Safe Haven Assets and Investor Behaviour under Uncertainty

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Abstract

We study two different safe haven assets, US government bonds and gold, and examine how the price changes of these assets can be used to infer investor behaviour under uncertainty. We find that investors are ambiguity-averse, that is they buy gold when faced with extreme uncertainty about the state of the economy or the financial system and when they receive ambiguous signals. In contrast, investors buy US government bonds when faced with extreme but unambiguous signals. We also show that there is overreaction to ambiguous signals.

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"Beside them, little pot-bellied men in light suits and panama hats; clean, pink men with puzzled worried eyes, with restless eyes. Worried because formulas do not work out; hungry for security and yet sensing its disappearance from the earth."

- John Steinbeck, *The Grapes of Wrath*

The role of uncertainty in the decisions of economic agents has rarely appeared more pertinent. In the economic sphere, recent years have seen a dramatic credit crunch precipitate the largest global financial crisis since the great depression. Bank failures and, more recently, fears over sovereign default, particularly within the Eurozone have forced investors to re-evaluate their models of risk. Events of a geopolitical nature in the Middle East and North Africa, and those of a geophysical nature in East Asia, have been adding to the sense of global uncertainty during 2011. Investors' desire for "security" in a world of heightened uncertainty, would appear to be driving the simultaneous demand for US Treasuries and gold.[1] Traditionally gold has been viewed as a hedge against inflation, while buying government bonds is essentially a bet against high inflation. Thus, the simultaneous demand for both US government bonds and gold represents a puzzle - one which may be explained by taking account of the role of uncertainty in investor decisions.

While in general, portfolio diversification may allow investors to reduce the risk of suffering large losses on their investments, during periods of financial market turmoil various asset classes tend to co-move strongly, even where macroeconomic fundamentals would not suggest strong interdependence (Dornbusch *et al.* , 2000; Forbes & Rigobon, 2002).[2] Such contagion effects, and the increased co-movement across asset classes during crisis periods, motivates the search for a safe haven asset, which will not move in tandem

[1] Gold prices have been hitting record highs, while demand for US Treasuries has hardly faltered, in spite of fears over the size of the US fiscal deficit. See for example "Safety Thirst", *The Economist*, 7 May 2011.

[2] The literature on financial crises and contagion examines the responses of investors to financial market shocks, and how those shocks get transmitted across markets and across asset classes. Boyer *et al.* (2006) present evidence that crises spread through the asset holdings of investors, as opposed to changes in economic fundamentals.

with other assets and holds its value during these specific episodes. We can therefore define a safe haven asset empirically, as an asset that is either uncorrelated or negatively correlated with other assets (e.g. stocks) during specific periods (e.g. when stocks are falling).[3]

Since it has also been shown that uncertainty increases in response to financial or economic shocks (Bloom, 2009), the prevalence of market uncertainty, and investor responses to it, may be crucial to a better understanding of how crises spread. Similarly, Lo & Mueller (2010) have argued that a better understanding of uncertainty is critical to determining the successes and failures of quantitative economic analysis and, by implication, the role of these "failures" in the recent financial crisis.

The distinction between risk and uncertainty has been around at least since Knight (1921). Knightian uncertainty refers to a situation in which investors are unable to form a unique estimate of expected value, due to a lack of reliable information on probabilities, resulting in overlapping distributions of potential outcomes (Alchian, 1950) among which investors are unable to choose.[4] Grossman & Stiglitz (1980) famously demonstrated the impossibility of informationally efficient markets, thus highlighting the prevalence of (at least some degree of) Knightian uncertainty in economic interactions.[5]

Standard (classical) economic models depict agents trading off known risks against expected pay-offs in order to arrive at an optimal allocation of investments that maximizes utility, given personal preferences or attitudes to risk (Engle, 2004). However, as Keynes recognized, sentiment and emotion can also play important roles in investor decisions, particularly under conditions of Knightian uncertainty (Epstein & Wang, 1994). More recently, Loewenstein (2000) has argued that "visceral factors" - i.e. short-term but

[3]More detailed definitions are provided in Baur & Lucey (2010) and Baur & McDermott (2010).

[4]In an effort to develop a better appreciation of the prevalence of uncertainty, Lo & Mueller (2010) describe a continuum of randomness between risk and uncertainty and propose a taxonomy that distinguishes between fully reducible, partially reducible and irreducible uncertainty. Lo & Mueller (2010, p.1) define these categories of randomness as follows; "Fully reducible uncertainty is the kind of randomness that can be reduced to pure risk given sufficient data, computing power, and other resources. Partially reducible uncertainty contains a component that can never be quantified, and irreducible uncertainty is the Knightian limit of unparametrizable randomness".

[5]Keynes recognized that the rational, utility-maximizing optimization behaviour - archetypal of neoclassical economic analysis - can only occur "in the special circumstances of full information" (Fitzgibbons, 2002, p.9).

powerful emotional states, such as fear and panic - play a particularly important role in decision-making under conditions of uncertainty.

In fact, economists have rarely, if ever, maintained that all of human behaviour can be fully captured by the rational, utility-maximizing archetype of standard economic analysis. Instead, this characterization has served as a useful benchmark - a standard (or "law") towards which we expect economic behaviour to *tend* at an aggregate level.[6] In other words, while deviations from this "standard" of behaviour at the individual level are to be expected, on average these deviations will be "washed out" by the majority who tend to conform to the standard characterization, at least most of the time. This view has persisted (implicitly or explicitly) throughout much of modern economic analysis (Lo & Mueller, 2010).

However, there is now an extensive literature that demonstrates *systematic* deviations from the rational, utility-maximizing archetype of classical economics (an early review is provided in Camerer & Weber (1992); and more recently by Starmer (2000)). This literature includes experimental evidence on such behaviour, building on the insights from Ellsberg (1961), and including the well known work of Daniel Kahneman and Amos Tversky (e.g. Tversky & Kahneman, 1974).[7] The findings from this "behavioral" economics literature, show that individual preferences and behaviour may not be stable but rather are contingent on factors, both internal to the individual - such as emotional or "visceral" states, and external - such as the prevailing economic or financial market climate.

If human behaviour *systematically* deviates from expected utility-maximization, under particular conditions, it should be possible both to predict such deviations and to identify trends in market data that correspond to such behaviour. We believe that our paper is

[6]In debating the nature and appropriate methods of Political Economy, the classical economists - chief among them Nassau Senior, John Stuart Mill and John E. Cairnes - argued that economics was an abstract or "hypothetical" science, whose laws were "tendency laws". In the absence of "disturbing causes" agents always *tended* to act in accordance with them. It was on these philosophical foundations that Paul Samuelson, and his successors, were able to build the deductivist infrastructure of modern economic analysis, as detailed in Lo & Mueller (2010).

[7]Another strand of this literature involves attempts to formalize the choice behaviour behind these deviations in various non-expected utility theories (e.g. Gilboa & Schmeidler, 1989; Epstein & Wang, 1994). These theories are generally based on a max-min decision rule, which characterizes investors as taking a worst-case scenario view of ambiguous alternatives.

among the first to present evidence of such trends at a market-wide (macro) level.[8]

Recently, a number of authors have used insights from the literature on ambiguity-aversion in attempting to explain episodes of financial crisis (e.g. Caballero & Krishnamurthy, 2008; Epstein & Schneider, 2008). However, relatively few studies have tested these theories empirically.[9] One of the reasons for the relative scarcity of empirical literature on this topic is that uncertainty remains difficult to quantify. In our empirical analysis, we use a number of different proxies for uncertainty - large market losses, high market volatility and specific crisis episodes.[10]

We should make explicit at this point the distinction - in our usage at least - between ambiguity and uncertainty. Essentially we intend these two terms to have the same meaning - referring to some degree of "unparametrizable randomness". However, we restrict our use of the term *ambiguity* to refer to a specific case, such as an ambiguous signal or scenario, or an individual's aversion to such ambiguity. We use the term *uncertainty*, on the other hand, to refer to a more general state of the macroeconomic or financial market environment.

We expect to derive new insights on the influence of uncertainty on investor behaviour by analyzing two typical but very different safe haven assets - bonds and gold. While bonds and gold are both commonly referred to as safe haven assets, they offer investors very different forms of "safety". Bonds are an obvious choice as safe haven asset, given that they offer a fixed return if held to maturity. The returns to gold, on the other hand, tend to be relatively volatile. However, gold offers investors protection from additional threats to which bonds are susceptible; that is inflation, currency risk and default risk.

Given that uncertainty is expected to be high during precisely those periods when the safe haven property is of relevance - i.e. following market shocks or during periods of high

[8] We do not, however, make any claims as regards prediction, and return to this issue in the conclusions.

[9] Uncertainty has been shown to affect the relationship between bonds and stocks (e.g. Connolly *et al.*, 2005; David & Veronesi, 2008), while Beber *et al.* (2009) examine the role of various Eurozone bonds with different characteristics (i.e. varying levels of liquidity risk and default risk) during periods of market stress.

[10] Bloom (2009) analyzes the macroeconomic - output, unemployment and investment - effects of "uncertainty shocks", as proxied by stock market volatility.

stock market volatility - price changes for two distinct safe haven assets offer a framework to examine the relationship between the degree of uncertainty and investor behaviour.

The evidence presented below finds that both bonds and gold act as "safe haven" assets during periods of market stress. However, our results also reveal an interesting distinction between the roles of these two assets. In general gold becomes more responsive to increasing uncertainty. The stronger reaction of gold at elevated levels of uncertainty is consistent with the risk-return properties of gold compared to bonds. In fact, it would be difficult to explain the observed patterns of investment in gold without reference to ambiguity-aversion, given that the relatively low returns and high volatility of gold would not make it an "efficient" investment from a purely rational-expectations, utility-maximizing perspective. More generally, our empirical findings correspond closely to the expected patterns of behaviour - in response to varying degrees of uncertainty - that we develop in our theoretical framework below.

The distinction between bonds and gold is most clearly illustrated in our graphical analysis of specific crisis episodes. In particular, for those episodes that most closely correspond to the idea of a "black swan" event - i.e. 9/11 and September 2008 (the collapse of Lehman Brothers) - the reaction of gold is both more rapid and stronger than that of bonds. Such "black swan" events are of particular interest for our study, given that they are most likely to generate large uncertainty. However, given their rarity such events may not be amenable to statistical analysis.[11] For this reason, we give serious consideration to the observed patterns of market responses to these isolated events, in addition to our systematic empirical analysis, in drawing conclusions on the role of uncertainty.

In previous work, we have demonstrated the potential for gold to act as a safe haven asset during periods of market stress (Baur & Lucey, 2010; Baur & McDermott, 2010).[12]

[11] "Black swan" events - the *unknown unknowns* that nobody predicted or foresaw - have been characterized by Nassim Taleb (Taleb, 2010) as events that carry extreme impacts. They are outliers in the sense that they lie outside the realm of regular expectations and are essentially unpredictable *a priori*. For this reason, "black swan" events, which had never been factored in to models of risk (because nobody believed, or imagined, that such an event would ever take place), are precisely the type of events that force agents to re-evaluate their world view - thus generating large uncertainties.

[12] In Baur & McDermott (2010), we also review the literature on safe haven assets and the financial characteristics of gold.

As far as we are aware, this is the first paper that jointly considers the role of both gold and bonds as safe haven assets during times of market uncertainty. The paper demonstrates the effects of changes in uncertainty on asset values and on the relationships between stocks, bonds and gold. We also contribute to the literature in several other respects. First, we analyze safe haven assets and investor behaviour within a theoretical framework and thus clearly distinguish this study from the purely empirical literature. Second, we use an econometric framework that explicitly accounts for the endogeneity possibly present between stock returns and safe haven assets. Third, we use a Vector Autoregressive model to allow for feedback effects and study the role of safe haven assets and their stabilizing or de-stabilizing role on the stock market. Fourth, we contribute to the literature with several novel empirical findings regarding safe haven assets. These findings include the overreaction of gold prices to news shocks, the inverted asymmetric reaction of the volatility of gold returns relative to bond and stock returns and the systematic and time-varying (causal) relationship between bonds and gold.

The rest of the paper is structured as follows. In Section 1 we present the theoretical framework for our analysis - a simple decision rule based on Ellsberg (1961)'s ambiguity-aversion, and show how the relative preference ordering amongst our three asset classes would be expected to change under varying degrees of uncertainty. In Section 2 we present a highly stylized dynamic illustration of how we expect uncertainty to vary in response to ambiguous news signals (or a market shock). This section also highlights a number of trends that we expect to find in our data on safe haven assets in response to uncertainty. In Section 3 we present our empirical analysis, including a graphical analysis of specific crisis episodes as well as a detailed, systematic empirical analysis. Section 4 summarizes the main findings and makes concluding remarks.

1 Theoretical Framework

To provide an explicit theoretical motivation for our empirical analysis, we set out a simple framework of investor decision-making under uncertainty in this section.

1.1 The Ellsberg Paradox: Demonstrating Ambiguity-Aversion

In his famous paradox, Ellsberg (1961) demonstrated that seemingly rational people tend to "irrationally" avoid ambiguity. Ellsberg conducted the following hypothetical experiment: You are faced with two urns. The first contains 100 red and black balls but in unknown proportions. The second, you can verify, contains exactly 50 red and 50 black balls. Whether betting on red or black, Ellsberg reports that the majority of people will choose to draw at random from urn two (where probabilities are known). From a probability viewpoint, such preferences are inconsistent, as they indicate the simultaneous belief that the probability of drawing either red or black from urn two is greater than from urn one. Thus, such behaviour may be (mis-)interpreted as "irrational". Once we allow for ambiguity-aversion, however, we can reinterpret the results as follows: Rather than revealing a seemingly irrational belief about the probability of drawing a particular ball from a particular urn, participants in the Ellsberg experiments are in fact revealing their preference for avoiding ambiguity.

Based on his insights regarding ambiguity-aversion, Ellsberg (1961) presents a simple decision rule, which emphasizes the degree of ambiguity of the available information:

$$max : \rho.est_x + (1-\rho)min_x \tag{1}$$

where est_x is the expected pay-off to asset x corresponding to a single estimated probability distribution, min_x is the minimum expected pay-off to x over a range of probability distributions, while ρ represents the degree of confidence in available information.[13]

According to Ellsberg:

> What is at issue might be called the ambiguity of this information, a quality depending on the amount, type, reliability and unanimity of information, and giving rise to one's degree of confidence in an estimate of relative likelihood.

[13] It is important to distinguish here between expectations - be they optimistic or pessimistic - and the degree of confidence associated with those expectations. Confidence - as represented by the parameter ρ in the above decision rule - is a *characteristic* of expectations relating to the certainty or conviction underlying an investor's optimism or pessimism with regard to the future (Dow, 2011).

(Ellsberg, 1961, pg. 657)

The decision rule is essentially a weighting scheme. Investors choose their optimal level of investment in each asset, x - which, for our current purposes, we can think of as representing either stocks, bonds or gold - in order to maximize the weighted sum of the expected pay-off from x and the minimum expected pay-off from x. The confidence parameter ρ decreases in proportion to the ambiguity associated with available information. Thus, when uncertainty - or ambiguity - is high, investors give greater weight to their "worst case scenario" (min_x) in choosing their optimal portfolio of assets. Coates & Herbert (2008) demonstrate the neuro-scientific basis for this relationship between uncertainty and a greater degree of caution.[14] In times of greater market uncertainty, therefore, investors withdraw from risk, favoring relatively "safe" assets; i.e. those to which the minimum expected pay-off - even in periods of market stress - will not be excessively negative.

1.2 A preference ordering among safe haven assets under varying degrees of uncertainty

To illustrate how the inclusion of ambiguity-aversion might be expected to affect investor choices in relation to the three asset classes we are interested in - i.e. stocks, bonds and gold - we assign values for est_x and min_x for each asset and consider how the relative preference ordering between these assets would change for different degrees of uncertainty (i.e. for different values of the confidence parameter ρ). In the absence of uncertainty, the only salient considerations from an investor's point of view are the relative risk return ratios of each asset. We thus assign values for est_x based on each asset's average Sharpe ratio, which is highest for stocks, then bonds and lowest for gold.

The min_x values represent the worst case scenario for each asset. For stocks, the worst case scenario would obviously be a total wipeout of shareholder value. For bonds,

[14]These authors find that investors' cortisol levels become elevated in response to market volatility (a common proxy for uncertainty). Cortisol plays a central role in our responses to stress and is "particularly sensitive to situations of uncontrollability, novelty and uncertainty" (Coates & Herbert, 2008, p.6167). Elevated cortisol levels will "promote a selective attention to mostly negative precedents ... feelings of anxiety; and produce a tendency to find threat and risk where none exist" (*ibid.*, p.6170).

in theory the worst case scenario would also be a total loss of value, in the case of a default - although a partial default or "haircut", might be more likely. For gold, given that it is a physical asset, it is unlikely ever to see its value completely destroyed - certainly not over the short time scales we are interested in. We therefore assign the largest negative value for min_x to stocks, then bonds, with gold considered to have the least negative worst case scenario.

*** Insert Table 1 about here ***

Figure 1 illustrates the relative preference ordering among stocks, bonds and gold for different values of the uncertainty parameter, based on the assigned est_x and min_x values. Under "normal" circumstances, i.e. when uncertainty is low, stocks are preferred to bonds or gold. As uncertainty rises, the relative "safety" of bonds and gold make them more attractive. For moderate levels of uncertainty bonds remain superior to gold. Eventually, for very high levels of uncertainty, gold is the dominant choice.

This characterization of the relative preference ordering of stocks, bonds and gold under varying degrees of uncertainty, makes sense given the differing characteristics of these assets. When stock markets are falling, investors look for protection from losses in the form of relatively safe assets. In this context, government bonds represent an obvious choice as "safe haven" assets, given that they offer a fixed nominal return if held to maturity. On the other hand, gold is more volatile and thus risky but offers investors protection from threats for which bonds do not provide shelter. Gold protects investors against inflation, currency risk and default risk.[15] The latter property deserves further attention. Gold is an uncontingent asset, that is it carries no default risk and its supply is not controlled by any single government or central bank, as are bonds and hard currency. Finally, it can be shown that the risk-return characteristics of gold do not result in an inclusion of this asset in a mean-variance-efficient portfolio with stocks, bonds and gold as

[15]Gold has been characterized in the financial media as an "attractive each way bet" against risks of inflation or stock market losses - further enhancing its attractiveness during periods of uncertainty.

available asset classes. Hence, to hold gold in a portfolio investors must expect some form of compensation or protection not covered by the mean-variance optimization framework. One obvious candidate is relative safety when faced with ambiguous signals or uncertainty.

There are also likely to be psychological or emotional factors at play in the choice of "safe haven" assets. Gold has a unique cultural status, given its historic links to the value of currencies and its role as a symbol of durability and high achievement. Gold is a physical, tangible asset and the market for gold is relatively easy to understand.[16] Gennaioli & Shleifer (2010)'s "local thinking" model of investor decision-making emphasises the inherent cognitive limitations of individuals faced with complex and uncertain choices. Initially at least, only some decision-relevant data come to mind, with the most representative scenarios tending to dominate. Given time and adequate information, decisions are made on the basis of the rational calculation of risk versus return. However, under pressure, with uncertainty high, "visceral" or emotional factors tend to dominate decision making (Loewenstein, 2000). Thus, during periods of market stress, when investors consider gold as a potential investment, "what comes to mind" - based on what gold represents - is likely to be a secure and solid store of value.

*** Insert Figure 1 about here ***

2 From shock to crisis, via uncertainty

In this section we present a highly stylized illustration of the dynamics around a market shock that could potentially turn a shock into a crisis, via the mechanism of heightened uncertainty. This is based on a number of assumptions, and is not intended as a general model of how financial crises occur, but rather as a means of illustrating how uncertainty might be expected to evolve in response to different kinds of news signals (or market shocks). The illustration exercise also serves to highlight the kind of trends we expect

[16] The historical and cultural status of gold is discussed in more detail in Baur & McDermott (2010).

to find in the data on safe haven assets, if market uncertainty - generated by ambiguous news signals - does indeed affect investor behaviour at an aggregate level, as we have postulated.

2.1 Ambiguous Signals and the "bad news principle"

The Ellsberg decision rule has been extended to a dynamic context by Epstein & Schneider (2008), using a model based on investors processing ambiguous news signals. For every market-related event, agents must assess the relevant information against the criteria listed by Ellsberg - the amount, type, reliability and unanimity of information - in order to inform their degree of confidence in estimates of expected returns. The degree of market uncertainty, and investor responses to it, therefore depend on the quality of the observed news signal.

Using Epstein and Schneider's terminology we can distinguish between tangible and intangible news signals. Tangible news signals are those for which investors have the experience or expertise necessary to be confident in their interpretation of the signal. Such events might include the release of financial or economic data, stock market corrections, earnings announcements etc. Following tangible news signals investors will update their beliefs in standard Bayesian fashion - gaining confidence from good news and losing confidence following bad news.

Intangible signals, on the other hand, generate uncertainty as a result of some combination of the novelty of the observation, or the investor's lack of expertise in processing that type of news. Such events might include speculation about a particular company, or political developments that are likely to have an impact on economic or financial activities. Unanticipated, or "black swan" events, could also be considered sources of intangible signals. By their nature, such events are rare in the extreme, with the result that investors have little experience to draw on in interpreting the implications of the event's occurrence.[17]

[17]These events are unpredictable precisely because they are unfamiliar or difficult to imagine. In psychology, the *availability bias* refers to the human tendency to overestimate the probability of events that

In the case of intangible signals, the associated uncertainty causes investors to take a worst case scenario view. They therefore "over-react" to intangible bad news signals, and under-react to intangible good news signals.[18] This is because, as Epstein & Schneider (2008) explain, the worst case scenario for an ambiguous bad news story from an investor's point of view, is that the story is true, whereas the worst case scenario for an ambiguous good news story is that the story is false. Such theories of asymmetric reactions to ambiguous news have their origins in the "bad news principle" in Bernanke (1983).[19] Similarly, Pastor and Veronesi (2011) show that policy changes with positive consequences for stock prices are largely anticipated - given the government's economic motivation - whereas negative policy announcements tend to contain a larger element of surprise. Pastor and Veronesi (2011) emphasize the uncertainty generated by political decisions due to a combination of the unpredictability of political choices and the further difficulty of assessing the economic implications of any changes in policy.

2.2 A dynamic illustration

We can use this characterization of investor responses to news signals of varying quality, to illustrate the expected dynamics of uncertainty - and its implications for our three asset classes - around a market shock. Figure 2 illustrates how the degree of market uncertainty might be expected to fluctuate around particular types of market shocks.

In period $t-1$ there are rumors about a particular company, sector or economy. These rumors generate uncertainty, leading some investors to become cautious and seek the relative safety of assets such as gold and bonds. We would expect to see a drop in stock markets and a rise in safe haven asset values.

can easily be imagined. Thus, shark attacks are far more terrifying to the average person than the idea of being hit by a falling piece of aircraft - even though the latter is, apparently, 30 times more likely (Oliver Burkeman, "Is the easy option simply mental laziness", *The Guardian*, 20 February 2010). Similarly, in a tendency known as *cognitive fluency*, we inherently give precedence to ideas that are relatively easy to think about.

[18] There is a link between tangible and intangible signals and tangible and intangible assets. We predict and show empirically that intangible signals tend to lead to the purchase of tangible assets (gold) while tangible signals lead to the purchase of intangible assets (stocks).

[19] There is a whole strand of literature on investor over- and under-reactions to news of uncertain quality. For example, Daniel & Titman (2000) show how investor over-confidence (in their own ability) biases their responses to new information. See also Daniel *et al.* (1998) and Barberis *et al.* (1998).

At period t, relevant news are released. In the case of a tangible signal representing either good or bad news about the company or economy under pressure - i.e. the release of financial or economic data - the uncertainty dissipates and investor caution is likely to be reversed. In this case - likely the most common scenario - markets reverse their previous day's movements; stocks regain their previous losses, while safe haven assets reverse any gains.

However, the announcement may take the form of an intangible signal, for example an unexpected earnings announcement by a company, or a central bank intervention in an attempt to "restore market confidence". The intangible signal may represent good news - for example a central bank decision to cut interest rates or to pursue quantitative easing, or a political decision such as the Irish government's announcement in 2008 of a blanket bank guarantee. Such good news is likely to have been anticipated by markets, however, and therefore the impact will be muted (Pastor and Veronesi, 2011).

On the other hand, the intangible signal could represent bad news. Markets may be disappointed by political indecision or inaction - as typified by the repeated failed attempts to produce a political solution to the euro crisis.[20] Or indeed, the announcement and the associated action may be unanticipated - such as the decision to allow Lehman Brothers to collapse.[21]

The unanticipated nature of the "bad news" signal represents a market shock. As a result stock markets fall. Furthermore, such *ambiguous* "bad news" signals generate large uncertainty. Investors "over-react" to the ambiguity, focussing on down-side risks and worst case scenarios, leading to a "crisis of confidence". The perceived shift in their "environment" forces investors to accept that they face Knightian uncertainty. As a result, investors question the validity or applicability of their mathematical models which are

[20] *The Economist* has characterized the financial market panic that has engulfed the euro-zone as resulting from European policymakers being "unable or unwilling to be bold enough" to regain market confidence ("Is this really the end?", *The Economist*, 26 November 2011).

[21] Lo & Mueller (2010, p.42) describe the "unanticipated reaction" of the US government to Bear Stearns' collapse - temporarily prohibiting the shorting of certain companies in the financial services sector - as "an example of irreducible uncertainty that cannot be modeled quantitatively, yet has substantial impact on the risks and rewards of quantitative strategies".

based on quantifiable uncertainty.

As described above, the increased level of uncertainty causes investors to become highly cautious, disengaging from long-term commitments and risks. Such trends lead to an intensification of the crisis and a contagion effect, or a classic flight to safety (Caballero & Krishnamurthy, 2008). This highly stylized illustration is suggestive of how a shock can be transformed into a crisis, via the mechanism of increased uncertainty.

*** Insert Figure 2 about here ***

The next section presents the empirical data and tests the expected effects of uncertainty on the relationship between stocks, bonds and gold, as outlined in sections 1 and 2.

3 Empirical Analysis

3.1 Data

The data used in our empirical analysis are accessed through Datastream. We use daily returns data for all variables. The sample period for our analysis is the 31-year period from 1 January 1980 to 31 December 2010. We thus have a sample of over 8,000 daily return observations (roughly 250 observations per year over a 31-year period). Prices - for the world stock market indices and gold bullion - are quoted in US dollars.

3.2 Descriptive Analysis

Figure 3 compares movements in the main series of interest - a global stock market index, US government bonds with different maturities (2 years, 10 years and 30 years) and gold spot prices (bullion) - over the sample period (1980-2010) using quarterly observations. Gold prices have seen a secular increase over the past decade. This follows a long period of relatively steady gold prices - if anything gold had been trending down through the 1980s and '90s, following its historic high (in real terms) in the late '70s. US government bonds of various maturities have been trending gradually upwards over the 30-year sample period, albeit with a notable cyclical quality to these time series. The shorter maturity bonds - 2 year bonds in particular - exhibit a less cyclical pattern over the sample period, whereas longer maturity bonds appear to experience much larger cyclical price swings.

*** Insert Figure 3 about here ***

While the world stock market index has also been on a rising trend over the past 30 years, figure 3 illustrates the dramatic peak-to-trough swings associated with the dot.com bubble and the recent global financial crisis, in particular. What is also clear from this graph is the strong inverse relationship between the global stock market index and the 30-year US government bonds over the past 15 years (since about the mid-90s), particularly during episodes of large movements in the stock market index. Such a pattern - exemplified by the dramatic spike in the 30-year US Treasury bond series at the height of the recent financial crisis - towards the end of 2008, around the time of the collapse of Lehman Brothers - would be consistent with the notion of bonds acting as “safe haven” assets.

Summary statistics for these variables are presented in table 2 and show that on average over the sample period, the daily stock returns index significantly outperforms both bonds and gold (average daily returns of 0.03% for the world stock market index, 0.004% for 10 year US government bonds, and 0.01% for gold bullion priced in US dollars). While the volatility of bond returns is significantly lower than stock returns (standard deviation of daily returns of 0.5% for 10 year US government bonds, versus 0.9% for the global stock market index), the volatility of gold spot (bullion) and futures returns (COMEX) is higher (standard deviation of daily gold returns of 1.3%).

*** Insert Table 2 about here ***

The lower part of table 2 presents a simple correlation analysis, looking at average correlations between stocks, bonds and gold over the sample period. We also analyze the relationship between these asset classes by quantiles of stock returns to see if the correlations differ from the average during periods of strong stock market increases or declines. Naturally, given our interest in safe haven effects, the focus here is on the bottom end of the stock returns distribution.

On average over our sample period (1980-2010), there is a negative - albeit relatively weak - correlation between stocks and bonds. Stocks and gold are positively correlated on average. However, this relation may partly be explained by movements in the dollar, which is strongly negatively correlated with both stocks and gold, and to a lesser extent with bonds. Gold and bonds are only weakly correlated on average, especially for longer maturity bonds.

When we look at these correlations sorted by the quantile of stock returns, a more interesting pattern emerges. Bonds and gold are both negatively correlated with stocks when stock returns are below the 10% (5% or 1%) quantile, indicating the potential for either of these assets to act as "safe havens" in the face of stock market losses. On the basis of these correlations, bonds appear to offer a stronger safe haven - i.e. bond returns are more negatively correlated with stocks during periods when stock markets are falling.

*** Insert Table 3 about here ***

Another way to look at correlations is to condition on time, that is to use a rolling window to calculate the correlation. Figure 8 illustrates the time-varying correlations for stock-bond, stock-gold and bond-gold returns using a 2-year window.

*** Insert Figure 8 about here ***

The time-varying correlations show that stock-bond correlations exhibit the widest range of values; between 0.5 and -0.5, followed by stock-gold correlations and bond-gold correlations. Stock-bond correlations have declined substantially from positive values from

1980 until 2000 to mostly negative values in the period from 2000 to 2010. The negative values around -0.4 in 2008 and 2009 imply that US government bonds were a hedge during the financial crisis in 2008.[22] The stock-gold correlations are smaller in absolute values and generally exhibit shorter periods of negative correlations. For example, during the financial crisis in 2008 the stock-gold correlations are only negative for a relatively short period and at levels relatively close to zero (-0.1). The substantially lower degree of negative correlations of stock-gold correlations relative to stock-bond correlations make US government bonds a stronger hedge against stock market turmoil on average than gold.

Finally, the bond-gold return correlations show when investors view bonds and gold as similar assets or alternatives. Positive correlation levels indicate that investors do not distinguish between bonds and gold whereas negative correlation levels indicate that investors have different views about the required protection against future uncertainty. For example, negative bond-gold correlations can be observed during the burst of the dot-com bubble in 2000 and September 11, 2001 and the period preceding the global economic and financial crisis. The bond-gold correlations exhibit positive values during the crisis in 2007 and 2008.

Our data selection and analysis is based on the perspective of an international investor who holds a global portfolio of stocks represented by the MSCI World stock index, US government bonds and gold whereas all assets are denominated in US dollar. The currency effect can be well illustrated with gold which is usually quoted in US dollar. This implies that the price of gold in US dollar changes if the value of the US currency changes. For example, when the dollar depreciates, gold denominated in dollars tends to gain nominal value, thus maintaining its real value.[23] This effect holds for all currencies and is thus not a specific feature of the US dollar.

[22] We avoid the term "safe haven" as the 2-year window is too long to be used to test for the existence of a safe haven.

[23] Purchasing power parity will ensure that the price of gold in US dollar is equal to the price of gold in Japanese yen for example. If P is the price of gold in US dollar, P^* is the price of gold in Japanese yen and S is the Japanese yen per US dollar exchange rate the following condition holds: $P^* = SP$

Hence, historical gold prices can fluctuate due to exchange rate changes. That said, exchange rate movements cannot explain the larger price changes for gold, e.g. the most recent substantial increase in the price of gold. While in part the price increase reflects a wider trend across commodity classes, the rise in the gold price would also appear to have been driven by increasing investor demand. Financial instability - and the uncertainty associated with the global financial crisis - may have played a role in driving up the "safe haven" demand for gold.

Empirically, a similar effect may be observed for bonds but the reasons are different. US government bonds are issued and denominated in US dollars. If the US dollar depreciates (appreciates), the value of a US government bond falls (increases) viewed from the perspective of an international investor. If international investors respond to the cheaper bond price with purchases of US bonds increasing the demand and the price of the bond, the intrinsic value of the bond may remain unchanged.

3.2.1 Safe haven assets during financial crisis

This section analyzes the evolution of stocks, bonds and gold during specific periods of financial turmoil or crisis to assess the performance of bonds and gold as safe haven assets. While an explicit focus on specific crisis episodes is somewhat arbitrary, due to the difficulty associated with attempting to define crisis periods, a graphical analysis avoids this problem to some degree since longer periods (some pre-crisis period and post-crisis period) can be shown and the reader can obtain her own interpretation.

The specific crisis episodes illustrated in figures 4 to 7 are (i) the 1987 stock market crash, (ii) the Asian financial crisis in 1997, (iii) the September 11th, 2001 terrorist attacks and (iv) the global economic and financial crisis in 2008.

The figures show that gold was a safe haven in the stock market crash in October 1987 and in September 2001 in the sense that it did not lose its value. Gold was a short-run safe haven following the October 1987 crash, but was outperformed by bonds after around 10 days. Gold performed better than bonds following the September 11 event in 2001.

The Asian financial crisis in 1997 is a good example of a regional crisis in which the safe haven property of international investors was not required and thus not evident in the evolution of the price of gold. Finally, the turmoil in late 2008 representing the peak of the global economic and financial crisis displays a positive evolution of the gold price from mid-September 2008 until mid-October consistent with a safe haven asset, but a negative evolution of the price of gold after around mid-October. Bonds do not qualify as a safe haven prior to mid-October but then outperform gold in the subsequent two months. In mid-December both gold and bonds are in positive total return territory with respect to September 15, 2008 consistent with a long-run safe haven asset.

Gold returns appear to have risen particularly strongly in response to the September 11th attacks and the culmination of the global economic and financial crisis in September 2008, likely reflecting the radical uncertainty created by the occurrence of such unforeseen "black swan" type events.

*** Insert Figure 4-7 about here ***

The September 11 terrorist attacks and the subprime or financial crisis in 2008 also display some details that are very important in the context of safe haven assets and investor behaviour. The September 11 event is special as gold only became a safe haven for investors one day after the attack. On the day of the attack, gold lost value with respect to the previous trading day. Only on the next day the price of gold increased significantly and outperformed bonds over the following days.

The peak of the subprime crisis in late 2008 demonstrates that a safe haven cannot be a safe haven in the long-run or at all times, that is if investors buy gold as a safe haven in response to a negative shock but this initial shock is followed by a sequence of similar or even larger negative shocks some investors may be forced to sell gold eventually depressing the price of gold and bringing the safe haven status of gold for that particular event to an end.

Table 5 summarizes the graphical analysis by displaying the aggregate returns over the specified episode of turmoil. It extends the above discussion by including the bond returns for all maturities and the 1998 Russian and Long-term capital management (LTCM) crisis as an additional example. The graphs focussed on the 30-year bond returns to ensure that each time-series can be easily identified.

*** Insert Table 5 about here ***

While the graphical analysis is indicative of the relationship we expect to find, the analysis focusses on idiosyncratic events. In the next section we present results of our systematic regression analysis.

3.3 Econometric Framework

This section introduces the econometric framework to analyze the behaviour of investors with respect to safe haven assets. As outlined above, we expect both US government bonds and gold to be safe haven assets. However, we expect that the decision of investors to buy these assets depends on the degree of economic and financial uncertainty.

We proceed as follows. First, we analyze how gold and bonds react to shocks in the stock market on average, that is what we call a 'systematic analysis'. The findings do not necessarily provide evidence for a safe haven but only a hedge.[24] In a second step, we analyze the reaction of these assets to shocks under extreme conditions, i.e. what we call a 'conditional analysis'. Since we condition on extreme events, the framework tests for the existence of a safe haven property.[25] The last part of the analysis entails a vector autoregressive model (VAR) with stocks, bonds and gold as endogenous variables. The VAR will be estimated both unconditionally (similar to the systematic analysis) and conditionally dependent on extreme stock market returns. The estimation results are

[24] The difference between a hedge and a safe haven was analyzed in Baur and Lucey (2010).

[25] We focus on safe haven assets for stocks, not on general safe haven assets as we do not test whether these assets depend on large shocks from the real economy, e.g. GDP growth announcements, unemployment rates etc.

analyzed in a separate section for two reasons. First, the VAR only models lagged effects and is thus not directly comparable to the above econometric specifications and second, the VAR allows the estimation of feedback effects from bonds or gold on stocks. A positive feedback effect implies a stabilizing role of the safe haven assets while a negative feedback effect implies a destabilizing role of the safe haven asset on the stock market. The feedback effect is an important aspect to assess the role and importance of safe haven assets and is thus discussed separately.

3.3.1 Systematic Analysis

The following model is estimated for both gold and bond returns in two separate regressions:

$$y_t = c + \boldsymbol{\alpha} \sum_{i=1}^{I} y_{t-i} + \boldsymbol{\beta} \sum_{j=0}^{J} y^*_{t-j} + \boldsymbol{\gamma} \sum_{k=0}^{K} x_{t-k} + \boldsymbol{\Phi} \boldsymbol{X}_t + e_t \tag{2}$$

where y_t denotes either the bond return (regression 1) or the gold return (regression 2) at time t. The return is regressed on a constant c, its own lagged returns and the contemporaneous and lagged returns of the other safe haven asset y^*. The reaction to contemporaneous and lagged stock market shocks is captured by the variable x. The matrix $\boldsymbol{X}$ includes control variables such as the value of the US dollar. The error term is denoted as e_t and follows an asymmetric GARCH(1,1) process (*a la* Glosten *et al.* (1993)). The parameters to be estimated are c, the vectors $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ and $\boldsymbol{\Phi}$.

The model above includes lags of the dependent variable and the regressor variables y^* and x to fully capture the evolution of the price of the haven asset through time. The model selection follows a general-to-specific estimation process which starts with a relatively high number of possible lags (we used a maximum of 5 lags) and then reduces the number of lags by one if the highest lag order is not statistically significant.

The econometric model can be used to test several hypotheses. First, it can test whether the potential safe haven asset is negatively influenced by contemporaneous stock market returns. The null hypothesis is $H_0 : \gamma(t = 0) \geq 0$ where the term in parenthesis indicates that the estimate refers to the contemporaneous effect $t = 0$. If H_0 is rejected, the alternative hypothesis $H_A : \gamma(t = 0) < 0$ is accepted. Second, it can test how fast the asset reacts to shocks in the stock market ($H_0 : \gamma(t - k) \geq 0$) and third, the model can assess whether there is an overreaction or underreaction of investors to shocks in the stock market ($H_0 : \alpha(t - 1) = 0$).

The model implicitly assumes that both potential safe haven assets are independent and can be modelled separately. The fact that we control for changes in the other asset y^* does not fully reduce the possible endogeneity. We use a 2-stage least squares (2SLS) estimation strategy to remedy this shortcoming and discuss differences with respect to the model when endogeneity is not explicitly accounted for. Another reason for presenting both models is that we are not aware of any research that employed a 2SLS model in the context of gold and safe haven assets. The first stage of the 2SLS regresses the bond return r_B (gold return r_G) on all exogenous variables, i.e. equation 2 is estimated for $y = r_B$ (r_G) and $\boldsymbol{\beta} = 0$ (y^* is not included in the regression). In a second stage the original specification is estimated with the predicted value (denoted by a $\hat{}$) of the endogenous variable on the right hand side, i.e. the bond return r_B is regressed on all exogenous variables and the predicted gold return $\hat{r}_G$ and the gold return r_B is regressed on all exogenous variables and the predicted bond return $\hat{r}_B$.

The framework described above is systematic in the sense that the effects are present on a daily basis and not specific to certain periods or conditions. While the systematic or average effect is not the primary focus of this paper it is important to compare the systematic reaction with the reaction in extreme conditions. Such a comparison can answer the question whether investors react differently in normal and extreme conditions.

What we are particularly interested in is the reaction of the potential "safe haven" assets in periods of increased market uncertainty. Uncertainty *per se* is difficult to measure directly. Instead, in the conditional analysis, we focus on the reaction of the safe haven assets to extreme negative shocks in the stock market or extreme volatility in the stock market, as proxies for uncertainty (e.g. Bloom, 2009).

3.3.2 Conditional Analysis

The conditional analysis is based on the model utilized for the systematic analysis but only uses observations on days when the stock market return exceeds a certain (lower tail) threshold or stock market volatility exceeds an upper tail threshold. We use the 10, 5 and 1 percent quantiles for the conditional return analysis and the 90, 95 and 99 percent quantiles for the conditional volatility analysis.

3.3.3 Vector Autoregression

The Vector Autoregression (VAR) model estimates the linkages among stock, bond and gold returns by treating them as endogenous. The change of the US dollar is treated as exogenous. Thus, the individual equations of the VAR are similar to the models estimated above. The VAR is estimated both as an unconditional model and a conditional model and thereby follows the structure of the models described above. The estimates can be compared only with regards to the lags as contemporaneous effects of the endogenous variables cannot be modelled with the VAR.

The VAR can be written as follows

$$\begin{pmatrix} r_{G,t} \\ r_{B,t} \\ r_{S,t} \end{pmatrix} = \boldsymbol{\alpha} + \boldsymbol{\Pi}_1 \begin{pmatrix} r_{G,t-1} \\ r_{B,t-1} \\ r_{S,t-1} \end{pmatrix} + \boldsymbol{\Pi}_2 \begin{pmatrix} r_{G,t-2} \\ r_{B,t-2} \\ r_{S,t-2} \end{pmatrix} + \sum_{i=1}^{i=3} \Phi_i \boldsymbol{X}_{t-i-1} + \begin{pmatrix} e_{G,t} \\ e_{B,t} \\ e_{S,t} \end{pmatrix} \tag{3}$$

where $\boldsymbol{\Pi}_i$ and $\boldsymbol{\Phi}_i$ are (3×3) parameter matrices.

The next section presents the estimation results based on the models described above.

3.4 Econometric Results

This section presents the estimation results and follows the structure set out in the previous sections. First, the results of the systematic model are presented followed by a conditional analysis of that model. The second part of this section presents the results of the vector autoregressive model estimated unconditionally and conditional on extreme stock returns and extreme stock return volatility.

3.4.1 Systematic Analysis

In table 6 we present the results of the systematic analysis using the full sample of daily observations from 1980 to 2010. The influence of stocks on bonds and on gold is estimated with two separate regressions; one with gold as the dependent variable and the other with bonds as the dependent variable. The regressions include a careful modelling of the dynamic structure of the influence of the right-hand side variables.

*** Insert Table 6 about here ***

The table consists of two panels, the left hand panel exhibits the estimation results for the US government bond and the right hand panel presents the estimation results for gold. Both panels contain the name of the variable, the associated coefficient estimates, standard errors, z-statistics and p-values. The model specifications in both panels include the lagged dependent variable, contemporaneous or lagged returns of the alternative haven asset, contemporaneous or lagged world stock market returns, changes of the US dollar (a trade-weighted index) and a constant. The heteroscedasticity of the returns is also modelled and the coefficient estimates of a Glosten *et al.* (1993)-asymmetric GARCH(1,1) model are reported.

The estimation results for the US government bonds can be summarized and interpreted as follows. The lagged bond return is positive, indicating serial correlation and thus some degree of underreaction to past shocks. The influence of contemporaneous, one-day and two-day lagged gold returns is negative which provides some evidence for the notion that gold and bonds are alternative assets. The world stock market index (rmswrld) enters this regression positively, indicating that on average, when stock markets rise (fall) bond returns also rise (fall). The positive contemporaneous effect of stock market returns on bond returns may seem to go against the safe haven hypothesis. However, as we have seen from the preliminary analysis, it may be that this relationship is reversed during periods of market stress - i.e. precisely when the safe haven property is of relevance. We will investigate this possibility further in the conditional analysis, reported below. Finally, changes in the value of the US dollar have a negative influence on the bond return. Hence, if the US dollar appreciates, the price of a bond goes down and vice versa.

The right hand side of the table shows the estimation results with gold returns as the dependent variable. The lagged gold return is negative and highly significant, indicating overreaction to past shocks or a reversal in contrast to the underreaction or momentum found for bond returns. Bond returns exhibit a negative influence on gold returns. This effect is similar to the result obtained for the model with bond returns as the dependent variable with the exception that only the contemporaneous effect is statistically significant but not the lags. The influence of the stock market on gold returns is represented by a contemporaneous and a one-day and two-day lagged effect. The contemporaneous effect is negative and the lagged effects are both positive. This suggests that the reaction of gold to shocks is consistent with a hedge but the property is short-lived since the initial effect is reversed within two days.

Changes in the value of the US dollar have a strong negative influence on the price of gold since the return series is based on gold denominated in US dollar.

In the lower portion of table 6 we analyze the coefficient estimates of the process representing the conditional volatility of bonds and gold. For bonds (left panel), the negative threshold ARCH (*tarch*) coefficient indicates that negative shocks increase the volatility of bond returns by more than positive shocks. This effect is similar to findings for stock market volatility (e.g. Glosten *et al.* , 1993). Turning to the volatility of gold, on the other hand, we find a negative asymmetric effect, which means that the volatility of gold increases more in response to positive as opposed to negative shocks. This finding is also reported in Baur (2012).[26] The inverse asymmetric response of gold return volatility

[26]The paper argues that the inverted asymmetric effect (i.e. that positive shocks increase volatility by more than negative shocks) is related to the safe haven characteristic of gold. If investors buy gold during periods of increased uncertainty or turmoil in other markets - especially the stock market - investors transmit the heightened volatility to the gold market.

with respect to past negative shocks is further evidence that gold is different from US government bonds, despite their common status as safe haven assets.

3.4.2 Accounting for Endogeneity - Two-Stage Regression Results

Table 7 presents the results from two-stage least squares (2SLS) regressions that explicitly account for the potential endogeneity of bond and gold returns. To the best of our knowledge, this potential endogeneity has not been accounted for in the literature to date. The estimation results are similar to those reported in table 6 but the magnitude of the bond to gold effect is significantly greater. The results show that bond returns negatively influence gold returns (right panel, coefficient estimate -1.6096) while gold returns do not significantly influence bond returns (left panel) if the endogeneity is explicitly accounted for. The estimates also illustrate that the contemporaneous influence of stock market returns on gold increases substantially and is estimated with a parameter of -0.1128 compared to -0.0148 in the initial specification in table 6.

*** Insert Table 7 about here ***

The negative and significant coefficient on the bonds variable on gold (right panel) indicates that, on average, when bond returns rise (fall), gold prices fall (rise). This result suggests that bonds and gold are assets with different properties and roles. On average, when investors buy bonds, they withdraw from gold; and vice-versa, when they sell bonds, gold prices rise suggesting a movement into gold. This pattern reveals that the flow of causation is from bond markets to gold prices and not the other way around. The result implies that investors generally use bonds to hedge against stock market losses and under certain circumstances they use gold as a hedge against bonds. That is, if both stocks and bonds exhibit losses, investors buy gold.

3.4.3 Conditional Analysis

The analysis so far has not particularly focussed on specific periods of increased uncertainty but analyzed the systematic (or average) impact of stock market shocks on gold and bond returns. This section analyzes the characteristics of gold and bond returns with respect to two indicators or triggers of uncertainty; (i) large negative stock market shocks and (ii) regimes of high volatility in the stock market (see Bloom, 2009).

This section reports results of regressions with an implicit crisis-specific analysis by focussing on periods of extreme negative stock returns (table 8) and extreme stock market volatility (table 9). An explicit econometric treatment of crisis periods would be somewhat arbitrary due to the difficulties associated with a definition of start and end dates for a given "crisis".[27] Rather than attempting to define crisis periods in an ad-hoc manner, we instead let the data speak for itself, by analyzing the relationship between stocks, bonds and gold, conditional on stock returns being at the lower end of the returns distribution (i.e. in or below the 10th, 5th and 1st quantiles) or, alternatively, conditional on the volatility of stock returns being above the 90th (95th, 99th) quantiles.[28]

*** Insert Table 8 about here ***

*** Insert Table 9 about here ***

Tables 8 and 9 show the effect of global stock market returns on bond returns and gold returns conditional on stock returns being below the 10th, 5th and 1st quantiles (Panel A) and conditional stock market return volatility being above the 90th, 95th and 99th quantiles (Panel B), respectively. We can see that the negative contemporaneous effect of

[27] A graphical analysis as provided above circumvents an exact definition of such episodes.

[28] The volatility index VIX is also considered as an alternative. The correlation of the VIX and the estimated volatility of the stock return index is very high (it is around 0.85). We use the estimated volatility as only this variable is available for the full sample period. Bloom (2009) uses the estimated volatility only for the sample for which the VIX is not available and merges the estimates with the VIX to obtain a measure of uncertainty for the entire sample period.

stocks on bonds is an order of magnitude stronger for extremely negative stock returns than for average stock returns (e.g. a coefficient of -0.3868 conditional on stock returns below the 10th percentile compared with 0.0203 for the full sample analysis). A similar effect is found for extreme levels of volatility but the coefficient estimates are smaller (e.g. the contemporaneous effect of a negative stock market shock is -0.2374 conditional on the 90th quantile).

The influence of global stock market returns on gold returns is also stronger for extreme negative stock market returns (1 % quantile) than for average stock returns. The coefficient for the lagged return is estimated at -0.4221 for the 1% quantile return threshold and at -0.0888 if the stock market volatility at $t-1$ exceeds the 99% quantile.

The finding that for the most extreme negative stock market returns (i.e. stock returns in the 1st percentile), the negative response of gold returns occurs only with a lag while bonds react contemporaneously suggests that investors generally buy bonds as a safe haven and only buy gold if uncertainty remains high one day after the shock. Another interpretation is that if uncertainty persists for more than a day, investors buy gold. This interpretation is fully consistent with the coefficient estimates conditional on extreme levels of volatility where the first lags are highly significant for all thresholds. The findings in this section are also consistent with the results for the "black swan" event on September 11, 2001 for which gold prices only reacted with a lag as discussed above.

3.4.4 Vector Autoregressions (VAR)

This section presents a summary of the estimation results of the unconditional VAR and the conditional VAR. Table 10 contains seven panels: panel A shows the signs of the estimated coefficients of the unconditional VAR, panel B, C and D present the signs of the estimated coefficients of the VAR conditional on extreme stock returns and panels E, F and G present the signs of the estimated coefficients of the VAR conditional on extreme stock return volatility. The panels show the impact of the endogenous variables at $t-1$ on the endogenous variables at t. For example, the results presented in panel A mean that there is a negative influence of gold returns at $t-1$ on gold returns at t (negative sign). The first row of panel A also shows that gold returns at $t-1$ have a negative impact on bonds at t and a positive influence on stocks at t. These results imply that gold overreacts to shocks indicated by the negative autocorrelation coefficient, positive (negative) gold returns at $t-1$ decrease (increase) bonds at t ceteris paribus and positive (negative) gold returns at $t-1$ increase (decrease) stock returns at t.

*** Insert Table 10 about here ***

The conditional results presented in panels B, C and D imply that gold is a strong safe haven with respect to extreme negative stock returns (negative sign in first columns and last row, stocks at $t-1$ on gold at t) while there is no clear evidence for bonds being a safe haven (second column, last row, stocks at $t-1$ on bonds at t). Panels E, F and G present the results for the VAR conditional on excess volatility and again show that gold is a strong safe haven when volatility or uncertainty is very high (90%, 95% and 99% quantiles). There is no effect (coefficients are zero economically and statistically) for bonds, i.e. when stock market volatility is high there is no positive effect from stock returns at $t-1$ on bond returns at t.

The conditional VAR results also provide estimates of the feedback effect from the safe haven assets on the stock market. If there is a positive feedback effect from the safe haven asset (gold or bond) to the stock market the price changes of the safe haven assets exert a stabilizing role on the stock market. For example, if there is a positive feedback effect from gold to stocks, an increased price of gold (caused by a falling stock market) tends to reduce the severity of the drop in stock prices and thus reduces the volatility and uncertainty in the stock market.

Panels B, C and D show that gold exhibits such a positive feedback effect on the stock market while bonds display a negative effect. The panels representing the estimates conditional on excess volatility (panels E, F and G) show that there is a positive feedback effect on stocks from both gold and bonds.

The finding that there is only a positive feedback effect from bonds in high volatility regimes but not in periods of extreme negative stock returns can be explained with the fact that volatility clusters and is persistent while extreme negative stock returns are usually reversed after a day, i.e. days of extreme negative stock returns are followed by days of positive stock returns.

3.5 Summary of empirical results

The results reported above clearly fit with the predictions of our "behavioural" theoretical framework - based on a simple decision rule incorporating ambiguity-aversion (Section 1). Our results indicate that ambiguity-aversion plays a significant role in investor responses to market shocks or volatility. In particular, the reported results for gold would be difficult to explain without reference to ambiguity-aversion, given the relatively poor risk-return ratio of gold returns.

We find that both bonds and gold act as "safe haven" assets during periods of market stress. However, our results also reveal an interesting distinction between the roles of these two assets. In general gold appears to be more responsive to uncertainty. This conclusion is based on a number of observations. First, gold prices are highly volatile. Gold also responds negatively to stock market movements on average, although the gains made by gold as stocks fall are, on average, reversed after two days of trading. This finding is suggestive of investors moving rapidly into and out of gold, over-reacting to ambiguous market signals and reversing their positions once the ambiguity is resolved. Such a pattern of behaviour is in line with the theoretical contributions of Epstein & Schneider (2008). Bonds on the other hand, on average respond positively (and weakly) to stock market movements, with positive autocorrelation further indicating an under-reaction or momentum in bond prices.

Furthermore, in our conditional analysis, the reaction of gold returns to stock market movements gets progressively stronger (and becomes more persistent) as we move from average stock returns to the most extremely negative returns. For bonds, if anything, this trend is reversed with the observed strongly negative reaction to large market losses (indicating the safe haven characteristic) becoming less pronounced for the most extreme (negative) stock returns. The quick reversal of gold returns, observed on average, does not occur for these more extreme scenarios. It is likely that the implications of a more extreme shock take longer to become clear and thus uncertainty prevails for longer - generating the more persistent movement into gold that we observe.

Our conclusion that gold is "more responsive" to uncertainty - in line with the predictions of our theoretical framework and illustration - is confirmed by a number of other interesting features of the results we presented above. For example, when we account for the potential endogeneity of bonds and gold in the 2SLS regressions, we find that the flow of causation is from bonds to gold and not the other way around. In other words, this finding indicates that investors use bonds as a hedge against stocks, but under certain circumstances, they use gold as a hedge against bonds - i.e. if both stocks and bonds fall, investors switch to gold. It appears that when uncertainty is particularly acute, gold is preferred - a conclusion that is further strengthened by the graphical analysis of specific crisis episodes contained in Section 3.2.

This trend is also apparent in the lagged effects in the conditional analysis. Bonds are a contemporaneous safe haven when stock markets fall. However, we observe some reversal of the movement into bonds after one trading day. Somewhat speculatively, we might interpret this as evidence of the kind of pattern that we highlighted in our illustration in Section 2.2. Following an initial shock, stock markets fall and investors buy both bonds and gold. However, the uncertainty created by the shock (or an ambiguous political response to the shock) could lead to an intensification of the crisis. As a result, investors fear the worst and seek out the additional protection offered by gold - i.e. an each-way bet against the threat of inflation or further stock market losses, and zero risk of default.

The VAR results are also consistent with this picture, indicating that gold maintains its safe haven status one period after the initial shock, whereas bonds do not. Based on the VAR results, it appears that on average when investors buy shorter maturity bonds (2-year or 10-year bonds), a period later they also buy gold. When they buy 30-year bonds, the response of gold is still positive one period later but not significant. The relationship between short-maturity bonds and gold is consistent with investors becoming highly cautious and disengaging from long-term commitments and risks (Caballero & Krishnamurthy, 2008).

It appears, therefore, as we would expect, that bonds and gold are used for somewhat different purposes by investors. According to the Ellsberg decision rule, as uncertainty rises investors place a greater emphasis on their "worst case scenario" expectations. It is thus perfectly "rational" for them to favour uncontingent, liquid assets - i.e. gold.

4 Conclusions

This paper follows in the wake of a string of recent literature in behavioural finance that draws on lessons from psychology and experimental economics in attempting to explain and understand investor behaviour in the context of financial crises (e.g. Caballero & Krishnamurthy, 2008).

We set out to investigate investor behaviour under conditions of market uncertainty. In particular, we analyze patterns of "safe haven" price changes, focussing on two specific "safe haven" assets - bonds and gold - and how they are treated by investors during periods of market stress. We construct a simple theoretical framework, based on the Ellsberg (1961) decision rule, to illustrate how investor preferences among these assets are expected to vary for different degrees of uncertainty. Essentially, under this decision rule, as uncertainty rises investors give greater weight to their "worst case scenario" expectations in forming their preferences over different assets. We also present a highly stylized illustration of the expected dynamics of uncertainty around an extreme (unanticipated) market shock.

In our empirical analysis we test the implications of the theoretical framework and the investment trends that we expect to observe based on our illustration exercise. First, we present a graphical analysis of a small number of specific crisis events. This analysis suggests that both bonds and gold tend to act as safe haven assets following stock market crises. However, these assets appear to differ in the timing of their responses to crisis events. Interestingly, for those events that most closely fit the description of "black swan" events - i.e. the 9/11 terrorist attacks and the recent global financial crisis - gold is the stronger and more immediate safe haven.

The results of our systematic analysis without a focus on idiosyncratic crisis events show that both bonds and gold are a safe haven if the stock market exhibits extreme negative returns. However, only gold is a hedge against stock market losses and bond market losses.

The results also show that in general, the response of gold to market shocks is quickly reversed, indicating that gold is a short-term haven, and also that gold is more responsive to uncertainty. For more extreme events, the relatively quick reversal of gold does not occur. This fits with our characterization of investor responses to shocks. For more extreme shocks, the associated uncertainty is likely to persist for longer. While both gold and bonds are found to act as "safe haven" assets, it is interesting to note that the response of gold becomes both stronger and more persistent following the most extreme shocks.

The findings presented in this paper support the conjecture that uncertainty is a crucial element in investor decisions, particularly in the aftermath of market shocks. Following an unanticipated event, fear of the unknown forces investors to seek safety in the form of secure assets. For the most extreme events - when uncertainty is most pronounced - investors turn to an asset that is quite literally "solid", tangible and that has been used as a store of value for centuries - i.e. gold. In the aftermath of a market shock, psychological and emotional factors are clearly at play in the decisions of investors.

In the introduction we argued that if investor preferences and behaviour were known to vary systematically in response to changes in "environmental" conditions - such as a rise in market uncertainty - then it should be possible to predict such patterns and also to identify these trends in market data. We believe we have provided sufficient evidence for the latter, and that our paper is among the first to demonstrate such systematic patterns of investor behaviour in response to uncertainty, at a market-wide (macro) level.

Ultimately the issue of prediction faces the problem that we can have only limited understanding of the underlying process that generates uncertainty - e.g. the occurrence of "black swan" events or political responses to the emergence of a financial or economic crisis. By their very nature, "black swan" events, by definition, are essentially unpredictable *a priori*, although human nature causes us to concoct explanations for their occurrence, assigning "retrospective" predictability *a posteriori* (Taleb, 2010).

That said, regardless of the limitations in terms of our ability to predict the timing of such events, we should not be put off attempting to move from a state of ignorance to some deeper level of understanding as to the likely investor responses once a shock has occurred and the wider market implications of these responses. Certainly, a greater awareness of both the prevalence of uncertainty, and its potential to wreak havoc in financial markets - through its effects on investor behaviour - represents a valuable insight in itself.

Thinking about the policy implications of our findings, opportunities to intervene to short-circuit the potential for uncertainty to turn a shock into a crisis should be sought out. In particular, if uncertainty is generated or exacerbated by ambiguous or unanticipated political interventions, then this suggests potential for a greater role for rule-based interventions and non-political institutions in financial crisis management.

While we have argued that the availability of a safe haven asset is beneficial for financial stability, as it protects wealth when it is most needed, it could be that investor awareness of the existence of such an asset either makes them bear more risk or leads to an increased demand for safe haven assets inflating the price and thus depriving the system from safe (haven) assets. In the global financial crisis, it was losses on what would have been considered relatively safe assets (CDOs, mortgage-backed securities etc.) that caused a dramatic loss of market confidence. This may be the next big risk that is unknown or not anticipated. In other words, a "bubble" in safe haven asset values, could turn out to be the next black swan event.

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Figure 1: Ellsberg Model: Index values and confidence parameter for stocks, bonds and gold

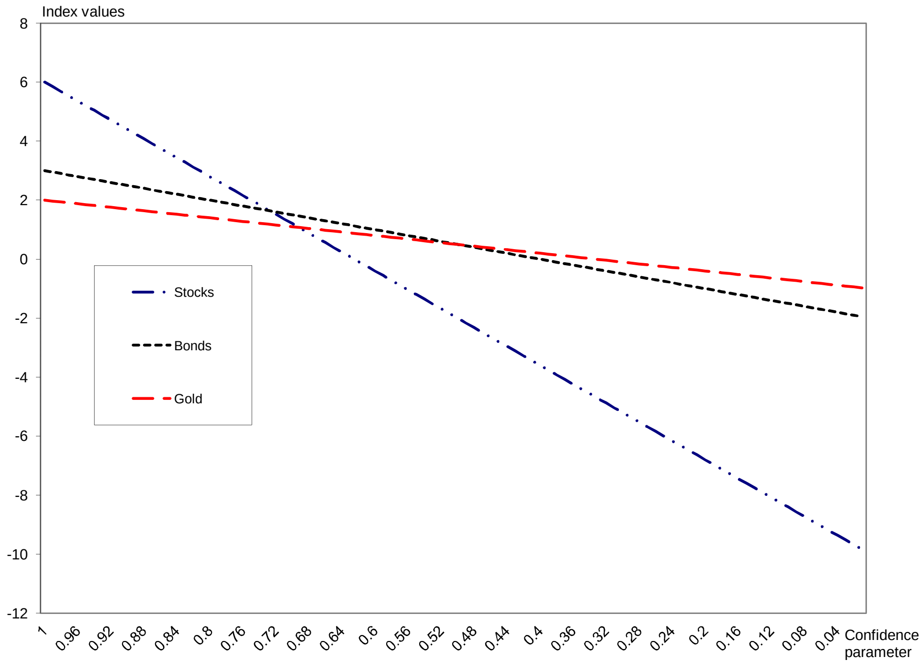

Figure 2: Dynamic extension of Ellsberg model

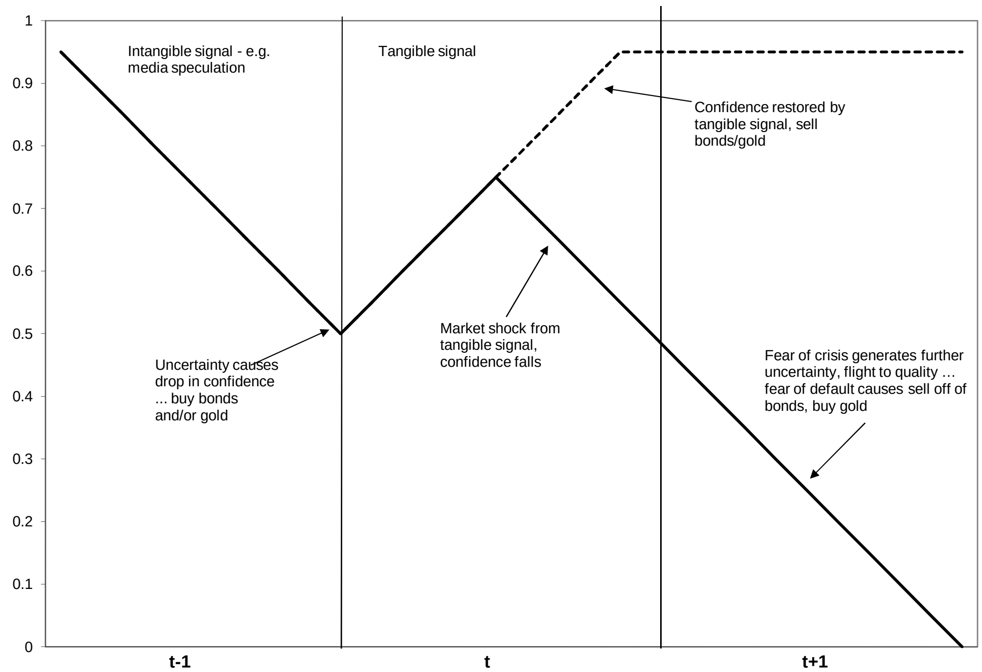

Table 1: Estimates used for Ellsberg Model

This table presents the estimates for $E(x)$ and $min(x)$ for stocks, bonds and gold used for the Ellsberg model and the simulation exercise.

	est (x 100)	min (x 100)
gold	0.9579	0.0434
bonds	1.5187	-0.0938
stocks	3.1577	-1.4832

Figure 3: Performance of stock market and safe haven assets

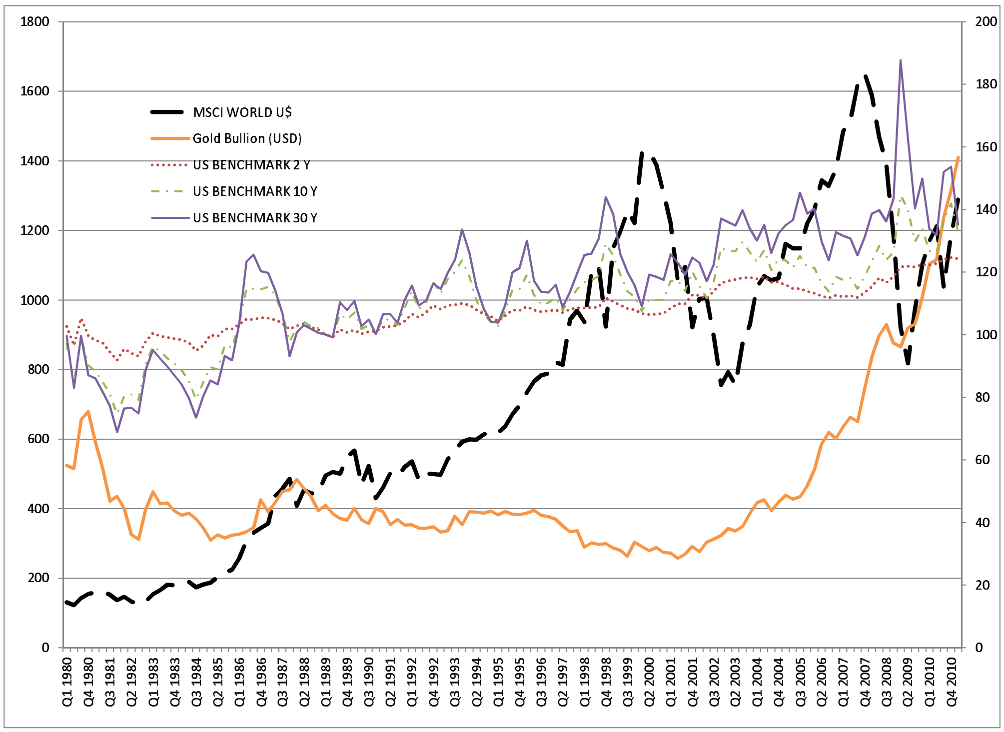

Figure 4: Graphical analysis of crash/ period of uncertainty: October 1987

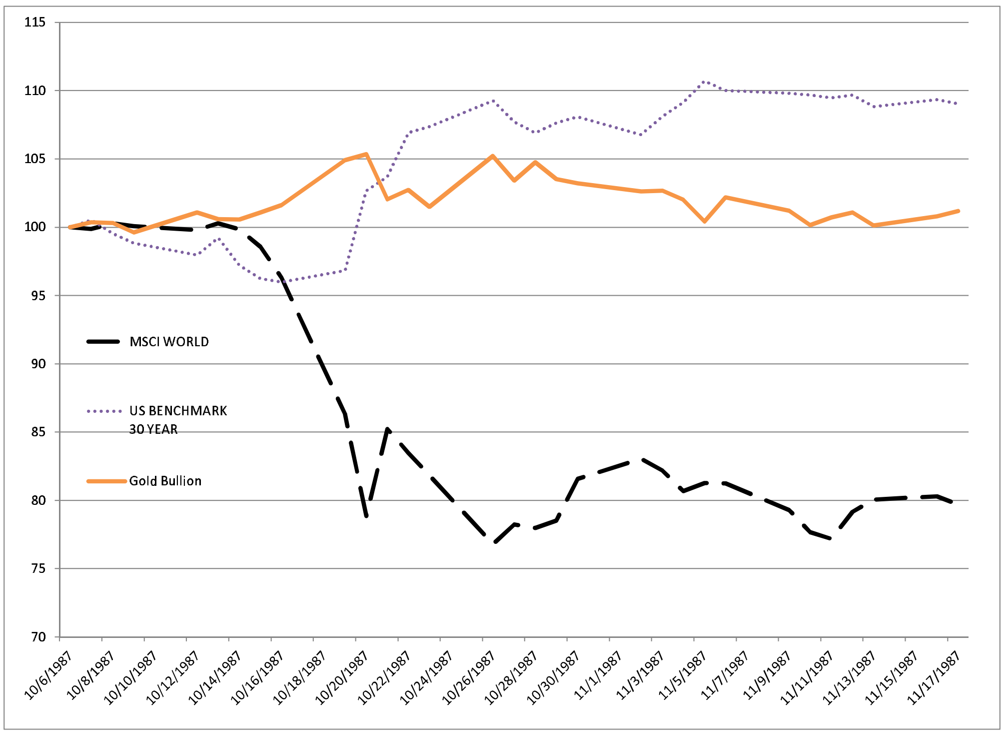

Figure 5: Graphical analysis of crash/ period of uncertainty: Asian financial crisis 1997

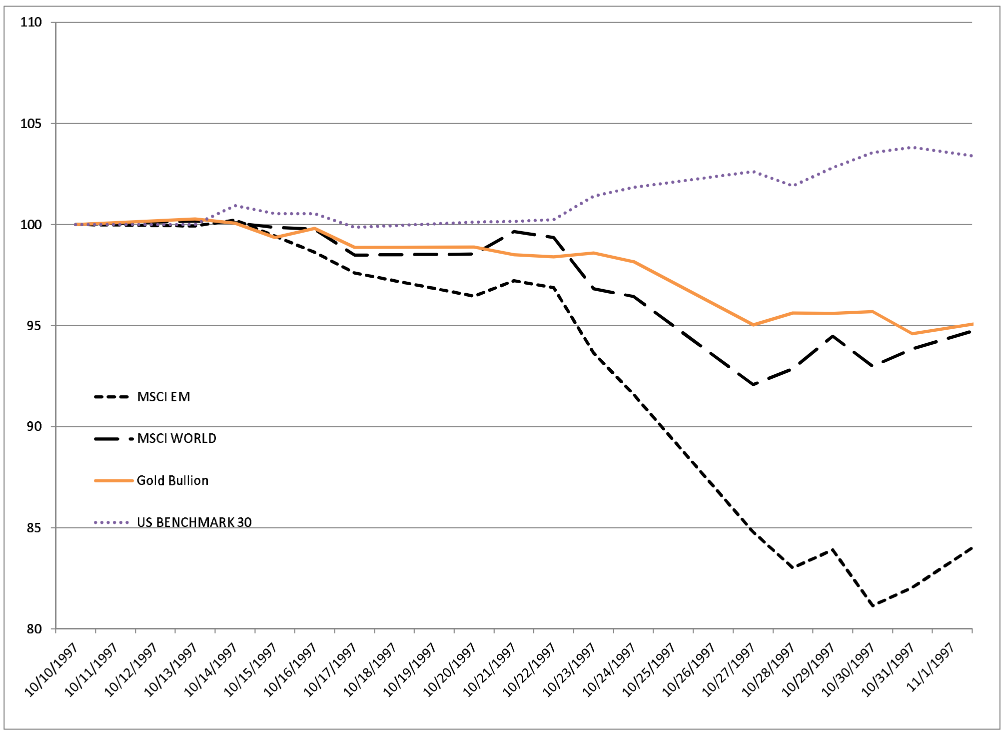

Figure 6: Graphical analysis of crash/ period of uncertainty: Terrorist attack September 11, 2001

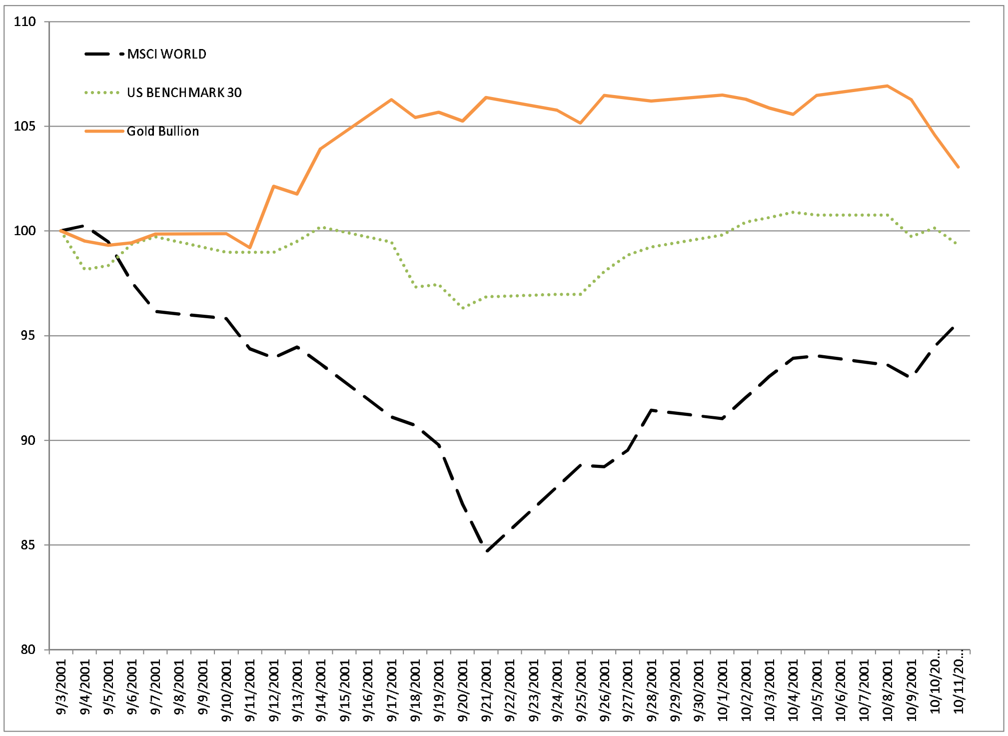

Figure 7: Graphical analysis of crash/ period of uncertainty: Global financial crisis Q4, 2008

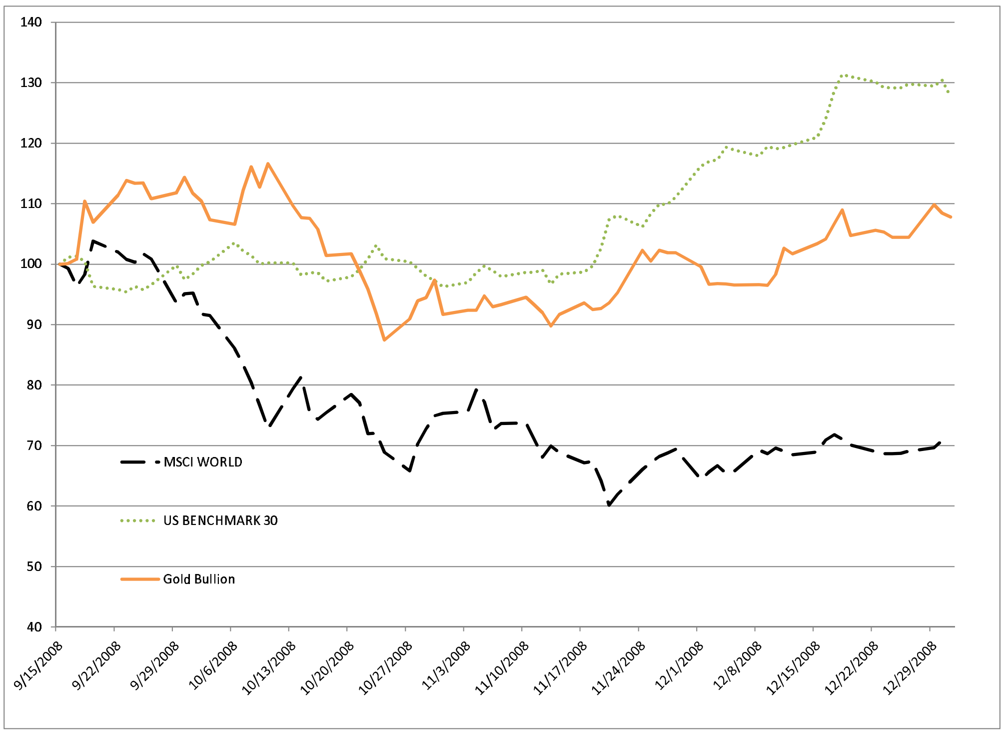

Figure 8: Time-varying return correlations

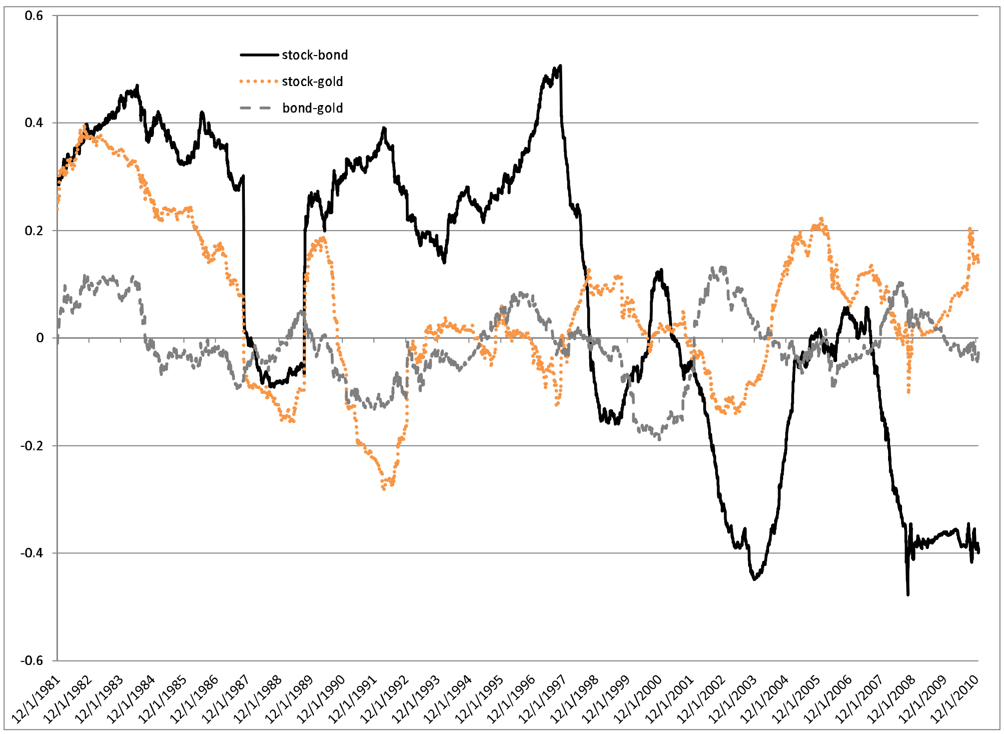

Table 2: Descriptive Statistics

	MSCI World	US bond (2y)	US bond (10y)	US bond (30y)	Gold Bullion	Gold (COMEX)
mean (x 100)	0.0282	0.0024	0.0039	0.0038	0.0122	0.0121
std. dev. (x 100)	0.8922	0.1560	0.5211	0.7861	1.2760	1.2030
min (x 100)	-10.3633	-1.4596	-3.8043	-4.1468	-16.0286	-10.0856
max (x 100)	9.0967	1.4183	4.0608	6.0263	12.5414	9.7448
skewness	-0.5154	0.3807	0.1252	0.0097	-0.0378	-0.0958
kurtosis	12.0700	13.8759	4.7931	3.2281	15.0640	8.5853
	MSCI World	**US bond (2y)**	**US bond (10y)**	**US bond (30y)**	**Gold Bullion**	**Gold (COMEX)**
MSCI World	1					
US bond (2y)	-0.0146	1				
US bond (10y)	-0.0235	0.7692	1			
US bond (30y)	-0.0419	0.6776	0.9168	1		
Gold Bullion	0.0705	0.0304	0.0041	-0.0092	1	
Gold (COMEX)	0.0883	0.0661	0.0192	0.0096	0.2788	

Table 3: Descriptive statistics conditional on extreme stock market returns (MSCI World)

Panel A		**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
MSCI World return < 10% quantile	**MSCI World**	808	-0.0159	0.0093	-0.1036	-0.0091
	US bond (2y)	808	0.0001	0.0020	-0.0146	0.0090
	US bond (10y)	808	0.0004	0.0070	-0.0288	0.0406
	US bond (30y)	808	0.0007	0.0107	-0.0388	0.0603
	Gold Bullion	808	-0.0021	0.0160	-0.1332	0.0647
	Gold (COMEX)	808	-0.0024	0.0167	-0.1009	0.0862
Panel B						
MSCI World return < 5% quantile	**MSCI World**	405	-0.0209	0.0111	-0.1036	-0.0131
	US bond (2y)	405	0.0004	0.0021	-0.0107	0.0090
	US bond (10y)	405	0.0015	0.0078	-0.0249	0.0406
	US bond (30y)	405	0.0022	0.0123	-0.0338	0.0603
	Gold Bullion	405	-0.0016	0.0155	-0.0772	0.0576
	Gold (COMEX)	405	-0.0028	0.0179	-0.0991	0.0862
Panel C:						
MSCI World return < 1% quantile	**MSCI World**	81	-0.0376	0.0153	-0.1036	-0.0246
	US bond (2y)	81	0.0015	0.0023	-0.0040	0.0090
	US bond (10y)	81	0.0051	0.0094	-0.0170	0.0406
	US bond (30y)	81	0.0089	0.0162	-0.0251	0.0603
	Gold Bullion	81	-0.0004	0.0201	-0.0472	0.0576
	Gold (COMEX)	81	-0.0015	0.0241	-0.0991	0.0862

Table 4: Conditional correlation analysis (conditional on extreme stock market returns)

Panel A: MSCI World return < 10% quantile

	MSCI World	**US bond (2y)**	**US bond (10y)**	**US bond (30y)**	**Gold Bullion**	**Gold (COMEX)**
MSCI World	1					
US bond (2y)	-0.3100	1				
US bond (10y)	-0.3027	0.7949	1			
US bond (30y)	-0.3184	0.7119	0.9367	1		
Gold Bullion	-0.0650	0.0882	0.0417	0.0174	1	
Gold (COMEX)	-0.0122	0.1481	0.0545	0.0422	0.3578	1

Panel C: MSCI World return < 5% quantile

	MSCI World	**US bond (2y)**	**US bond (10y)**	**US bond (30y)**	**Gold Bullion**	**Gold (COMEX)**
MSCI World	1					
US bond (2y)	-0.3615	1				
US bond (10y)	-0.3309	0.7960	1			
US bond (30y)	-0.3556	0.7074	0.9454	1		
Gold Bullion	-0.0873	0.1042	0.0456	0.0323	1	
Gold (COMEX)	-0.0412	0.2159	0.0849	0.0554	0.4137	1

Panel C: MSCI World return < 1% quantile

	MSCI World	**US bond (2y)**	**US bond (10y)**	**US bond (30y)**	**Gold Bullion**	**Gold (COMEX)**
MSCI World	1					
US bond (2y)	-0.4258	1				
US bond (10y)	-0.3507	0.7168	1			
US bond (30y)	-0.3274	0.5779	0.9419	1		
Gold Bullion	-0.0770	0.1969	0.0809	0.0579	1	
Gold (COMEX)	0.0319	0.1749	0.0139	-0.0218	0.3713	1

Table 5: Summary: aggregate returns for specific crisis episodes

	MSCI WORLD	US BM 2 Y	US BM 10 Y	US BM 30 Y	Gold Bullion
1987 crash: Oct and Nov	-0.2074	0.0128	0.0395	0.0696	0.0821
1997 Asian financial crisis: Oct and Nov	-0.0465	-0.0019	0.0112	0.0304	-0.1200
1998 crisis: Aug and Sep	-0.1133	0.0197	0.0795	0.0908	0.0238
2001 September 11 attacks: Sep and Oct	-0.0140	0.0141	0.0190	0.0115	0.0473
2001 September 11 attacks: Sep (only)	-0.0458	0.0127	0.0201	0.0025	0.0634
2008 Financial crisis: Sep	-0.1211	0.0078	-0.0021	0.0172	0.0677
2008 Financial crisis: Oct	-0.2361	0.0061	-0.0098	-0.0041	-0.1538

Table 6: Estimation Results

This table presents the estimation results testing US government bonds (left panel) and gold (right panel) for a safe haven within a GARCH framework without explicitly accounting for endogeneity. The coefficient estimates show that US government bonds co-move with the stock market and gold displays characteristics of a hedge against the stock market.

US government bond (dependent variable)					**gold (dependent variable)**				
	Coef.	**Std. Err.**	**z-stat.**	**P>|z|**		**Coef.**	**Std. Err.**	**z-stat.**	**P>|z|**
rbmus30y (t-1)	0.0282	0.0121	2.33	0.02	rgold (t-1)	-0.0809	0.0100	-8.12	0.00
rgold (t)	-0.0259	0.0064	-4.07	0.00	rbmus30y (t)	-0.0235	0.0117	-2.02	0.04
(t-1)	-0.0121	0.0059	-2.03	0.04	rmswrld (t)	-0.0148	0.0086	-1.73	0.08
(t-2)	-0.0092	0.0063	-1.46	0.15	(t-1)	0.0109	0.0106	1.03	0.31
rmswrld (t)	0.0216	0.0081	2.65	0.01	(t-2)	0.0320	0.0115	2.79	0.01
Δboeusa (t)	-0.0011	0.0001	-7.87	0.00	Δboeusa (t)	-0.0040	0.0002	-25.01	0.00
const.	0.0000	0.0001	0.60	0.55	const.	0.0001	0.0001	0.61	0.54
volatility (GARCH)					**volatility (GARCH)**				
arch	0.0422	0.0031	13.67	0.00	arch	0.0425	0.0019	21.99	0.00
tarch	-0.0107	0.0033	-3.21	0.00	tarch	0.0429	0.0032	13.61	0.00
garch	0.9563	0.0032	302.75	0.00	garch	0.9349	0.0012	763.89	0.00
const.	0.0000	0.0000	6.12	0.00	const.	0.0000	0.0000	13.14	0.00
Number of obs.		8085			Number of obs.		8089		
Wald chi2(7)		107.39			Wald chi2(6)		694.76		
Log-likelihood		28407.21			Log-likelihood		25907.56		

Table 7: Estimation Results

This table presents the estimation results testing US government bonds (left panel) and gold (right panel) for a safe haven within a 2-stage GARCH framework accounting for endogeneity. The coefficient estimates show that US government bonds co-move with the stock market while gold and stocks are negatively correlated. The estimates also indicate that there is a strong negative feedback effect from bonds to gold implying a positive effect on gold from the bond market if stock prices fall.

US government bond (dependent variable)					**gold (dependent variable)**				
	Coef.	**Std. Err.**	**z-stat.**	**P>|z|**		**Coef.**	**Std. Err.**	**z-stat.**	**P>|z|**
rbmus30y (t-1)	0.0301	0.0121	2.48	0.01	rgold (t-1)	-0.0811	0.0100	-8.12	0.00
rgold (t)	0.0203	0.0559	0.36	0.72	rbmus30y (t)	-1.6096	0.4286	-3.76	0.00
(t-1)	-0.0244	0.0239	-1.02	0.31	rmswrld (t)	-0.1128	0.0250	-4.51	0.00
(t-2)	-0.0111	0.0233	-0.48	0.64	(t-1)	0.0118	0.0106	1.11	0.27
rmswrld (t)	0.0206	0.0082	2.52	0.01	(t-2)	0.0321	0.0115	2.80	0.01
Δboeusa (t)	-0.0009	0.0004	-2.23	0.03	Δboeusa (t)	-0.0065	0.0007	-9.86	0.00
const.	0.0000	0.0001	0.61	0.54	const.	0.0001	0.0001	1.39	0.16
volatility (GARCH)					**volatility (GARCH)**				
arch	0.0420	0.0031	13.66	0.00	arch	0.0430	0.0019	22.33	0.00
tarch	-0.0110	0.0034	-3.28	0.00	tarch	0.0430	0.0032	13.38	0.00
garch	0.9564	0.0032	302.83	0.00	garch	0.9347	0.0012	751.30	0.00
const.	0.0000	0.0000	6.17	0.00	const.	0.0000	0.0000	12.90	0.00
Number of obs.		8084			Number of obs.		8086		
Wald chi2(6)		83.4			Wald chi2(6)		694.76		
Log-likelihood		28395.5			Log-likelihood		25907.56		

Table 8: Estimation Results - Conditional Analysis for bond returns

This table presents the estimation results of a conditional analysis using stock market returns and return volatility as the conditioning variables.

Dependendent variable: bonds (30 years)							
			Coef.	**Std. Err.**	**t-stat.**	**p-value**	**R-squared**
Panel A	**10%**	stocks (t)	-0.3868	0.0392	-9.86	0.00	0.13
return threshold		(t-1)	0.0651	0.0313	2.08	0.04	
		(t-2)	-0.0264	0.0308	-0.86	0.39	
	5%	stocks (t)	-0.4271	0.0539	-7.92	0.00	0.17
		(t-1)	0.1005	0.0421	2.38	0.02	
		(t-2)	-0.0398	0.0427	-0.93	0.35	
	1%	stocks (t)	-0.3803	0.1285	-2.96	0.00	0.17
		(t-1)	0.1394	0.1186	1.18	0.24	
		(t-2)	0.0103	0.0982	0.10	0.92	
Panel B	**90%**	stocks (t)	-0.2374	0.0216	-10.98	0.00	0.15
volatility threshold		(t-1)	0.0477	0.0214	2.23	0.03	
		(t-2)	-0.0562	0.0217	-2.59	0.01	
	95%	stocks (t)	-0.2412	0.0280	-8.62	0.00	0.20
		(t-1)	0.0750	0.0282	2.66	0.01	
		(t-2)	-0.0487	0.0286	-1.70	0.09	
	99%	stocks (t)	-0.1881	0.0568	-3.31	0.00	0.20
		(t-1)	0.0397	0.0590	0.67	0.50	
		(t-2)	0.0100	0.0609	0.16	0.87	

Table 9: Estimation Results - Conditional Analysis for gold returns

This table presents the estimation results of a conditional analysis using stock market returns and return volatility as the conditioning variables.

Dependendent variable: gold							
			Coef.	**Std. Err.**	**t-stat.**	**p-value**	**R-squared**
Panel A	**10%**	stocks (t)	-0.1548	0.0618	-2.51	0.01	0.12
return threshold		(t-1)	-0.0355	0.0469	-0.76	0.45	
		(t-2)	0.0145	0.0459	0.32	0.75	
	5%	stocks (t)	-0.1423	0.0730	-1.95	0.05	0.15
		(t-1)	-0.0878	0.0535	-1.64	0.10	
		(t-2)	-0.0327	0.0540	-0.61	0.55	
	1%	stocks (t)	0.0913	0.1580	0.58	0.57	0.28
		(t-1)	-0.4221	0.1295	-3.26	0.00	
		(t-2)	-0.0304	0.1140	-0.27	0.79	
Panel B	**90%**	stocks (t)	-0.0632	0.0339	-1.86	0.06	0.09
volatility threshold		(t-1)	-0.0816	0.0313	-2.60	0.01	
		(t-2)	0.0187	0.0320	0.58	0.56	
	95%	stocks (t)	-0.0622	0.0448	-1.39	0.17	0.10
		(t-1)	-0.1043	0.0416	-2.51	0.01	
		(t-2)	0.0241	0.0423	0.57	0.57	
	99%	stocks (t)	-0.0086	0.0983	-0.09	0.93	0.13
		(t-1)	-0.0888	0.0946	-0.94	0.35	
		(t-2)	0.0374	0.0977	0.38	0.70	

Table 10: Estimation Results - Vector Autoregressions (VAR)

This table presents the estimation results of a unconditional VAR and a conditional VAR using stock market returns and return volatility as the conditioning variables.

Panel A: unconditional VAR

		t		
		gold	**bonds**	**stocks**
t-1	**gold**	-	-	+
	bonds	+	+	+
	stocks	+		+

Panel B: conditional VAR (10% return threshold)

		t		
		gold	**bonds**	**stocks**
t-1	**gold**	-	-	+
	bonds	-	+	-
	stocks	-		+

Panel E: conditional VAR (90% volatility threshold)

		t		
		gold	**bonds**	**stocks**
t-1	**gold**	-	-	+
	bonds	-	+	+
	stocks	-		+

Panel C: conditional VAR (5% return threshold)

		t		
		gold	**bonds**	**stocks**
t-1	**gold**	-		+
	bonds	-	+	-
	stocks	-	+	+

Panel F: conditional VAR (95% volatility threshold)

		t		
		gold	**bonds**	**stocks**
t-1	**gold**	-	-	+
	bonds	-	+	+
	stocks	-		+

Panel D: conditional VAR (1% return threshold)

		t		
		gold	**bonds**	**stocks**
t-1	**gold**	+		+
	bonds	-	+	-
	stocks	-		+

Panel G: conditional VAR (99% volatility threshold)

		t		
		gold	**bonds**	**stocks**
t-1	**gold**	-	-	+
	bonds	-	+	+
	stocks	-		+