and the one from Fama and French (1993) and even though a very different time period is used, there is no evidence to support that the term structure has changed significantly during this time period.

Because of the insignificance of the term structure, a second regression on treasury bonds was done, only this time excluding the term structure variable. The results of the regression were more or less the same as the previous regression, only the abnormal return went up with 0.1 percentage point to 0.43% per month along with its significance. The r-squared of both regressions is 42%, which is much lower than the 85-90% Fama and French (1993) found, but in line with the value found in other studies that use monthly data like Bessembinder et al. (2008). The fact that the r-squared doesn't drop after excluding the term structure variable, shows the insignificance of this variable's explanatory power over the returns of treasury bonds. According to both regressions, treasury bonds are an interesting investment for investors which seek protection against bad times, because they obtain both a significantly positive abnormal return and excess return during months which are defined as bad times within this study.

For corporate bonds, there are also two regressions performed which try to find whether this asset captures an abnormal return during bad times. The first regression looks at the Fama French 5 factor bond model, while the second regression looks at the Elton et al. (1995) 3 factor model. The regression using the Fama French 5 factor model returned an abnormal return of 0.54% per month, significant at the 5% level. Showing the attractiveness of this asset for investors who seek protection against bad times. However, these findings contradict my hypothesis and differ from the results found in previous research. Both Fama and French (1993) and Elton et al. (1995) find no statistical evidence that corporate bonds capture an abnormal return. The difference in results might be due to the very different time samples used between this study and the two previously mentioned or the different corporate bond index used. The Δ is negative, just like the Δ in the treasury bond regression. Looking at the coefficient of the Δ along with its confidence interval, there is a large possibility that the abnormal return during good times will also be greater than 0. The market beta of corporate bonds seems to lie just above 0, but not by a large amount when looking at the confidence interval of this coefficient. The value of 0.07 is in line with the findings of Fama and French (1993) and my hypothesis. As expected, the market beta of corporate bonds is higher than the market beta of treasury bonds. Just like Fama and French (1993), this study fails to find evidence to support that the SMB and HML factors have any explanatory power over the excess returns of corporate bonds. In the regression results of this study, these variables are very insignificant and excluding these variables doesn't influence the goodness of fit of the model at all. For the default risk premium, there seems to be a weakly significant positive relationship with the excess returns of corporate bonds. This result is in line with my hypothesis and the findings of previous studies like Fama and French (1993). The positive relationship suggests that the excess return of corporate bonds increase when the default risk premium increases. It was, however, expected that the DRP coefficient would be higher and that the significance would be greater, since this was found in previous studies like Fama and French (1993). But, just as was the case for treasury bonds, the different time period used between the samples of this study and others could explain the different findings for a large part. On the term structure variable, no useful inference could be made because of its very wide confidence interval. The fact that no significant term structure coefficient was found in both the treasury bond regression as well as the corporate bond regression could indicate that this variable was computed wrongly. It could also indicate that this variable has no significant influence on bond returns anymore. Another explanation could be that the dependant variables used for the bond regressions in this study have no significant relation towards term structure. The reason for this is that both the treasury and corporate bond dependant variable are indices and these indices are invested in multiple bonds with different maturities. This makes them less vulnerable to interest rate changes, since some of the bonds will go up in price, while others will drop. However, which reason explains the insignificant term structure could be looked at in a different study. When removing the SMB and HML factor, the Elton et al. (1995) regression remains. The results of this regression are almost identical to the results found in the regression which used the Fama and French (1993) model, emphasizing the insignificance of the SMB and HML factors. The r-squared is very low at 10% in comparison to other research like Fama and French (1993), who found r-squared values for corporate bonds of up to 90%. This means that this model doesn't explain the excess returns of corporate bonds very well. This could for a large part be caused by the insignificant term structure variable found in this study.

Table 6
Bond main regression results

This table shows the main multifactor regression results for the two bond categories discussed in this study. The regression performed for each bond category looks the following;

$$R_{i,t}^{e} = \alpha_i^b + \Delta_i 1_t^g + \beta_i(Mkt_t - Rf_t) + f_t'\Theta_i + \varepsilon_{i,t}$$

Where $R_{i,t}^{e}$ is the excess return of asset i, α_i^brepresents the abnormal return of asset i during bad times, Δ_i shows the difference in abnormal return between bad and good times, 1_t^g is a dummy variable equal to 1 if the month is defined as a good month and 0 otherwise, β_i represents the market exposure, f_t' is a vector of a relevant factor' excess return and Θ_i represents the exposure of this factor towards the asset of interest' excess return. The relevant factors for the bonds are s_i, which measures the exposure of the asset towards small stocks, h_i, which shows the exposure of the asset towards value stocks, d_i, which shows the exposure of the asset towards the default risk premium and lastly, t_i, which shows the exposure of the asset towards the term premium. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively, according to heteroskedastic robust t-statistics.

	Treasury bonds				Corporate bonds			
Coefficient	Estimate	Conf. int	Estimate	Conf. int	Estimate	Conf. int	Estimate	Conf. int
α^b	0.32**	[0.02 0.62]	0.43***	[0.18 0.68]	0.54**	[0.08 1.01]	0.55**	[0.09 1.01]
Δ	-0.19	[-0.52 0.15]	-0.20	[-0.52 0.13]	-0.40	[-0.95 0.14]	-0.41	[-0.96 0.14]
β	0.04*	[-0.00 0.07]	0.04*	[-0.00 0.07]	0.07**	[0.00 0.14]	0.07**	[0.00 0.14]
s					-0.01	[-0.06 0.04]		
h					0.01	[-0.04 0.07]		
d	-0.24***	[-0.29 -0.19]	-0.24***	[-0.29 -0.19]	0.09*	[-0.03 0.20]	0.09*	[-0.01 0.18]
t	0.67	[-0.25 1.61]			0.04	[-1.38 1.46]	0.02	[-1.43 -1.47]
R^2	42%		42%		10%		10%	

4.2 Bad times robustness

The main goal of this robustness check is to find whether the main regression results remain more or less the same when a different definition of good and bad times is used. 3 definitions of bad times different to the main bad times definition within this study will be used in this robustness check. The first definition for this robustness check is based on Gormsen and Greenwood (2017). For a month to be classified as a bad time by them, it has to satisfy two conditions. Firstly, the market excess return of the year or quarter in which the month finds itself has to be in the bottom quintile of the sample. Secondly, the month has to be registered as a recession month by the NBER. When the month satisfies both the first and the second condition, it will be classified as a bad time. The months which end up being classified as bad times are the same as the months in the research of Gormsen and Greenwood (2017), with the addition of February and March 2020. This is mainly due to the fact that the NBER hasn't classified any months as recession months between July 2009 and January 2020. The second bad time definition is based on Pagan and Sossounov (2003) among others and looks at bull and bear markets. Naturally, a month which falls in a bear market period is classified as a bad time and vice versa for bull market months. The months which are classified as bad times in this study, are based on the methodology of Bry and Boschan (1971) and Pagan and Sossounov (2003). In this methodology some initial turning points are determined and some censoring rules are added after that to come up with a good bull/bear month classification[6]. The classification of months in good and bad times resulted in the same good and bad months which were used in the research of Geertsema and Lu (2020). The final bad times definition used in this robustness is based on the market return. Here a month is classified as a bad month when the market return is negative, like in the research of Lakonishok et al. (1994). Note that this definition isn't the same as the main definition of bad times used in this paper. This definition of bad times looks at the raw market return, whereas the main bad times definition used in this paper looked at the excess market return. On top of that, the main bad times definition uses the bottom quartile of the market risk premium returns as a proxy for bad times, while the market return definition of bad times classifies all the months which have a raw market return that is negative as bad times. The raw market return definition of bad times is more often used in research as a bad time robustness check, like in the study of Geertsema and Lu (2020). The results of the bad times robustness are shown in table 7.

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[6] The exact turning points criteria and additional censoring rules used to determine bull and bear markets can be found in the appendix of; Pagan, A. R., & Sossounov, K. A. (2003). A simple framework for analysing bull and bear markets. *Journal of applied econometrics*, *18*(1), 23-46.

This table shows that the various bad times definitions have surprisingly differing results for most asset classes. It was expected that the raw market return (MR) definition of bad times would display some different results, since this definition takes a more lenient approach to classify a month as a bad time. It can be observed that the Gormsen and Greenwood (2017) (G&G) bad times definition along with the bull and bear market (B&B) bad times definition, indeed display more or less the same results, while the MR bad times definition gives some different results for certain assets. One example for this occurrence is the gold regression, where the G&G and B&B regression return more or less the same results as the main regression, while the MR bad times definition regression actually finds evidence that gold captures an abnormal return significantly greater than 0 at the 10% level.

The same can be observed for the small value fund regression, where the G&G and B&B regression return a negative bad times abnormal return coefficient, while the MR bad times definition provides evidence that the abnormal return of these funds is greater than 0 at the 5% significance level. For the dedicated short bias strategy, the same story seems to hold. The G&G and B&B regression actually provides evidence at the 10% level that the abnormal return of these funds is negative, while the MR regression gives an insignificant positive coefficient. When looking at the managed futures robustness regression results, every bad times definition displays different results. The G&G regression returns an abnormal return which is not significantly different from 0, while the B&B definition finds evidence that the abnormal return of these funds is positive. On the other hand, the MR bad times definition finds evidence that the abnormal return during bad times is negative. On top of that, the MR definition finds a very significant difference in abnormal return between good and bad times. This result might suggest that the managed futures strategy obtains abnormal returns in times when the market performs either really well or really poor and that this strategy achieves a negative abnormal return in times when the market risk premium or excess market return is between -1 to 1% per month. The reason for this suggestion is because the good times alpha is only significant when the definition of bad times is more lenient, so only in the MR regression. The abnormal return coefficient in bad times is positive for all other definitions of bad times and only significant for the B&B regression. The shift from a very negative bad times alpha coefficient to a positive, weakly significant, alpha coefficient between these definitions could be caused by the phenomenon explained above and thus regressing the managed futures strategy using a definition which captures even worse times than any other definition used in this study, might lead to a very positive and significant bad times alpha for managed futures. Moreover, whether or not this is true could be investigated in another study.

Table 7
Bad times robustness

This table checks if the results found in tables 4, 5 and 6 still hold when a different definition of bad times is used. Here G&G stands for Gormsen and Greenwood and represents the bad times measure which is proposed by Gormsen and Greenwood (2017). B&B means bull and bear markets and is based on the classification of Pagan and Sossounov (2003). MR stand for market return and defines a month as a bad time when the raw market return of that month is negative. Furthermore, this table repeats the regression analysis done in the empirical results section, meaning that the excess returns of several asset classes are regressed on multiple factors, while controlling for good times in order to find whether the respective strategy obtains an abnormal return during bad times;

$$R_{i,t}^{e} = \alpha_i^b + \Delta_i 1_t^g + \beta_i(Mkt_t - Rf_t) + f_t'\theta_i + \varepsilon_{i,t}$$

Where $R_{i,t}^{e}$ is the excess return of asset i, α_i^brepresents the abnormal return of asset i during bad times, Δ_i shows the difference in abnormal return between bad and good times, 1_t^g is a dummy variable equal to 1 if the month is defined as a good month and 0 otherwise. The other factors used along with their abbreviations are the same as the factors used in table 4, 5 and 6. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively, according to heteroskedastic robust t-statistics.

	Gold			Hedge fund strategies					
				Small Value			Dedicated short bias		
	G&G	B&B	MP	G&G	B&B	MP	G&G	B&B	MP
α^b	-0.01	0.32	0.97*	-0.77	-0.88	1.39**	-1.24*	-0.86*	0.37
Δ	0.58	0.26	-0.88	1.85	2.08**	-0.93	1.35*	0.97*	-0.78
β	-0.07	-0.09	0.01	0.02	-0.01	0.14	-0.84***	-0.84***	-0.74***
s				0.28***	0.08*	0.27***	-0.30***	-0.31***	-0.32***
h				0.29**	0.30**	0.31**	0.09	0.10*	0.10*
m				-0.09	-0.07	-0.06	-0.00	0.01	0.02
γ	0.04	0.06	0.04						
δ	0.20	0.20	0.20						
R^2	1%	1%	1%	7%	8%	7%	74%	74%	73%

	Hedge fund strategies			Bonds					
	Managed futures			Treasury bonds			Corporate bonds		
	G&G	B&B	MP	G&G	B&B	MP	G&G	B&B	MP
α^b	0.20	0.94*	-0.75**	0.26	0.45***	0.35***	0.35*	0.42**	0.62***
Δ	-0.05	-0.96	1.53***	0.03	-0.19	-0.11	0.12	-0.29	-0.22
β	0.11**	0.14**	-0.03	0.02	0.03*	0.03	0.04*	0.04**	0.03
s	-0.07	-0.08	-0.08						
h	0.08	0.07	0.07						
m	0.13***	0.13***	0.12***						
c	0.04***	0.01***	0.04***						
g	0.02	0.02*	0.02						
b	0.03**	0.01*	0.03**						
d				-0.24***	-0.23***	-0.24***	0.09*	0.09*	0.09*
t							0.07	0.05	0.06
R^2	16%	17%	18%	41%	42%	41%	9%	10%	10%

However, the abnormal return results for the bond regression are robust across all bad times definitions, except for the G&G definition for treasury bonds. All the regressions return more or less the same bad times abnormal return and this abnormal return is significantly greater than 0 at the 1% level for the B&B treasury bond regression and the MR corporate bond regression. On top of that, when a Wald test is done to test if the good times abnormal return is greater than 0, I find this to be the case for all the bond regressions apart for the G&G treasury bond regression. This robustness not only amplifies the attractiveness of treasury and corporate bonds as an investment during bad times, but also during good times. When looking at the coefficients of all the other factors, no noteworthy changes were found and everything seems to be in line with the findings in the main regression. The same holds for the goodness of fit of the different regressions, which changes only marginally for some regressions, providing no evidence that one model is better than another.

All in all, this robustness shows that the classification of the data in good and bad times can have some serious consequences for most assets on the abnormal return findings. However, this robustness also shows that the abnormal return findings for bonds are robust for nearly all bad times looked at in this study, further emphasizing the attractiveness of bonds as an investment for bad times.

4.3 Time-varying beta

In this robustness part, it will be checked whether the main regression results stay the same when accounting for time variation in the betas. Several studies have provided evidence of time variation in the betas of certain risk factors. Lewellen and Nagel (2006) show for instance that the value beta varies considerably over time and Cao et al. (2014) find that the dedicated short bias strategy has a significantly different market, value, size and momentum beta between good and bad times. Not taking into account this possible time variation, might cause the main regression results to be inaccurate. To account for the possible time variation in my model, a good and bad times beta is created for all the factors used in the main regressions of this study. To get the beta of the specific factor during good times, the excess returns of the factor is multiplied with a dummy which is equal to 1 for good times and 0 otherwise. The same thing is done to get the beta of the respective factor during bad times, only now using a dummy which is equal to 1 when an investor finds herself in bad times and 0 otherwise. In table 8, the results of the main regressions for the asset classes are displayed, only now with time varying betas for all the factors.

Several remarkable observations can be made from the results displayed in table 8. The most surprising observation is the drastic change and significance in abnormal returns during bad times for the hedge fund styles and bonds compared to their values in the main regression models which didn't account for possible time variation in the explanatory factors. The abnormal return during bad times of small value funds, for instance, has a lower bound in its 95% confidence interval of 1.75% per month. This is more in line with the findings of Gormsen and Greenwood (2017), who find an abnormal return during bad times for small value stocks of approximately 2% per month and it is considerably more than the 0.1% found in the main regression. Managed futures funds, on the other hand, achieve a significantly negative abnormal return during bad times according to the results in table 8, contradicting the results of Cao et al. (2014) and Frydenberg et al. (2017). Both studies found no evidence that managed futures funds generate a significantly negative alpha during bad times. The difference in results could be due to the difference in the definition of bad times, the difference in the funds used in the dataset, the difference in time period or ample other factors. The result of the significantly negative abnormal return for this regression along with the insignificant abnormal return found in the main regression (table 5) for the managed futures fund category, indicates that managed futures are not an great investment when an investor wants to optimally protect herself against bad times.

In the main regression, a significantly positive abnormal return was already found for both treasury and corporate bonds. However, when time variation of betas is considered, these abnormal returns become even greater in value and more significant. For treasury bonds, the abnormal return during bad times is 1.38% per month according to the regression results in table 8. Its confidence interval also shows that this asset is very likely to capture an abnormal return greater than 0.4% per month during bad times. The Δ on the other hand is also significant at the 1% level, but its coefficient is greater than the abnormal return during bad times. This means that there is a high likelihood that, according to this regression, the abnormal return of this asset during good times is negative. When looking at the corporate bond regression results in table 8, almost the same observations can be made for the corporate bond results. The abnormal return of this asset rises substantially compared to the main regression results to approximately 2.5% per month, thus becoming even more positive. Therefore, when taking into account possible time variation in beta's, both the bond classes become even more of a good investment for investors who seek protection against large stock market drops.

Every significant abnormal return during bad times is accompanied by a significant Δ that has a value in the opposite direction. This means that the Δ is negative when the abnormal during bad times is positive and vice versa. Even though this doesn't necessarily mean that the abnormal returns of the assets during good times is negative when the abnormal return of the respective assets during bad times is positive, it tells us that the abnormal return is lower (higher) during good (bad) times than the abnormal return during bad (good) times.

When looking at the specific factors of the assets, several things can be noticed. For gold, there seems to be a lagged effect of the gold price, but only during bad times. This lagged variable is significantly greater than 0, suggesting that the return on gold is positive, when the return on gold in the prior period was positive and when this period is classified as a bad time. This result confirms the findings of Baur and Lucey (2010), who also found a lagged effect, but only for times when the stock market return was in the lowest 5% of their sample. In the small value fund regression, the change in beta between good and bad times is very remarkable. From the research of Gormsen and Greenwood (2017), it was expected that the overall beta would be approximately 0, as was the case. However, when the possible time variation in the beta's was accounted for, it can be seen that these funds have a significantly negative market beta during good times and a significantly positive one during bad times. The expectation was that this would be the other way around. This partially explains, on the other hand, why the average returns of this strategy were so much lower than the markets during good times. The time variation in the market factor along with the time variation in the SMB factor could be an explanation for the sudden increase in the bad times abnormal return of this asset.

In line with the Research of Cao et al. (2014) and other studies, the dedicated short bias strategy actually reduces the magnitude of its negative exposure to the market during bad times, reducing the hedging value of its market exposure. The coefficients of the managed futures regression in table 8 are in line with other studies. The market beta of this asset tends to fluctuate between good and bad times, as is also shown by Frydenberg et al. (2017). Additionally, the exposure of this asset class to the currency and commodity trend following factors reduces when switching to bad times, as is also the case in the study of Cao et al. (2014). The market beta for bonds stays more or less the same over time, but the term structure and default risk premium certainly change over time. This is also shown in the studies of, for example, Chen (1991) and Fama and French (1993). Its coefficients and significance levels are, however, still lower than the values found in comparable studies. The R-squared of all the asset classes increased, but this increase wasn't very noteworthy. The robustness results show that the abnormal returns become much more extreme when accounting for possible time variation in the factor exposures. This causes the bond categories to be even more of an attractive asset to invest in when investors seek protection against bad times. However, this robustness also shows that small value funds should definitely be considered as a very interesting asset to hold during bad times.

Table 8

Time varying factor robustness

This table shows the multifactor regression results with time varying risk factors for gold, small value funds and dedicated short bias hedge funds. The regression performed for each asset class looks the following;

$$R_{i,t}^{e} = \alpha_i^{b} + \Delta_i 1_t^{g} + \beta_i(Mkt_t - Rf_t) + f_t'\Theta_i + \varepsilon_{i,t}$$

Where $R_{i,t}^{e}$ is the excess return of asset i, α_i^{b}represents the abnormal return of an asset during bad times, Δ_i shows the difference in abnormal return between bad and good times, 1_t^{g} is a dummy variable equal to 1 if the month is defined as a good month and 0 otherwise. β_i represents the market exposure, f_t' is a vector of a relevant factor' excess return and Θ_i represents the exposure of this factor towards the asset of interest' excess return. The other relevant factors for the gold, small value fund and dedicated short bias fund regressions are; γ_i, which represents the exposure to the 1-month lag of the market risk premium, δ_i, which shows the exposure towards the 1-month lag of the excess gold return, s_i, which measures the exposure of the asset towards small stocks, h_i, which shows the exposure of the asset towards value stocks and m_i, which represents the exposure of the asset towards momentum stocks. To account for time variation in the risk factors, every risk factor is indicated with either 'b', which represents the exposure towards the factor during bad times or 'g', which shows the exposure towards the factor during good times. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively, according to heteroskedastic robust t-statistics.

Coefficient	Estimate	Confidence interval		Coefficient	Estimate	Confidence interval		Coefficient	Estimate	Confidence interval	
Gold				**Small value**				**Dedicated short bias**			
α^b	0.61	[-1.23	2.44]	α^b	3.21***	[1.75	4.66]	α^b	1.13	[-0.76	3.02]
Δ	-0.09	[-2.06	1.88]	Δ	-1.39*	[-3.03	0.25]	Δ	-1.16	[-3.08	0.77]
β^g	-0.08	[-0.26	0.10]	β^g	-0.28**	[-0.54	-0.02]	β^g	-0.84***	[-0.95	-0.73]
β^b	-0.01	[-0.31	0.29]	β^b	0.50***	[0.14	0.86]	β^b	-0.60***	[-1.02	-0.19]
γ^g	-0.02	[-0.15	0.10]	s^g	0.16*	[-0.01	0.34]	s^g	-0.30***	[-0.44	-0.17]
γ^b	0.06	[-0.14	0.26]	s^b	0.58***	[0.29	0.88]	s^b	-0.39***	[-0.66	-0.13]
δ^g	0.01	[-0.08	0.11]	h^g	0.21	[-0.08	0.50]	h^g	0.07	[-0.07	0.20]
δ^b	0.20***	[0.05	0.35]	h^b	0.33	[-0.13	0.80]	h^b	-0.13	[-0.07	-0.33]
				m^g	-0.10	[-0.33	0.14]	m^g	0.02	[-0.04	0.09]
				m^b	-0.09	[-0.36	0.18]	m^b	-0.01	[-0.20	-0.18]
R^2	1%			R^2	11%			R^2	74%		

Table 8 (continued)

Time varying factor robustness

This table shows the multifactor regression results with time varying risk factors for the managed futures funds, corporate bonds and treasury bonds asset classes. The regression performed for each asset class looks the following;

$$R_{i,t}^{e} = \alpha_i^b + \Delta_i 1_t^g + \beta_i(Mkt_t - Rf_t) + f_t'\Theta_i + \varepsilon_{i,t}$$

Where $R_{i,t}^{e}$ is the excess return of asset i, α_i^brepresents the abnormal return of an asset during bad times, Δ_i shows the difference in abnormal return between bad and good times, 1_t^g is a dummy variable equal to 1 if the month is defined as a good month and 0 otherwise. β_i represents the market exposure, f_t' is a vector of a relevant factor' excess return and Θ_i represents the exposure of this factor towards the asset of interest' excess return. The other relevant factors for the managed futures funds, corporate bonds and treasury bonds asset classes are; s_i, which measures the exposure of the asset towards small stocks, h_i, which shows the exposure of the asset towards value stocks, m_i, which represents the exposure of the asset towards momentum stocks, c_i, which shows the exposure of the asset towards the Fung Hsieh currency trend following factor, g_i, which shows the exposure of the asset towards the Fung Hsieh commodity trend following factor, b_i, which shows the exposure of the asset towards the Fung Hsieh bond trend following factor, d_i, which shows the exposure of the asset towards the default risk premium and lastly, t_i, which shows the exposure of the asset towards the term premium. To account for time variation in the risk factors, every risk factor is indicated with either 'b', which represents the exposure towards the factor during bad times or 'g', which shows the exposure towards the factor during good times *,**,*** indicate significance at the 10%, 5% and 1% levels respectively, according to heteroskedastic robust t-statistics.

Coefficient	Estimate	Confidence interval	Coefficient	Estimate	Confidence interval	Coefficient	Estimate	Confidence interval
Managed futures			**Treasury bonds**			**Corporate bonds**		
α^b	-1.56***	[-2.87 -0.25]	α^b	1.38***	[0.42 2.34]	α^b	2.47***	[0.71 4.23]
$\Delta 1^g$	1.47**	[0.05 2.89]	$\Delta 1^g$	-1.56***	[-2.55 -0.57]	$\Delta 1^g$	-1.97**	[-3.76 -0.16]
β^g	0.19**	[0.03 0.36]	β^g	0.02**	[0.00 0.04]	β^g	0.04	[-0.02 0.10]
β^b	-0.18	[-0.40 0.04]	β^b	0.06**	[0.03 0.09]	β^b	0.10	[-0.10 0.29]
s^g	-0.08	[-0.22 0.05]	d^g	-0.26***	[-0.32 -0.21]	d^g	0.03	[-0.07 0.13]
s^b	-0.09	[-0.33 0.15]	d^b	-0.21***	[-0.24 -0.17]	d^b	0.14*	[-0.02 0.30]
h^g	0.02	[-0.16 0.20]	t^g	0.88*	[-0.06 1.81]	t^g	0.19	[-1.27 1.65]
h^b	0.04	[-0.11 0.21]	t^b	0.03	[-2.34 2.40]	t^b	-0.91	[-4.55 2.73]
m^g	0.11**	[0.02 0.19]						
m^b	0.22***	[0.06 0.38]						
c^g	0.04***	[0.02 0.07]						
c^b	0.02	[-0.02 0.07]						
g^g	0.03**	[0.01 0.06]						
g^b	-0.01	[-0.06 0.04]						
b^g	0.01	[-0.02 0.05]						
b^b	0.07***	[0.04 0.10]						
R^2	22%		R^2	43%		R^2	10%	

5. Conclusion

The main objective of this study is to find assets which protect an investor against bad times. Bad times are defined as months which have an excess market return that falls in the bottom quartile of the sample. There are three main asset classes this study looks at, which are gold, hedge funds and bonds. For hedge funds, 3 fund styles are looked at, which are small value, dedicated short bias and managed futures, while for bonds, treasury and corporate bonds are examined. Almost all these assets are a good investment against bad times when an investor is solely interested in excess returns, since all these assets have a positive excess return during bad times, except for the small value hedge funds and corporate bonds.

However, when looking at abnormal returns, not all these assets are a good investment during bad times. In the gold regression, no statistical evidence was found to support the claim that this asset captures an abnormal return during bad times that is different from 0. For all the 3 hedge fund styles the same can be said. None of these strategies returned an abnormal return which was significantly different from 0 during bad times. For bonds, however, both treasury and corporate bond regressions returned a significantly positive abnormal return during bad times of 0.43% and 0.55% per month respectively. These findings were significant at the 1% level for treasury bonds and at the 5% level for corporate bonds. The results suggest that both treasury and corporate bonds are an attractive asset to hold when an investor wants to protect herself against a big market drop.

Next to the main regression, a robustness test on different bad times definitions was performed. The main finding of this robustness was that the gold and hedge fund abnormal return results were not robust across all bad times definitions and actually tend fluctuate significantly between the different bad times definitions. However, both the treasury and corporate bond bad time abnormal return results are robust for nearly all different bad time variations looked at. This further emphasizes the attractiveness of this asset as a possible investment for protection against bad times.

Lastly, a final robustness check was done in which possible time variation in the explanatory variables was accounted for. The abnormal return findings in this robustness are much more extreme than the findings in the main regression. The small value funds actually look like a very attractive investment in this robustness with an abnormal return of 3.21% per month, significant at the 1% level. On top of that, the results for both bond categories are also greater and more significant than the findings in the main regression. For the rest of the assets, however, still no evidence was found that indicated that these assets are a good investment for protection against bad times.

All in all, this study finds that both treasury and corporate bonds provide a significantly positive abnormal return during bad times and that they are the best possible investment when an investor seeks protection against big market drops. These results are robust for different bad time definitions and robust for regressions were time varying explanatory variables are accounted for. On top of that, small value funds might also be an interesting investment after the abnormal return findings in the time varying explanatory variable regression. This study, on the other hand, finds no evidence that gold, dedicated short bias and managed futures funds are good investments when an investor seeks to protect herself against large stock market drops. However, the relatively low betas along with the positive excess returns of all the assets during bad times shows that these assets could still be an interesting investment when an investor is solely interested in excess returns during bad times. Other future studies could look at other assets like different hedge fund strategies, real estate, commodities or private equity to see if these assets might potentially be an interesting investment during bad times.

6. References

- Baele, L., Bekaert, G., Inghelbrecht, K., & Wei, M. (2020). Flights to safety. *The Review of Financial Studies*, *33*(2), 689-746.
- Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, *45*(2), 217-229.
- Bessembinder, H., Kahle, K. M., Maxwell, W. F., & Xu, D. (2008). Measuring abnormal bond performance. *The Review of Financial Studies*, *22*(10), 4219-4258.
- Bry, G., & Boschan, C. (1971). Standard business cycle analysis of economic time series. In *Cyclical Analysis of Time Series: Selected Procedures and Computer Programs* (pp. 64-150). NBER.
- Cao, C., Rapach, D., & Zhou, G. (2014). Which Hedge Fund Styles Hedge Against Bad Times?. *Available at SSRN 2311464*.
- Capocci, D., & Hübner, G. (2004). Analysis of hedge fund performance. *Journal of Empirical Finance*, *11*(1), 55-89.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, *52*(1), 57-82.
- Chen, N. F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of business*, 383-403.

- Chen, N. F. (1991). Financial investment opportunities and the macroeconomy. *The Journal of Finance*, *46*(2), 529-554.
- Connolly, C., & Hutchinson, M. C. (2011). Dedicated short bias hedge funds: Diversification and alpha during financial crises. *The Journal of Alternative Investments*, *14*(3), 28-41.
- Coudert, V., & Raymond, H. (2011). Gold and financial assets: are there any safe havens in bear markets. *Economics Bulletin*, *31*(2), 1613-1622.
- Dichev, I. D., & Yu, G. (2011). Higher risk, lower returns: What hedge fund investors really earn. *Journal of Financial Economics*, *100*(2), 248-263.
- Elton, E. J., & Gruber, M. J., & Blake, C. R. (1993). The performance of bond mutual funds. *Journal of business*, 371-403.
- Elton, E. J., Gruber, M. J., & Blake, C. R. (1995). Fundamental economic variables, expected returns, and bond fund performance. *The Journal of Finance*, *50*(4), 1229-1256.
- Erb, C. B., & Harvey, C. R. (2013). The golden dilemma. *Financial Analysts Journal*, *69*(4), 10-42.
- Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, *47*(2), 427-465.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, *33*(1), 3-56.
- Fama, E. F., & French, K. R. (2010). Luck versus skill in the cross-section of mutual fund returns. *The journal of finance*, *65*(5), 1915-1947.
- Frydenberg, S., Hrafnkelsson, K., Bromseth, V. S., & Westgaard, S. (2017). Hedge Fund Strategies and Time-Varying Alphas and Betas. *The Journal of Wealth Management*, *19*(4), 44-60.
- Fung, W., & Hsieh, D. A. (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. *The review of financial studies*, *14*(2), 313-341.
- Fung, W., & Hsieh, D. A. (2004). Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal*, *60*(5), 65-80.
- Geertsema, P., & Lu, H. (2020). Where is the risk in risk factors? Evidence from the Vietnam war to the COVID-19 pandemic. *Working paper.(June 6, 2020)*.

- Ghazali, M. F., Lean, H. H., & Bahari, Z. (2013). Is gold a hedge or a safe haven? An empirical evidence of gold and stocks in Malaysia. *International Journal of Business & Society*, *14*(3).
- Gormsen, N., & Greenwood, R. M. (2017). Rainy day stocks. *Harvard Business School working paper series*.
- Gutierrez, R., Maxwell, W., & Xu, D. (2007). *Performances and Flows of Corporate-Bond Funds*. University of Arizona working paper. Gutierrez, R., Maxwell, W., & Xu, D. (2007). *Performances and Flows of Corporate-Bond Funds*. University of Arizona working paper.
- Hamilton, J. D., & Lin, G. (1996). Stock market volatility and the business cycle. *Journal of applied econometrics*, *11*(5), 573-593.
- Hammami, Y. (2011). Is the stock market efficient in bad times and inefficient in good times?. *Applied Financial Economics*, *21*(12), 905-915.
- Henkel, S. J., Martin, J. S., & Nardari, F. (2011). Time-varying short-horizon predictability. *Journal of financial economics*, *99*(3), 560-580.
- Huang, D., Jiang, F., Tu, J., & Zhou, G. (2014, July). Forecasting stock returns in good and bad times: The role of market states. In *27th Australasian Finance and Banking Conference*.
- Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The journal of finance*, *49*(5), 1541-1578.
- Lewellen, J., & Nagel, S. (2006). The conditional CAPM does not explain asset-pricing anomalies. *Journal of financial economics*, *82*(2), 289-314.
- Pagan, A. R., & Sossounov, K. A. (2003). A simple framework for analysing bull and bear markets. *Journal of applied econometrics*, *18*(1), 23-46.
- Perez-Quiros, G., & Timmermann, A. (2000). Firm size and cyclical variations in stock returns. *The Journal of Finance, 55*(3), 1229-1262.
- Petkova, R., & Zhang, L. (2005). Is value riskier than growth?. *Journal of Financial Economics*, *78*(1), 187-202.
- Ruhm, C. J., & Black, W. E. (2002). Does drinking really decrease in bad times?. *Journal of health economics*, *21*(4), 659-678.
- Schwert, G. W. (1989). Why does stock market volatility change over time?. *The journal of finance*, *44*(5), 1115-1153.

- Sortino, F. A., & Van Der Meer, R. (1991). Downside risk. *Journal of portfolio Management*, *17*(4), 27.
- Tomz, M., & Wright, M. L. (2007). Do countries default in "bad times"?. *Journal of the European Economic association*, *5*(2-3), 352-360.
- Zechmeister, E. J., & Zizumbo-Colunga, D. (2013). The varying political toll of concerns about corruption in good versus bad economic times. *Comparative Political Studies*, *46*(10), 1190-1218.

7. Appendix

Table 9
Summary statistics of several portfolios of hedge fund strategies

This table reports some summary statistics on 12 hedge fund style strategies obtained from the Credit Suisse data library. The strategies are listed in the left column and the summary statistics are divided between good and bad times and the entire sample. For every strategy the annualized mean, standard deviation (sd) and sharpe ratio (sr) are reported.

	Mean (%)	Sd. (%)	SR	Mean (%)	Sd. (%)	SR	Mean (%)	Sd. (%)	SR
	Entire sample			Bad times			Good times		
CS Hedge fund index	4.6	6.7	0.69	-15.5	6.3	-2.46	10.5	5.9	1.78
Convertible arbitrage	3.7	6.2	0.60	-4.1	9.1	-0.45	6.1	4.8	1.27
Dedicated short bias	-7.1	16.2	-0.44	58.4	14.5	4.03	-27.2	11.6	-2.34
Emerging markets	4.5	13.1	0.34	-30.4	13.7	-2.22	14.9	11.3	1.32
Event driven	4.5	6.5	0.69	-13.8	7.4	-1.86	9.9	5.2	1.90
Event driven distressed	5.5	6.3	0.87	-12.2	7.6	-1.61	10.7	4.9	2.18
Event driven multi strategy	4.0	7.2	0.55	-14.7	7.8	-1.88	9.6	6.1	1.57
Event driven risk arbitrage	2.8	4.0	0.70	-5.0	4.6	-1.09	5.1	3.5	1.46
Fixed income	2.5	5.1	0.49	-4.1	7.4	-0.55	4.4	4.0	1.10
Global macro	6.6	8.5	0.78	-4.7	8.6	-0.55	11.2	8.3	1.35
Managed futures	2.6	11.3	0.23	5.5	12.7	0.43	1.8	10.8	0.17
Multi strategy	4.5	4.9	0.92	-4.5	6.2	-0.73	7.2	4.2	1.71