
AN INVESTIGATION INTO SAFE HAVEN ASSETS

PRECIOUS METALS AND OTHERS

BY

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Declaration

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Abstract

During the financial market turmoil of recent decades, asset classes tend to co-move more strongly, even without strong fundamental linkages, hence the contagion effect. A serious implication for portfolio management is that the benefits of diversification are reduced when they are needed the most. This motivates the search for “safe” assets during market distress which would move against the falling markets. Gold’s reputation as a historical safe haven and other precious metals (i.e. silver, platinum and palladium)’s hedging ability in portfolio diversification motivate the investigation of whether silver, platinum and palladium have acted as safe haven across markets in periods of distress.

This research firstly overviews the conceptual and theoretical aspects of safe haven assets, including its relationship with other market-linkages during market distress such as flight-to-safety. It then examines the safe haven properties of precious metals in eleven major world economies over the period 1994 to 2016. It finds that, on average, precious metals are weak safe haven about 33% of the time against stocks and 31% of the time against bonds, when asset returns fall below the lower 5% quantile range. Additionally, no precious metal provides safe haven status consistently over time or across asset classes. And, finally, strong safe haven is rare. The analysis then examines robust political, economic and financial determinants of precious metals as safe haven. Political risk is found to be a positive and robust determinant in most countries when gold is safe haven against stock and bond markets tail events. Stock volatility also sees positive and robust results across countries but only against stock market stress. Exchange rate, interest rate and credit spreads tend to have large coefficient values but results are quite mixed for different markets and not robust. Finally, inspired by recent

studies on how investor attention could affect asset pricing, and the availability of online search data which is argued as a direct and new measure of investor attention, this research conducts spillover analysis between gold and safe haven currencies with their related search activities. It finds that, in general, spillovers from search volumes to returns are higher than spillovers from returns to search activities in the US, UK, Germany and China. Furthermore, the spillovers from searches to returns increase during market stress times in the recent decade.

Summary

During the financial market turmoil of recent decades, asset classes tend to co-move more strongly, even without strong fundamental linkages such as trade and financial associations, hence the contagion effect. A serious implication for portfolio management is that the benefits of diversification are reduced when they are needed the most. This motivates the search for “safe” assets during market distress which would move against the falling markets. There has been an increasing number of studies on safe haven asset and related flight-to-safety phenomena in the recent decade.

This research firstly conducts a comprehensive overview of the conceptual and theoretical aspects of safe haven assets, by summarizing various definitions of safe haven assets in the academic literatures, as well as applying Forbes and Rigobon [1999]’s classic analytical framework of contagion to safe haven and flight-to-safety. By which, it discusses in detail the relationships between safe haven and other market-linkages during market distress such as flight-to-safety, contagion, interdependence and decoupling.

While most commodity prices dropped significantly during flight-to-safety episodes, precious metals, especially gold, prices increased. Gold’s reputation as a historical safe haven and other precious metals (i.e. silver, platinum and palladium)’s hedging ability in portfolio diversification motivate the investigation of whether silver, platinum and palladium have acted as safe haven across markets in periods of distress. This thesis attempts to fill this gap by testing the safe haven properties of precious metals in eleven major world economies over the period January 1994 to July 2016. These economies are the US, UK, Germany, France, Italy, Switzerland, Canada, Japan, China, India and South Africa. Regression with quantiles

is applied, which is in line with the most used methods for detecting safe havens Baur and Lucey [2010], Baur and K.J.McDermott [2010]. In addition, this thesis adds minor modifications to the original procedure to generate daily safe haven results. Rolling regressions are further applied to examine how safe haven properties evolve by time. It finds that, on average, precious metals could provide weak safe haven hedge about 33% of the time against stocks and 31% of the time against bonds, when asset returns fall below the lower 5% quantile range. Additionally, gold is not the most frequent safe haven across eleven countries. In general, precious metals provided protection at different times across countries. No precious metal provides safe haven status consistently over time or across asset classes, and, finally, strong safe haven is rare. These dynamic relationships between precious metals market and stocks and bonds are also explored with Engle [2002]’s Dynamic Conditional Correlations (DCC). Results show negative conditional correlations between gold and stock market during 2007–2009 Global Financial Crisis in most countries, as well as decoupling between equity and bond markets.

The analysis then characterizes those safe haven periods in which, under certain political, economic and financial conditions, precious metals are more likely to become safe haven assets. By applying zero-inflated Poisson regression and Extreme Bound Analysis (EBA), political risk is found to be a positive and robust determinant across most countries when precious metals are safe haven against market tail events. While stock volatility, exchange rate, interest rate and credit spreads usually have large coefficient values, results are quite mixed for different markets and not robust.

Finally, there has been an increasing interest in the investor sentiment aspect of safe haven studies. Inspired by recent studies which show how investors’ limited attention could affect asset pricing, as well as the availability of online search data which is considered as a new and direct measure of investors attention, this research also conducts spillover analysis between gold and safe haven currencies with their related search activities. It finds that, in general, spillovers from search volumes to returns are higher than spillovers from returns to search activities in the US, UK, Germany and China. Furthermore, the spillovers from searches to returns increase during market stress times such as the 2007–2009 Global Financial Crisis,

2009–2012 European sovereign debt crisis, and during the recent political uncertainty of Brexit and the US presidential election in 2016–2017.

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Chapter 1

Introduction

1.1 Background and Motivation

During the financial market turmoil of recent decades, asset classes tend to co-move more strongly, even without strong fundamental linkages such as trade and financial associations, hence the contagion effect. A serious implication for portfolio management is that the benefits of diversification are reduced when they are needed the most. This motivates the search for “safe” assets during market distress which would move against the falling markets. There has been an increasing number of studies on safe haven asset and related flight-to-safety phenomena in the recent decade.

Whether safe haven assets exist during market distress, and an understanding of their characterized macroeconomic environment are crucial due to the following reasons. First, investors’ sudden capital inflow to perceived safe haven assets during periods of market distress could drive up asset prices abruptly and significantly. Longstaff [2004] finds that flight-to-safety premium can represent as much as 10% – 15% of the value of the US Treasury bond, which cannot be explained by differences in perceived credit risk, transaction costs, and other costs. Studies of safe haven episodes provide new perspectives for understanding price movements during extreme market distress periods. Second, it helps us to understand market co-movements during those extreme times. The existence of safe haven assets highlights limits to the propagation of financial market crises and thus can provide diversification benefits

in market distress when they are needed the most. Therefore, this understanding has significant implications for portfolio management where covariances between assets are crucial in determining the portfolio returns and risks. Third, safe haven assets have significant impact on the macroeconomy. The existence of safe haven assets has been indicated as a lack of risk taking in the market and blamed as an important source of financial instability (e.g. see Caballero and Kurlat [2008]). Research centres in international economics, global financial policy making organizations such as the International Monetary Fund and central banks of large economies have all published studies regarding to safe haven in response to financial crises ¹.

While most commodity prices dropped significantly during flight-to-safety episodes, precious metals, especially gold, prices increased (Baele et al. [2013]). Gold has a historical role and reputation as safe haven. Other three precious metals, silver, platinum, and palladium, also have effective hedging ability in portfolio diversification (Hillier et al. [2006]). Furthermore, there are interesting cross-metal interactions with regard to historically closely followed gold-silver ratio (see Lucey and Tully [2006b]) and recently examined volatility spillover between four metals (see Sensoy [2013]). The above empirical findings motivate this research to investigate the other three precious metals' role as safe haven, that is, their hedging ability against market crashes.

In addition, there has been an increasing interest in the investor sentiment aspect of safe haven studies. Some studies define safe haven properties as when investors' risk aversion suddenly and sharply increases which fundamentally changes the transmission channel of risk between assets. In particular, within sentiment analysis, recent studies have provided theoretical frameworks as well as empirical evidence on how investors' limited attention could affect asset pricing. With the increasing use of the internet in finding information, Google Search makes available a massive database of where public interest and attention is focused. Inspired by the rapidly growing amount of research using online search data to gauge investors'

¹For example, International Monetary Fund Baig and Goldfajn [1999], Bolton and Jeanne [2011], Lam and Tokuoka [2011]; Bank for International Settlements Cairns et al. [2007], Mccauley and Mcguire [2009]; European Central BankP.Hartmann et al. [2001], Beck and Rahbari [2008], Habib and Stracca [2012], Chudik and Fratzscher [2012] ; Federal Reserve Bank Throop et al. [1991], Mora [2007]; Deutsche Bundesbank Upper [2000], Dötz and Fischer [2010]; and Swiss National Bank Rinaldo and Soderlind [2010]

attention, for example Choi and Varian [2009b], Da et al. [2011] and Stephens-Davidowitz [2017], this thesis attempts to obtain probably the first empirical results of how investors' attention on safe haven assets may have interacted with their price movements in the last ten years.

1.2 Research Questions

Four main research questions are addressed in this thesis. First, theoretically, what is safe haven within the broad discussion of cross-market linkages? The existing literature has defined safe haven asset in similar ways but also from different perspectives. Is it an asset that is uncorrelated or negative correlated with another asset or portfolio in times of market stress? Or is it more about sudden increase in investors' risk aversion? What is the relationship between safe haven, flight-to-safety and contagion? What is the relationship between safe haven and hedge? These questions help clarify what we mean when talk about safe haven assets.

Second, considering gold's historical role and reputation as safe haven and the other three precious metals (silver, platinum and palladium)' hedging ability as found in previous studies, whether these other three metals have functioned as safe haven across countries? Moreover, how have their safe haven properties changed across time? There are extensive studies on gold's role as safe haven. However, they mostly focus on a few large economies such as the US and UK, and often take a static view, that is obtaining a yes or no answer to the whole sample period. Therefore, this thesis expands the analysis to all four precious metals, to developed and developing countries, and in a time-varying fashion.

Third, most studies on safe haven assets focus on obtaining empirical evidence rather than the associated characterized macroeconomic environments. However, there are some very useful studies of this kind on other market linkages such as flight-to-safety and contagion. Therefore, the third research question asks what are the associated economic and financial environments when precious metals are acting as safe haven in each market and what are robust determinants if there are any, which have not yet been explicitly investigated in the

literature.

Finally, are there any interrelations between investor attention and safe haven assets? Safe haven assets have significant sentiment attributes for economic and historical reasons. There is a large number of studies focusing on the sentiment aspect of safe haven assets, however no studies have used recently made available internet search data to gauge investor attention. As a direct and new measure of public interests and attention, this thesis therefore investigates the interrelations between investors' search interests on potential safe haven assets and their returns movements.

1.3 Main Findings and Contributions

This thesis firstly overviews conceptual and theoretical aspects of safe haven assets and its related flight-to-safety phenomenon. It provides a list of various definitions of safe haven assets in the academic literature. Then it applies Forbes and Rigobon [1999]'s classic analytical framework of contagion to safe haven and flight-to-safety. The analytical framework classifies different definitions into three types, which emphasizes the magnitude of the linkages, changes of the level, and transmission mechanisms respectively; it also helps clarify the relationships between safe haven and other market-linkages during markets distress, such as flight-to-safety, contagion, interdependence and decoupling.

The first empirical analysis in this study explores dynamic dependence with Engle [2002]'s Dynamic Conditional Correlation (DCC) between the precious metal markets, equity and bond markets across eleven countries including the US, UK, Germany, France, Italy, Switzerland, Canada, Japan, China, India and South Africa. The decoupling between equity and bond markets is observed across markets, which is consistent with previous studies. Similar patterns are also obtained across metals and countries, such as negative correlations between gold and the stock market during the 2007–2009 Global Financial Crises, which suggests further investigation of gold and other precious metals as safe haven in these countries.

The second part of the analysis examines precious metals' time-varying safe haven status in each country. Whilst mostly applying existing modelling procedures as demonstrated in

Baur and Lucey [2010] and Baur and K.J.McDermott [2010], a few modifications are made to generate a series of daily weak and strong safe haven incidents for each metal. In addition, results are aggregated to calculate the average weak and strong safe havenness for each metal in each country, which refers to the proportion of time when a metal functions as a weak or strong safe haven over the examined time frame. Results show that precious metals could provide weak safe haven hedge about 33% of the time against stocks when the loss is in the lower 5% region, and 31% of the time against bonds when the loss is also under the 5% quantile. On average, gold is not the most frequent safe haven across eleven countries. In general, precious metals provided protection at different times across countries. No precious metal provides safe haven status consistently, over time or across asset classes. And, finally, strong safe haven status is rare.

The analysis then goes on to characterize those periods that under what kind of political, economic and financial conditions, gold, silver, platinum and palladium are more likely to become safe haven assets and hedge the risks of market declines. Zero-inflated Poisson regression is applied first, then model averaging techniques are applied with Extreme Bound Analysis (EBA) proposed by Leamer [1985] and Sala-I-Martin [1997] to identify robust determinants. Political risk is found to be a positive and robust determinant across countries when gold is safe haven against stock and bond markets tail events. Stock volatility also sees positive and robust results across countries but only against stock market stress. Exchange rate, interest rate and credit spreads tend to have large coefficient values but results are quite mixed for different markets and not robust. A portfolio analysis shows that trading strategies built on those exogenous determinants could generate good returns especially when hedged with gold and sometimes other precious metals as well.

The last part of the analysis looks into the sentiment aspect of safe haven assets, focusing in particular on investor attention as measured by online search interests. It goes beyond precious metals and includes considered safe haven currencies including the US dollar, Japanese Yen, and Swiss Franc. Diebold and Yilmaz [2009]’s spillover index is obtained between asset returns and search volume changes from 1-quarter rolling windows over the whole sample period. On average, spillovers from search volumes to returns are found to be higher than

spillovers from returns to search activities in the US, UK, Germany, China and worldwide. In general, the spillovers from searches to returns increase during market stress times such as the 2007–2009 Global Financial Crisis, 2009–2012 European sovereign debt crisis, and during recent political uncertainty in the UK and US in 2016–2017.

1.4 Thesis Structure

Chapter 2 provides an overview of three strands of the literature, these are safe haven assets, the economics of precious metals markets and sentiment aspects of the safe haven assets. Chapter 3 outlines statistical models and tests applied in all conducted empirical analysis. The empirical studies start in Chapter 4, which examines market dependence between precious metals market, stock and bond markets; Chapter 5 obtains time-varying safe haven evidence of each metal across eleven countries; Chapter 6 attempts to identify macroeconomic determinants of precious metals as safe haven in each country; Chapter 7 assesses spillovers between safe haven assets price movement and related search activities. Chapter 8 concludes the main findings of the thesis and discusses limitations and future works.

1.5 Publications

The conceptual and measurement issues of safe haven and flight-to-safety assets in Chapter 2 Section 2.1 were discussed at the International Financial Integration Conference (INFINITI) 2013:

- Sile Li and Brian M. Lucey, A Review of Conceptual and Empirical Issues of Flight-to-Safety and Safe Haven Assets. International Financial Integration Conference (INFINITI) 2013, 11–12 June, Aix-en-Provence, France.

Large part of Chapter 5, 6 and 7 were discussed in 2015 INFINITI Conference in Ljubljana and the 2016 International Finance and Banking Society (IFABS) Conference in Barcelona, and were published as two journal articles in *Applied Economics Letters* and *Journal of Commodity Markets*:

- Brian M. Lucey and Sile Li. What Precious Metals Act as Safe Havens, and When? Some US Evidence. *Applied Economics Letters*, 22(1), 35–45, 2015
- Sile Li and Brian M. Lucey. What Colour is Your Haven and Why? Reassessing the Role of Precious Metals as Safe Havens. *Journal of Commodity Markets*, 7, 1–14, 2017

The return spillover analysis of online search interests in safe haven assets in Chapter 8 was presented in 2017 INFINITI Conference in Valencia:

- Sile Li and Brian M. Lucey. In Search of Safe Haven Assets. INFINITI 2017, 12–13 June, Valencia, Spain.

Chapter 2

Overview of Consulted Literature

The review of consulted literature consists three parts: safe haven assets, the economics of precious metals markets, and sentiment aspects of the safe haven assets.

The existence and efficient pricing of safety assets are critical in an economy or any financial market. To quote the International Monetary Fund in the Global Financial Stability Report [IMF, 2012, p. 81]:

Safe assets are used as a reliable store of value and aid capital preservation in portfolio construction. They are a key source of liquid, stable collateral in private and central bank repurchase (repo) agreements and in derivatives markets, acting as the lubricant or substitute of trust in financial transactions. As key components of prudential regulation, safe assets provide banks with a mechanism for enhancing their capital and liquidity buffers. As benchmarks, safe asset support the pricing of other riskier assets. Finally, safe assets have been a critical component of monetary policy operations.

2.1 Safe Haven Assets

2.1.1 Introduction

The concept of “Safe haven assets” is related to some separated yet closely linked economics and finance literature strands including safe asset, hedge, tail-risk, capital flight, market linkages and co-movements. The networks among key topics of these literatures are mapped out in Figure 2.1 based on two hundred and thirty six articles ¹ with a software tool VOSviewer². The colour bar indicates the latest development on each topic. We can see roughly five clusters in the map. The most active (red) topics are safe haven related with hedge and gold; going anti-clockwise, we have capital flight as the next topic showing emphasis on market liquidity; safe asset, on the right side of the map, is associated with supply, shortage, shock and interest rate, indicating concerns over the shrinking supply of safe assets; on the top right of the map there are risk free rate, tail risk and volatility risk premium; and finally market linkages is clustered with market integration, determinants, correlation, etc. Some common key words for all studies are portfolio, crisis, stock market, asset, model and economy. Next I discuss the critical papers in each strand and their key findings.

2.1.2 Safe (risk-free) Asset

Conceptual issues

The concept of “safe asset” rather than “safe haven asset” appears more often in financial economics theoretical research (e.g. Gorton [2012], Gorton and Ordoñez [2013], Gorton [2016], IMF [2012], Barro et al. [2017]), while the latter is discussed mostly in applied finance literatures with emphasis on statistical modelling techniques and empirical findings (e.g. Baur and Lucey [2010], Baur and K.J.McDermott [2010]).

Gorton [2016] defines a “safe asset” as an asset that is (almost always) valued at face value without expensive and prolonged analysis; there is no extra benefit to producing (private) information about its value, which is common knowledge. And therefore, it is immune to

¹This network visualization is based on 236 relevant articles title and abstract text downloaded from Web of Science Core Collection, while the consolidated articles are not limited to this.

²VOSviewer is a software tool for constructing and visualizing bibliometric networks (www.vosviewer.com)

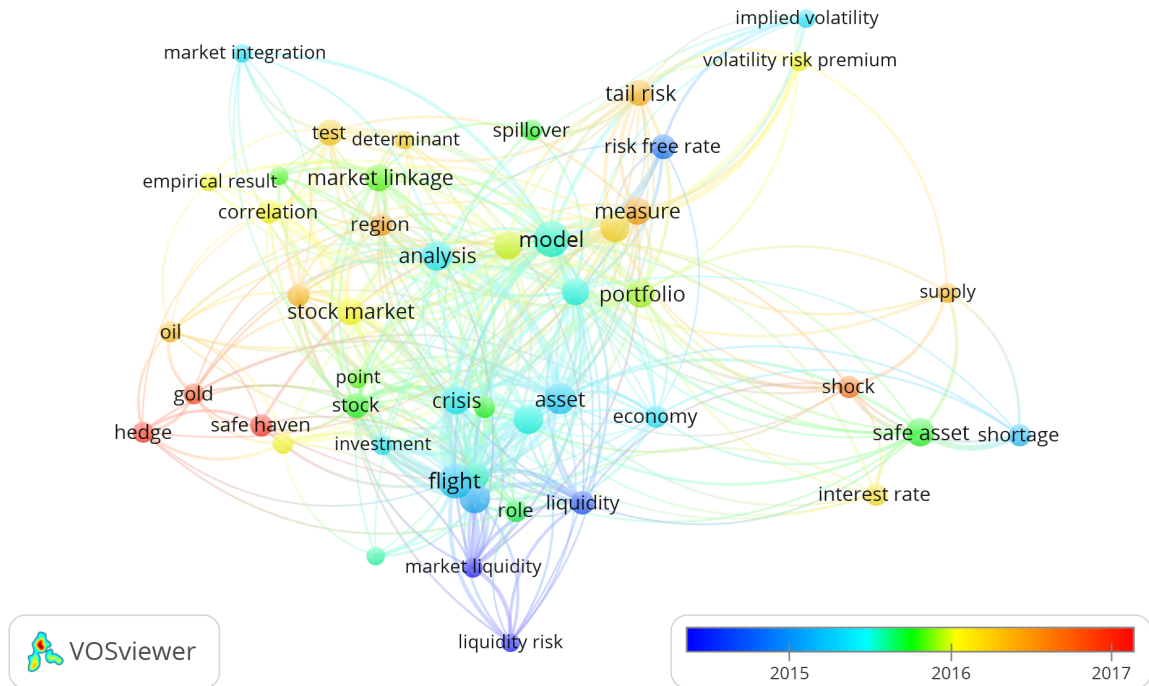


Figure 2.1: Clusters in the safe haven asset related literature strands (1945-2017) by term co-occurrence analysis on title and abstract fields

adverse selection in trading because agents have no desire to acquire private information about the current state of the issuer. Similarly, according to IMF [2012], safe assets could be viewed as equivalent to a portfolio of Arrow - Debreu securities³, which have an identical pay-off in a particular state of the world across time, and a zero pay-off in all other states. When an investor constructs a portfolio including an Arrow-Debreu security for each state of the world (given that financial markets are complete), they are essentially holding a safe asset. Arrow-Debreu security is “safe” because there is no variance around the expected return; and in finance, risk is viewed in terms of the variance in actual returns around the expected return (e.g. Damodaran [2010]). Safe assets normally have the following characteristics: (1) low credit and market risks, (2) high market liquidity, (3) limited inflation risks, (4) low exchange rate risk, (5) limited idiosyncratic risks.

³See more on Arrow - Debreu securities in Appendix X

Gold coin, sovereign debt and money market instruments as safe asset

Historically, coins made of precious metals perform the role of a quintessential safe asset (e.g. see Vilar [1976]). See more discussions and empirical findings in the Section 1.2.4 *Precious Metals as Hedge and Safe Haven*. According to Gorton [2016], only since the start of the 18th century have certain types of debt come to prevalently serve as safe assets, such as government debt and even some privately produced debt. Government debts are normally viewed as “the” risk-free asset or safe asset considering government’s power to control tax and money supply, nevertheless they may subject to default risk (e.g. Bodie et al. [2009]):

...only the government can issue default-free bonds. Even the default-free guarantee by itself is not sufficient to make the bonds risk-free in real terms. The only risk-free asset in real terms would be a perfectly price-indexed bond. Moreover, a default-free perfectly indexed bond offers a guaranteed real rate to an investor only if the maturity of the bond is identical to the investor’s desired holding period. Even indexed bonds are subject to interest rate risk, because real interest rates change unpredictably through time. When future real rates are uncertain, so is the future price of indexed bonds.

Damodaran [2010] discussed what happens when governments default and presented ways of estimating the risk free rate when confronted with market rates that have default risk embedded in them.⁴

Money market instruments, such as bank certificates of deposit (CDs), and commercial paper (CP), are also viewed as risk-free because their short maturity makes them interest rate insensitive as do their relatively low default and credit risks. However, producing a paper currency that would be accepted as safe at its par value is very recent in history. In addition,

⁴The paper outlined three ways to estimate a riskfree rate of default free government bonds. First, leverage pricing of derivatives. If there is no risk free rate of a currency, but there are forward or futures contracts on currencies, a riskfree rate in one currency can be derived if riskfree rate in the other is available by $(1 + i_f) = \frac{S}{F}(1 + i_d)$, where F is the forward exchange rate, S is the current spot exchange rate, i_d is the interest rate in domestic currency (base currency), i_f is the interest rate in foreign currency (quoted currency), and exchange rate of XXX/YYY indicate how much of the quote currency YYY is needed to buy one unit of the provided base currency XXX. Second, adjusted government bond rates by estimate default spreads for bonds in different sovereign ratings classes. And third, by estimate expected inflation and the expected real rate from long term real economic growth rate, since the riskfree rate is the sum of both.

Gorton [2016] distinguishes between long-term safe assets and short-term safe assets. That is, long-term safe assets can store value over time or be used as collateral such as sovereign debt, while short-term safe assets can be used to exchange for goods or services or to exchange for another asset easily, which are essentially money or money-like assets.

The role of safe assets for different investors

In a perfect Lucas-tree world (Robert E. Lucas [1978]), as Barro et al. [2017] argued, if agents are homogeneous, the economy's equilibrium quantity of safe assets will be nil. This is because in a Lucas-tree world, a safe asset is insulated from shocks, including declines in GDP due to rare disasters, and the aggregate risk reflects the uncertainty in the process for GDP. If the GDP process is given, safe assets cannot mitigate overall risk but can only redistribute this risk across agents. In a representative-agent setting, the redistribution of aggregate risk cannot occur, therefore the equilibrium quantitative of safe assets will be nil, this is why any meaningful analysis of safe asset requires heterogeneity across agent. In practice, different investors usually have different risk appetite. As discussed in IMF [2012], for instance, investors with long-term liabilities such as pension funds and insurance companies place limited emphasis on market liquidity. In addition, if they have exposure to inflation and no inflation indexed securities, the real emphasis would be on the real capital preservation aspect of safe assets. However, for global reserve managers, all of these criteria are important as they all play a part in determining the share of credit instruments denominated in foreign currencies and their need to maintain ready liquidity. Finally, gold as safe asset is largely driven by perceptions of its store of value, with less regard to its market risk.

The pricing and shrinking supply of safe assets

The pricing and its mechanism of “safety” could change as investors perceptions towards safe asset change in evolving economic and financial market conditions. In short, safety is more than likely to be less-priced during boom period via over-supplied high credit ratings and optimistic views, and over-priced in economic or financial crisis which result in sudden risk-off episodes. Gorton [2012] shows that in the long term (since 1952), the percentage of

all US assets that are “safe” has remained stable at about 33 percent. While Barro et al. [2017] argues that the steady-state ratio of safe to total assets ranges up to 15% of economy-wide assets. They explain the Gorton [2012]’s measured ratio of safe to total assets is higher because their concept of total assets mainly value physical capital while in their theory total assets comprise the discounted value of the whole GDP including human capital. However, in recent years, many studies have warned a global shortage of safe assets supply (see *inter alia* IMF [2012], Credit Suisse [2012], Gourinchas and Jeanne [2012]). According to the IMF [2012], there will be rising demand for safe assets, but fewer of them will be available, increasing the price for safety in global markets.

2.1.3 Safe Haven Asset

The consolidated safe haven asset literatures focus on statistical modelling techniques and empirical findings. A wide range of safe haven assets studies are seen since the 1980s. Empirical findings suggest different assets played as safe haven in various markets at various times, which are summarized briefly in Appendix B.1. Main papers are discussed in this section. Precious metals as safe haven is discussed extensively in the next section, and therefore only briefly mentioned here.

The US Assets

Brown [1987] discusses the history of international money movements through the modern era (1931 to the present), and the shifting perception by investors of different currencies as safe havens in the age of volatile floating exchange rates. For example, the movement of funds between the France Franc and the US dollar in the five years from sterling’s devaluation in September 1931 until the France Franc’s own break with gold.

Thomas and Michael [1987] examine the appreciation of the dollar over the period 1980 to 1985 and if it is as a result of increased demand for dollar assets due to safe haven perceptions towards United States assets. Their findings, however, suggest that the dollar’s appreciation was mainly due to a decrease in the supply of dollar deposits at various times.

Ayanian [1989] analyses the relationship between the value of the dollar and geopolitical national security variables and finds that “safe haven” investment decisions have affected real dollar exchange rates over the period of 1973-1986.

Safe haven could also be relative to a rare event such as fears towards the Year 2000 (Y2K) technology problems. According to Kaul and Sapp [2006], US assets are widely believed as safe haven for investors fleeing Year 2000 technology problems. The paper assesses the impact of safe haven flows on market liquidity by examining the bid-ask spread in the Euro-US dollar spot and forward markets around Y2K. And it concludes that safe haven flows into the US dollar before Y2K cause dealers to quote wide spreads as they attempt to manage inventory risk, and by which safe haven flows can have significant impact on market liquidity.

The Germany Assets

Over the period of January 1974 to April 1992, Kumah [1995] finds that unanticipated monetary policy shocks and increases in the interest rate differential drive German investors abroad whereas domestic interest rate increases and currency depreciations demonstrate the “safe-haven” effect, that is domestic investors prefer having investments in assets denominated in Deutsche Mark.

Upper [2000] studies financial market liquidity during the 1998 turbulences. It argues that due to the large-scale portfolio re-balancing, investors shifted a large part of their holdings into cash or “safe haven” assets, among which were government securities. According to the paper, the purchases of long-term German government securities by non-residents, which had average monthly number of 11.4 billion MD during the first half of 1998, were more than doubled in July with 34.5 billion DM and remained at the same level in August. As a result, the ten-year government debt yields fell accordingly. The safe-haven effect didn’t last long though, and the purchase fell back to 8.6 billion DM in September after the turbulences reached their peak in early October.

Beyer et al. [2008] argue that Germany achieved a high degree of domestic stability and provided safe haven for investors in times of turmoil in the international financial system. The paper examines the conduct of monetary policy in Germany in the 1970s and the 1980s, and

concludes that by focusing on anchoring inflation and inflation expectations, the Bundesbank successfully kept price level stable and gained its reputation.

Jank and Wedow [2008] examines German money market funds' role as safe haven during the liquidity crisis of 2007–2008. Runs are found on money market funds with enhanced and illiquid portfolios. However, money market funds with more liquid portfolios had no significant outflows and thus, functioned as a safe haven.

Safe Haven Currencies

Although producing a paper currency which could be accepted as safe at its par value is recent historical development Gorton [2012], there are many studies analysing safe haven properties of currencies.

Throop et al. [1991] argue that a “safe-haven” effect for the dollar, with higher personal saving and an improved investment climate for business, have stimulated capital inflows and increased the value of the dollar during the Reagan Years, particularly from 1974 to 1984. They concluded that although a safe haven effect would not necessarily have been a response to Reagan fiscal policy, it could have provided an offset to the burden of fiscal policy created in the Reagan years by increasing the capital stock for future generations.

Doroodian and Caporale [2000] investigates whether the dollar's role as a safe currency may affect its value over what could be fundamentally justified. It applies a GARCH-M framework to data on four bilateral exchange rates versus the US dollar and finds that the dollar's value did increase during periods of increased uncertainty due to political risk, and thus supports the safe-haven hypothesis.

Cairns et al. [2007] examines Asia-Pacific currencies' responses against global equity and bond market volatility, and concludes that high-yielding currencies tend to depreciate while low-yielding ones tend to serve as a safe haven. Relatively low-yielding currencies such as the Swiss Franc, the Yen and the Euro appreciated against the US dollar during 2001's volatile periods, while currencies with higher-yield such as the Russian Ruble, Brazilian Real and Turkish Lira tend to depreciate. It is further supported by examples of Asia-Pacific low-yielding currencies such as the New Taiwan dollar, the Singapore dollar and high-yielding

Indonesian Rupiah and the Philippine Peso.

Ranaldo and Soderlind [2010] studies safe haven currencies by analysing high-frequency exchange rates over the period from 1993 to 2008. They find that the Swiss Franc and Japanese yen appreciate against the US dollar when US stock prices decrease and US bond prices and FX volatility increase. The Euro has similar but weaker performance, while the British pound might not be regarded as a safe haven at all. Furthermore, these safe haven properties materialize over different time frames (e.g. on frequencies from a few hours to several days) and have a non-linear relationship with the volatility factor during crises. However this paper doesn't discuss the real drivers of safe haven events.

ECB have also published papers on this topic. Beck and Rahbari [2008] argues that the US dollar and Euro are as safe haven currencies in different regions, which are referred to as currencies, more likely to appreciate during sudden stops as investors redirect capital to mature markets. The paper reaches this conclusion by computing optimal central bank portfolios. It finds that the optimal dollar share rises in Asia and Latin America, while the optimal Euro share rises in emerging European countries when sudden reversals in capital flows (sudden stops) happen. In a following paper, Habib and Stracca [2012] investigates the fundamentals of safe haven currencies by studying a large panel of 52 currencies in advanced and emerging countries over almost 25 years of data. They find that only a few drivers associated with a safe haven status, including: (a) the net foreign asset position, as an indicator of external vulnerability; (b) whether currencies have been a successful hedge during uncertain times in the past; (c) how open the financial markets are, finding that a less opened economy is likely to be a better hedge during global risk aversion shocks. Similar to Ranaldo and Soderlind [2010]'s study, they also document non-linear relationships between safe haven currencies and their fundamentals.

2.1.4 Flight-to-Safety(FTS)

A closely linked concept with safe haven is flight-to-safety (FTS), which refers to the phenomenon that in periods of uncertainty, distress or bad news, there is often capital flight from risky assets like stocks to less risky assets like bonds, which results in insufficient risk taking

activities. FTS can also refer to bank lending preferring to less risky borrowers. Depending on what mainly drives the capital movement, it is sometimes referred to as flight-to-quality (FTQ) or flight-to-liquidity (FTL).

A common phenomenon of FTS is that after a crash in stock markets, government bond markets rise (see as discussed in P.Hartmann et al. [2001], Longstaff [2004], Brière and Szafarz [2008], Briere et al. [2008], Goyenko et al. [2011], Durand et al. [2011]). Although at normal times, the bond and stock returns are expected to be positively correlated as they both represent long duration assets Baele et al. [2013]. For example, Brocato and Smith [2010] defines FTS as a daily 5% equity decrease coupled with a 1% government bond index increase. Other studies define it as when the correlation between the returns of stocks and sovereign bonds switches sign from positive (in the normal times) to negative (during stock market crashes), leading to decoupling that higher correlations within the equity markets but negative correlations between equity and bonds (e.g. Gulko [2002], Favero and Giavazzi [2002], Briere et al. [2008]). In an early study, Campbell and Ammer [1993] find that over the full sample 1952 – 1979, stock and bond returns had a modest positive correlation of 0.20. The real interest rate changes tended to result in stock and bond returns moving in the same direction. While the temporal low correlated returns is due to the balance among several offsetting factors, for example, rising long-run expected inflation is bad news for the bond market but good news for the stock market. In a later study, Baur and Lucey [2009] further differentiates FTS with decoupling that, FTS from stocks to bonds occurs when either there is a significant decrease in their correlation during a stock market crisis period, when compared to a benchmark period, which results in a negative correlation level, or a negative stock-bond correlation level in pre-crisis period while having a significant negative change in the crisis period. Another strand of the literature focuses on the investor risk aversion and shift of market sentiment in which they define FTS as sudden and sharp increases in investors risk aversion (e.g. Eichengreen et al. [2001], Vayanos [2004], Kim et al. [2006], Fostel and Geanakoplos [2008], Acharya et al. [2010]).

Main papers and their findings are discussed in chronological order as follows. One of the earliest studies of capital flight seems to be Brendan Brown's book *The Flight of In-*

ternational Capital—a Contemporary History 1987, which is discussed previously. In this book, Brendan documented a couple of well-known cross country capital flows in history, including the movement of funds between the France Franc and US dollar during Sterling’s devaluation and the France Franc’s breaks with gold in the 1930s; the capital flight to the US before the World War Two; to dollar and Swiss Franc from the 1940s to the 1950s; to the Deutsche Mark in western Europe’s “miracle years” of the late 1950s and early 1960s; and finally against to the US miracle in the first half of 1980s. Brendan also points out that waves rather than continuous flow is as one critical property of any capital flight driven by fears of future disaster, because the alarming new information, which as a frequent cause of shifts in probability assessment is by its very nature, sudden.

There were two important papers published in the 1990s on flight-to-quality phenomenon in banking activities. The “quality” here refers to the credit conditions of borrowers. It suggests that tight credit conditions will reduce the relative amount of lending to riskier borrowers, which in turn, would have a significant impact on the real economy. Lang and I.Nakanura [1995] analyses the data on new bank loans from the Federal Reserve’s Survey on Terms of Bank Lending from 1979 to 1992 and finds that there is a rise in the relative quantity of safe loans following recessionary movements in both real GDP and inventory investment. Since riskier and lower net worth borrowers are those more dependent on bank lending than larger and less risky borrowers, riskier borrowers are disproportionately affected in the early stages of tight money episodes. Bernanke et al. [1996] also discusses FTQ from the perspective of bank lending. Based on firms’ quarterly financial report data from the 1970s to the 1990s, they show strong evidence that economic downturns differentially affect both the access to credit and the real economic activity of high-agency-cost borrowers. The significance of which is that it could amplify any worsening credit-market conditions and act as a financial accelerator.

Since 2000, there have been an increasing number of studies on the FTS phenomenon. A majority of these studies focus on the relationship between stock market crashes and government bond markets rise (see e.g. P.Hartmann et al. [2001], Longstaff [2004], Brière and Szafarz [2008], Briere et al. [2008], Goyenko et al. [2011], Durand et al. [2011]).

Ebrahim [2000] identifies two distinct regimes of stock-bond interaction. The prevailing regime features low volatility of stocks and low excess return of bonds. The other regime features high volatility of stocks and high excess return of bonds, representing a temporary FTQ from equities to treasury bonds.

Eichengreen et al. [2001] analyse the bond markets in the Mexican, Asian, and Russian crises of the 1990s. They find changes in both fundamentals such as volumes, spreads and maturities and market sentiment following each of the three crises. The paper points out that FTQ refers to this shift in market sentiment, and that how credit-markets access is impaired by these sharp shifts in investor sentiment has not received commensurate attention.

ECB published a paper in 2001 (P.Hartmann et al. [2001]) which studied asset market linkages in crisis periods. It examines various extreme co-movements between stock and bond markets including simultaneous crashes, stock-bond contagion and flight-to-quality from stocks into bonds. By applying an external dependence measure on G-5 countries weekly returns from February to November 1999, they find that stock markets realize a co-crash in about one out of five crashes, while this number is lower for bond markets and co-crash between a stock and a bond market (contagion). The FTQ phenomenon is about as common as the co-crash of a bond and a stock market, which highlights limits to the propagation of financial market crises.

Favero and Giavazzi [2002] argues that interdependence connecting financial markets in normal times tends to break down after unusually large shocks. By studying the propagation of devaluation expectations among seven European countries over the period 1988 to 1992, the paper concludes that the international propagation of financial shocks may be non-linear, which could produce a response whose sign is the opposite of what we observe in normal times, suggesting a FTQ phenomenon.

Gulko [2002] provides empirical evidence that sometimes stocks decline by 2 to 5 percentage points while Treasury bonds rally by approximately the same magnitude, which represents the FTQ over the period October 1987 to 2002.

Meanwhile, Vayanos [2004] emphasizes the differences and linkages between FTQ and FTL. During FTQ periods, the risk premium investors require per unit of volatility increases,

while during FTL periods, liquidity premia widen dramatically. They define an asset's liquidity as its exogenously given transaction cost. For example, during the 1998 financial crisis, the yield spread between off- and on-the-run thirty-year US Treasury bonds increased to 24 basis points (bp), from 4 bp the pre-crisis value, indicating FTL. Based on the findings, they propose a theory of time-varying liquidity premia and explore its asset-pricing implications.

Similarly, Longstaff [2004] examines the FTL premium in Treasury bond prices. The paper examines whether there is FTL premium by comparing them with prices of bonds issued by Refcorp, a US government agency. Longstaff finds a large liquidity premium, accounting for more than 15% of the value of some Treasury bonds, suggesting that the popularity of Treasury bonds directly affects their value.

Kim et al. [2006] examines the dynamic relationship between daily stock and government bond returns of US, European countries and Japan from 1996 to 2006. It finds evidence of cross-market volatility interdependence, which supports the FTQ hypothesis, that when positive news hits one asset market, volatility is dampened in the other as investors tend to stick with their asset allocations; but when negative news hits, investors tend to switch towards perceived "quality" investments thereby increasing cross-market volatility.

Brunnermeier and Pedersen [2008] argues that their findings shed new light on FTQ, showing that risky securities become especially illiquid. During uncertain periods, the link between volatility and liquidity is strengthened, as when speculators are poorly financed, high-volatility securities are more affected by speculator wealth shocks.

Brière and Szafarz [2008] refers to the FTQ effect as the situation where all volatilities increase but the correlations between the safest and the riskiest assets decrease. They examined seven financial crises between 1998 and 2007, using datasets which contain weekly returns of government and corporate bond indices in the US and in the Eurozone. Results show that the FTQ has a key effect in the bond class.

Differing from Vayanos [2004] who measures liquidity as transaction cost, Fostel and Geanakoplos [2008] model an asset's liquidity as its capacity as collateral to raise cash. By analysing Emerging Market issuance of dollar-denominated sovereign bonds covering the period 1997 to 2002, they find that in an anxious economy, asset prices generally fall but

assets with higher collateral values fall less, hence FTL occurs.

In the paper by Briere et al. [2008], they test globalization, contagion and FTQ by analysing a large dataset including weekly returns to indices for equities, government bonds and corporate bonds for the US, the Eurozone, Japan, and the UK. Results confirm that the instability of correlations points to a combination of globalization and FTQ, while it emphasizes that contagion on the equity markets appears as an artefact due to globalization. In addition, they find that the FTQ effect remains after adjusting for globalization, which the authors argue is good news for investors as they would be able to hedge against risks from this decorrelation during crises.

Pavlova and Rigobon [2008] refers FTQ to a transmission pattern of a negative shock. Their model results show that a negative shock to one of the Periphery countries reduces its stock price, decreases the stock price of other Periphery country (contagion), but increases the stock market price in the cent (FTQ).

Caballero and Kurlat [2008] provides a thorough literature review of FTQ and bailouts. It draws implications from the policy perspective, notably that policy must take into account incentives for behaviour during the crisis, discouraging excessive prudence.

Goyenko et al. [2011] studies the term structure of bond market liquidity and its implications for expected bond returns. The paper finds that during recessions, illiquidity increases and the difference between spreads of long- and short-term bonds significantly widens, indicating a FTL.

Baur and Lucey [2009] analyses the existence of flights from stocks to bonds and vice versa. They also propose a definition and a test for flight-to-quality, flight-from-quality and cross-asset contagion and examine their characteristics and effects for the financial system. Based on results obtained from eight developed countries including the US, the UK, Germany, France, Italy, Australia, Canada and Japan from January 1994 to September 2006, the paper shows that flights exist and are a common feature in many crises. In addition, they also show that capital flights are not only country-specific but occur simultaneously across countries.

Acharya et al. [2010] studies the exposure of the US corporate bond returns to liquidity shocks of stocks, and sovereign debts from 1973 to 2007. Their findings suggest liquidity risk

of corporate bond returns is time-varying and there are episodes of FTL.

He and Xiong [2012] shows that the credit spreads of BB-rated firms are more sensitive to the same shock to market liquidity than those of A-rated firms. In addition, increased default risk contributes to a greater fraction of the credit spread increase for the BB-rated firm, given debt maturity. He and Xiong argue that the results indicate the FTQ occurrence.

The Hong Kong Monetary Authority also published research on this topic. Zhang et al. [2009] looks into how the US 2007-2008 credit crisis affected the Asia-Pacific economics based on a general equilibrium model. They find that the importance of various financial channels differs across economics. Stock market contagion is most important for advanced economies, however FTQ across borders plays a critical role in less developed economies.

Berger and Turtle [2011] finds contagion effects in US small size portfolios during emerging market crises. Capital flights from risky assets to safer larger stocks receive positive abnormal returns.

Dieckmann [2011] argues that rare events, heterogeneous beliefs, and an incomplete market lead to countercyclical risk premiums and FTQ episodes.

Durand et al. [2011] discusses fears and its role in the Fama-French factor model. It argues that investors' expectations of market volatility as captured by the VIX affects the expected returns of US equities. They find that an increase in expected volatility is associated with FTQ and increases in estimated required returns.

In another working paper by ECB, Chudik and Fratzscher [2012] analyse the differences of transmission of liquidity shocks and risk shocks to global financial markets between the 2007-08 financial crisis and the 2010-11 sovereign debt crisis. Applying a Global VAR model, they find that a FTS phenomenon across asset classes has become particularly strong during the 2010-11 European sovereign debt crisis, and that risk shocks drive down bond yields in key advanced economies.

A recent paper by Baele et al. [2013] offers the first empirical characterization of FTS episodes for 23 countries over the period January 1980 to January 2012. They identify and characterize FTS episodes based on stock and bond market returns. They find that on average, FTS days comprise less than 5% of the sample, and bond returns exceed equity returns

by 2 to 3%. They find the stock-bond return correlation is -2.4% on average in normal periods and -9.12% overall. They also find that FTS events are mostly country-specific and not global. Furthermore, it documents the macroeconomic environment associated with FTS episodes, but not causality relationships. They find that right after FTS episodes, inflation is significantly lower, GDP and industrial production growth (IP) decreases significantly for most countries, and unemployment increases significantly. A year after the FTS, inflation declines, and unemployment increases substantially, while GDP growth and industry production growth is expected to be negative. FTS also comes with increasing VIX, decreasing in consumer sentiment, appreciations of the Yen, Swiss Franc, and the US dollar. On the industry level, the financial, basic materials and industrial industries tend to under-perform in FTS episodes, while the Telecom industry out-performs. Commodity prices, except for metals including gold, have abnormal negative returns, along with the money market instruments and corporate bonds. Their approach is different from most previous studies which use data only from the financial sectors.

2.1.5 Market Linkages during Crises Periods

Another strand of literatures related to safe haven assets is market linkages and, in particular, market linkages during crises periods. I have discussed, previously, papers which address this strand as they also covered safe haven assets and flight-to-safety phenomenon. However, they are also discussed in this strand as it is important to see the development of scholarly understanding on this topic separately. More importantly, it provides an interesting theoretical framework which covers various measurements on safe haven assets, FTS, contagion, and other types of market co-movements, which I will also discuss.

A positive market linkage at stable times suggest that common macroeconomic variables drive both markets, and vice versa. However, correlation changes during periods of financial crises are a different issue, since fundamental relationships linking asset returns appear to break down, both across national boundaries and across asset classes (Solnik [2001], Dungey and Martin [2007], Chan et al. [2011]).

Market linkages during crisis periods have been discussed as early as the 1960s. Morgen-

stern [1959] describes this as a tendency of economic life disturbances to spread from one country to another. In this book *International Financial Transactions and Business Cycles*, he refers to capital flights, with devaluation, free exchange rates, going off gold, import prohibitions and quotas as the “large fluctuations” in business cycles, and he believes that an in-depth statistical analysis would be challenging due to the relatively short period of each condition.

Studies in the 1990s focus on price co-movement and volatility spillovers within the same asset class across nations, mainly in stock market (King and Wadhwani [1989], Hamao et al. [1990], Eng), few on bond (Borio and McCauley [1996]) and some empirical work on currency crisis (Eichengreen et al. [1996], Kaminsky and Reinhart [2000]).

Since 2000, a number of studies started to discuss cross-assets co-movements (therefore either within a country or cross-country), mainly focusing on the linkages between stock and bond markets. The first hard quantitative examination of the cross-asset extreme linkages and related flight-to-quality phenomenon is by P.Hartmann et al. [2001]. They conclude that national borders do not seem to matter much between G-5 countries (France, Germany, United Kingdom, United States and Japan) in terms of the spread of crashes. Other studies include Gulko [2002], Dopfel [2003], Gonzalo and Olmo [2005], Forbes and Rigobon [2002], Baur and Lucey [2009] among many others.

Recent studies have covered more asset classes, for instance, corporate bonds (Brière and Szafarz [2008]), gold (Piplack and Straetmans [2010], Chevallier [2012]), oil (Chan et al. [2011], Chevallier [2012]), commodity market index (Swamy and S [2011]), real estate (Chan et al. [2011]), and credit derivatives markets (Ding and Pu [2012]).

Types of Market Linkages in Crises Periods

A couple of different types of market linkages have been defined and re-defined by previous studies; however, there are no agreed common definitions for all, which is not only due to different understandings, but also different methodologies being used.

Among all types of market linkages, contagion is by far the most analysed one which is commonly understood as strong co-movement between markets without fundamental linkages,

while studies on flight-to-safety phenomenon have increased significantly in recent years. Take contagion as an example, three main different definitions have been given according to Forbes and Rigobon [1999]. Ordered from less stringent definition to more stringent definition, they are:

- Definition 1: the phenomenon that a shock to one country is transmitted to another country;
- Definition 2: the phenomenon that a shock to one country is transmitted to another country, AND it causes a significant change in cross-market relationships. This is phrased as “shift-contagion” by Forbes and Rigobon [1999];
- Definition 3: only certain types of transmission mechanisms constitute contagion, no matter what the magnitude and changes of market relationships.

As shown above, Definition 1 emphasizes on the level or magnitude of market linkages; while level and magnitude does not necessarily reflect contagion according to Definition 2, which argues that there should be a statistically significant change in market relationships; Definition 3 focuses on the underlying reasons for contagion. It argues that it is impossible to define contagion just through simple statistical tests of magnitude and changes in cross-market relationships. The argument is around whether shocks are transmitted through existed or real mechanisms i.e. trade linkages, financial linkages, etc., or whether shocks are transmitted through mechanisms which did not exist before the crises, i.e. due to changes in investors’ expectations, endogenous liquidity shocks, etc.⁵ Forbes and Rigobon argues that

⁵Forbes and Rigobon [1999] summarized shocks propagation theories as two groups accordingly:

First, crisis-contingent theories, which argue that crisis could cause structural shift, thus crisis transmit from country to country through the channels that does not exist before the crisis. There are three mechanisms: 1) multiple equilibria: a crisis in one country could change investors’ expectations, which could shift other markets from a good equilibrium to a bad equilibrium; 2) endogenous liquidity: a crises in one country could reduce investors’ liquidity in general, thus force them to re-allocate portfolios and sell assets, which then further transmit liquidity shocks to other countries; 3) political economy: this is in the case of European exchange rate regimes.

Second, non-crises-contingent theories assume that transmission mechanisms are the same during a crises as during more stable periods. It is, therefore, real linkages. They further break down real linkages as four types, which are trade, policy coordination, country re-evaluation or learning, and random aggregate shocks or global shocks.

only transmissions through the second mechanism should be contagion. Some papers, on the contrary, avoid defining contagion and just focusing on measuring the specific transmission channels.

I apply Forbes and Rigobon [1999]’s classic analytical framework of contagion to FTS and safe haven in the following Figure 2.2. Various definitions of FTS and safe haven could be classified into three types. I also add interdependence and decoupling as a comparison, as they are also frequently discussed market-linkages.

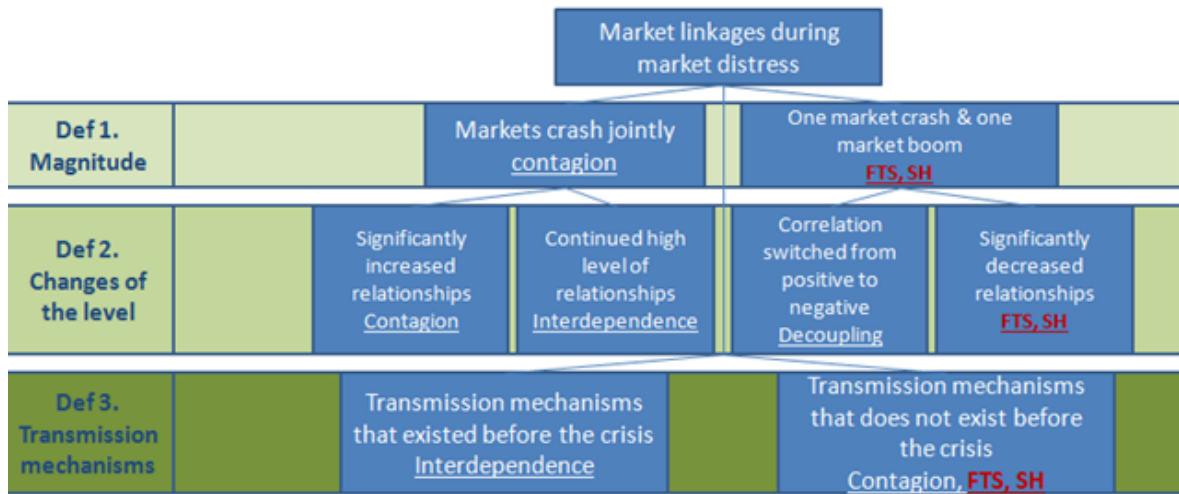


Figure 2.2: Three types of definitions of market linkages during crises periods

According to this framework, definitions of FTS and safe haven assets could be classified as follows.

- Definition 1: FTS refers to when one market crash is accompanied by a boom in other markets (e.g. P.Hartmann et al. [2001], Favero and Giavazzi [2002], Briere et al. [2008]); safe haven is an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress (e.g. Baur and Lucey [2010]).
- Definition 2: Decoupling is indicated by a switched sign of correlation between two markets (e.g. Gulko [2002]), different from FTS which only occurs when the correlation coefficient decreases significantly in a crisis period compared to a benchmark period resulting in a negative correlation level between two markets (e.g. Baur and Lucey

[2009]).

- Definition 3: a defining feature of FTS and safe haven is a sudden and sharp increase in investors risk aversion or Knightian uncertainty aversion, a decreased demand for risky assets and shift of market sentiment (e.g. Eichengreen et al. [2001], Vayanos [2004], Kim et al. [2006], Fostel and Geanakoplos [2008], Caballero and Kurlat [2008], Acharya et al. [2010], Baur and K.J.McDermott [2010]).

A few studies also seek the relationship between FTS and contagion. Pavlova and Rigobon [2008] emphasize that both FTS and contagion are transmission patterns of a negative shock. Baur and Lucey [2009] define that flights and cross country contagion are mutually exclusive, i.e. if there is FTS from stocks to bonds, contagion between stocks and bonds cannot exist, and vice versa.

2.1.6 Market Distress and Crises

Safe haven studies look into asset performances during market distress periods. However, market distress could be triggered by different incidents such as political turmoil or a major corporate bankruptcy, and are associated with different characteristics such as liquidity flights or consumers increasing risk aversion. According to Persaud [2009], the global economies have experienced many times of economic crisis since it was recorded. Some big economic crises in recent history include:

- 1997 Asian Financial Crisis

The crisis began in Thailand when the Thai government was forced to float the currency Baht due to lack of foreign currency to support its peg to the US dollar. The Baht depreciated sharply which later impacted on all Asian currencies due to contagion affects (except for Chinese Yuan and the Hong Kong dollar). On average, these currencies lost 30% of their market value and the stock markets 30%–60% (Kindleberger and Aliber [2011]). In the end, Indonesia, South Korea, Hong Kong, Laos, Malaysia, Philippines, Brunei, China, Singapore, Taiwan, Vietnam and Japan were all affected.

- The Dot-Com Bubble collapse in 2001

This occurred after a period of rapidly growing investment in internet-based companies, many of which did not succeed. The NASDAQ Composite stock market index grew from 1000 in 1995 to 5048 at its peak on March 10, 2000. However large high-tech companies started to sell-off their stocks at the market peak, which triggered panics, and the market subsequently lost its 10% value within a few weeks.

- 2007–2009 the Global Financial Crisis

The low interest rates and large inflows of foreign funds (mainly from Asia) created easy credit conditions in the US for a number of years prior to the crisis, fuelling a housing market boom and encouraging debt-financed consumption during 2001–2007. Started with the sub-prime mortgage market crisis in the US in 2007, it soon developed into a global banking crisis with the collapse of the investment bank Lehman Brothers on September 15, 2008. Many more global financial institutions were impacted severely and had to be bailed out in the end such as Fannie Mae and Freddie Mac, Merrill Lynch, and Anglo Irish Bank.

Economic Cycle

The traditional model to interpret the financial crises in the United States, Great Britain and other market economies, as discussed in Minsky [1992] and Kindleberger and Aliber [2011], is to focus on the pro-cyclical increases in the supply of credit in good times and its decrease during less buoyant economic situations. It works as follows: during the economy expanding period, investors are optimistic about the future and they revise upward their expectations of the profitability of a wide range of investments, and became more eager to borrow credits. Meanwhile, both the lenders' assessments of the risk of individual investments and their risk averseness decline and they become more willing to lend credits. However, this can turn into economic euphoria where business become increasingly up-beat and investment spending surges, investors tend to seek short-term capital gains from the increases in the prices of real estate and of stocks rather than long-term investments. Next, an event, like a policy change

or a big sell-out could lead to a pause in the increase in asset prices; and soon previous investors turn into distress sellers.

In addition, Kindleberger and Aliber [2011][p.256-265] outlined historical financial crises from 1618 to 1998 including which countries or cities were involved, related events, preceding speculations, where the monetary expansion is from and who played as the lender of last order. More triggers to financial crisis were listed such as a change in the ratio of the prices of gold and silver under bimetallism, an unexpected success of some flotation of a stock or bond, a sharp reduction in interest rates as a result of a massive debt conversion, or a rapid expansion of the monetary base. The National Bureau of Economic Research (NBER) provides reference dates of US business cycle expansions and contractions (see <http://www.nber.org/cycles>) from 1854 to 2010. Shiller [2003] relates economic cycles to the cycle of human behaviour and motivations, or the “animal spirits”: that during periods of prosperity, everything seems right, prices go up, people are getting wealthier, more confidence, and greedy; and in competing for new sources of investment opportunities, people become complacent about the risk of loss, make rash decisions and even encourage corruption. However, when panic appears, people lose confidence, get scared, and eventually trigger a recession.

Black Swan Event

In addition, an important characteristic of recent financial crisis is that they occurred suddenly and at unexpected magnitude, or as “black Swan” events. “Black Swan” event in the financial markets, according to Taleb [2008], refers to unexpected and severe loss in the markets. They are essentially unknown unknowns and extreme outliers. Some studies examine safe haven assets by examining their performances during “Black Swan” events in particular, such as Baur and K.J.McDermott [2012a] and Bekiros et al. [2017].

Market Stress Measurement

Regulators, independent research institutes, and central banks have been publishing indicators to measure and monitor market stress, which can be broken down into three types: financial market stress, political stress and consumer sentiment. Financial crisis used to be

measured by a binary variable. However, this lacks the intensity of crisis and it also fails to measure near-miss events. The Financial Stress Index (FSI) was created to address that, which is a continuous variable with a spectrum of values where extreme values are called a crisis. Several research institutions and central banks have created FSI combining a number of factors, which differ across countries to reflect their specific characteristics. One of the earliest indices is Illing and Liu [2006]’s FSI for Canada which combines the stress measures of banking sector, foreign exchange market, debt market and equity market. They apply factor modelling using the principal-component analysis to construct the FSI. Their methodology was later adapted and developed further by Federal Reserve Kansas City (Hakkio and Keeton [2009]), International Monetary Fund (Cardarelli et al. [2011]), Balakrishnan et al. [2011] for emerging economies, Corbet and Twomey [2014] for the UK and Bjornskov et al. [2008] for Germany.

Second, political stability plays a key role. Economic Policy Uncertainty (EPU) Index published by Baker et al. [2013] proxies for movements in policy-related economic uncertainty. The EPU index is based on newspaper coverage frequency of political uncertainty related keywords, including “economic” or “economy”; “uncertain” or “uncertainty”; and one or more of “congress”, “deficit”, “Federal Reserve”, “legislation”, “regulation”, or “White House”.

Third, consumer sentiment must also be considered. There are survey based sentiment indicators such as the University of Michigan Consumer Sentiment Index, which is based on telephone interviews with United States households to gauge their attitudes and expectations with respect to income, wealth, prices, and interest rates, according to Barnes and Olivei [2013]; or the European Commission Economic Sentiment Indicators, which are also calculated from regular harmonised surveys (see ec.europa.eu/info). There is also market information based measurement, such as the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), the “fear index”.

2.1.7 Conclusion

In this section, I reviewed previous literatures on safe haven assets and its related topics including theoretical aspects of the safe asset, empirical findings of flight-to-safety episodes

across country as well as asset class, analytical framework of market linkages during crisis periods, and finally historical economic crises triggered by various reasons and different types of market stress measurements. Next I will discuss the economics of precious metals market (gold, silver, platinum and palladium) and their potential as safe haven assets.

⁷There is a large amount of literature on the historical gold standard, and monetary role of precious metals coins, however they are excluded from this visualization.

2.2.2 Determinants of Precious Metals Prices and Volatilities

To study the price of commodity, real price and nominal price need to be discussed separately. According to the concept of neutrality of money (Lucas [1972]), in the long run real prices of goods are determined by real supply and demand factors; while nominal prices of goods are influenced by the general price level and determined by the supply and demand for money without regard to relative goods prices. Nominal price can be converted to real price by adjusting inflation rate. However, in the short term the above simple relationship does not hold. For instance, monetary policy as reflected in real interest rates is an important determinant of the real prices of some commodities as argued in a series of papers by Frankel (1985, 2006, 2014). Nevertheless, I will firstly discuss supply and demand factors for precious metals; then monetary factors such as money supply, interest rate and exchange rate; and, finally, other important determinants of precious metals prices.

Demand, supply and stock

Tables 2.1 to 2.7 display demand, supply, and above-ground stock statistics for gold, silver, platinum and palladium, as well as total volumes traded across commodity exchanges around the world.

Gold

As Table 2.1 shows, the total supply of gold in 2016 is 4511 tonnes, among which 71% (3222 tonnes) is from mine production, 28% (1268 tonnes) from scrap and 21 tonnes from net hedging supply. On the physical demand, jewellery has the largest share with 1891 tonnes (53%), followed by retail investment with 1057 tonnes (30%), industrial fabrication with 354 tonnes (10%) and finally the official sector with 257 tonnes (7%). ETFs have built up 524 tonnes of inventory in 2016 and exchange built 86 tonnes of inventory. COMEX is the largest exchange for gold (Table 2.2), with total volume of 179047 nominal tonne equivalents in 2016, followed by Shanghai Futures Exchange (SHFE) 34760 tonnes, Shanghai Gold Exchange (SGE) 11793 tonnes and Tokyo Commodity Exchange 8541 tonnes.

Flow supply and demand for gold have a relatively small impact on the price considering

its small size compared to above-ground stocks (Abken [1992]). In 2016, the total supply of gold was 4511 tonnes and the physical demand was 3559 tonnes. Circa 186200 tonnes of gold have been produced in human history and much of this is still in circulation according to the CFMS Gold Survey 2017. However, not all 186200 tonnes of gold is near-to-market, for instance gold used in electronics before the 21st century would not have been recycled and would, therefore, have been wasted, and many gold bars and items of jewellery will have been lost or taken to the grave, the liquid stock of near-to-market is still many times larger than the annual physical demand of gold. The volumes of gold traded in 2016 in COMEX alone are approximately 179047 tonnes, with an estimated value of 7.9 trillion US dollars. The total traded gold is about 56 times mine production. In addition, the new supply of gold that comes to the market has not changed substantially over the past decade even though the price of gold has increased fivefold from 2002 (309 US dollars per troy ounce) to 2012 (1669). Therefore it is assumed that rather than annual supply and demand determining the gold price, it is the price that determines how much new physical supply and demand are attracted to the market each year O'Connell et al. [2015a] [p.9].

Silver

Similarly, silver is not only an industrial metal but also an investment product. As Table 2.3 shows, the total supply of silver is 28511 tonnes in 2016, six times more than gold. Mine production contributes 25112 tonnes of silver, more than 80% of total supply and there are 3960 tonnes from scrap. Finally, there is de-hedging by producers for the first time since 2013 that the total supply dropped in 2016. The total above-ground stock in 2016 is 78067 tonnes, almost three times larger than the annual supply ⁸. The demand is dominated by industrial usage with 15930 tonnes (55%), among which almost half is in use in electronics, others include brazing alloys and solders, and photography, although this has been reducing significantly for the past 10 years. The total physical demand was 29318 tonnes in 2016,

⁸Different from gold, the total above-ground stock of silver does not include silverware, jewellery or other fabricated products that are, in one form or another, available in the market place. Only when the silver fabricated products get recycled into an homogeneous form (e.g. bars and coins) will they re-enter the calculation and count as scrap.

dropping by 11% year-over-year. Jewellery consumes 20% of the silver (5868 tonnes), which is 10% down from 2015. 20% of the demand for new silver in 2016 came from the physical coin and bar, which is 29% less from 2015 and it is the first time it dropped in the past three years. Although the physical demand declined, the ETF inventory and exchange inventory have increased significantly in 2016 with 1332 and 2262 tonnes built respectively. Regarding silver's exchange activities, the COMEX is the largest exchange with 90638 tonnes traded in 2016. It is followed by SHFE with 41716 tonnes, SGE 19711 tonnes, MCX 147 6931 tonnes and so on. Therefore, the total volume of silver traded on exchanges is more than six times more than mined, and it is about twice the size of the total above-ground stock. Silver has an active Over-the-Counter (OTC) market owing primarily to its role as institutional investment product. Therefore, demand, supply balances as well as economic and political factors could influence silver price to some extent. For instance, the downward trend in 2014 was heavily impacted by the slowdown in China on silver demand and higher interest rate expectation and the stronger US dollar according GFMS World Silver Survey [O'Connell et al., 2015b, p.12].

Platinum and Palladium

Compared with gold and silver, platinum and palladium have much smaller annual production: the total supply of platinum is 216 tonnes and palladium 284 tonnes in 2015 (see Tables 2.5-2.6). Both have 80% of their annual supply from mine production. Autocatalyst scrap contributes another 12% of platinum and 19% of palladium. Jewellery scrap accounts for the remaining 3-4%. The physical demand for platinum and palladium is dominated by industrial use (61% of platinum and 96% of palladium), especially as autocatalyst (40% of platinum and 73% of palladium). Additionally, platinum has a fair amount of demand from jewellery, about 30%, and a small but growing demand from retail investment (6%). The stock movements of platinum is 6.0 tonnes and palladium 16.4 tonnes. ETFs have built stocks on both metals in 2015 with 7.4 tonnes of platinum and 20.1 tonnes of palladium. As platinum and palladium are primarily industrial metals, demand and supply have the major impact on their prices. Factors include mine production in South Africa and autocatalyst in-

dustry demand, rather than investment flow. Investment flow is relatively bigger with regard to platinum than palladium due to its historically proportionately higher jewellery demand which is similar to gold. As Table 2.7 shown, platinum and palladium are mainly traded in COMEX and TOCOM. The net investment positions of platinum on COMEX are 26.1 tonnes, and platinum 53.7 tonnes in 2015; and on TOCOM, they are 30.3 tonnes and 0.71 tonnes respectively.

Monetary Factors

As discussed above, demand and supply structures of gold, silver, platinum and palladium are quite different from each other. While demand and mine production balance has a relatively large impact on prices of palladium and platinum, it is not so much important on gold and silver. The monetary determinants of precious metals prices are now discussed. In the following, nominal prices are simply referred to as prices.

Theoretically commodity prices are determined by the money supply in the long run (Frankel [2006], Cronin and Browne [2007]). Take monetary expansion as an example, it will temporarily decrease the real interest rate, whether via a fall in the nominal interest rate, a rise in expected inflation, or both. Consequently, real commodity prices increase. In the long run, the real money supply, real interest rate, and real commodity price eventually return to their previous level. However, it is a bit more complicated in the short run due to the “overshooting” phenomenon (Frankel [1985, 1986]). In the short run, commodity prices will experience an “overshooting” period, during which commodity prices will increase until they are considered “overvalued” before they eventually falls back to long term equilibrium. The fundamental reason for the overshooting phenomenon is due to prices for different types of goods adjusting differently. Prices for customer goods are sticky in the short run due to imperfect information, costs to changing prices, and so forth. And prices for auction goods or flex-price goods are free to respond to fluctuations in demand. In a paper in 2006, Frankel argues that gold and other minerals prices move faster than the sluggish prices of manufactured goods and services and therefore they used to be considered as leading indicators of inflationary expectations. Precious metals’ ability to hedge against inflation is also discussed

by Labate [1994], Taylor [1998] and recently by Lucey et al. [2017] in a time-varying framework. Since precious metals prices are more flexible to move, overshooting phenomenon will have a weak impact on their short term price movement. The dollar exchange rate drives precious metals prices partly because they are denominated in the dollar currency (e.g. see Connor and Lucey [2012]). When expected inflation is high, investors would consider a move from dollar-denominated soft assets to dollar-denominated physical assets. Lucey and Tully [2006a] find gold to be particularly sensitive to the US dollar/Euro exchange rate in that most of the imports and exports come from the US and the European countries and changes in this exchange rate would impact on the prices more. However in a recent paper by Baur and Lucey [2017], they find that global factors such as commodity prices, equity prices and currencies are important factors, while bond yields, interest rates and consumer prices are not. In addition, a time-varying analysis shows that there is significant variation in the importance of factors. This paper applies Bayesian Model Averaging on a large set of factors that potentially influence the price of gold to address the issue of model uncertainty and prior knowledge.

Other Determinants

There are many studies investigating the relationship between oil and gold prices (see for example Baffes [2007], Sari et al. [2010]). Baffes [2007] examines the effect of crude oil prices on the prices of 35 internationally traded primary commodities for the period 1960-2005 and finds that the transmission of crude oil price changes to the overall non-energy commodity index is 0.16. At a disaggregated level, the pass-through to metals is 0.11 and they have a strong response to crude oil price. Sari et al. [2010] examines the relationship between precious metals with oil price and the US dollar/Euro exchange rate between January 1999 to October 2007. By applying the impulse response function, the paper shows that the initial impacts of precious metals' prices on oil spot prices are positive and significant, however these impacts die out quickly. Narayan et al. [2010] provides a theoretical framework for understanding the relationship between oil and gold prices. The hypothesis is that a rise in oil price generates inflation, which drives up gold price. Applying cointegration test on daily

data from January 1995 to March 2009, the paper finds that gold and oil spot and futures markets up to the maturity of 10 months were cointegrated which implies that investors do use the gold market as a hedge against inflation and oil could be used to predict gold prices.

In addition, seasonality is also found to be a factor especially for gold prices in many studies (see for example Ball et al. [1982], Ma [1986], Lucey and Tully [2006b], Aggarwal and Lucey [2007]). There are also an increasing number of studies examining the relationship between news sentiment and gold returns. For instance, Smales [2014] examines commodity specific news sentiment data from Thomson Reuters News Analytics over the period 2003–2012 and gold future returns. It finds that negative news has greater impact on returns. Furthermore, the business cycle also affects the relationship; during recession the news impact is larger. Recent studies have also identified more complex non-linear behaviour in gold returns such as evidence from the compass rose Batten et al. [2017b].

Precious Metals Volatilities

Volatility provides a proxy for information flow in that its structure provides additional and valuable insights into the price dynamics rather than returns Ross [1989]. Cai et al. [2001] provides a detailed characterization of the intra day return volatility in gold futures contracts traded on the COMEX. They find that employment reports, gross domestic product, consumer price index and personal income have the biggest impact on intra day patterns of gold prices. Batten et al. [2010] looks into the monthly price volatilities of four precious metals and investigates the macroeconomic determinants including business cycle, monetary environment and financial market sentiment of these volatilities. They find that gold volatility could be explained by monetary variables, but this is not true for silver. Overall there is limited evidence that the same macroeconomic factors jointly influence the volatility processes of the four precious metal price series, although there is evidence of volatility feedback between the precious metals. These results are consistent with the view that precious metals are too distinct to be considered a single asset class. A recent paper by Batten et al. [2017a] investigates the intra day periodicity, correlation and volatility interaction of returns, volatility and volume for gold, silver, platinum and palladium. They find that the volume of trades

of precious metals has increased substantially while the bid-ask spread has decreased which suggests the increase in efficiency and liquidity of precious metals markets. Besides, they find bi-directional Granger causality between volatility and returns indicating that past volatility (returns) has significant explanatory power in current returns (volatility).

Precious Metals Inter-Linkages

Another interesting research area is co-movement between precious metals prices and volatilities. Sari et al. [2010] examines daily data between January 1999 to October 2007. The generalized variance decomposition shows there is a strong relationship between gold price return and other precious metals' prices and changes in the exchange rate. They find that gold explains about 16% of the variation in silver, 10% variation in platinum, and 7% on palladium; and silver explains approximately 23% of the variance in the gold price in the long run, 10% variation in both platinum and palladium. A substantial cross-metal interaction among convenience yields has also been found (see e.g. Chng and Foster [2012]). In particular the convenience yield of gold and silver also affect the return and volatility processes of other precious metals, and this influence changes over time as the global economy conditions changes. Sensoy [2013] applies a relatively new approach to detect the volatility transmission between precious metals returns from 1999 to 2013 and finds that precious metals get strongly correlated with each other in the last decade. It argues that gold has a uni-directional volatility shift contagion effect on all other precious metals and silver has a similar effect on platinum and palladium. It is, however, different for platinum and palladium in that there seems to be an insensitivity in the correlation dynamics to the volatility shifts in platinum and palladium prices, probably due to the fact that they only became alternatives to gold and silver investment recently as argued by Sensoy [2013].

2.2.3 Precious Metals as Hedge and Safe Haven

There are a large number of studies focusing on the role of precious metals as a historically safe asset, a hedge in portfolio diversification considering its general low or negative correlation with stocks and bonds. From J.Sherman [1983], Jaffe [1989] to Hillier et al. [2006], Conover

and Jensen [2009], Baur and Lucey [2010], Mccown and Shaw [2013], Baele et al. [2013], Gorton [2016], and the consensus is that a typically small allocation of asset holdings to precious metals (particularly gold) can improve portfolio performance.

Gorton [2016] provides a brief survey of precious metal coins historical role as a safe asset. He argues that precious metals in the form of coins played the role of safe assets through most of human history considering its liquidity and its ability to store value in times of stress which could be used to pay off debts. However, there are some main problems that could potentially lead to the collapse of a coinage system, such as the shortage of small change, and coin clipping. As a result, the quality of coins could vary. The impact of political tension on the gold price was examined in 1983 by Ariovich. They find that there is a positive relationship between political tension as measured by the Hudson Institute and gold price, despite the fact that using the political tension does not increase the power of the explanatory model of gold pricing. Abken [1992] argues that throughout history gold has been considered the ultimate store of value and a haven for the preservation of wealth particularly in times of turmoil. Citak [1999] believes that gold was a safe haven since the middle of 1980, after the second oil shock in 1979 and the following inflation panic in US, and the halted sales by the IMF and the US Treasury.

Recent studies have showed empirical evidence that gold is a safe haven against stock market crash in a short time across some countries. Baur and Lucey [2010] analyses stock and bond indices in the US, UK and German from November 1995 to November 2005, and find that gold is a hedge against stocks on average and a safe haven in extreme stock market conditions for a short period of time. Baur and K.J.McDermott [2010] further define weak and strong safe haven and extend the analysis to thirteen countries over a 30 year period from 1979 to 2009. They find that gold is both a hedge and a safe haven ⁹ for major European stock markets and the US but not for Australia, Canada, Japan and large emerging markets such as the BRIC countries (Brazil, Russia, India and China). Coudert and Raymond [2010] focus on the recession periods of the US stock market and argue that in the short run, gold

⁹They differentiate hedge from safe haven that a hedge is defined as an asset that is uncorrelated or negatively correlated with another asset or portfolio on average; while safe haven is defined as an asset that is uncorrelated or negatively correlated with another asset or portfolio in terms of market stress or turmoil.

acts as a weak safe haven, while in the long run this does not always work. In addition, Ciner et al. [2010] find that gold can be regarded as a safe haven against exchange rates in both US and UK, which highlighting its role as a monetary asset. By applying a smooth transition regression on data from 18 economics and five regional indices on a monthly frequency, Beckmann et al. [2015] find that gold generally serves as both a hedge and a safe haven, however it depends on the specific economic environment under observation that factors such as market turnover, stock price volatility might be responsible for the differences.

Gold's role as a hedge and safe haven in the financial markets since the 2007 global financial crisis sparked a movement towards utilizing other precious metals in hedging and diversifying commodity portfolios Sari et al. [2010]. Hillier et al. [2006] argue that precious metals as a whole exhibit some hedging capability during periods of abnormal. Agyei-ampomah et al. [2013] find that palladium offers a greater compensation than gold in the period immediately after bond market losses. Baele et al. [2013] attempts to identify FTS episodes and goes on to characterize FTS episodes by examining the co-movement of FTS with a large number of financial and economic variables. They find that commodity prices generally decline on FTS days (ranging from -14 basis points for Livestock to -84 basis points for Brent Crude Oil). However precious metals and its main component gold both have positive FTS betas of on average 32 and 35 basis points respectively.

2.2.4 Conclusion

This section discusses the economics of the precious metals market focusing mainly on price and volatility determinants and empirical findings on gold and other three metals as safe haven. There is significantly more research on gold than silver, platinum and palladium. Gold's role as safe haven has motivated studies on silver, platinum and palladium's potential as safe haven in recent years.

2.3 The Sentiment Aspect of Safe Haven Assets

2.3.1 Introduction

An important aspect of safe haven assets is that how investor behaviour influences safe haven properties. Some studies define safe haven properties as when investors risk aversion suddenly and sharply increases which fundamentally changes the transmission channel of risk between assets such as Vayanos [2004] and Baur and K.J.McDermott [2012b]. Baur and Glover [2012] applies Ells berg decision rule ¹⁰ to analyse safe haven assets and investor behaviour. They find that gold is the ultimate safe haven when investors receive ambiguous signals; while when investors face extreme but unambiguous signals, they buy US government bonds. In a later study, Baur and Glover [2012] argue that the perception of gold as safe haven encourages investors to hold gold before the shock, which could, however, cause downward pressure on the gold price, thus damage its safe haven property. Clustering analysis is used again here on 1142 papers' titles and abstracts related to safe asset or safe haven asset, and investors sentiment and attention ¹¹. As Figure 2.4 shows, some common topics include investor attention as measured by search, investor attention on firm level, investor fear, uncertainty, safe haven, safety, measurement, model, price and so on.

2.3.2 Investors Attention and Sentiment Analysis

According to the Efficient-Market Hypothesis (EMH) of Fama [1965b,a, 1970], an asset's prices always "fully reflect" available information and hence stock prices should follow a random walk, that price changes should be random and unpredictable. However, this classic assumption has been challenged by behavioural economists in the cognitive psychology and decision making domain, who contribute the imperfections in financial markets to a combination of various human errors in reasoning and information processing (e.g. Bondt and Thaler [1994] and Shiller [2003]).

¹⁰Related to Ells berg paradox, in which people's choices violate the postulates of subjective expected utility, as an evidence for ambiguity aversion.

¹¹The network visualization is based on 1142 relevant papers title and abstract text downloaded from Web of Science Core Collection, however the consulted literature is not limited to these papers.

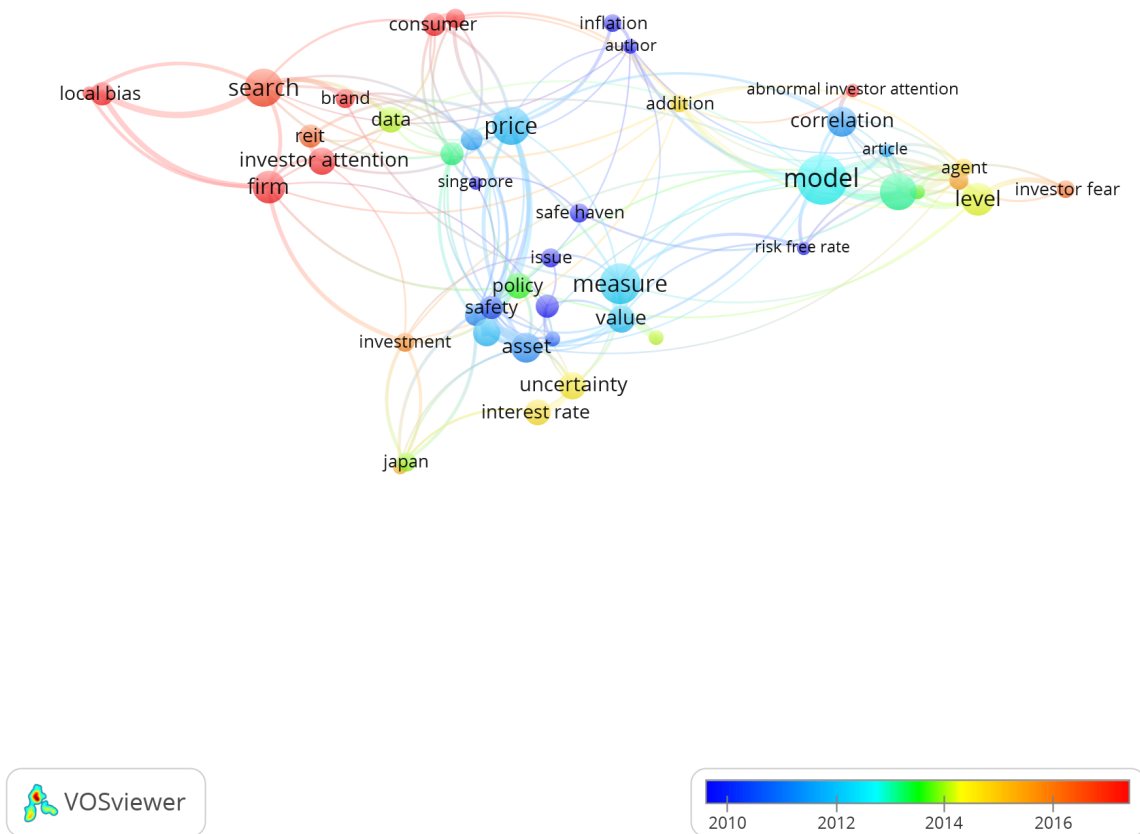


Figure 2.4: Clusters in the safe haven asset and sentiment analysis related literature strands (1945-2017) by term co-occurrence analysis on title and abstract fields

For instance, traditional asset pricing models assume perfect information. From an investor's perspective, it assumes that investors allocate sufficient attention to the asset. However, in reality, our attention is a scarce resource ¹², especially in this information-rich world. As remarked by Herbert Simon [1971], Nobel Laureate in Economics:

... in an information-rich world, the wealth of information means a dearth of something else: a scarcity of whatever it is that information consumers. What information consumes is rather obvious: it consumes the attention of its recipients. Hence a wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it.

Recent studies have provided theoretical frameworks as well as empirical evidence on how limited attention could affect asset pricing. Merton [1987] developed a capital market equilibrium model with incomplete information ¹³. According to Merton [1987], an increase in the relative size of the firm's investor base would reduce the firm's cost of capital and increase the market value of the firm. And the investor base of a firm could be expanded without the firm spending anything, rather by capturing widespread attention of investors via mass media. For example, stock price sometimes reacts to a widely-circulated report about the firm, even when all the substantive information in the report has been previously released publicly. In the paper *Implications of Rational Inattention*, Sims [2003] introduces individual's limited information-processing capacity in modelling behaviour in macroeconomic models and find that doing so alters the behaviour implied by these models. Hirshleifer and Teoh [2002] discuss firm's choices between alternative means of presenting information and the effects of different presentations on market prices given investors have limited attention and processing power. Peng and Xiong [2006] model investors' attention allocation and find that limited investor attention leads to category-learning behaviour, that is investors tend to process more market and sector level information rather than firm specific information. When they combine limited

¹²For more information on attention studies within the psychology domain, please see Kahneman [1973].

¹³Incomplete information suggests that the diffusion of every type of publicly available information does not take place instantaneously among all investors and that there are significant delays among investors acting on the same information (Merton [1987]).

attention with overconfidence, the model is able to capture important features observed in return co-movement which is unable to be explained via rational expectation assumption. Da et al. [2011] is the first study which uses Google Search Volume Index (SVI) as a new and direct measure of investor attention. Built on the attention theory that individual investors are net buyers of attention-grabbing stocks and, hence, an increase in individual investor's attention results in temporary positive price pressure, they find that an increase in SVI predicts higher stock prices in the next 2 weeks and an eventual price reversal within the year, as well as large first-day return and long-run under-performance of IPO stocks. Furthermore, SVI captures investor attention in a more timely fashion, and offers information not captured by existing proxies of investor attention.

On the other hand, even when investors allocate sufficient attention to market news, they could under- or over-react to news, and by which influence the price discovery process. Sentiment analysis in the finance domain assumes that the market is at least weekly efficient, and that stock prices already reflect all information that can be derived by examining market trading data such as the history of past prices, trading volume, or short interest. However, investors may under- or over-react to news. Therefore, sentiment of investors can affect the movements of the markets to some extent. There is a large amount of studies on investors sentiment (see for example Barberis et al. [1997], Barberis and Thaler [2003], Baker and Wurgler [2007]), and they generally conclude that sentiment is an increasingly important approach through which to address many critical questions in behavioural finance. Recent studies such as Kearney and Liu [2014] and Loughran and McDonald [2016] have provided extensive reviews on methods, models and empirical findings of sentiment analysis in accounting and finance. According to which, sentiment could be interpreted as either investors sentiment, i.e. their beliefs about future cash flows and investment risks that are not justified by the facts at hand, or textual sentiment, i.e. the degree of positivity-negativity, bullish-bearish, strong-weak or active-passive revealed by text (Kearney and Liu [2014]).

2.3.3 Investors Attention as Measured by Internet Search Data

The internet has become central to how people find information. According to Internet Live Stats¹⁴, there are more than 3 billion Google Searches every single day. Google Searches have become a massive database which can reveal various aspects of people's thoughts and behaviours. In a recent book by Stephens-Davidowitz [2017], he refers to Google Searches as the "most important dataset ever collected on the human psyche".

How Google Trends and Baidu Index are Calculated

In short, Google Trends is an index, which measures normalized query share using broad match. However, there are a number of characteristics of the index to be considered when analysing it, which are listed below ¹⁵.

- *Relative popularity* Google Trends is an index updated daily, which measures the relative popularity of a term over the specified time period in a certain region. Relative popularity means that it is impossible to infer absolute search volume and make comparison of that across regions.
- *History* Starting from January 2004, the data is updated on a daily basis. For some popular terms, it could update on a hourly basis.
- *Frequency* Monthly, weekly and daily index values are available depending on the time period chosen on the platform, i.e. daily index value is available if you select a time period of less than 90 days.
- *Re-scaling* The highest popularity during this time period in this region is set at 100 and the rest points are re-based accordingly. Data is also adjusted, for instance, searches from the same person over a short time period is excluded, and searches with low volume will appear at 0.
- *Re-sampling* In addition, the index is based on a random sample of all searches on Google. A new sample is drawn when a new query is made. However, the sample will

¹⁴Please find more information at www.internetlivestats.com

¹⁵Please find more information on Google Trends at: <http://support.google.com/trends>

be stored on the day, so a repeated query will be based on the same sample. Due to the random sampling, the same query over the same time period will give different results on different days.

- *Zero values* Searches with low volume will appear at zero. There have to be at least 50 observations to appear in Google Trends due to privacy policy.
- *Boolean query* It supports simple Boolean query to combine search volume of multiple terms. For example, “tennis + squash” will return searches containing the word tennis OR squash; and “tennis - shoes” specify searches containing the word tennis, but exclude searches with the word shoes.
- *Search category* It can also limit the search within a specific category, for example you can specify “Apple” as a company rather than the fruit. However, the category specification couldn’t exclude all irrelevant searches.
- *Web sources* You can also specify the sources of searches, such as Google News, You Tube, Google Shopping, etc.

Baidu Index share a similar concept with Google Trends that it intends to measure online search volume, however there are a few of major differences between both ¹⁶.

- *Absolute Search Volume* A major difference from Google Trends is that, Baidu Index is not subject to re-scaling and re-sampling, the index value is weighted from absolute search volume without taking into account the total search volumes over a certain period in a given region. As a result, historical values of Baidu Index do not change over time.
- *History* Desktop data goes back to January 2006 and from mobile back to January 2011.
- *Frequency* Daily and weekly index values are available, i.e. daily index value is available for a time period of up to half a year.

¹⁶For more information on Baidu Index please visit <http://index.baidu.com/Helper>

- *Demographic information* You have to log into a Baidu account in order to use Baidu Index. As a result, Baidu collects more demographic information on the people behind the searches, including age and gender.
- *Sources* Baidu Index also provides search volumes from PC, mobile, or combined.

Advantages of Internet Search Data and Potential Issues

There are many advantages of internet search data compared with traditional economic and financial data. First, it is simply a new information. It has been considered a new, direct and objective measure of investor attention. Also it is extremely timely compared to most economic data. Additionally, it covers much broader issues compared to collecting data via pre-determined survey questions. And finally it provides easy access, especially with statistic packages such as gtrendR in R.

However, there are also a few potential issues with using the data: First, it has a relatively short history compared to other economic activities, as internet use is a relatively new phenomenon; second, internet search use is probably biased towards younger generation and developed regions. Therefore an economic shock may hit people using/not using internet search differently; next search behaviours can be diverse, in that different users may use different search queries to find the same information, as well as dynamic where search queries to find the same information can change over time. Equally, similar search queries may reveal totally different search intentions. This ambiguity makes it hard to differentiate specific search activities e.g. job search and unemployed job search (Francesco [2009]). For example, people using the internet for job searches may be unemployed at the moment or employed but looking for better jobs. Search behaviour only tells about what information people are looking for but it cannot tell us precisely what the person's current employment conditions are; last but not least, a critical idea noted by Antenucci et al. [2014] is that economic indicators and social media indices built for economic activities track related but not identical phenomena. Although a prediction model with input of social media shows the value of it in measuring economic activity, it should be noted that social media data, whether it is from Twitter, Google or elsewhere, is essentially different from official series.

They measure the same general economic concept, thereafter they are expected to co-move strongly. However, they are not to be expected to correlate perfectly, because again they are not tracking identical phenomena, i.e. the underlying data generation process is different. Ideally, social media indices can track official economic indicators, as well as provide incremental information relative to official statistics. The latter means that the index has independent movements, statistically or anecdotally. Essentially, what does internet search data measure? The above listed are potential sources of noise in internet search data. Nevertheless, positive/negative associations between search-term volume and economic activities have been found across various economic activities.

Interpretation of Search Behaviour

People reveal information regarding to their needs, wants, interests, and concerns via their internet search behaviour. The terms submitted to search engines can reflect this information to some extent. Internet search behaviour has been interpreted as a measure of revealed expectations (see Guzmán [2011]), in that people are presumed to search for information on topics they want to know more about.

It is also seen as a new and direct measure of investor attention (see Da et al. [2011]). Tracking the search volume of a particular product e.g. iPhone6 shows consumer interests in purchasing this product; while tracking terms such as “crisis”, “recession” etc. can reveal public sentiment to some extent, e.g. Da et al. [2011] construct a Financial and Economic Attitudes Revealed by Search (FEARS) index based on Google Trends. It has also been referred to as internet Buzz e.g. Sacconaghi et al. [2015], suggesting concerns that the data maybe noisy. One potential source of noise coming from the ambiguity of search behaviour is listed as one of the disadvantages, which is discussed previously. Nevertheless, positive/negative associations between search-term volume and economic activities have been found across various economic activities. Sometimes the relationship is stronger between the same time period, sometimes it is stronger with lagging economic indicators. Therefore it would be hard to establish a universal theory on the timing for search behaviour turning into consumption or other economic activities, the approach will be likely based on individual cases.

Applications in Economics and Finance Research

The first scientific application of Google Search Volume Index (SVI) is probably the study on detecting influenza epidemics using Google search query data by Ginsberg et al. [2009]¹⁷. Since then, SVI has been rapidly applied to economics studies. Choi and Varian [2009b] is one of the earliest studies using search data to predict a number of economic activities such as employment, home sales, automotive sales in US, tourist visitors in Hong Kong and Consumer Confidence Index for Australia. Subsequent analyses have shown that SVI also has value in predicting stock market returns and volatility (e.g. Da et al. [2011]), as well as inflation (e.g. Guzmán [2011]). The Bank of England has been continuously monitoring Google Trend data and believes it is “likely to become an increasingly useful source of information about economic behaviour” (McLaren and Shanbhogue [2011]). Next I review literatures of internet search data in the order of its applications on different markets.

Precious Metals

Basistha et al. [2015] analyse all commodities for which Google search activity data is available including gold, silver, copper, crude oil, natural gas and corn. They find that Google search activity has predictive value in volatility of all six commodities in both in-sample and out-of-sample analysis. They also find that Google search activity is even more strongly correlated with the ETFs trading volume than with the commodity futures trading volume, therefore suggesting search data as potential sentiment measure of retail investors. Baur and Dimpfl [2016] investigated the impact of investor attention on precious metals. They found a positive relationship of gold price volatility and search queries, as well as a strong asymmetric effect of negative gold price changes, which indicates a preference to mine (Google) bad news rather than good news, and these findings are unique to gold. Balcilar et al. [2017] applies Da et al. [2011]’s FEARS index as a proxy for investor sentiment to examine its non-linear casual effects on gold return and volatility. They found that the effect of sentiment on gold is

¹⁷The model of Google Flu Trends Estimates was launched in 2008. However it has gone wrong in predicting the 2009 influenza virus A(H1N1) pandemic, possibly due to changed internet search behaviour during pH1N1 according to Cook et al. [2011]. The model was updated in 2009, 2013, and 2014, but eventually stopped publishing estimates since August 2015.

channelled via the discontinuous (jump) component of intra-day volatility, and suggest that measures of sentiment could be utilized to model volatility jumps in safe haven assets.

Employment

The internet has taken on a central role in how people seek jobs (see Stevenson [2013]). According to a 2015 survey by the Pew Research Centre¹⁸, a majority of the US adults (54%) have gone online to look for job information, and 45% have applied for a job online. Therefore internet search data may be useful for monitoring the labour market. A consideration is how long it takes for search behaviour turning into employment or unemployment activity and how long it will be reflected on official data, which is usually based on survey. There should be some time delay, however it is difficult to match them exactly. Some studies have found stronger correlation between search data and employment data for the same time period, while other studies re-scale search data few weeks ahead for analysis Francesco [2009].

As early as 2005, Ettredge et al. [2005] found strong positive association between search data with lagged US unemployment rate, however they didn't carry on to test the predictive value of search data in standard time series modelling as they believed additional work is required. Following studies have shown the predictive value of search data in monitoring employment activities across a variety of countries such as the US, UK, Germany, Israel, Norway and Japan. Choi and Varian [2009a] show how Google Trends data could help predict the "Initial Jobless Claims (ICJ)" published weekly by the US Department of Labour, a leading indicator for the unemployment rate. Adding two search series, search term 'Jobs' and search category 'Welfare & Unemployment', to a standard ARIMA model, the out-of-sample mean-absolute-error can be improved by 15.74% over the period from January 2004 to July 2009. In another study on IJC D'Amuri and Marcucci [2010] show a stronger improvement that the mean-squared-error (MSE) of their best model using trends data (for term "jobs") is 29% lower than the best model not including it, regardless of the estimation sample and the econometric specification. Search data also shows value in predicting unemployment rate in the UK according to McLaren and Shanbhogue [2011]. They also test at state level, and

¹⁸www.pewinternet.org

in more than 70% of the cases, models including the search data outperform the others. A baseline ARIMA model for the UK Labour Force Survey (LFS) unemployment is improved when search data of term “JSA” is added with higher R squared, lower Akaike Information Criterion (AIC) and lower out-of-sample error. Similarly, Askitas and Zimmermann [2009] show the value of search data to predict the Germany unemployment rate, and Francesco [2009] show how search data can improve short term predictions on the quarterly unemployment rate of Italy.

Housing

When people are interested in buying and selling houses, they also go online and search market information. Therefore online search data is potentially useful to monitor housing market conditions. Housing price data is, however, different from employment data in that it is much timelier, and the lag is more between search and actual purchase/sell. As McLaren and Shanbhogue [2011] shows, search volume growth for the term ‘estate agent’ is highly correlated with house price growth in the UK. Additionally, a baseline ARIMA model for house price is improved by adding search data of it.

Consumption

More and more people are purchasing online. However internet search data has enormous value in estimating not only e-commerce sales¹⁹, but also overall consumption. According to the US market research firm eMarketers, store sales are influenced three times higher than e-commerce sales, since internet users search and compare products online even when they eventually buy the products in stores (Vosen, Torsten Schmidt [2009]). In an earlier study by Vosen, Torsten Schmidt [2009], they have shown the predictive value of Google search data on US consumption. They selected 56 consumption-relevant categories of Google Trends which best match the product categories of personal consumption expenditures in the US. They

¹⁹E-commerce sales are sales of goods and services where the buyer places an order, or the price and term of the sale are negotiated over an internet, mobile device (M-commerce), Electronic Data Interchange (EDI) network, or other comparable online system. Payment may or may not be made online according to the US Census Bureau. According to the US Census Bureau, it was \$89.2 billion in the fourth quarter of 2015, less than 10% of total retail sales

then apply factor modelling to all the category data to obtain four factors, which explain 61% of the total variance of the underlying data. Those factors are then added to the baseline ARIMA model of consumption. The Michigan Consumer Sentiment Index (MCSI) and the Conference Board Consumer Confidence Index (CCI) are also added to baseline model as benchmark²⁰. As a result, a baseline model with Google search data outperforms the others.

Stock Market Return and Volatility

One of the earliest work in the stock market analysis with Google Trend is Da et al. [2011], in which they propose to use Google Trends as a new and sometimes better measure of investor attention and they find that Google Trends contribute to the first-day return estimates of Russell 3000 stocks from 2004 to 2008, however the effect will be offset by a price reversal within the year. The assumption is that investors may start to pay attention to a stock in anticipation of a news event, and in a vector autoregressive (VAR) framework, they find that (log) SVI leads extreme returns and news for example. Heiberger [2015] analyse Google Trends for each corporation listed in the Standard and Poor's 100 index. They then create a trading strategy which utilizes collective attention as an indicator for "bad news" and treats an increase in collective search queries as a signal to go "short". They find that their strategy outperforms S&P100. While Bijl et al. [2016] discussed Google searches and stock returns and find that their strategy considering Google Trends outperforms buy-and-hold and benchmark trading strategy over a 120 days period. Baidu Index has also shown positive results to predict stock market returns in previous studies. Liu et al. [2012] have identified keywords which have a stable leading relationship with the China Stock Market Index. These keywords have high correlations (above 90%) with the Shanghai Composite Index, and the Granger Causality test confirms that they have significant prediction ability. Zhang et al. [2013] find that investor attention as measured by the Baidu Index exhibits a strong contemporary relationship with abnormal stock returns. Similarly Ying et al. [2015] uses the Baidu Index as a measure of investor attention and find that it has a significant and

²⁰Both are survey-based sentiment indicators which are typically considered as leading indicators to predict consumption.

positive effect on the stock return within a week in China's stock market.

2.3.4 Conclusion

This final section of the literature review is on the sentiment aspect of safe haven assets, mainly sentiment as measured by investor attention. It firstly reviews the theoretical background of sentiment analysis on asset pricing, then it reviews studies on how investor attention may influence the price discovery process, next it discuss how investor attention could be measured by online search data, how data is collected and how the index is constructed, and finally it looks at its applications in economics and financial research. Overall, online search data has shown predictive value in returns or volatilities in economic activities or financial markets.

Table 2.1: Gold Supply and Demand (tonnes)

	2011	2012	2013	2014	2015	2016
Total above-ground stock	171300	174100	176000	183600	186200	187200
Supply						
Mine production	2868	2883	3077	3172	3209	3222
Scrap	1704	1700	1303	1158	1172	1268
Net Hedging Supply	18	-40	-39	108	21	21
Total supply	4590	4543	4341	4438	4402	4511
Demand						
Jewellery	2091	2061	2610	2469	2395	1891
Industrial Fabrication	471	429	421	403	365	354
of which Electronics	343	307	300	290	258	254
of which Dental & Medical	43	39	36	34	32	30
of which Other Industrial	85	83	85	79	76	70
Net Official sector	457	544	409	466	436	257
Retail Investment	1616	1407	1873	1163	1162	1057
of which Bars	1247	1056	1444	886	876	787
of which Coins	369	351	429	278	286	271
Physical Demand	4635	4441	5314	4501	4357	3559
Physical Surplus/Deficit	-45	102	973	-62	44	952
ETF Inventory Build	185	279	-880	-155	-125	524
Exchange Inventory Build	-6	-10	-98	1	-48	86
Net Balance	-224	-167	5	92	217	342
Gold Price (LBMA PM, US\$/oz)	1571.7	1669.0	1411.2	1266.4	1160.1	1250.8

Note: Total above-ground stock shows cumulative historical mine production through centuries.

Source: Metals Focus; GFMS, Thomson Reuters; ICE Benchmark Administration; World Gold Council.

Table 2.2: Gold Traded on Commodity Exchanges (tonnes)

	2013	2014	2015	2016
COMEX	147093	126028	130135	179047
SHFE	20088	23858	25317	34760
SGE	5365	4931	7288	11793
TOCOM	12225	8745	7928	8541
MCX	8945	3972	3947	4094
SGE Spot	\	2645	4756	3699
DGCX	426	426	312	412
ICE Futures US	1116	508	294	354
Borsa Istanbul	438	239	256	243

COMEX: Commodity Exchange, a division of the New York Mercantile Exchange (NYMEX)

SHFE: Shanghai Futures Exchange

SGE: Shanghai Gold Exchange

TOCOM: Tokyo Commodity Exchange

MCX: Multi Commodity Exchange of India Ltd.

DGCX: Dubai Gold & Commodities Exchange

Note: All SGE contracts excluding SGE spot

Source: GFMS, Thomson Reuters; relevant exchanges.

Table 2.3: Silver Supply and Demand (tonnes)

	2011	2012	2013	2014	2015	2016
Total above-ground stock	49311	48767	54295	56249	71578	78067
Supply						
Mine production	21497	22444	23351	24624	25254	25112
Net Government Sales	340	210	224	\	\	\
Scrap	7374	7195	5415	4686	4000	3960
Net Hedging Supply	346	-1335	-987	476	221	-522
Total supply	29557	28514	28004	29787	29475	28551
Demand						
Jewellery	5429	5313	6288	6461	6472	5868
Coins & Bars	5908	4513	6821	6634	8241	5863
Silverware	1338	1239	1667	1721	1783	1477
Industry Fabrication	18750	17010	17137	16888	16148	15930
of which Electrical & Electronics	8244	7561	7541	7467	6971	6622
of which Brazing Alloys & Solders	1792	1732	1806	1891	1743	1571
of which Photography	1735	1537	1432	1375	1321	1281
of Which Photovoltaic	2149	1650	1585	1469	1622	2172
of which Ethylene Oxide	176	133	218	142	289	289
of which Other Industrial	4652	4394	4559	4550	4207	3997
Physical Demand	31425	28072	31916	31703	32644	29138
Physical Surplus/Deficit	-1865	442	-3909	-1916	-3169	-587
ETF Inventory Build	-680	1568	71	43	-502	1332
Exchange Inventory Build	346	1763	249	-150	357	2262
Net Balance	-1531	-2889	-4230	-1809	-3025	-4182
Silver Price (US\$/oz)	35.1	31.2	23.8	19.1	15.7	17.1

Different from gold, the total above-ground stock of silver does not include silverware, jewellery or other fabricated products that are, in one form or another, available in the market place. Only when the silver fabricated products get recycled into an homogeneous form (e.g. bars and coins) will they re-enter the calculation and count as scrap.

Source: GFMS, Thomson Reuters/The Silver Institute

Table 2.4: Silver Traded on Commodity Exchanges (tonnes)

	2013	2014	2015	2016
COMEX	72375	69485	67272	90638
SHFE	82971	93296	69825	41716
SGE	6881	8024	12935	19711
MCX	15676	7497	7454	6931
ICE Futures US	500	188	135	147
TOCOM	31.0	28	20	20

COMEX: Commodity Exchange, a division of the New York Mercantile Exchange (NYMEX)

SHFE: Shanghai Futures Exchange

SGE: Shanghai Gold Exchange

MCX: Multi Commodity Exchange of India Ltd.

ICE Futures US: The New York Board of Trade

TOCOM: Tokyo Commodity Exchange

Note: All SGE contracts excluding SGE spot

Source: GFMS, Thomson Reuters; relevant exchanges.

Table 2.5: Platinum Supply and Demand (tonnes)

	2011	2012	2013	2014	2015
Total above-ground stock		135	137	200	224
Supply					
Mine production	181.6	164.3	170.4	137.7	174.6
Autocatalyst Scrap	28.2	26.2	29.6	30.8	26.4
Old Jewellery Scrap	17.2	14.5	13.9	14.6	15.2
Total Supply	226.9	205.0	214.0	183.1	216.2
Demand					
Autocatalyst	84.8	81.0	80.6	83.8	85.4
Jewellery	67.7	73.3	75.0	72.2	69.6
Chemical	13.8	11.3	12.2	16.9	14.0
Electronics	6.4	5.5	4.8	4.6	4.3
Glass	9.6	9.2	2.4	-1.4	4.6
Petroleum	4.1	3.6	3.0	3.5	2.8
Other Industrial	15.8	17.6	18.4	19.8	20.4
Retail Investment	8.8	8.0	4.0	3.7	13.4
Total Demand	211.0	209.4	200.4	203.2	214.6
Physical Surplus/Deficit	15.9	-4.5	13.5	-20.1	1.5
Stock Movements	-6.9	-15.3	-53.6	30.7	6.0
of which ETF Release/Build	-4.1	-6.8	-25.3	-6.2	7.4
Net Balance	9.0	19.7	40.1	10.6	7.5
Platinum Price (LBMA PM, US\$/oz)	1721.9	1551.5	1486.7	1385.7	1052.9

Total above-ground platinum and palladium include stocks in the terminal markets, allocations to physically-backed ETFs and declared stock holdings on futures exchanges. In addition, an estimate of Russian government stocks of palladium and stocks of refined metal that may be held by industrial consumers and producers over and above normal levels are also included.

Source: GFMS, Thomson Reuters; LBMA

Table 2.6: Palladium Supply and Demand (tonnes)

	2011	2012	2013	2014	2015
Total above-ground stock		312.8	273.8	253	284
Supply					
Mine production	194.5	184.2	183.4	174.0	190.3
Autocatalyst Scrap	42.9	41.7	45.0	51.4	45.5
Old Jewellery Scrap	7.0	6.3	6.5	7.0	7.5
Total Supply	244.5	232.2	234.9	232.4	243.4
Demand					
Autocatalyst	157.6	174.1	179.7	187.2	195.3
Jewellery	19.1	16.9	14.9	13.6	9.8
Dental	16.1	15.5	14.5	13.5	12.7
Chemical	10.9	10.7	11.6	11.2	11.4
Electronics	42.2	42.5	39.1	38.5	34.3
Other Industrial	2.9	3.1	3.1	3.3	3.3
Retail Investment	1.7	1.0	1.1	1.3	1.3
Total Demand	250.4	263.8	264.0	268.4	268.0
Physical Surplus/Deficit	-6.0	-31.6	-29.1	-36.1	-24.6
Stock Movements	36.3	4.2	-8.5	-8.5	16.4
of which ETF Release/Build	15.1	-12.7	0.0	-25.5	20.6
Net Balance	30.4	-35.7	-37.6	-44.5	-8.2
Palladium Price (LBMA PM, US\$/oz)	733.6	543.2	725.1	803.2	691.6

Total above-ground platinum and palladium include stocks in the terminal markets, allocations to physically-backed ETFs and declared stock holdings on futures exchanges. In addition, an estimate of Russian government stocks of palladium and stocks of refined metal that may be held by industrial consumers and producers over and above normal levels are also included.

Source: GFMS, Thomson Reuters; LBMA

Table 2.7: Platinum and Palladium Traded on Commodity Exchanges (tonnes equivalent)

	Platinum			Palladium		
	2013	2014	2015	2013	2014	2015
COMEX	46.10	76.32	26.11	48.22	113.14	53.67
TOCOM	21.12	26.42	30.33	0.60	0.60	0.71

COMEX: Commodity Exchange, a division of the New York Mercantile Exchange (NYMEX)

TOCOM: Tokyo Commodity Exchange

Source: GFMS, Thomson Reuters; TOCOM, CFTC

Chapter 3

Methodology

3.1 Introduction

The methodology chapter contains five sections, they are: dependence measurement, generalized linear modelling, time series modelling, model uncertainty and search term selection. Models, statistical metrics and tests discussed in dependence measurement and time series modelling are critical since they help clarify how market linkages and safe haven are measured or modelled statistically. Most of the techniques discussed are applied in Precious Metals as Safe Haven — Evidence in Chapter 5, and safe haven assets' interrelationships with search interests in Chapter 7 In Search of Safe Haven Assets; generalized linear modelling and model uncertainty are implemented in the search of robust determinants of precious metals as safe haven in Chapter 6; search term selection methods are applied to collect online search data in Chapter 7.

3.2 Dependence Measurement

3.2.1 Introduction

There are a couple of statistical metrics and econometric models commonly used in the literature to measure dependence structure between market returns. These measurements mainly include cross-market correlation coefficients, conditional correlation obtained from

ARCH or GARCH model and copula (see e.g. Engle [2009]). This thesis mainly discusses and applies the first two correlation based methods, while the last method is discussed briefly in the Chapter 8 where I discuss potential avenues for future work.

3.2.2 Correlation

Correlation is a common statistical measurement of linear dependence between two random variables. The Pearson’s product-moment coefficient is the most familiar measure. The theory of bivariate correlation was first defined by Sir Francis Galton in 1885, together with the term “regression”. Inspired by this, Karl Pearson developed the Pearson’s r a decade later. Before that, there was no scientific approach to discuss or measure the association between variables that lacked a causal relationship according to Rodgers and Nicewander [1988]. The mathematical formula Pearson first developed in 1895 is as follows, which describes r as the centred and standardized sum of the cross-product of two variables, or the covariance of the two variables divided by the product of their standard deviations:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}} \quad (3.1)$$

Correlation coefficient constitutes the principal statistical methodology for observational experiments in many disciplines including economics and finance. It is crucial to understand correlations between financial assets in the asset management and risk analysis practice. Engle [2009] offers an in-depth discussion on the economics of correlation between financial assets, its dynamics, and innovative models for prediction. Engle firstly discusses the economics behind movements in asset prices, that the value of an asset is intrinsically linked to forecasts of the future prospects of the asset, and these forecasts are changed by investors when “news” is received. In other words, the correlations between asset returns depend on information (or “news”) that is used to update investors prospects of these assets; Engle goes on to explain the reasons why correlation between asset returns change. He points out that every (relevant) piece of news has an effect on all asset prices to some extent depending on the economics of the asset. As a result, correlation changes mainly due to either the fun-

damental economics (or news process) changes, the characteristics of the news change, or in some cases by events such as “contagion” that herding behaviours not the previous two move the correlations.

The first major paper using correlation coefficient to measure and study cross-market dependence during market distress periods is by King and Wadhwani in 1990. Their paper tests for increased stock market correlations between the US, UK, and Japan. It finds that correlations between cross-market returns increased significantly after the US market crash in 1987 and argues it as evidence of “contagion” effects. In a later study by Sang B. and Jung [1993], this analysis is extended to 12 markets and further evidence of contagion as measured by increasing correlation is found after the 1987 US market crash, that average weekly cross-market correlations increased from 0.23 to 0.39 after the crash. Other studies also use coefficient as a baseline measurement, and a changed dependency structure such as contagion or flight-to-quality is defined as only when a structural break happens to be the correlation. Papers applying this approach include Forbes and Rigobon [2002], Corsetti et al. [2005], Briere et al. [2008], Baur and Lucey [2009], and Ding and Pu [2012] A step-by-step model implementation can be found in Corsetti et al. [2005][p.7].

However, correlation coefficient has its limitations in measuring dependence. It is constructed as an average of deviations from the mean, thus makes no distinction between large and small realizations and positive or negative returns; it assumes a linear relationship in that it can be biased by non-linear relationship where two random variables could have perfect dependence but their correlation is less than 1 because their dependence is non-linear (see discussions in Boyer et al. [1999], Baur [2004], Poon et al. [2004], Engle [2009]). Essentially, Pearson’s correlation coefficient is unconditional that it is time invariant and assumes covariance stationary ¹; while conditional correlation is an alternative measurement, which is the time series correlation conditional on previous information set.

¹Covariance stationary sequences are also called weakly stationary. that all the terms of the sequence have mean μ and the covariance $Cov[y_t, y_{t-s}]$ depends only on s and not on t .

3.2.3 Dynamic Conditional Correlation

Conditional correlation has been used to measure cross-market dependence in many studies. In studying flight-to-quality, Baur and Lucey [2009] apply Dynamic Conditional Correlation (DCC) to show time-variation of the correlation estimates between stocks and bonds across eight countries. In a recent paper, Klein [2017] implemented a flexible modification of the DCC to account for asymmetry and long memory in variance and applied it to the study of precious metals as safe haven in developed countries. The essence of models for conditional correlations, according to Engle [2009], is to: “seek parameterizations for the covariance matrix of a set of random variables, conditional on a set of observable state variables, typically taken to be the past filtration of the dependent variable”.

Dynamic Conditional Correlation or DCC, introduced by Engle [2002], is a generalized form from Constant Conditional Correlation (CCC), which was firstly introduced by Bollerslev in 1990. CCC model restricts conditional correlation between each pair of assets to be time invariant, while DCC allows the correlations to vary. This change can be expressed as the following:

$$H_t = D_t R D_t, \text{ where } D_t^2 = \text{diag} H_t \quad (3.2)$$

where H_t is the conditional covariance matrix, R is a correlation matrix containing the conditional correlations, and the notation $\text{diag}[A]$ refers to a matrix that has the same diagonal elements as A but has all other elements 0. The dynamic correlation model allows R to be time varying:

$$H_t = D_t R_t D_t \quad (3.3)$$

Three steps are outlined in Engle [2009] in the specification and estimation of a DCC model. First, estimate the volatility to construct standardized residuals or volatility-adjusted returns, which can also be called the “DE-GARCHING”²; second, estimate quasi-correlations

²The basic model that gives its name to the procedure is the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, which is discussed in detail in Section 3.4.

in a dynamic fashion based on these standardized residuals; and finally, rescale the estimated quasi-correlation matrix to make sure it suits a correlation matrix. The estimation of the DCC model can be formulated as a maximum-likelihood problem once a specific distributional assumption is made about the data. It is assumed that the data are multivariate normal with the given mean and covariance structure. The estimation process of the DCC model is discussed in detail in [Engle, 2002, p.10] and [Engle, 2009, p.43-58].

However, studies such as McAleer et al. [2008] and Caporin and McAleer [2013] argue that DCC should just be used as a diagnostic check which can capture the dynamics in measured conditional correlations, since DCC is a special case of generalized autoregressive conditional correlation (GARCC) which could cause model misspecification.

3.2.4 Regression with Quantiles

Baur and Lucey [2010] and Baur and K.J.McDermott [2010] developed an econometric model to test safe haven. By including stock and bond returns that are in the $q\%$ quantile, they analyse the role of gold in times of stress or extreme tail market events, which is consistent with safe haven hypothesis. For example, to test gold safe haven properties during stock market crashes, the following equations are estimated using OLS.

$$r_{gold,t} = \alpha + \beta_t r_{stock,t} + \epsilon_t \quad (3.4)$$

$$\beta_t = C_0 + C_1 D_t(r_{stock}q_5) + C_2 D_t(r_{stock}q_{2.5}) + C_3 D_t(r_{stock}q_1) \quad (3.5)$$

Equation 3.4 models the relation of gold and stock returns. The parameter β_t is modelled as a dynamic process by Equation 3.5. The dummy variables denoted as $D()$ capture extreme stock market movements and:

$$D_t(r_{stock}q_x) = \begin{cases} 1 & \text{if } r_{stock,t} < r_{stock}q_x \\ 0 & \text{if } r_{stock,t} \geq r_{stock}q_x \end{cases} \quad (3.6)$$

where $r_{stock}q_x = x\%$ threshold given by the 5%, 2.5% and 1% quantile of the return

distribution over the full sample period.

The decision rules follow Baur and K.J.McDermott [2010] that:

- if at least one coefficient of three quantile dummy variables in (2) is negative and significant over the period, then there is non-linear relationship between gold return and market return;
- if all coefficients, including C_0 in (2), are negative, then gold is a *weak* safe haven;
- if all coefficients, including C_0 , are negative and significant at 10% level, then gold is a *strong* safe haven.

In addition, they specify an asymmetric GARCH process³ for the errors in Equation 3.4.

3.3 Generalized Linear Modelling

Generalized Linear Models (GLM) were formulated firstly by Nelder and Wedderburn [1972] to unify various statistical models other than the ordinary linear regression, including logistic regression and Poisson regression. Following [Gelman and Hill, 2006, p.109]’s notation, a GLM involves:

1. A data vector $y = (y_1, \dots, y_n)$;
2. Predictors X and coefficients β , forming a linear predictor $X\beta$;
3. A link function g so that transformed data $\hat{y} = g^{-1}(X\beta)$ are used to model the data.
4. A data distribution;
5. Possibly other parameters in the predictors, link function, and data distribution, e.g. variances and overdispersions.

³GARCH models are explained in detail in Section 3.4.2

In GLM, the transformation function g and the data distribution p are subject to specifications. In a linear regression, the transformation is the identity function i.e. $g(u) \equiv \mu$ and the data distribution is normal, with standard deviation σ estimated from data. Two common generalized linear models are logistic-binomial model and the Poisson model:

- The *logistic-binomial* model is used where each data point y_t represents the number of successes in some number n_i of tries. The transformation g is the inverse-logic and the data distribution is binomial.
- The *Poisson* model is used for count data where each data point y_i can take the values of natural numbers. The usual transformation g used is the logarithmic, so that $g(\mu) = \exp(\mu)$ transforms a continuous linear predictor $X_i\beta$ to a positive $\hat{y}_i$. The data distribution is Poisson.

3.3.1 Logistic Regression

Logistic regression is a common way to model binary outcomes, which is, data y_i that take on the values 0 or 1. And it is a special case of Generalized Linear Models (GLM). Rather than modelling the response y_i directly, logistic regression models the probability that y_i belongs to a particular category (i.e. 0 or 1), hence it models the relationship between $p(X) = \Pr(Y = 1)$ and X . Since y_i only takes on the values 0 and 1, a continuous linear regression model would not be suitable, which may estimate negative or above 1 values of probability. So to solve this problem, a function should be used that gives outputs between 0 and 1 for all values of X . In logistic regression the logistic function is used:

$$p(X) = \frac{e^{\beta_0 + \beta_1 X}}{1 + e^{\beta_0 + \beta_1 X}} \quad (3.7)$$

Equation 3.7 can be also written as:

$$\frac{p(X)}{1 - p(X)} = e^{\beta_0 + \beta_1 X} \quad (3.8)$$

The quantity $\frac{p(X)}{1 - p(X)}$ is called the odds. Taking the logarithm of both sides of Equation

3.8, we have:

$$\log\left(\frac{p(X)}{1-p(X)}\right) = \beta_0 + \beta_1 X \quad (3.9)$$

The left side of the equation is called the *log-odds* or *logit* and it shows that the logistic regression (3.7) has a logit that is linear in X .

In a linear regression $Y = \beta_0 + \beta_1 X$, β_1 gives the average change in Y associated with a one-unit increase in X . However, in logistic regression, a one-unit increase in X changes the log odds by β_1 , or the odds $\frac{p(X)}{1-p(X)}$ by e^{β_1} . And since it is non-linear, the value of β_1 changes depending on the current value of X .

Maximum Likelihood

The logistic regression can be estimated with maximum likelihood. Although other methods could also be used, such as non-linear least squares, maximum likelihood is preferred due to superior statistical properties according to James et al. [2014]. In general, maximum likelihood maximizes the likelihood of a regression model, which means that the probability of the data given the parameters and inputs are maximized. The likelihood function for logistic regression can be written as:

$$L(\beta_0, \beta_1) = \prod_{i: y_i=1} p(x_i) \prod_{i': y_{i'}=0} (1 - p(x_{i'})) \quad (3.10)$$

Where $p(x_i)$ is the probability that for each individual observation y_i equals to one. The estimates $\hat{\beta}_0$ and $\hat{\beta}_1$ are chosen so that the likelihood function is maximized.

Multiple Logistic Regression

Multiple logistic regression is applied when there are multiple predictors for a binary response, therefore Equation 3.9 can be generalized as:

$$\log\left(\frac{p(X)}{1-p(X)}\right) = \beta_0 + \beta_1 X_1 + \dots + \beta_p X_p \quad (3.11)$$

where $X = (X_1, X_2, \dots, X_p)$ are p predictors. By taking logarithmic on both sides, Equation 3.11 can also be written as:

$$p(X) = \frac{e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}} \quad (3.12)$$

Similarly, $\beta_0, \beta_1, \dots, \beta_p$ can be estimated with maximum likelihood as discussed previously.

3.3.2 Poisson Regression

The Poisson distribution is used to model variation in count data (i.e. data that can take 0,1,2,...). The usual transformation g used is the logarithmic, so that $g(u) = \exp(u)$ transforms a continuous linear predictor $X_i\beta$ to a positive $\hat{y}_i$. The data distribution is Poisson. The basic Poisson regression model has the form:

$$y_i \sim \text{Poisson}(\theta_i) \quad (3.13)$$

in which, the parameter θ_i must be positive, so it makes sense to fit a linear regression on the logarithmic scale:

$$\theta_i = \exp(X_i\beta). \quad (3.14)$$

When interpret the impact from a unit change of X to Y , the coefficient β could be exponentiated and treated as multiplicative effects. In the same way with general regression models, each coefficient is interpreted as a comparison in which one predictor differs by one unit while all the other predictors remain at the same level.

- **Overdispersion**

Overdispersion refers to the presence of greater variability (statistical dispersion) in a data set than would be expected from a theoretical model. It occurs more often when fitting simple parametric models, such as Poisson regressions, which do not supply a variance parameter σ to be adjusted independently of the mean Gelman and Hill [2006]. Under the Poisson

distribution the variance equals the mean, namely the standard deviation equals the square root of the mean. The standardized residuals of the model 3.13 can be defined as:

$$z_i = \frac{y_i - \hat{y}_i}{sd(\hat{y}_i)} \quad (3.15)$$

If the Poisson model is true, then the z_i 's should be approximately independent (not exactly independent, since the same estimate $\hat{\beta}$ is used in computing all of them, each with mean 0 and standard deviation 1. If there is overdispersion, the z_i 's should be larger in absolute value, indicating the additional variation beyond what should be predicted under the Poisson model.

Overdispersion can be tested in Poisson regression by computing the sum of squares of the n standardized residuals, $\sum_{i=1}^n z_i^2$, and comparing this to the χ_{n-k}^2 distribution, which is what is expected under the model. The χ_{n-k}^2 distribution has average value $n - k$, and hence the estimated overdispersion in the data compared to the fitted model, that is overdispersion ratio, can be calculated as follows:

$$\text{estimated overdispersion} = \frac{1}{n - k} \sum_{i=1}^n z_i^2, \quad (3.16)$$

A large overdispersion ratio and high p-value suggesting that the probability is very small that a random variable from a χ_{n-k}^2 distribution would be equal to this large number.

- **Zero-inflated Poisson Model**

Overdispersion can result from the rare occurrence of an event, *or* a natural discrete aspect of the underlying data, in that the estimated variance is larger than what would be expected. The latter means that the excess zeros are generated by a separate process from the count values and they should be modelled independently. The zero-inflated Poisson model has two parts, a Poisson count model as well as the logit model for predicting excess zeros.

It can be defined as:

$$y_i = \begin{cases} = 0 & \text{if } S_i = 0 \\ \sim \text{overdispersed Poisson}(e^{X_i\beta}) & \text{if } S_i = 1 \end{cases} \quad (3.17)$$

And S_i can be modelled using logistic regression:

$$\Pr(S_i = 1) = \text{logit}^{-1}(Xi\gamma), \quad (3.18)$$

This model is, however, not simple if S_i 's are not observed or estimated directly.

3.4 Time Series Modelling

3.4.1 ARIMA

Box and Jenkins first introduced ARIMA in 1976. The term drives from: AR (autoregressive); I (integrated), and MA (moving average). ARMA models combine a moving average process with a linear difference equation, following the notation of Enders [2004], the p th order difference equation is as follows:

$$y_t = \alpha_0 + \sum_{i=1}^p \alpha_i y_{t-i} + x_t \quad (3.19)$$

And let x_t be the MA(q) process ⁴:

$$y_t = \alpha_0 + \sum_{i=1}^p \alpha_i y_{t-i} + \sum_{i=0}^q \beta_i \epsilon_{t-i} \quad (3.20)$$

As 3.20 shows, if the homogeneous part of the difference equation contains p lags and the model for x_t contains q lags, the model is called an ARMA(p, q) model. If the characteristics roots of 3.20 are all in the unit circle, Y_t is called an autoregressive moving-average (ARMA) model for Y_t . However, if one or more characteristic roots of 3.20 is greater than or equal to unity, the Y_t sequence is said to be an integrated process and it can be modelled

⁴ ϵ_t is a white noise process which is explained later in Section 3.4.1

by an ARIMA model. Next, I discuss the concepts of white noise, stationarity, the Box-Jenkins model selection method, unit root, the Dickey-Full tests, GARCH, and so on since they are either applied or relevant for the time series modelling part in Chapters 4, 5, 6 and 7.

Stationarity

If y_t is a stationary series, the mean, variance, and autocorrelations should have the following properties:

$$E(y_t) = E(y_{t-s}) = \mu, \quad (3.21)$$

$$\text{var}(y_t) = \text{var}(y_{t-s}) = \sigma_y^2, \quad (3.22)$$

$$\text{cov}(y_t, y_{t-s}) = \text{cov}(y_{t-j}, y_{t-j-s}) = \gamma_s \quad (3.23)$$

where $s = 1, 2, \dots$, μ , σ_y^2 , and γ_s are all constants.

A time series is covariance stationary if its mean and all autocovariances are unaffected by a change of time origin, which is also called covariance-stationary, weakly stationary, second-order stationary, or wide-sense stationary process.

White Noise

A sequence ϵ_t is a white-noise process if each value has a mean of zero, a constant variance and it is uncorrelated with all other values. It can be expressed with the followings:

$$E(\epsilon_t) = E(\epsilon_{t-s}) = \dots = 0, \quad (3.24)$$

$$\text{var}(\epsilon_t) = \text{var}(\epsilon_{t-s}) = \dots = \sigma^2, \quad (3.25)$$

$$\text{cov}(\epsilon_t, \epsilon_{t-s}) = \text{cov}(\epsilon_{t-j}, \epsilon_{t-j-s}) = 0 \quad (3.26)$$

where $s = 1, 2, \dots$, and σ^2 is constant.

Box-Jenkins Model Selection

Box and Jenkins [1976] illustrated a three-stage method of selecting an appropriate model for estimating and forecasting a univariate time series, which are: identification, estimate and diagnostic checking. In the identification stage, the time plots of time series are examined to spot any outliers, missing values, structural breaks and stationarity. ACF (autocorrelation function, or correlogram) and PACF (partial autocorrelation function) are also computed, plotted and compared with theoretical patterns in determining the true values of p and q .

Autocorrelation is the linear dependence of a variable with itself at two points in time. For a stationary process, autocorrelation between any two observations only depends on the time lag- s between them. Lag- s autocorrelation is given by:

$$\rho_s = \text{corr}(y_t, y_{t-s}) = \frac{\text{cov}(y_t, y_{t-s})}{\text{var}(y_t)} \quad (3.27)$$

While correlation between two variables can also result from a mutual linear dependence on other variables. *Partial autocorrelation* is the autocorrelation between y_t and y_{t-s} after removing any linear dependence on $y_1, y_2, \dots, y_{t-s-1}$. The partial lag- s autocorrelation is denoted ϕ_t . Properties of the ACF and PACF for various ARMA models can be found in [Enders, 2004, p.66].

Unit Root

The previous sections discuss how to model a time series when it is stationary. However a time series can also follow various non-stationary processes. In general, a linear stochastic difference equation consists of three parts as follows:

$$y_t = \text{trend} + \text{stationary component} + \text{noise} \quad (3.28)$$

The *trend* part is of particular interest here. Usually there are two ways to develop models

that mimic the behaviour of trending variables: *differencing* and *detrending*. Detrending can be achieved by including a constant in the regression, while a series containing a unit root can be made stationary by differencing. ARIMA(p, d, q) indicates that the time series is stationary after d th difference. For example, the random walk plus drift model is an “ARIMA(0,1,0)” model:

$$y_t = Y_0 + \alpha_0 t + \sum_{i=1}^t \epsilon_i \quad (3.29)$$

And when the first difference is taken, we have:

$$\Delta_t = \alpha_0 + \epsilon_t \quad (3.30)$$

And the Δ_t sequence, a constant plus a white-noise, is stationary. When unit root or trend present, it could cause the problem of a *spurious regression*. A spurious regression can have high R^2 and significant t-statistics but lack economic meaning.

Dickey-Fuller Tests

Said and Dickey [1984] augmented the basic autoregressive unit root test under the general ARMA(p, q) models, which is known as the Augmented Dickey-Fuller (ADF) test. The ADF test tests the null hypothesis that a time series y_t is integrated at first order, or $I(1)$ against the alternative hypothesis that it is trend-stationary, or $I(0)$. The test procedure is applied to the model:

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \alpha_2 t + \sum_{i=2}^p \beta_i \Delta y_{t-i+1} + \epsilon_t \quad (3.31)$$

where α_0 is a constant, α_2 is the coefficient on a time trend and p is the lag order of the autoregressive process. The unit root test has the null hypothesis that $\gamma = 0$ against the alternative hypothesis of $\gamma < 0$, and the value of the test statistic is based on the least

squares estimates of Equation 3.31:

$$ADF_t = t_{\gamma=1} = \frac{\hat{\gamma} - 1}{SE(\gamma)} \quad (3.32)$$

3.4.2 GARCH

Many economic time series have changing volatilities, characterized by periods of volatility clustering followed by periods of relative tranquillity. In these cases, the ARCH model introduced by Engle [1982] would be applied, which estimates the mean and the variance of a series simultaneously. Suppose we have model $y_t = \alpha_0 + \alpha_1 y_{t-1} + \epsilon_t$, the conditional variance of y_{t+1} is:

$$var(y_{t+1} | y_t) = E_t[y_{t+1} - \alpha_0 - \alpha_1 y_t]^2 = E_t(\epsilon_{t+1})^2 \quad (3.33)$$

When hetroskedasticity is present, the conditional variance can be modelled as an AR(q) process as follows:

$$\hat{\epsilon}_t^2 = \alpha_0 + \alpha_1 \hat{\epsilon}_{t-2}^2 + \dots + \alpha_q \hat{\epsilon}_{t-q}^2 + v_t \quad (3.34)$$

where v_t is a white-noise process. Equation 3.34 is called an autoregressive conditional heteroskedastic (ARCH) model and can be used to forecast the conditional variance at $t + 1$ as:

$$E_t \hat{\epsilon}_{t+1}^2 = \alpha_0 + \alpha_1 \hat{\epsilon}_t^2 + \alpha_2 \hat{\epsilon}_{t-1}^2 + \dots + \alpha_q \hat{\epsilon}_{t+1-q}^2 \quad (3.35)$$

Bollerslev [1986] proposed a generalization of the ARCH process introduced by Engle [1982] to allow for past conditional variances in the current conditional variance equation, GARCH models. The error process can be modelled as the following:

$$\epsilon_t = v \sqrt{h_t} \quad (3.36)$$

where $\rho_v^2 = 1$ and

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^p \beta_i h_{t-i} \quad (3.37)$$

Since v_t is a white-noise process, the conditional and unconditional means of ϵ_t are equal to zero. And the conditional variance of ϵ_t is the ARMA process given by the h_t in Equation 3.37. Therefore, the generalized ARCH(p, q) model — GARCH(p, q) — allows for autoregressive and moving average components in the variance.

Engle's ARCH Test

A time series exhibiting conditional heteroscedasticity or autocorrelation in the squared series is said to have autoregressive conditional heteroscedastic (ARCH) effects. Engle's ARCH test is a Lagrange multiplier test to assess the significance of ARCH effects. The procedure is as follows:

- Estimate the best fitting ARIMA model: $y_t = \alpha_0 + \sum_{i=1}^p \alpha_i y_{t-i} + \sum_{i=0}^q \beta_i \epsilon_{t-i}$;
- Obtain the squares of the error ϵ_t^2 and regress them on a constant and m lagged values:
 $H_1 : \epsilon_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \dots + \alpha_m \epsilon_{t-m}^2 + v_t$;
- The null hypothesis is that $H_0 : \alpha_0 = \alpha_1 = \dots = \alpha_m = 0$, and the alternative hypothesis is that, at least one of the estimated parameters α_i is not zero and significant.

where v_t is a white-noise process and m needs to be specified. The test statistic for Engle's ARCH test is the usual F statistic for the regression on the squared residuals. A large critical value indicates rejection of the null hypothesis in favour of the alternative.

3.4.3 Multivariate ARMA

Vector Autoregressive Moving Average (VARMA) model extends ARMA in the multivariate setting. It is applied when we are not sure if a variable is exogenous so each variable is

treated symmetrically. VARMA incorporates feedbacks because each variable is allowed to affect each other. A simple two-variable first-order VAR can be expressed as follows:

$$y_t = b_{10} - b_{12}z_t + \gamma_{11}y_{t-1} + \gamma_{12}z_{t-1} + \epsilon_{yt} \quad (3.38)$$

$$z_t = b_{20} - b_{21}y_t + \gamma_{21}y_{t-1} + \gamma_{22}z_{t-1} + \epsilon_{zt} \quad (3.39)$$

where it is assumed that:

both y_t and z_t are stationary, ϵ_{yt} and ϵ_{zt} are white-noise disturbances with no correlation and standard deviations of σ_y and σ_z , respectively.

A general extension of the above is the Vector Autoregressive Moving Average (VARMA(p,q)) model, which can be written as:

$$y_t = c + \sum_{i=1}^p A_i y_{t-i} + \sum_{j=1}^q B_j \epsilon_{t-j} + \epsilon_t \quad (3.40)$$

where y_t is the vector of response time series variables at time t and it has n elements; c is a constant vector of offsets, with n elements; A_i are n -by- n autoregressive matrices for each i and there are p autoregressive matrices; B_j are n -by- n moving average matrices for each j and there are q moving average matrices. ϵ_t are multivariate normal random vectors with length n .

3.4.4 Multivariate GARCH

Similarly, multivariate GARCH extends the GARCH models to a multivariate setting. It estimates the conditional volatilities of the variables simultaneously, and examines how contemporaneous shocks to variables correlate with each other. In addition, it allows for volatility spillovers which means that volatility shocks to one variable could affect the volatility of other related variables. The Dynamic Conditional Correlation (DCC) as explained in 3.2.3 is derived from multivariate GARCH. Despite the simple concept, multivariate GARCH can be difficult to estimate due to the large number of parameters. Therefore the estimation usually

puts restrictions on the conditional covariance matrix (see [Enders, 2004, pp. 165-174] for mathematical derivation).

3.4.5 Spillover Index

Based on forecast-error variance decomposition, Diebold and Yilmaz [2009] proposed a simple quantitative measure of financial market interdependence, which they call a spillover index. It also comes with associated tools i.e. spillover tables and spillover plots. This measure examines the intensity of return and volatility spillovers and how it changes across time.

With the framework of N -variable VAR, for each asset i , they add the shares of its forecast error variance coming from shocks to asset j , for all $j \neq i$, and then they add across all $i = 1, \dots, N$. It can be expressed with a simple covariance stationary first-order two-variable VAR as follows:

$$X_t = \Phi X_{t-1} + \epsilon_t, \quad (3.41)$$

where $X_t = (X_{1t}, X_{2t})$ and Φ is a 2×2 parameter matrix.

By covariance stationarity, the MA representation of the VAR exists as:

$$X_t = \Theta(L)\epsilon_t, \quad (3.42)$$

where $\Theta(L) = (I - \Phi L)^{-1}$. It can also be rewritten as:

$$X_t = A(L)u_t, \quad (3.43)$$

where $A(L) = \Theta(L)Q_t^{-1}$, $u_t = Q_t\epsilon_t$, $E(u_t u_t') = I$, and Q_t^{-1} is the unique lower-triangular Cholesky factor of the covariance matrix of ϵ_t . To calculate 1-step-ahead forecasting, the optimal forecast is:

$$X_{t+1,t} = \Phi X_t, \quad (3.44)$$

and its associated 1-step-ahead error vector is:

$$e_{t+1,t} = X_{t+1} - X_{t+1,t} = A_0 u_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix} \quad (3.45)$$

which has covariance matrix:

$$E(e_{t+1,t} e'_{t+1,t}) = A_0 A'_0. \quad (3.46)$$

Therefore the variance of the 1-step-ahead error in forecasting x_{1t} is $a_{0,11}^2 + a_{0,12}^2$, and the variance of the 1-step-ahead error in forecasting x_{2t} is $a_{0,21}^2 + a_{0,22}^2$.

The above variance decomposition split the forecast error variances of each variable into parts attributable to the various system shocks. As a result, we could answer questions such as: what fraction of the 1-step-ahead error variance in forecasting x_1 is due to shocks to x_1 and shocks to x_2 , respectively? and, equivalently, what fraction of the 1-step-ahead error variance in forecasting x_2 is due to shocks to x_1 and shocks to x_2 , respectively?

Diebold and Yilmaz [2009] further define two measurements, *own variance shares*, which refers to the fractions of the 1-step-ahead error variances in forecasting x_i due to shocks to x_i , and *cross variance shares* or *spillovers*, which refer to the fractions of the 1-step-ahead error variances in forecasting x_i due to shocks to x_j , for $i \neq j$.

Therefore, in the above example of first-order two-variable VAR, there are two possible spillovers: x_{1t} shocks that affect the forecast error variance of x_{2t} (with contribution $a_{0,21}^2$) and x_{2t} shocks that affect the forecast error variance of x_{1t} (with contribution $a_{0,12}^2$). Hence the total spillover is $a_{0,12}^2 + a_{0,21}^2$. The total spillover can be converted to an index by expressing it relative to total forecast error variation, which is $a_{0,11}^2 + a_{0,12}^2 + a_{0,21}^2 + a_{0,22}^2 = \text{trace}^5(A_0 A'_0)$. Hence the *Spillover Index*, expressed as a ratio percentage, is:

$$S = \frac{a_{0,12}^2 + a_{0,21}^2}{\text{trace}(A_0 A'_0)} \times 100. \quad (3.47)$$

⁵The trace of an n -by- n square matrix A is defined to be the sum of the elements on the main diagonal of A . It is the sum of the eigenvalues and it is invariant with respect to a change of basis.

Now for the general case of a p^{th} -order N -variable VAR, using H -step-ahead forecasts, we have:

$$S = \frac{\sum_{h=0}^{H-1} \sum_{i,j=1, i \neq j}^N a_{h,ij}^2}{\sum_{h=0}^{H-1} \text{trace}(A_h A_h')} \times 100. \quad (3.48)$$

However, Diebold and Yilmaz [2009]’s approach suffers from order-dependent results driven by Cholesky factor orthogonalization. In their following work, Diebold and Yilmaz [2012] apply the generalized VAR framework of Koop et al. [1996], hereafter KPPS, which produces variance decomposition invariant to ordering.

Explore all VAR orderings for calculating spillovers

Building on a divide-and-conquer strategy, Stefan and Wagner [2013] provide an algorithm for timely calculation of the range of the spillover index due to different orderings. The true range obtained from this method can be as much as three times wider than the range calculated from randomly chosen permutations, which is used in Diebold and Yilmaz [2009].

3.5 Model Uncertainty

According to Leamer [2014], there are two kinds of errors that afflict the regression coefficients estimation: the first is statistical uncertainty with estimation as measured by t-values and p-values, and the second is model ambiguity, which can be revealed by a sensitivity analysis that perturbs features of the model (or prior) to determine if the estimates change very much.

Sensitivity analysis here mainly refers to the form of model averaging. Model averaging is usually implemented in a Bayesian manner. Its logic, to put it briefly, is that one should obtain results for every model under consideration and average all of them, and the weights used in the averaging are the posterior model probabilities. As Koop [2003] argued that the concept of model averaging does not have a rigorous statistical foundation since frequentist econometrics does not treat models (or their truth) as random variables. Nevertheless, there are various ad hoc frequentist methods of model averaging such as the Extreme Bound Analysis (EBA).

For instance, Moral-benito [2010] provides a great summary of model averaging methods including Frequentist Model Averaging (FMA) and Bayesian Model Averaging (BMA) and their implementations in economics research. It is believed that, in theory, BMA should provide better average predictive performance than any single model that could be selected, and it has been supported in various studies according to Hoeting et al. [1999]. Next I discuss the theory behind EBA in the frequentist domain.

3.5.1 Extreme Bound Analysis

Extreme Bound Analysis (EBA) is a sensitivity test examining how robustly the dependent variable of a regression is related to a variety of possible determinants. It identifies the variables most robustly associated with the outcome variable and tests whether minor changes, such as inclusion or exclusion of a plausible explanatory variable can fundamentally alter the conclusions of empirical research results. EBA has been applied to deal with model uncertainty in many economics and finance studies. Some early studies include Sala-I-Martin [1997] on economic growth, Hafner-Burton [2005] on the repression to globalization, Hegre [2006] on civil wars, and more recently, Chakrabarti and Zeaiter [2014] on the determinants of sovereign default, and Raputsoane [2014] on the relationship between financial stress indicator variables and monetary policy interest rate in South Africa.

The initial version of EBA was proposed by Leamer [1985], which looked at the upper and lower extreme bounds of regression estimate. Sala-I-Martin [1997] subsequently developed a more flexible version of EBA which considers the entire distribution of regression coefficients. Applying the R package *ExtremeBounds* developed by Hlavac [2004], results of both versions can be obtained.

Given a large number of possible variables, EBA allows us to see the extent to which each variable impacts across a wide variety of possible specifications. Set $\mathbf{X}$ as the vector of possible explanatory variables which can impact on the dependent variable y ; we can then draw $\mathbf{D}$ variables from $\mathbf{X}$ and estimate the regression, repeating for all possible combinations of $\mathbf{D}$ from $\mathbf{X}$. If there are theoretical or *a priori* empirical reasons to include a set of free variables $\mathbf{F}$ in all regressions, these can be specified. In essence, evaluating the coefficients

of the elements of $\mathbf{D}$ we are interested in seeing whether these retain statistical significance across a wide range of the estimated models. Consider the regression:

$$y = \alpha + \beta_j v + \gamma_j \mathbf{F} + \delta_j \mathbf{D} + \epsilon \quad (3.49)$$

where v is the variable of interest, an element of $\mathbf{D}$, the subset of the set of doubtful variables $\mathbf{X}$. k variables are drawn from $\mathbf{D}$ in each pass. Typically in the literature $k=3$. We collect the estimated regression coefficient $\hat{\beta}_j$ and the corresponding standard errors $\hat{\sigma}_j$ for each pass of the regression for later evaluation. Leamer [1985] investigates the upper and lower extreme bounds, defined as:

$$\hat{\beta}_j \pm \tau \hat{\sigma} \quad (3.50)$$

where τ is the critical value for the 95% confidence level. A severe drawback of Leamer's (1985) approach is the binary nature of the possible outcomes: *robust* or *fragile*. A focus variable is identified as *robust* if all extreme bounds of the vast multitude of estimated models have the same sign; which tends to be rather unlikely when running thousands of regressions. Independent of the field of research, papers that applied a Leamer [1985] testing procedure tend to rush to the conclusion that most variables under study are *fragile* (Levine and Renelt [1992], Bartley and Cohen [1998]), and therefore not worth taking seriously Leamer [1985]. Aware of this shortcoming, Sala-I-Martin [1997] focuses on the *entire* distribution of the regression coefficients, hence providing the researcher with a level of confidence for the robustness of each variable. Examination here is not done on the bounds but instead on the cumulative distribution function — the percentage of coefficients that lie either side of zero. The author proposes two variants, one assuming that the coefficients are normally distributed, the other one, less restrictive, allows a more general distribution of the coefficients. Formally, Sala-I-Martin [1997] augment Leamer's testing procedure by first computing the weighted mean of both the regression coefficients $\hat{\beta}_j$ and the variance $\hat{\sigma}_j^2$, where the weighting w_j is specified by the researcher as proportional to the integrated likelihood to give greater weight to models that provide a better fit. The aggregated CDF(0) for the given regression

coefficient is given as:

$$\Phi(0) = \sum_{j=1}^M w_j \phi_j(0|\hat{\beta}_j, \hat{\sigma}_j^2) \quad (3.51)$$

$$\omega_j = \frac{L_j}{\sum_{i=1}^M L_i} \quad (3.52)$$

where Φ is the weighted average of all individual CDF(0)'s and $\phi_j(0|\hat{\beta}_j, \hat{\sigma}_j^2)$ is the individual CDF(0) for each estimated regression model.

McAleer et al. [1985] propose a multistage approach to Extreme Bounds Analysis, akin to the general-to-specific econometric methodology of Hendry [1980]. To some extent this addresses the argument advanced in Hendry and Krolzig [2004] — a simplistic model — where all possible determinants are included is run first. Any *robust* variables are then fixed, and a second stage model uses only those *fragile* variables.

3.6 Search Terms Selection

Related to variable selection in regression analysis, there are also nuances for search terms selection when collecting online search data. Indeed, deciding search terms is a crucial element of using Internet search data. Some considerations are discussed as follows.

In most cases terms which move most correlate with economic data are selected e.g. McLaren and Shanbhogue [2011] uses one term “JSA” to predict UK unemployment and Choi and Varian [2012] using “Free shipping” to predict the US model sales. Sometimes Google Correlate⁶ is used to facilitate the selection.

Most popular terms are also preferred, which is likely to be a general term and shows the highest incidence among different related search terms. Besides terms with high absolute search volume tend to show stable Google Trend across time. For example, Ettredge et al.

⁶Google Correlate is a tool on Google Trends which enables you to find queries with a similar pattern to a target data series. The target can either be a real-world trend that you provide (e.g., a data set of event counts over time) or a query that you enter. For more information see www.google.com/trends/correlate

[2005] identified six most frequently used job related terms from the WordTracker's Top Long Term Keyword Report published by Rivergold Associates Ltd, which are "job search", "jobs", "monster.com", "resume", "employment" and "job listings". Similarly D'Amuri and Marcucci [2010] used the term "jobs" which has the highest search volume.

Some studies prefer to use Google categories. For instance, to predict the US consumption, Vosen, Torsten Schmidt [2009] selected 56 consumption-relevant categories in Google Trends which best match the product categories of personal consumption expenditures in the US (e.g. Automotive, Auto Parts, and Auto Financing are selected to match the category Motor Vehicles and Parts). Choi and Varian [2012] also use categories data to predict Initial Jobless Claims (e.g. Jobs, Welfare and Unemployment).

Scott and Varian [2014a] and Scott and Varian [2014b] applies Bayesian variable selection on search data to nowcast the University of Michigan monthly Consumer Sentiment. They start with 151 economics relevant categories from Google Trends and select the top five predictors with highest probability of inclusion i.e. Financial Planning, Investing, Business News, Search Engines and Energy Utilities.

For those studies which only select a few search terms, it is not necessary to construct an index. However, recent studies tend to emphasize the diversity and dynamics of search behaviour, in that usually a list of tens or hundreds of terms are monitored, and indices are constructed based on aggregated information. Studies have aggregated information from multiple search terms in different ways. For example, Ettredge et al. [2005] measures weekly job search activity by summing normalized search volume from selected six job-search terms. Da et al. [2011] construct the Financial and Economics Attitude Revealed Index (FEARS) from 30 terms. The index is calculated from a dynamic list of top positively and negatively correlated search terms in a backward expanding window. So, as time goes by, the relationship between search term and economic metric changes, and a term may be selected or dropped from the top list to calculate the index value. Other cases use more advanced techniques such as topic extraction. Dong and Bollen [2015] also construct an index from many search terms. They firstly identify consumer confidence related search terms by extracting topics and keywords from the Economist's Confidence Questionnaire (ECQ). They selected the top

44 topics including “Municipal Bond”, “Inflation”, “Food Price”, etc., and then use the fitted value from linear regression with top principal components from all 45 terms as the online search index for Chinese consumer confidence. Applying principal component analysis suggest the important assumption that it is the latent variable which is most responsible for the co-movement of search terms. Constructing indices by PC, however, has an potential issue of instability when updating index value by adding new observations. This issue has been particularly discussed in Hakkio and Keeton [2009].

Chapter 4

Measure Market Dependence with DCC

4.1 Introduction

In this chapter, cross-market dependences between precious metals returns and stock, bond indices returns are measured with Dynamic Conditional Correlations (DCC) as discussed in the methodology chapter. In addition, as a comparison, Pearson's Correlation Coefficients are also obtained over the full sample period, which provide an overview of the average linear dependence structures between market returns. The analysis is carried out across eleven countries: the US, UK, Germany, France, Italy, Switzerland, Canada, Japan, China, India and South Africa.

4.2 Data

Eleven countries are selected for the analysis. The group includes the G7 countries, the US, Japan, Germany, UK, France, Italy, Canada, the seven largest advanced economies in the world. Three of the BRICS countries, China, India, and South Africa are included as well, which are the largest emerging economies in the world. Brazil and Russia are not selected due to their relatively short history of data especially for the explanatory analysis in Chapter

6. Although South Africa has a relatively smaller economy, it was a major gold supplier historically that its mines generated about 45% of total gold mine supply in the world from 1900 to 1970 Green [1968] and it remained as a dominant producer until 2006. Switzerland is added in the analysis due to its significant gold market, that it has the second largest physical bar investment in Europe in 2017 with 42.5 Tonnes as well as the second largest official gold holdings in 2018 with 1040 Tonnes according to the World Gold Council. The stock market indices used for those countries are as follows: United States S&P500 index, United Kingdom FTSE100 index, Germany DAX30 index, France CAC40 Index, Italy FTSE MIB Index, Switzerland Swiss Market Index (SMI), Canada S&P/TSX Composite Index, Japan NIKKEI225 index, China Shanghai Stock Exchange Composite Index (SHCOMP), Indian NIFTY50 Index and South Africa FTSE/JSE Africa Top40 Index. The bond indices studied are the benchmark 10-year government bond indices of each country respectively¹. Precious metal data are spot market prices in dollars for the US, and in local currency for other countries. Prices in local currency are calculated by using the daily spot exchange rate against the US dollar, thus assuming unhedged investors. The period covered is from January 1994 to July 2016 for most countries. Data are plotted in Figures D.1 – D.12, and the descriptive statistics of the data are summarized in Table 4.1 and 4.2. As the Augmented Dickey-Fuller(ADF) test show that almost all the input data at level are not stationary, while all their log returns are.

4.3 Results

4.3.1 Pearson's Correlation Coefficients

Figures 4.1 – 4.11 visualize the correlation matrix, along with the significance of correlation (0.05, 0.01, 0.001), scatter plot matrix, histograms and kernel density overlays ², which are produced with R package PerformanceAnalytics by Peterson and Carl [2014]. The correlation coefficients show the strength of the linear dependence, while the significance of the

¹All data are sourced from the Bloomberg.

²Kernel density estimation (KDE) is a non-parametric way to estimate the probability density function of a random variable.

relationship shows how unlikely the given correlation will occur from the sample, if there is no relationship in the population.

Gold returns have a weak and insignificant negative correlation (-0.021) with S&P500 returns from 1994 to 2016, while silver, platinum and palladium returns have positive and significant correlations with S&P500 returns (0.11, 0.14, 0.17 respectively). While four metals all have quite low correlations with US government bond index returns, which are within the range of $[-0.1, 0.1]$, 0.093, -0.019, -0.065, and -0.083 for gold, silver, platinum and palladium respectively, and silver's correlation is also insignificant. Gold returns have similar low and insignificant correlation coefficients with stock markets in the UK (-0.0016) and France (-0.0001); while in Italy (-0.044), India (-0.06) and South Africa (-0.05) the correlations are negative but significant; however, gold returns are positively (though quite weak sometimes) correlated with Germany (0.012), Switzerland (0.094), Canada (0.0001), Japan (0.11), and China (0.055) stock market returns. Gold returns are mostly positively and significantly correlated with bond market returns, except in Italy (-0.025), India (-0.046) and South Africa (-0.14). Correlations between silver, platinum, palladium returns and stock, bond returns are quite similar across markets. They are generally positively and significantly correlated with stocks with correlations around 0.1, and weakly but also significantly correlated with bond returns. This is not the case for South Africa, where platinum is -0.14 correlated with bond returns, stronger than palladium and silver. Precious metals returns are seen strongly positively and significantly correlated with each other across all markets during the examined period, suggesting strong linear dependences. In addition, negative correlations are seen between stock and bond market returns in most markets, except for Italy (0.16), India (0.098) and South Africa (0.16) and they are all significant.

4.3.2 DCC

Figures 4.12 – 4.22 contain Dynamic Conditional Correlations (DCC) between stock and bond markets returns, and their conditional correlations with precious metals returns respectively in eleven countries. In the US, estimated correlation decreases significantly between equity and bond indices since 1998, which is consistent with findings in Baele et al. [2013]. Baele

et al. explains this negative correlation between bond and stock returns as mainly caused by the relatively high incidence of flight-to-safety in the last 30 years. This declining correlation starting around 1998 is also observed in the UK, Germany, France, Italy, Switzerland and Canada. The estimated conditional correlation between gold and stock indices share some similarities across countries in that it switched from positive to negative during the 2007–2009 Global Financial crisis in the US, UK, Germany, France, Italy, Switzerland, Canada, Japan, and for a shorter period in China, India and South Africa. This is mostly consistent with findings in Baur and K.J.McDermott [2010], which examined gold’s role as safe haven in crisis periods, including the 2008 Global Financial crisis. Silver is also seen having periods of negative conditional correlation with equity indices in most studied countries. The patterns for platinum and palladium are mixed across countries. In US, both see correlations fluctuated but positive most of the time before 2008, then followed by an strengthening positive correlation from 2008 to 2011, before it reverts back to an almost zero correlation at the beginning of 2015. In general, gold and silver have a relatively similar pattern of conditional correlations with equity and bond indexes, while platinum and palladium share some similarities.

In addition, rolling Pearson’s correlation coefficients with a window of 1-quarter and 1-year are also obtained and included in the Appendix as a reference. Despite different methodologies, when compared with DCC, rolling correlation look more volatile and with more extreme values.

4.4 Conclusion

This chapter explores dynamic dependence between precious metals, equity and bond markets across eleven countries. Correlation matrix is firstly used to show linear dependence over the whole sample period; then DCC is applied to further examine how these relationships evolve across time. The decoupling between equity and bond markets is observed across markets, which is consistent with previous studies. Similar patterns are also obtained cross metals and countries such as negative correlations between gold and stock market during the 2007–2009 Global Financial crises, which suggests a need for further investigation of gold and other

precious metals as safe haven across countries. In addition, 1-quarter and 1-year rolling correlations are included in the Appendix as a comparison.

Table 4.1: Summary of Data - level

Country	Data	Mean	S.D	Skew.	Kurt.	Min.	Max.	ADF	P Value	Obs.
US	AUUSD	726.4	466.6	0.7	-0.9	252.6	1897.5	-1.83	0.65	5563
	AGUSD	12.2	9.0	1.3	0.9	4.1	48.4	-2.11	0.53	5563
	PTUSD	936.9	485.6	0.4	-1.1	335.0	2250.5	-2.22	0.49	5563
	PDUSD	408.4	230.4	0.6	-1.0	114.8	1110.5	-2.43	0.40	5563
	SP500	1213.8	407.6	0.3	-0.1	438.9	2163.8	-1.49	0.79	5563
	US10YR	268.0	105.2	0.3	-1.2	111.9	477.1	-2.89	0.20	5563
UK	AUGBP	449.3	300.4	0.8	-0.9	157.2	1178.9	-1.72	0.70	5628
	AGGBP	7.5	5.7	1.3	0.8	2.5	29.1	-2.01	0.58	5628
	PTGBP	569.3	289.0	0.4	-1.2	196.6	1187.0	-2.43	0.40	5628
	PDGBP	254.3	152.3	0.6	-0.9	68.1	763.0	-2.08	0.54	5628
	FTSE100	5294.9	1076.9	-0.5	-0.9	2876.6	7104.0	-2.29	0.45	5628
	UK10YR	347.3	141.8	0.4	-1.0	131.8	655.2	-1.56	0.76	5628
GERMANY	AUEUR	580.7	345.0	0.8	-0.9	237.7	1378.1	-2.00	0.58	5611
	AGEUR	9.7	6.5	1.2	0.6	3.4	32.7	-2.17	0.50	5611
	PTEUR	750.8	326.6	0.1	-1.2	280.6	1474.3	-2.76	0.26	5611
	PDEUR	344.3	207.0	0.9	0.3	89.0	1201.3	-1.96	0.60	5611
	DAX	292.3	113.7	0.4	-0.9	123.2	535.4	-1.51	0.79	5611
	G10YR	5693.8	2356.4	0.4	-0.3	1911.7	12374.7	-2.20	0.49	5611
FRANCE	AUEUR	582.4	345.2	0.8	-0.9	237.7	1378.1	-2.00	0.58	5620
	AGEUR	9.7	6.5	1.2	0.6	3.4	32.7	-2.18	0.50	5620
	PTEUR	752.4	326.3	0.1	-1.2	280.6	1474.3	-2.74	0.27	5620
	PDEUR	344.8	207.1	0.9	0.3	89.0	1201.3	-1.91	0.61	5620
	CAC	3893.4	1134.4	0.1	-0.4	1721.1	6922.3	-1.86	0.64	5620
	F10YR	313.3	125.4	0.4	-0.8	124.5	594.6	-1.08	0.93	5620
ITALY	AUEUR	639.9	352.2	0.5	-1.2	237.7	1378.1	-2.08	0.54	4627
	AGEUR	10.8	6.6	1.0	0.1	3.8	32.7	-2.15	0.51	4627
	PTEUR	840.1	288.5	-0.1	-1.0	280.6	1474.3	-2.57	0.34	4627
	PDEUR	391.7	198.0	0.8	0.4	123.1	1201.3	-1.84	0.65	4627
	FTSEMIB	27703.6	9045.4	0.4	-0.9	12362.5	50109.0	-2.69	0.29	4627
	IT10YR	482.4	156.8	0.8	-0.2	260.8	863.7	-0.56	0.98	4627
SWISS	AUCHF	793.5	373.9	0.7	-1.0	380.2	1668.7	-2.20	0.49	5594
	AGCHF	13.2	7.4	1.1	0.5	5.3	42.3	-2.24	0.48	5594
	PTCHF	1058.5	415.2	0.3	-0.7	447.0	2363.0	-2.07	0.55	5594
	PDCHF	479.9	270.8	1.5	3.2	143.4	1833.4	-2.10	0.54	5594
	SMI	6386.9	1786.8	-0.5	-0.5	2450.3	9531.5	-2.01	0.57	5594
	SWISS10YR	192.0	54.3	0.2	-1.0	98.1	301.4	-2.09	0.54	5594
CANADA	AUCAD	845.3	450.1	0.7	-1.1	375.5	1879.4	-1.99	0.58	5575
	AGCAD	14.0	8.4	1.1	0.5	5.8	46.1	-2.43	0.40	5575

Table 4.2: Summary of Data - log return

Country	Data	Mean	S.D	Skew.	Kurt.	Min.	Max.	ADF	P Value	Obs.
US	AUUSD	0.00	0.01	-0.07	7.46	-0.10	0.10	-17.85	0.01	5562
	AGUSD	0.00	0.02	-0.98	9.59	-0.20	0.13	-17.77	0.01	5562
	PTUSD	0.00	0.01	-0.33	5.05	-0.10	0.09	-16.10	0.01	5562
	PDUSD	0.00	0.02	-0.02	6.62	-0.17	0.19	-16.64	0.01	5562
	SP500	0.00	0.01	-0.31	8.20	-0.09	0.10	-18.60	0.01	5562
	US10YR	0.00	0.00	-0.09	2.49	-0.02	0.04	-16.21	0.01	5562
UK	AUGBP	0.00	0.01	0.37	10.00	-0.09	0.13	-17.59	0.01	5627
	AGGBP	0.00	0.02	-1.03	10.43	-0.20	0.11	-17.75	0.01	5627
	PTGBP	0.00	0.01	-0.16	5.21	-0.09	0.10	-17.09	0.01	5627
	PDGBP	0.00	0.02	-0.08	6.79	-0.17	0.19	-16.70	0.01	5627
	FTSE100	0.00	0.01	-0.15	5.68	-0.09	0.09	-19.06	0.01	5627
	UK10YR	0.00	0.00	-0.10	2.06	-0.02	0.02	-16.67	0.01	5627
GERMANY	AUEUR	0.00	0.01	0.07	6.73	-0.09	0.09	-17.73	0.01	5610
	AGEUR	0.00	0.02	-0.97	9.47	-0.20	0.12	-18.17	0.01	5610
	PTEUR	0.00	0.01	-0.27	4.56	-0.09	0.09	-17.32	0.01	5610
	PDEUR	0.00	0.02	-0.13	7.20	-0.16	0.19	-16.95	0.01	5610
	DAX	0.00	0.01	-0.13	4.22	-0.09	0.11	-17.77	0.01	5610
	G10YR	0.00	0.00	-0.23	1.81	-0.02	0.02	-16.98	0.01	5610
FRANCE	AUEUR	0.00	0.01	0.06	6.72	-0.09	0.09	-17.81	0.01	5619
	AGEUR	0.00	0.02	-0.97	9.48	-0.20	0.12	-18.13	0.01	5619
	PTEUR	0.00	0.01	-0.30	4.53	-0.09	0.09	-17.20	0.01	5619
	PDEUR	0.00	0.02	-0.11	6.89	-0.16	0.19	-16.92	0.01	5619
	CAC	0.00	0.01	-0.04	4.34	-0.09	0.11	-17.73	0.01	5619
	F10YR	0.00	0.00	-0.25	2.38	-0.02	0.02	-16.23	0.01	5619
ITALY	AUEUR	0.00	0.01	0.09	6.35	-0.09	0.09	-16.49	0.01	4626
	AGEUR	0.00	0.02	-1.09	9.51	-0.20	0.12	-16.67	0.01	4626
	PTEUR	0.00	0.01	-0.30	4.43	-0.09	0.09	-15.87	0.01	4626
	PDEUR	0.00	0.02	-0.31	4.94	-0.16	0.13	-15.25	0.01	4626
	FTSEMIB	0.00	0.02	-0.21	4.30	-0.13	0.11	-15.43	0.01	4626
	IT10YR	0.00	0.00	0.66	20.83	-0.03	0.06	-15.49	0.01	4626
SWISS	AUCHF	0.00	0.01	-0.60	16.07	-0.17	0.08	-17.95	0.01	5593
	AGCHF	0.00	0.02	-1.15	10.78	-0.19	0.12	-18.08	0.01	5593
	PTCHF	0.00	0.01	-0.61	8.39	-0.17	0.09	-17.12	0.01	5593
	PDCHF	0.00	0.02	-0.22	7.62	-0.21	0.20	-16.98	0.01	5593
	SMI	0.00	0.01	-0.14	6.10	-0.09	0.11	-17.89	0.01	5593
	SWISS10YR	0.00	0.00	-0.12	3.10	-0.02	0.02	-16.97	0.01	5593
CANADA	AUCAD	0.00	0.01	0.23	7.03	-0.08	0.11	-18.03	0.01	5574
	AGCAD	0.00	0.02	-0.92	9.70	-0.20	0.14	-17.66	0.01	5574

Figure 4.1: Correlation matrix of market returns — US

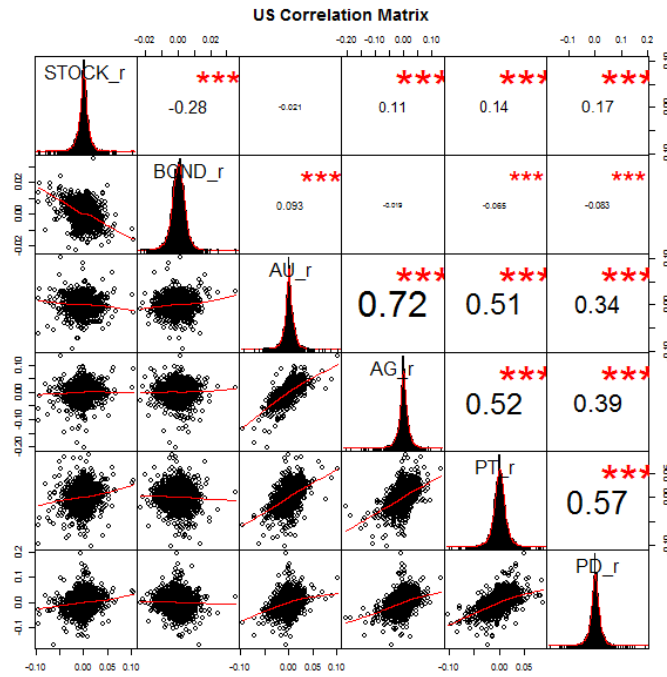


Figure 4.2: Correlation matrix of market returns — UK

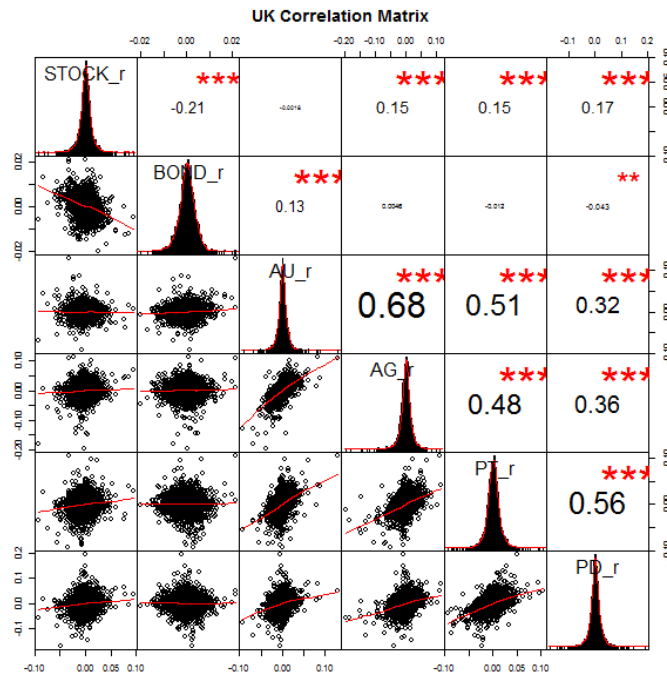


Figure 4.3: Correlation matrix of market returns — Germany

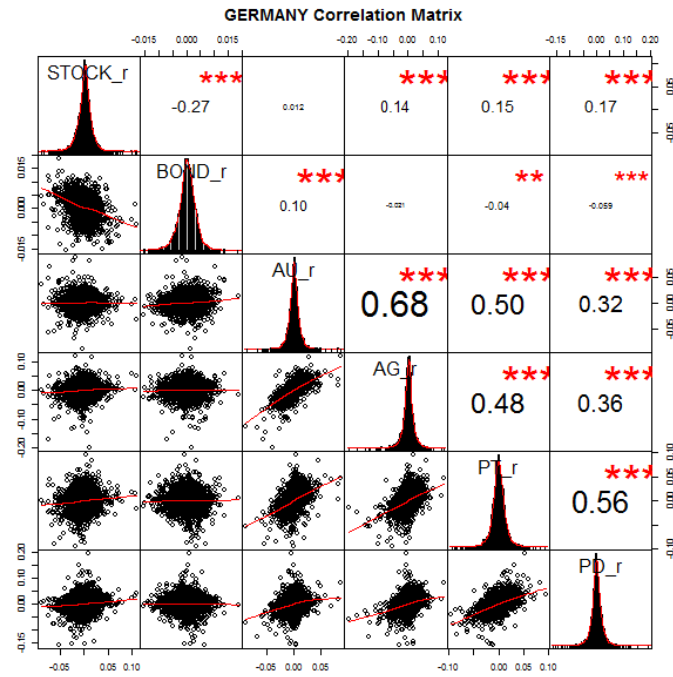


Figure 4.4: Correlation matrix of market returns — France

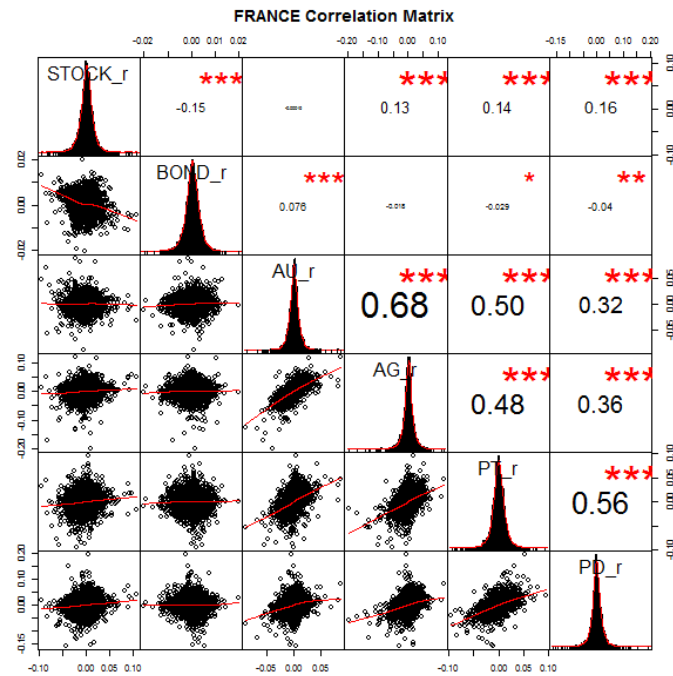


Figure 4.5: Correlation matrix of market returns — Italy

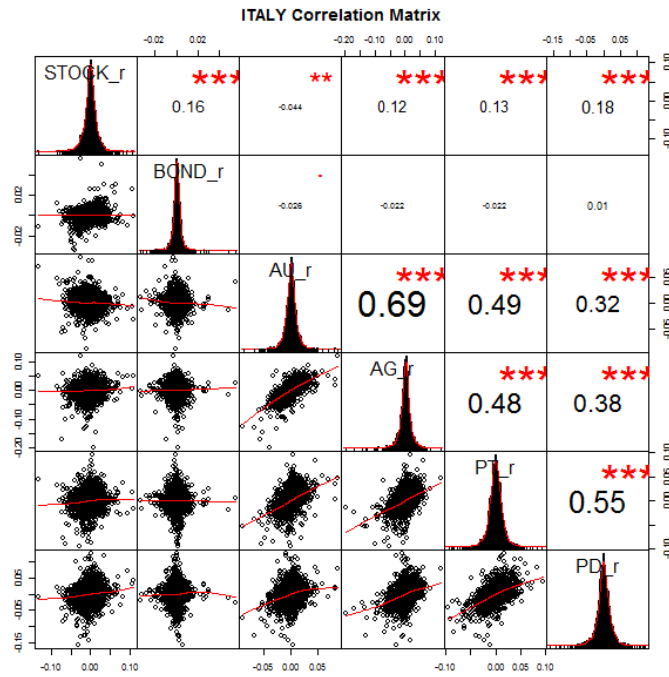


Figure 4.6: Correlation matrix of market returns — Switzerland

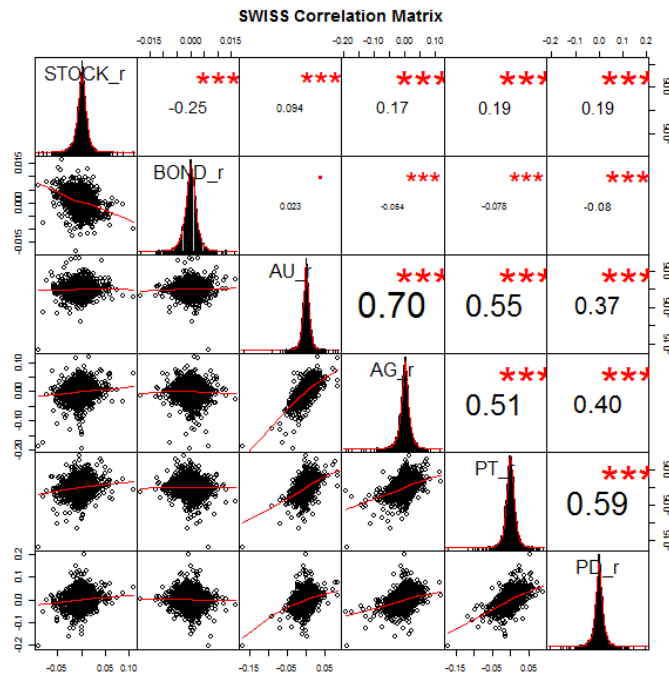


Figure 4.7: Correlation matrix of market returns — Canada

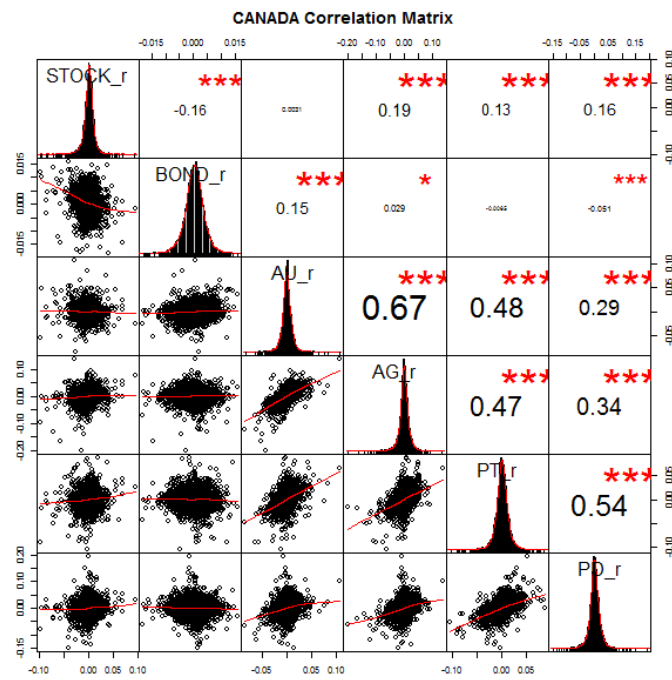


Figure 4.8: Correlation matrix of market returns — Japan

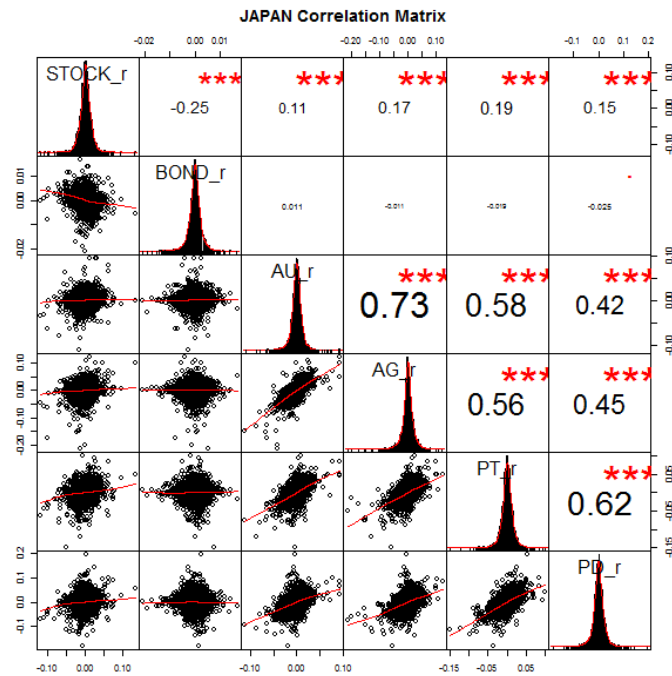


Figure 4.9: Correlation matrix of market returns — China

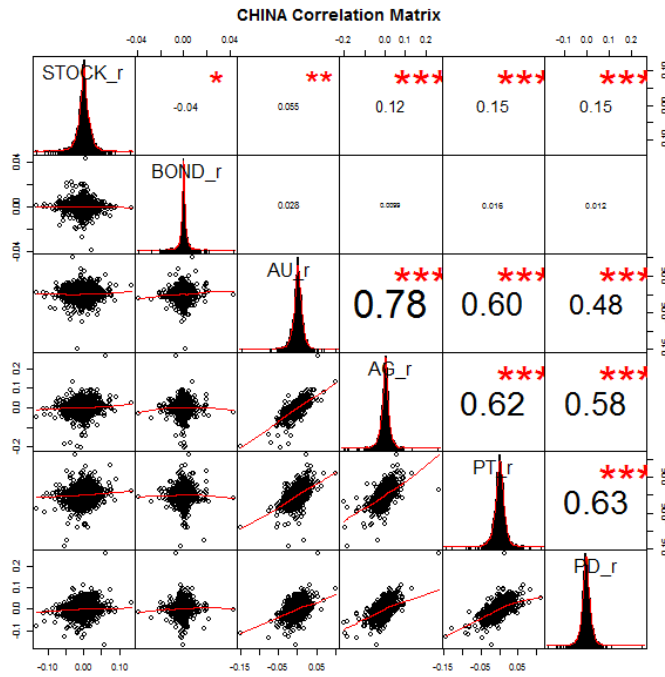


Figure 4.10: Correlation matrix of market returns — India

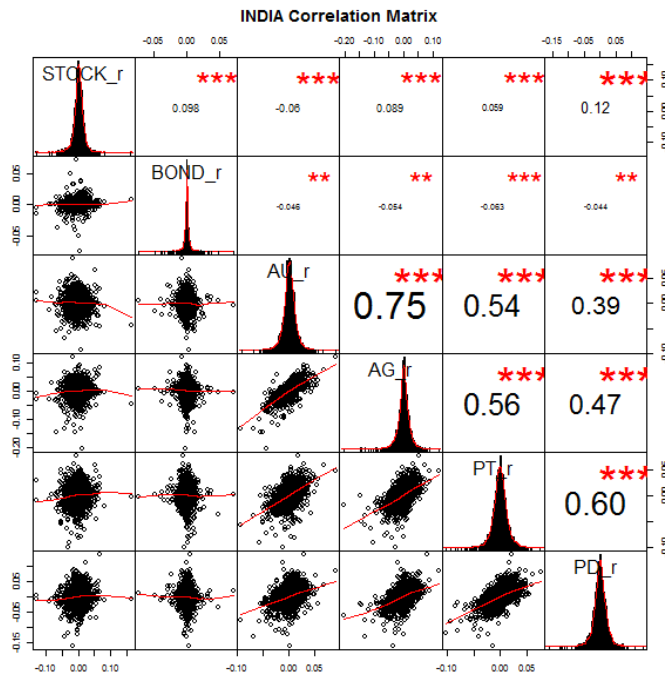


Figure 4.11: Correlation matrix of market returns — South Africa

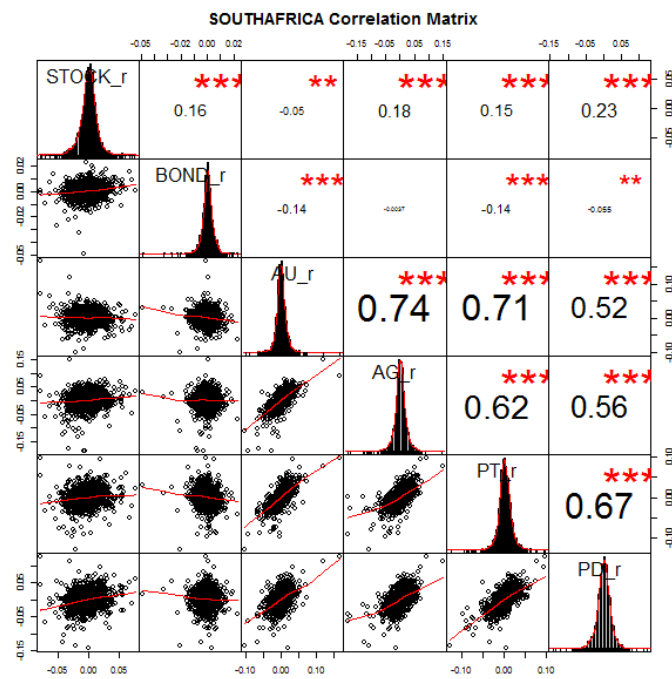


Figure 4.12: Dynamic conditional correlation — US

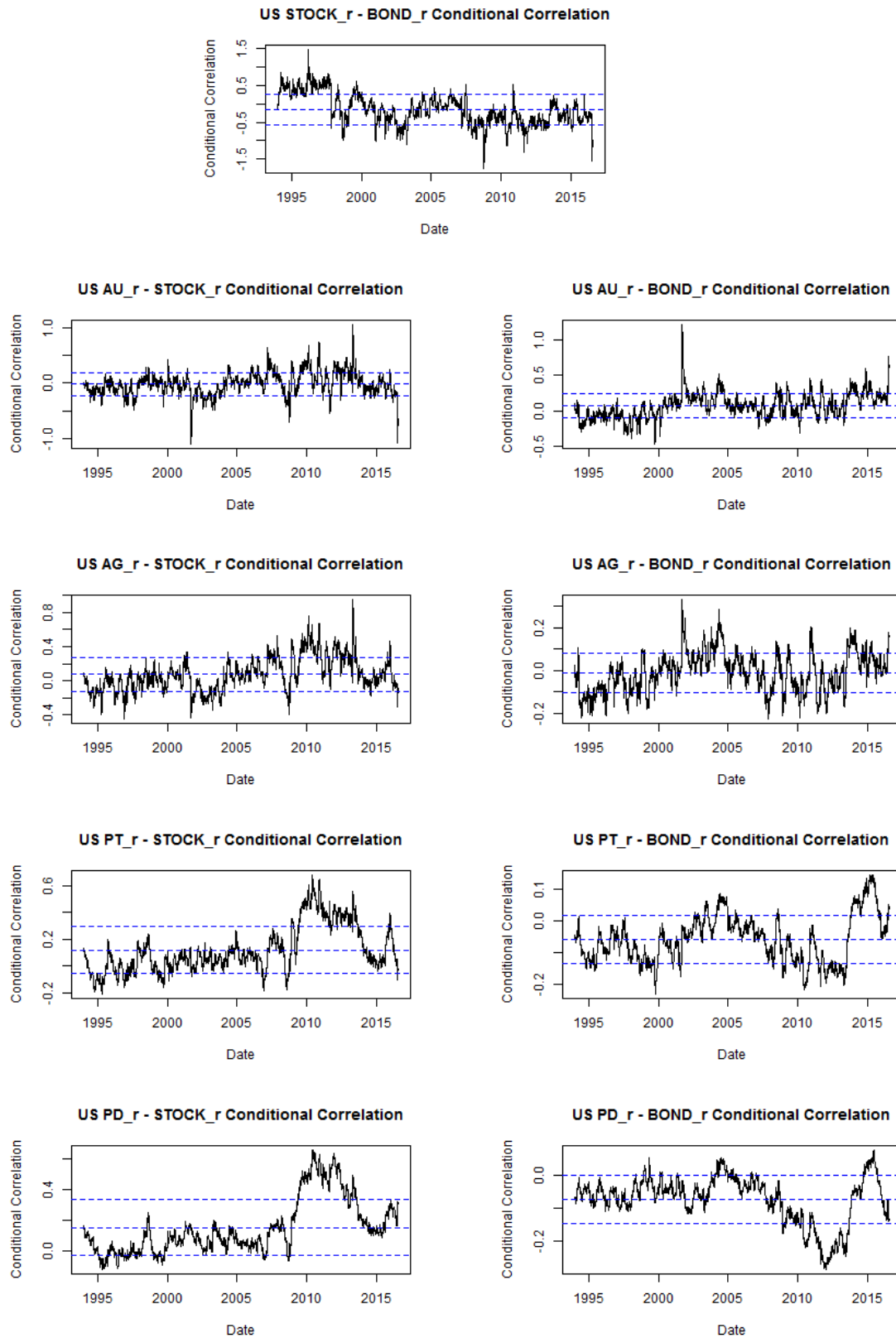


Figure 4.13: Dynamic conditional correlation — UK

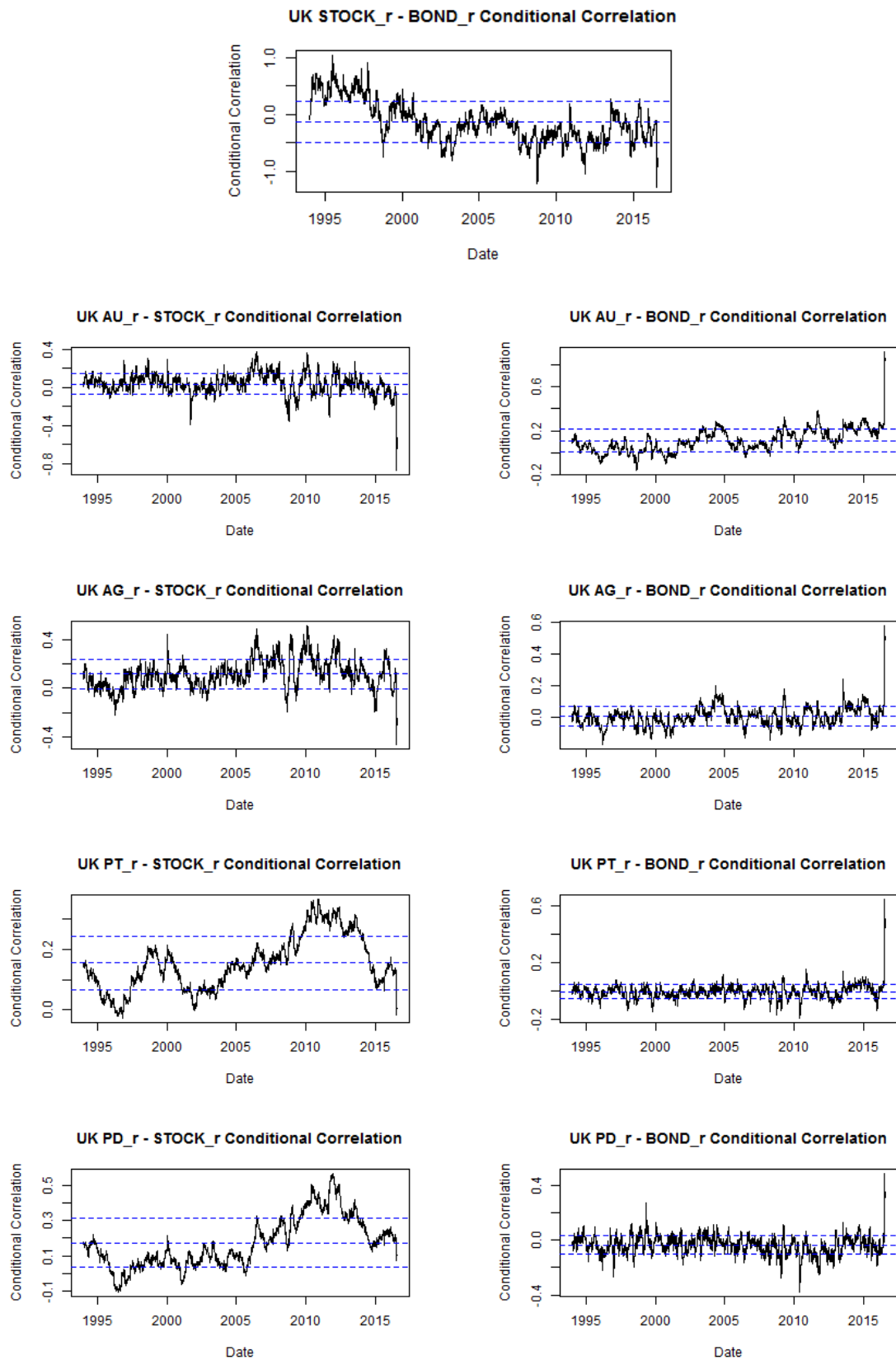


Figure 4.14: Dynamic conditional correlation — Germany

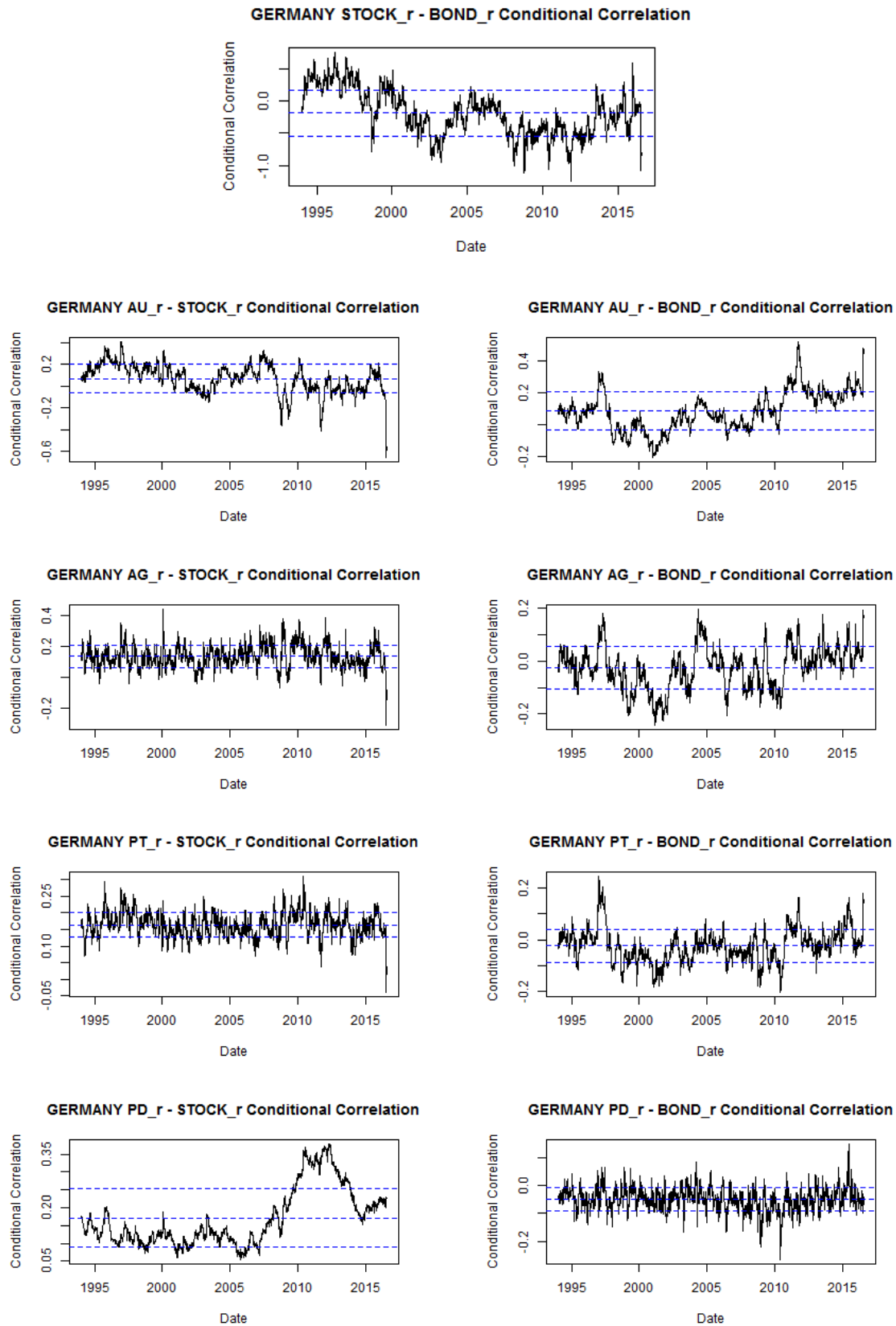


Figure 4.15: Dynamic conditional correlation — France

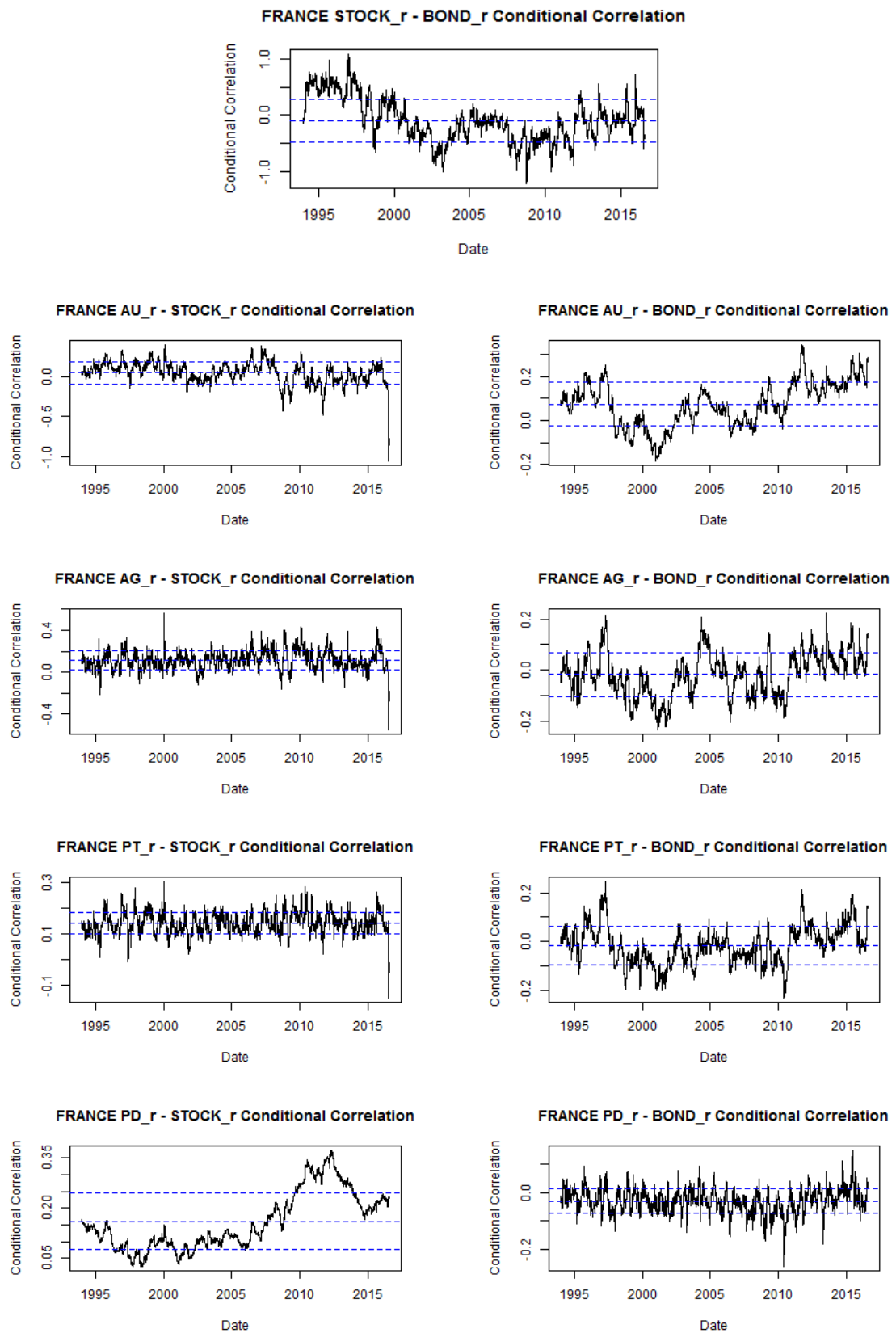


Figure 4.16: Dynamic conditional correlation — Italy

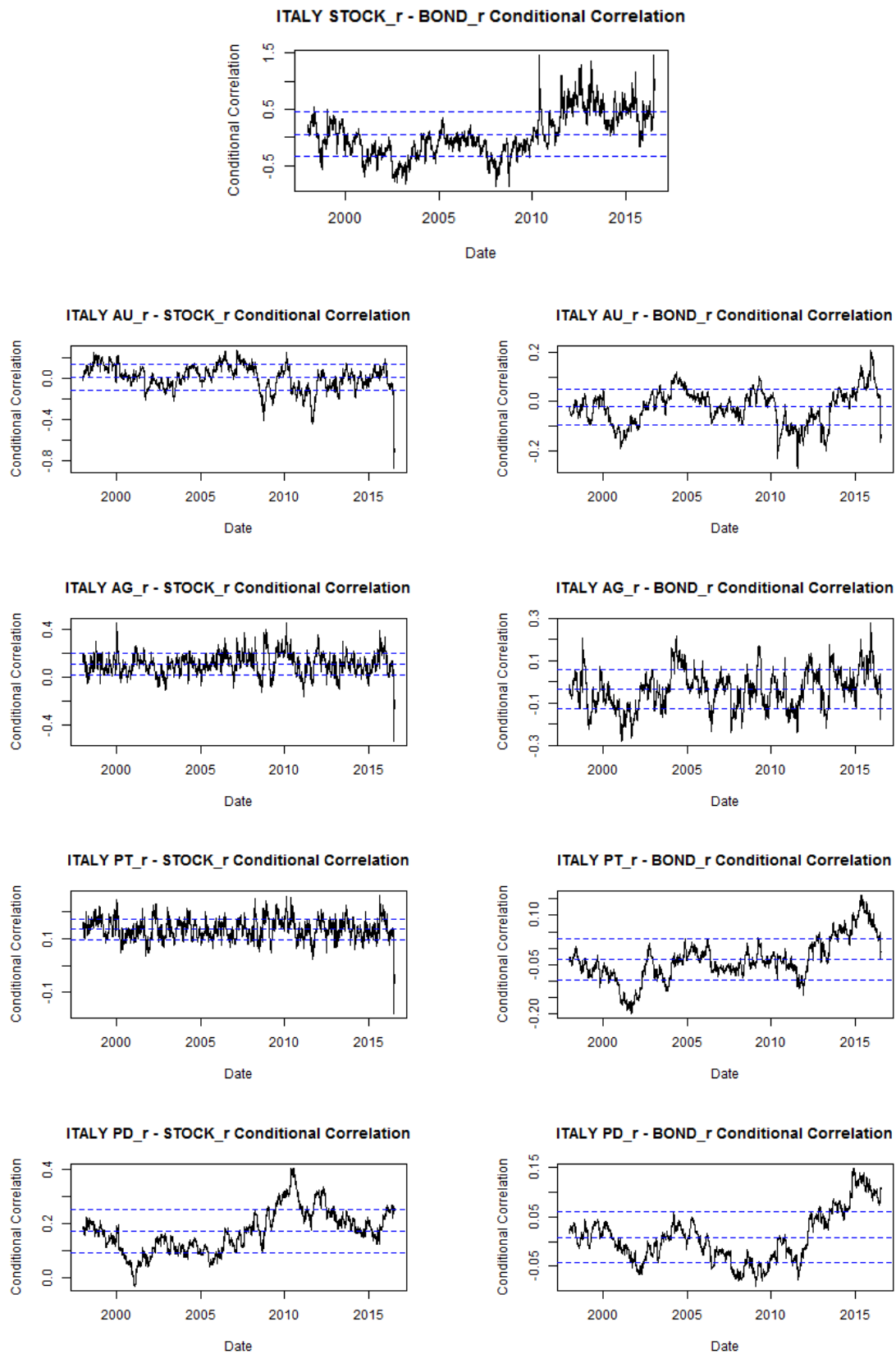


Figure 4.17: Dynamic conditional correlation — Switzerland

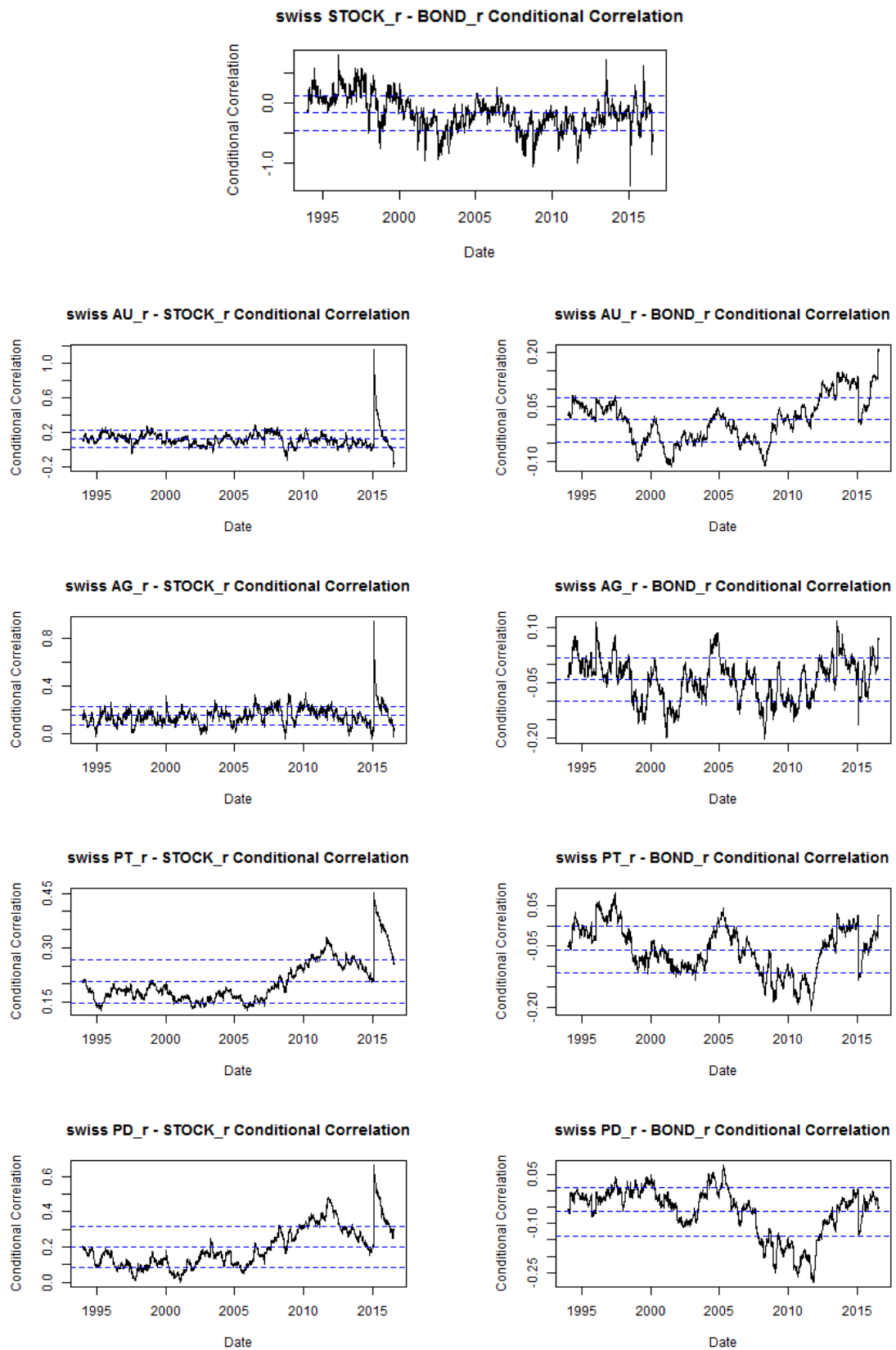


Figure 4.18: Dynamic conditional correlation — Canada

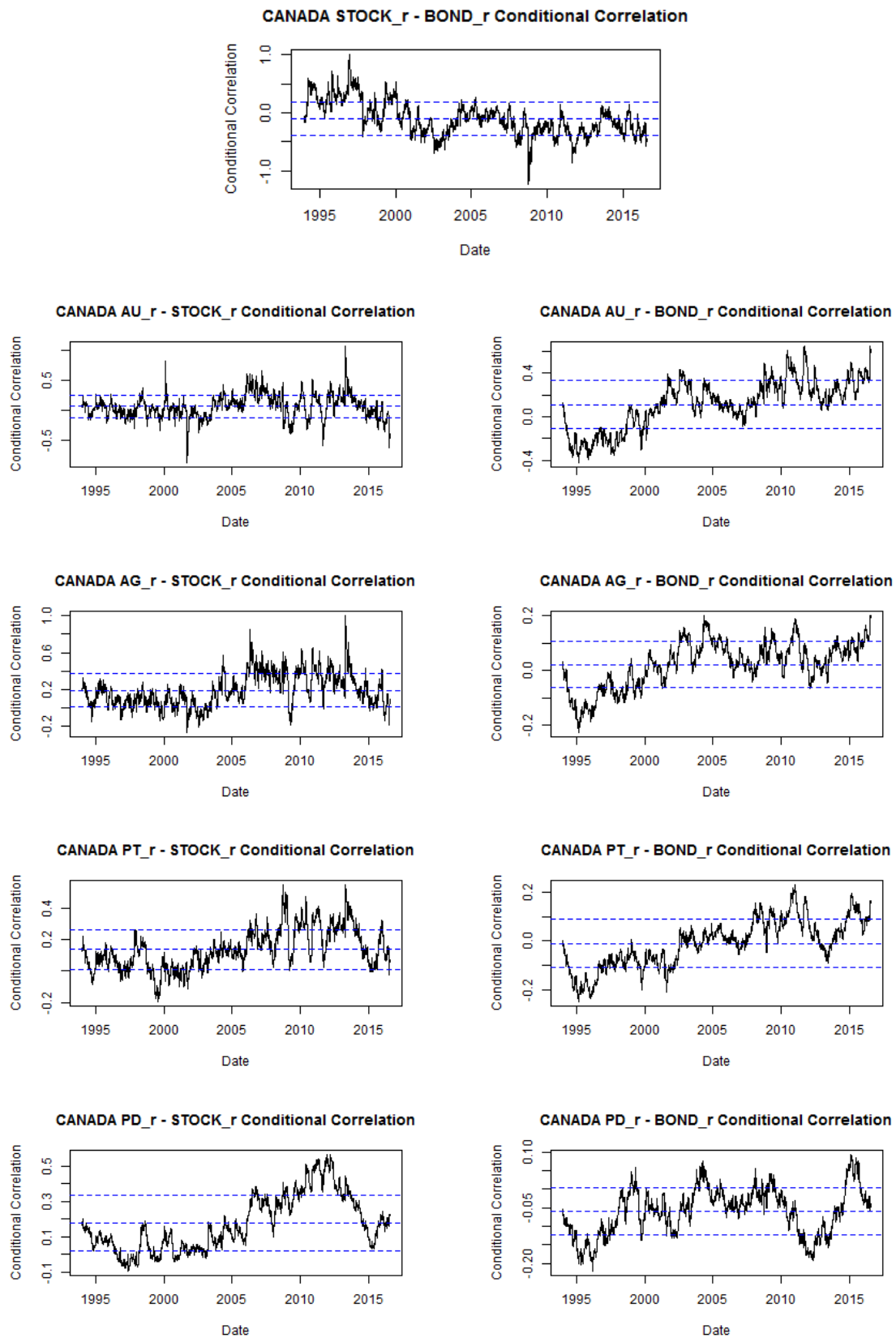


Figure 4.19: Dynamic conditional correlation — Japan

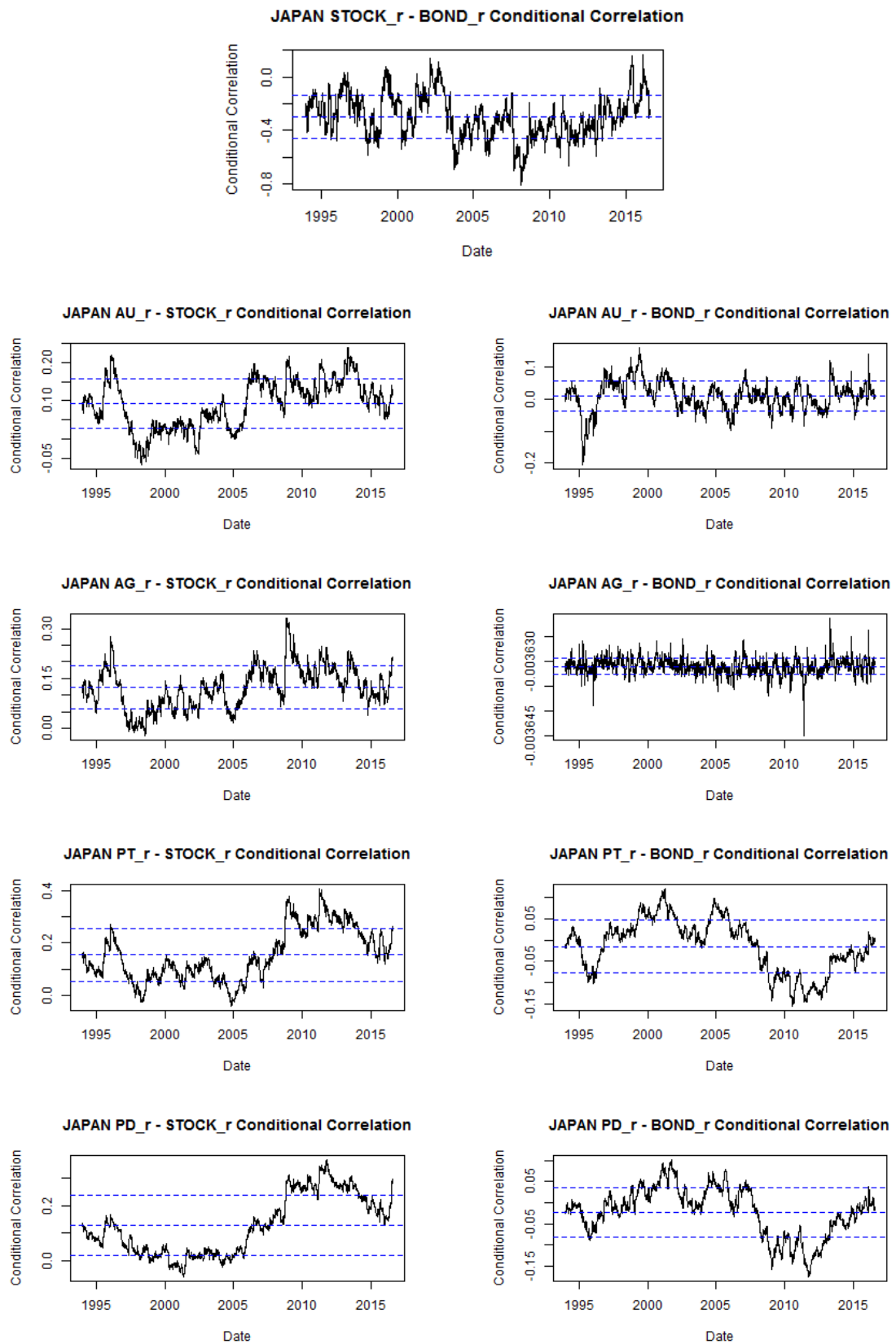


Figure 4.20: Dynamic conditional correlation — China

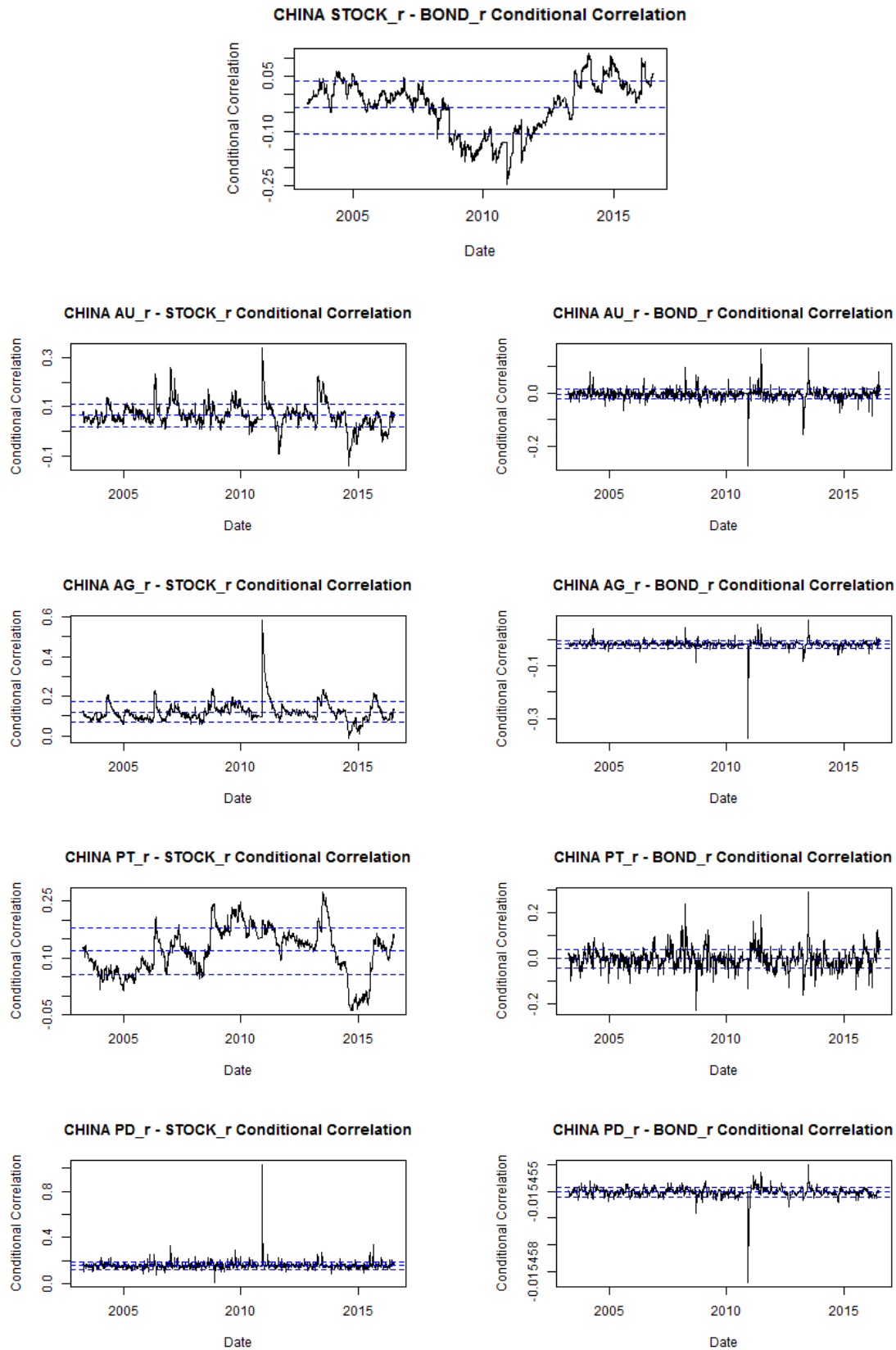


Figure 4.21: Dynamic conditional correlation — India

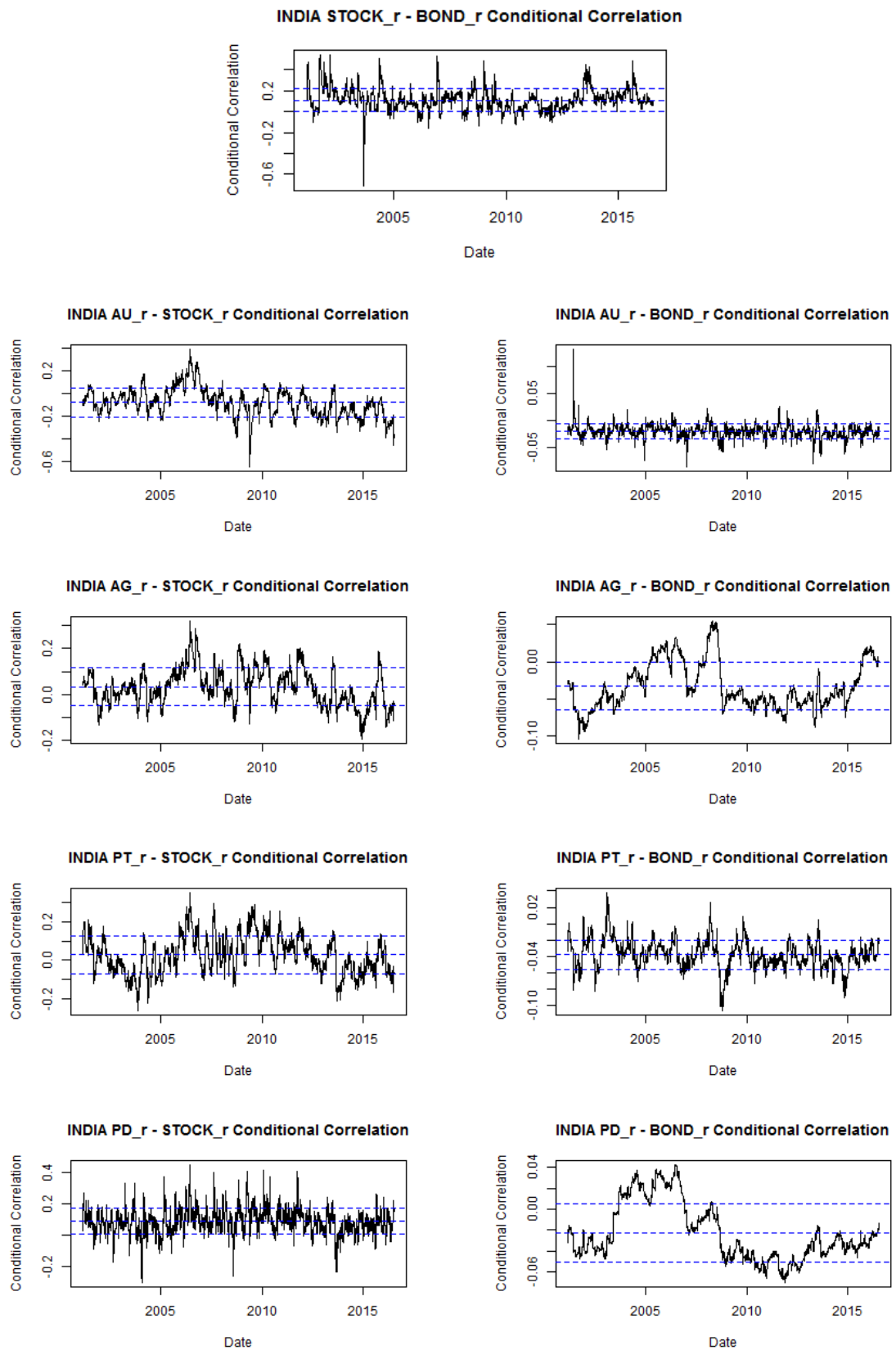
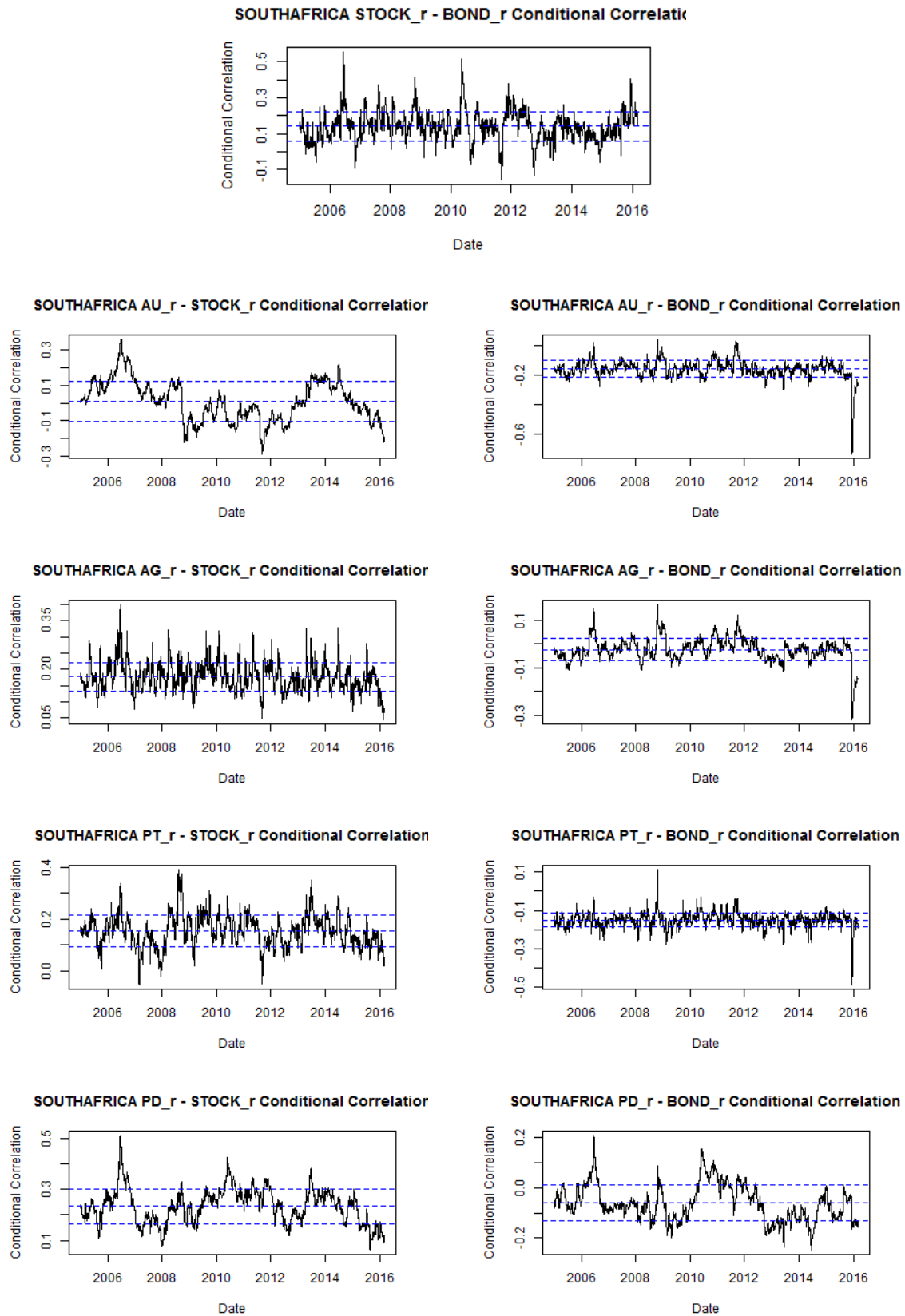


Figure 4.22: Dynamic conditional correlation — South Africa



Chapter 5

Precious Metals as Safe Haven — Evidence

5.1 Introduction

Following previous analysis of the dynamics between the four precious metals returns with stock or bond market returns by applying Engle [2002]’s Dynamic Conditional Correlation (DCC) across eleven countries including the US, UK, Germany, France, Italy, Switzerland, Canada, Japan, China, India and South Africa, this chapter evaluates the safe haven properties of four precious metals in those countries. Based on Baur and K.J.McDermott [2010] and Baur and Lucey [2010]’s methodology, a few modifications have been made in the modelling process to generate a series of daily safe haven incidents for each metal against stock and bond markets in each country.

5.2 Model

The standard approach to test for a safe haven, as outlined in Baur and K.J.McDermott [2010] and Baur and Lucey [2010], is applied. In identifying a daily safe haven status for metals, however, I apply a minor modification on the final safe haven dummy as explained below. For example, to test gold safe haven properties during stock market crashes, the

following equations are estimated using OLS:

$$r_{gold,t} = \alpha + \beta_t r_{stock,t} + \epsilon_t \quad (5.1)$$

$$\beta_t = C_0 + C_1 D_t(r_{stock}q_5) + C_2 D_t(r_{stock}q_{2.5}) + C_3 D_t(r_{stock}q_1) \quad (5.2)$$

Equation 5.1 models the relation of gold and stock returns. The parameter β_t is modelled as a dynamic process by Equation 5.2. The dummy variables denoted as $D()$ capture extreme stock market movements and:

$$D_t(r_{stock}q_x) = \begin{cases} 1 & \text{if } r_{stock,t} < r_{stock}q_x \\ 0 & \text{if } r_{stock,t} \geq r_{stock}q_x \end{cases} \quad (5.3)$$

$r_{stock}q_x = x\%$ threshold given by the 5%, 2.5% and 1% quantile of the return distribution over the full sample period, which are consistent with the thresholds specified in previous studies including Baur and Lucey [2010], Baur and K.J.McDermott [2010]. Please see Table 5.1 for the values.

The decision rules follow Baur and Lucey [2010] in that:

- If all coefficients, including C_0 in (5.2), are negative, then gold is a *weak* safe haven;
- If all coefficients, including C_0 , are negative and significant at 10% level, then gold is a *strong* safe haven. A 10% significance level is selected due to relatively rare incidence at higher significance level.

In some cases when the daily return falls under the 5% quantile but above 2.5% and 1%, hence $D(r_{stock}q_{2.5})$ and $D(r_{stock}q_1)$ are zeros, the above rule only applies to C_0 and C_1 . In order to obtain daily safe haven status, I made a few minor modifications:

- First, I run the above regressions over a quarter (i.e. 62 days¹). If the results meet the above requirements, I assign a preliminary safe haven dummy value as 1 to each day within this quarter;

¹The average number of business days of a quarter is 62 for our sample.

- Next, I sum up all these preliminary safe haven dummy results over the whole sample, by which accumulating results for each day from all the regressions containing this day, approximately 62 regressions on average. The result is a count falling within the range of $[0, 62]$;
- However, the accumulated safe haven results are only intermediate results, which are used to calculate the modified safe haven results by taking into account the extreme market returns. For those days in which the market return is not in the lower 5% quantile, the safe haven result is modified to 0. Hence the existence of a safe haven is aligned with exact dates of market stress.

I firstly obtain daily weak and strong safe haven results. Since strong safe haven status is extremely rare, this is an interesting finding in and of itself, I conduct the explanatory analysis only on weak safe haven results in Chapter 6. For ease of exposition I show the accumulated daily and final safe haven results as a series of graphs (see Figures 5.1 – 5.11 for weak safe haven results and Figures F.1 – F.11 in the Appendix F for strong results). In these graphs, I highlight on what day each precious metal is found to be a weak or strong safe haven against bonds or equities in each country. In addition, I calculate the average *percentage* of time when a precious metal is as safe haven for each country (see Tables 5.2 and 5.3.) Finally, the numbers of daily incidents when precious metals act as weak and strong safe havens across countries are summed up and shown in Figures 5.12 and 5.13, finally, the top ten days along with market news on that day are listed in Table 5.4.

5.3 Results

5.3.1 The US

Precious metals are found as a weak safe haven 31% of the time against equity market stress and 24% of the time against bond market stress (i.e. return under 5% quantile), but extremely rare strong safe haven periods (0.8% against stocks and 0.1% against bonds). Strong safe haven status is fleeting and rare. Gold is less frequent than silver and palladium as a weak

safe haven against the S&P500. It functions as a weak safe haven relatively frequently in August 1997 and September 1998 during the Asian financial crisis, and it is a very good safe haven after the dot.com bubble burst in that it offered consecutive protection in February, April, July, October and December 2000. Although during this time period the S&P500 was rising and gold was sliding in general, gold hedged against daily market turbulence. Apart from this, gold offered safe haven protection in July 2007 just before the Global Financial Crisis but failed to offer further protection in the following market loss until June 2008. Gold was also a safe haven in late January 2010 driven by worries about the White House's bank plan, Ben Bernanke's term end and China's lending curbs; as well as on 15 April 2013, when the stock market fell by the second worst amount that year due to a steep fall in commodity prices. The most recent safe haven episode was on 13 January 2016 when S&P500 dropped by 2.5% following the crash in crude oil prices and China's stock market tumbling into a bear market. Silver, platinum and palladium coincide with gold as a safe haven during some periods such as July 1998, July 2008, August 2015 and recently January 2016. However, there are many periods when other precious metals are a safe haven while gold is not.

5.3.2 The UK

Results from the UK show that on average precious metals acted as a weak safe haven 28% of the time against FTSE100 extreme falls and 27% of the time against the bond market (less than average level among eleven countries). Strong safe haven results are rare as well, on average 0.4% and 1.7% of tail events in stock and bond markets respectively. Gold was a safe haven against FTSE100 34% of the stressful times, one of the highest among the eleven countries considered here. The periods when gold acted as a weak safe haven against FTSE100 are clustered during September 2001 (including 11th September when the FTSE100 dropped by 5.9%), July and September 2008, April 2012 and most recently on 2nd February 2016 when the FTSE100 fell by 2.3% and 20th January 2016, then FTSE100 fell by 3.5%. Silver, platinum and palladium share many similar pattern with gold as a safe haven against FTSE100 such as September 2001, July 2008, May 2012, June 2013 and January 2016. However, precious metals fail to provide safe haven hedge during the market panic

following the Brexit referendum on 24th June 2016. Regarding the bond market, gold is also better than the other three as safe haven against bond index falls 36% of the time. Precious metals have offered safe haven hedge for some of the largest falls in bond market such as on 2nd April 2009 when the index fell by 1.7% and 29th December 2009 when there was a 1.5% fall.

5.3.3 Germany

In Germany, precious metals offer slightly more safe haven opportunities against stock market falls than bond market falls (36% and 27% of the stress time respectively on average). On average, gold functions as weak safe haven much more frequently than the other three metals with 40% of the stress time in stock market. It was a safe haven against DAX30 in April 1997, October 1998, March 1999, September 2001, September 2008, and most recently on 5th April 2016 when the index fell by 2.7%. On 11th September 2001 when DAX30 dropped the most in the examined period of 8.9%, only gold was the safe haven, while others not. However silver, platinum and palladium do share many other safe haven results with gold such as in April 1997 and March 1999. And they have all been safe haven after the Global Financial Crisis breakout in 2007. Precious metals as safe haven against German bond index is less than the average level among the eleven countries. Precious metals again share similar results such as in April 1994, August 2002, August 2011 and January 2013. Precious metals have provided some protection against one of the largest index falls such as on 24th May 1994 when the index dropped by 1.4%.

5.3.4 France

Precious metals provided more safe haven opportunities against bond market falls than stock market falls in France (31% of the stock market stress time and 35% of the bond market stress time). On average, platinum is the most frequent safe haven against stock and bond markets falls. For the stock market, precious metals have offered safe haven opportunities on some of the biggest single day crashes, for instance gold was a safe haven on 11th September 2001 when the CAC dropped by 7.7%, and other metals failed to be a safe haven. Similarly

on 24th March 2003 and 14th September 2001 when gold was safe haven while others are not. However, there are also cases when other metals functioned as safe haven while gold is not, such as on 21st January 2008 when CAC dropped by 7.1% and only palladium was safe haven, as well as on 15th and 19th July 2002 when the index dropped by more than 5%, only silver was safe haven. Precious metals as safe haven during the Global Financial Crisis in 2007–2008, however, last a relatively short time compared with other countries. Regarding the bond market, safe haven periods are mainly clustered in May 2001, July 2002, March 2008, June 2012, December 2013 and most recently November 2015.

5.3.5 Italy

Similar to Germany and France, precious metals function as safe haven 36% and 35% of the stock and bond markets extreme time respectively. Gold is the best safe haven in that it is safe haven 40% of the stock market extreme events, followed by silver, platinum and palladium. The biggest drop of the FTSEMIB index from January 1998 to June 2016 is on 24th June 2016 following the Brexit referendum, however precious metals failed to provide protection. Nevertheless, gold has been a safe haven on the second and third biggest losses on 6th October 2008 when FTSEMIB fell by 8.6% and on 11th September 2001 when it dropped by 7.9%. Silver, platinum and palladium share similar pattern with gold that they are safe haven in November 2000, September 2001, August 2007, September 2008, September 2015, and most recently January 2016. As to the bond market, silver is actually the most frequent safe haven followed by platinum, palladium and gold. Safe haven events clustered mainly in June 1999, March 2003, 2008, and most recently on 7th April when the bond index dropped by 0.75%.

5.3.6 Switzerland

On average, precious metals act as a safe haven against the Swiss Market Index (SMI)'s extreme events 34% of the time and against the Swiss government 10Y bond extreme falls 35% of the time from 1994 to July 2016. This is slightly above the average level of the eleven countries considered here. Silver is actually the most frequent safe haven against both SMI

and bond index. Gold functions as safe haven again on 11th September when SMI fell by 8.1% , though not against bond market falls, and other metals did not have the similar effect. Silver, platinum, and palladium did function as safe haven against some other big losses in the market, such as on 22 March 2001 when the SMI fell by 3.8% as a result of deepening gloom about the outlook of the American economy and its spillover to the world economy. Other safe haven periods are around September 2001, May 2008, August and September 2011 due to fears of contagion of the European sovereign debt crisis, and most recently in January 2016. Regarding the bond market, precious metals are a safe haven mainly in August 2014, 2008, May 2010, June 2012 and December 2015.

5.3.7 Canada

Precious metals are safe haven against stock market falls in Canada 29% of the time, one of the lowest among all countries, and against bond market extreme events 37% of the time, the highest among all. Precious metals as safe haven against stock market crashes are mainly around September 2001, July and October 2002, June and July 2008. Only gold and silver are safe haven in the end of 2009 though. And only silver, platinum and palladium are safe haven in January 2006, while gold is not. Besides, unlike the previously discussed countries, on 11th September, all four precious metals functioned as safe haven. As to the bond market, four precious metals share some similar results such as June 1995, February 1999, July and August 2002, September 2008, July 2014, end of 2015 and more recently February 2016.

5.3.8 Japan

Gold is better than others as safe haven against Nikkei225 index fall in Japan, 36% of the extreme events, while silver is the most frequent one against Japan government bond index fall, 39% of the stress time. On average precious metals are safe haven against stocks stress 30% of the time, and against bond index crashes 34% of the time, about the average level compared with other countries. There are some clustering periods when all metals are safe haven against Nikkei225, such as in July 2001, March 2002, March 2007, April 2009, May 2012, August 2013 as well as January 2016. During Asian financial crisis from 2007 to 2009,

however, it is mainly gold and silver functioned as safe haven. In addition, unlike other countries, only platinum functioned as safe haven after the September 11 attack in 2001, while gold failed, when Nikkei225 fell by 6.9%. As to the bond market, precious metals offers safe haven hedge around October 1994, first quarter of 1998, January 2000, July 2008, and more recently May 2015 and March 2016.

5.3.9 China

Quite the opposite of Japan, platinum is the most frequent safe haven against stock market index SHCOMP, while gold is the least frequent. Results for bond market are similar though. On average, precious metals are safe haven about 32% and 35% of the stock and bond markets extreme events respectively. Some biggest falls of the SHCOMP index are during 2015 to 2016 stock market turbulence such as August 24 the “Black Monday” when the index lost 13%. However precious metals did not act as safe haven in these events. During the Global Financial Crisis, however, both silver and platinum are safe haven such as on February 27 and June 4 2007 when the index dropped by 9.3% and 8.6% respectively. Gold is safe haven against stocks in May 2006, April 2009, May 2010, July 2011, December 2014 and May 2015. Silver, platinum and palladium share many of the same results with gold. As to the bond market, there are some biggest loss in a single day in the third quarter of 2013, and all precious metals have provided safe haven opportunities. Other times include July 2008, March 2009, July 2011, and December 2014.

5.3.10 India

Precious metals acted as a safe haven against NIFTY50 32 of the extreme time, about the average level among all countries. Palladium is the most frequent safe haven against stocks followed by silver, gold and platinum. All precious metals are safe haven in September 2003, March 2004, and May 2015. And palladium offers some unique safe haven hedge in the fourth quarter of 2008 such as on October 24 2008 when NIFTY50 lost more than 13%, while gold and silver are safe haven only in the first and second quarter of 2008. On September 11 2001, NIFTY50 lost 4.1% and only platinum and palladium function as safe haven, while gold and

silver did not. In general, safe haven result for bond market is less frequent with 26% of the extreme time. And gold is the most frequent among four metals followed by platinum, silver and palladium, however the difference is quite small. Safe haven episodes are mainly around May 2002, April 2005, first and second quarters of 2007, third quarter of 2009, and most recently May 2015.

5.3.11 South Africa

In South Africa, precious metals offer much more safe haven hedge against stock market crashes than bond market falls. Precious metals were a safe haven against JSE40 falls 43% of the time, and platinum offer safe haven hedge more than half of the extreme events, exceptionally high. For bond market, it only offer safe haven hedge 26% of the time. JSE40 has some biggest loss in 2008, when precious metals offered safe haven hedge, such as on June 10 when JSE40 lost by 8%, October 15 when it dropped by 7.8% and so on. In general all metals have positive safe haven results in July 2002, February 2006, August 2010, November 2011, December 2014, and most recently September 2015. Gold is rarely the only safe haven metal. Platinum is the most frequent safe haven against bond market crashes, about 30% of the time, followed by palladium, silver and gold. Safe haven results are mainly around March 2001, July 2003, June 2005, third quarter 2006, fourth quarter 2013, December 2014 and March 2015. And platinum offer some unique safe haven hedge in the first quarter of 2000 and fourth quarter 2010.

5.3.12 Average safe havenness

Table 5.2 and Table 5.3 show the average weak and strong safe havenness for each metal in each country, which refers to the proportion of time when a metal functions as a weak or strong safe haven over the examined time frame. As Table 5.2 shows, precious metals could provide weak safe haven hedge about 33% of the time against stocks and 31% of the time against bonds, when the asset return fall is in the lower 5% region. On average, gold is *not* the most frequent safe haven across eleven countries.

In general, precious metals perform better as weak safe haven in the US, Germany, Italy,

Switzerland and South Africa. In the US, silver is the best safe haven against S&P500 and bond market falls (50% and 28% of the time respectively), followed by palladium (35% against stock and 19% against bond), gold (31% against stock and 26% against bond) and platinum (26% against stock and 24% against bond). However gold is the best safe haven in UK, against both stock and bond market events, 34% and 36% of the time respectively, followed by the others. In Europe, precious metals as a safe haven against stock market events is slightly more common in Germany and Italy than Switzerland and France; while against bond market 5% drawdowns, it is more common for France and Italy than Germany and Switzerland. Gold is the most common safe haven against stock market in Germany and Italy, but not in France and Switzerland. Gold is more usual than the other three metals as safe haven against Canadian bond market declines (42% of the time), while silver is more common against Canadian stock market falls (32% of the time). Gold is the most common against Nikkei225 index falls (36% of the time) but the least common against Japanese bond index declines (30% of the time). Results for China are at the average level across countries. Interestingly, gold is the least common safe haven for both stock and bond market declines in China. Gold is a safe haven against India stock market declines 30% of the time, less frequent than palladium and platinum, however it is more likely than the others to hedge bond falls. Precious metals are much more of a safe haven against South African stock market falls (43% of the time), than bond market (only 25% of the time). Gold is not as frequently a haven as are platinum and palladium in South Africa. Strong safe haven results are very sparse across all countries as shown in Table 5.3, on average less than 1% of the time.

5.4 Conclusion

Most literatures examining precious metals' safe haven properties focus on gold as safe haven against stock markets, and the analysis is usually carried out over the entire history rather than in a time-varying fashion. Therefore, most of the safe havenness results obtained in this chapter are quite novel. However, some patterns are consistent with previous studies. For example, the finding that gold is safe haven against the US stocks more often than it is

against the US bond index (31% vs 26%) in this study, is consistent with findings in Ciner et al. [2010]. Despite of using a different rolling regression method to obtain time-varying safe haven status, Ciner et al. [2010] find that gold functions as safe haven against US bonds 59% of the time, compared with 55% of the time against bonds from 1990 to 2010. Similarly, results in UK is also consistent with this study that gold is safe haven slightly more often against the UK bond index than against the stock index (44% vs 43% of the time). In addition, this study finds that gold is safe haven against Canadian stock market in only 29% of the time compared with 34% on average among eleven countries, and also the least among G7 countries. This finding is also consistent with previous studies such as Baur and K.J.McDermott [2010] and Beckmann et al. [2015]. Canada has many more natural resource firms in the stock market index than other G7 countries. As a result, its stock market is more likely to co-move with commodity prices. In addition, previous studies find mixed results regarding to whether gold is safe haven against developed countries but not emerging economies stock markets. For example, Baur and K.J.McDermott [2010] find that gold is not a safe haven for large emerging markets such as the BRIC countries. However, in a later study with a different model, Beckmann et al. [2015] concludes that gold is a safe haven in China, South Africa and particular a strong safe haven in India. Applying rolling regressions, this study finds that although emerging markets don't always respond to global shocks in the similar way with developed markets. There are incidents when they also park investments in precious metals to avoid the global risks, as highlighted in Table 5.4.

In summation, precious metals provided protection at different times across countries. No precious metal provides safe haven status consistently, over time or across asset classes. Strong safe haven status is rare. Given these findings, I now turn to the explanation for why safe haven status does or does not occur in each country at specific times in the next chapter.

Table 5.1: Values of 1%, 2.5% and 5% quantile in market returns

	1% Quantile	2.5% Quantile	5% Quantile
US Bond	-1.1%	-0.9%	-0.7%
US Stock	-3.3%	-2.4%	-1.8%
UK Bond	-0.9%	-0.7%	-0.6%
UK Stock	-3.2%	-2.5%	-1.9%
Germany Bond	-0.9%	-0.6%	-0.5%
Germany Stock	-4.4%	-3.2%	-2.4%
French Bond	-0.9%	-0.6%	-0.5%
French Stock	-4.1%	-3.0%	-2.3%
Italian Bond	-1.1%	-0.8%	-0.6%
Italian Stock	-4.8%	-3.5%	-2.6%
Switzerland Bond	-0.6%	-0.5%	-0.4%
Switzerland Stock	-3.6%	-2.5%	-1.9%
Canadian Bond	-0.9%	-0.7%	-0.5%
Canadian Stock	-3.2%	-2.3%	-1.7%
Japanese Bond	-0.7%	-0.5%	-0.4%
Japanese Stock	-4.1%	-3.1%	-2.4%
Chinese Bond	-1.1%	-0.7%	-0.4%
Chinese Stock	-5.5%	-4.0%	-2.9%
Indian Bond	-1.2%	-0.8%	-0.5%
Indian Stock	-4.2%	-3.3%	-2.3%
South Africa Bond	-1.2%	-0.8%	-0.6%
South Africa Stock	-3.8%	-3.0%	-2.2%

Figure 5.1: Weak safe haven results accumulated vs. modified — US

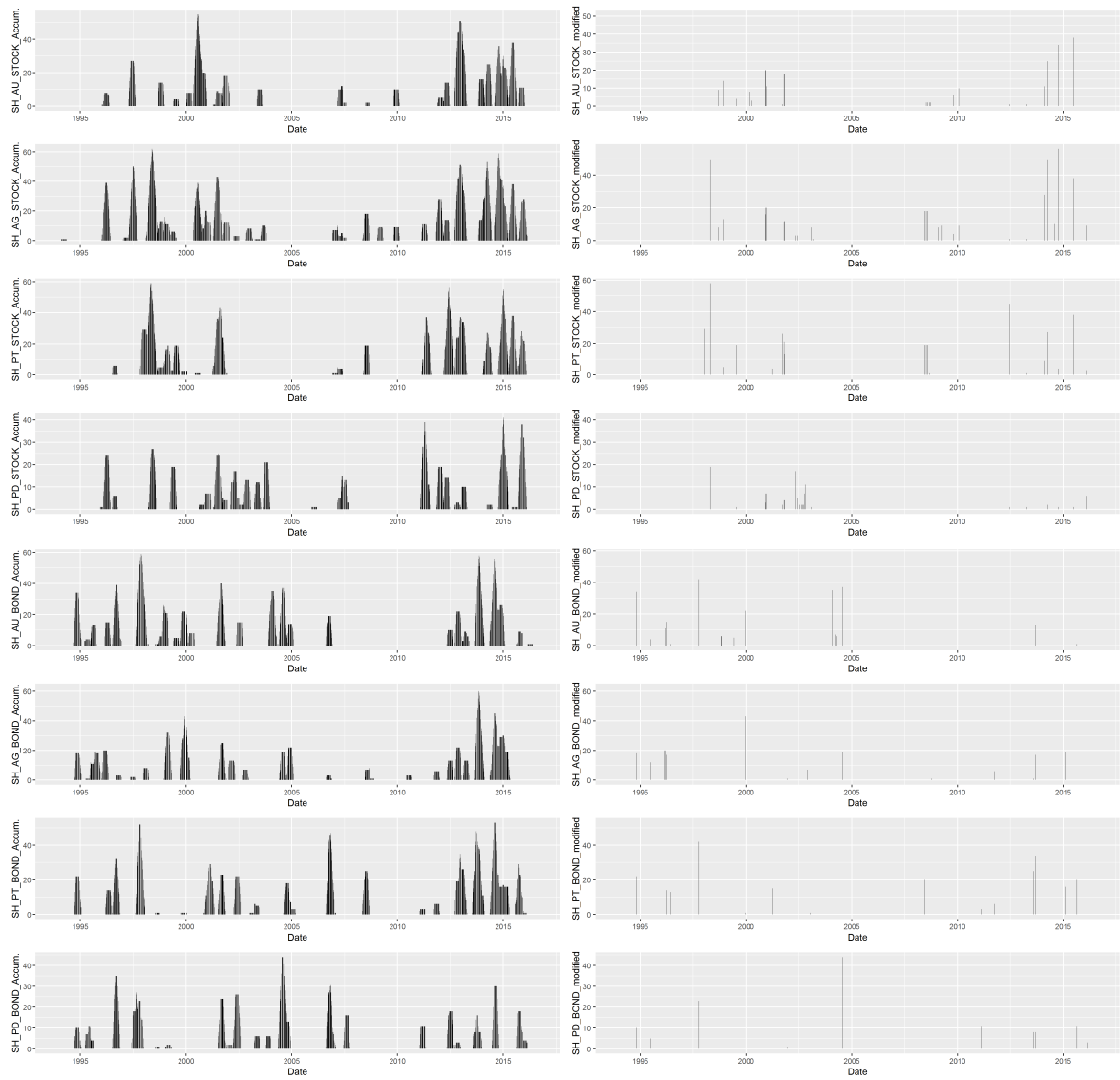


Figure 5.2: Weak safe haven results accumulated vs. modified — UK

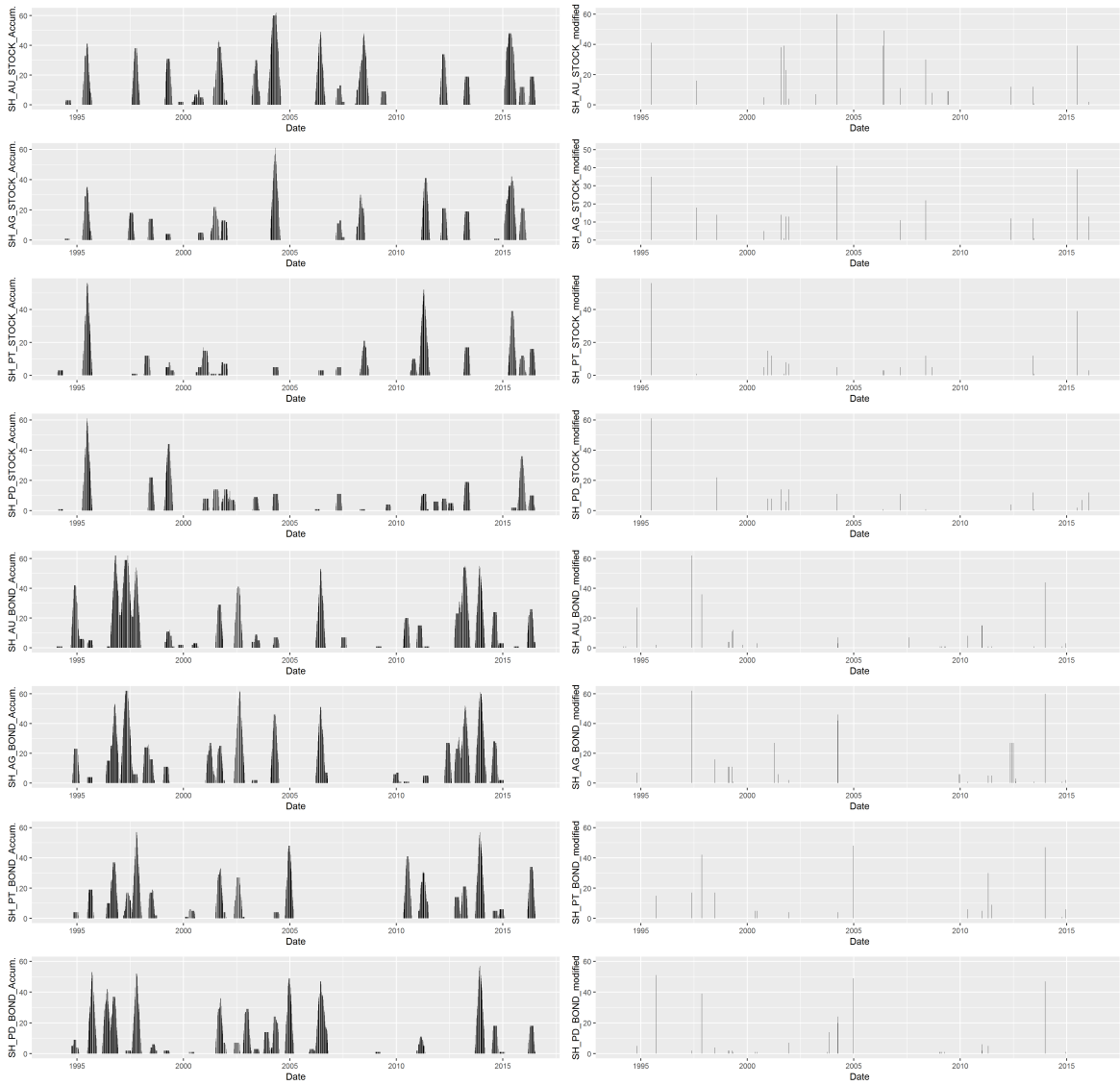


Figure 5.3: Weak safe haven results accumulated vs. modified — Germany

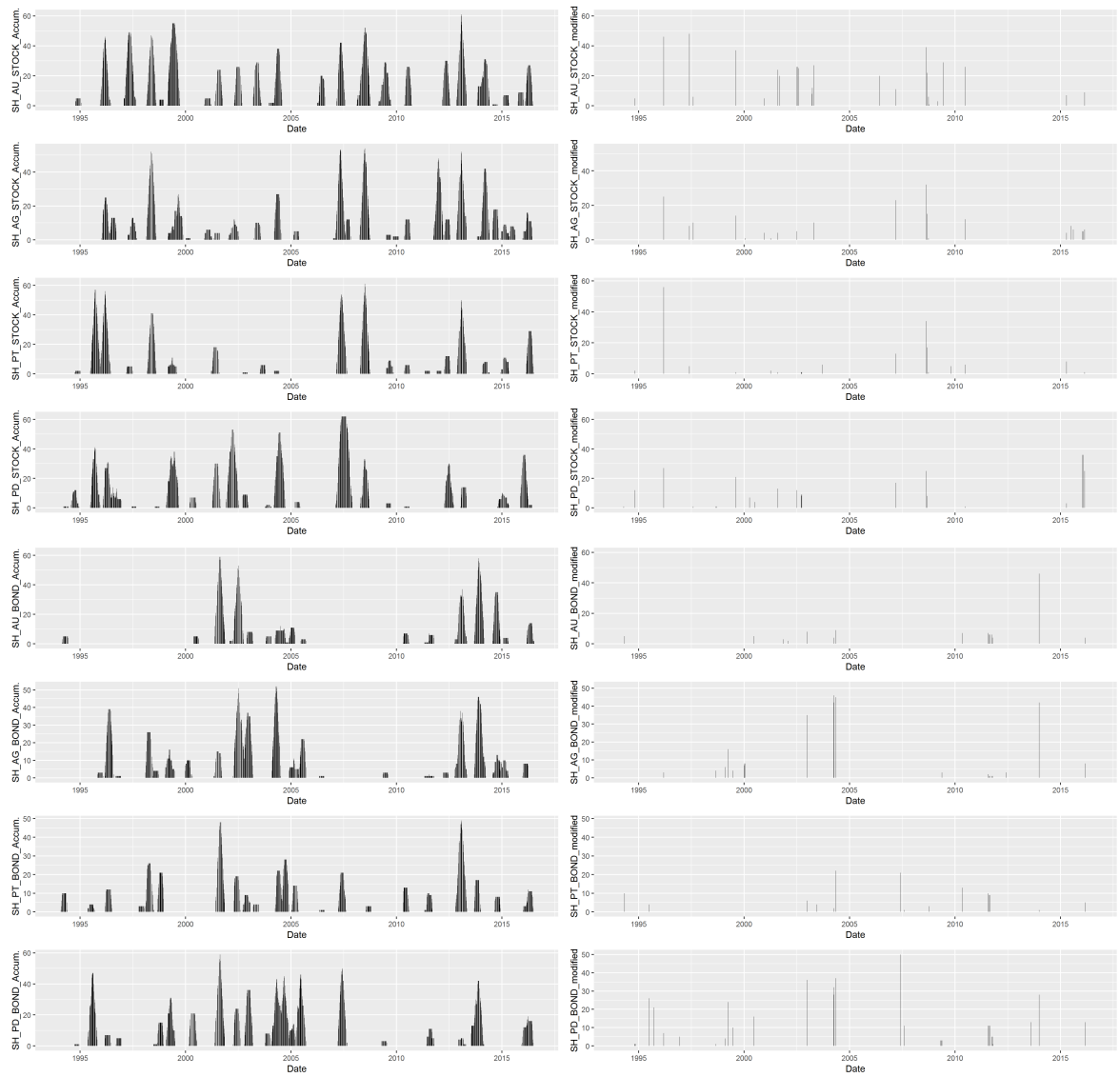


Figure 5.4: Weak safe haven results accumulated vs. modified — France

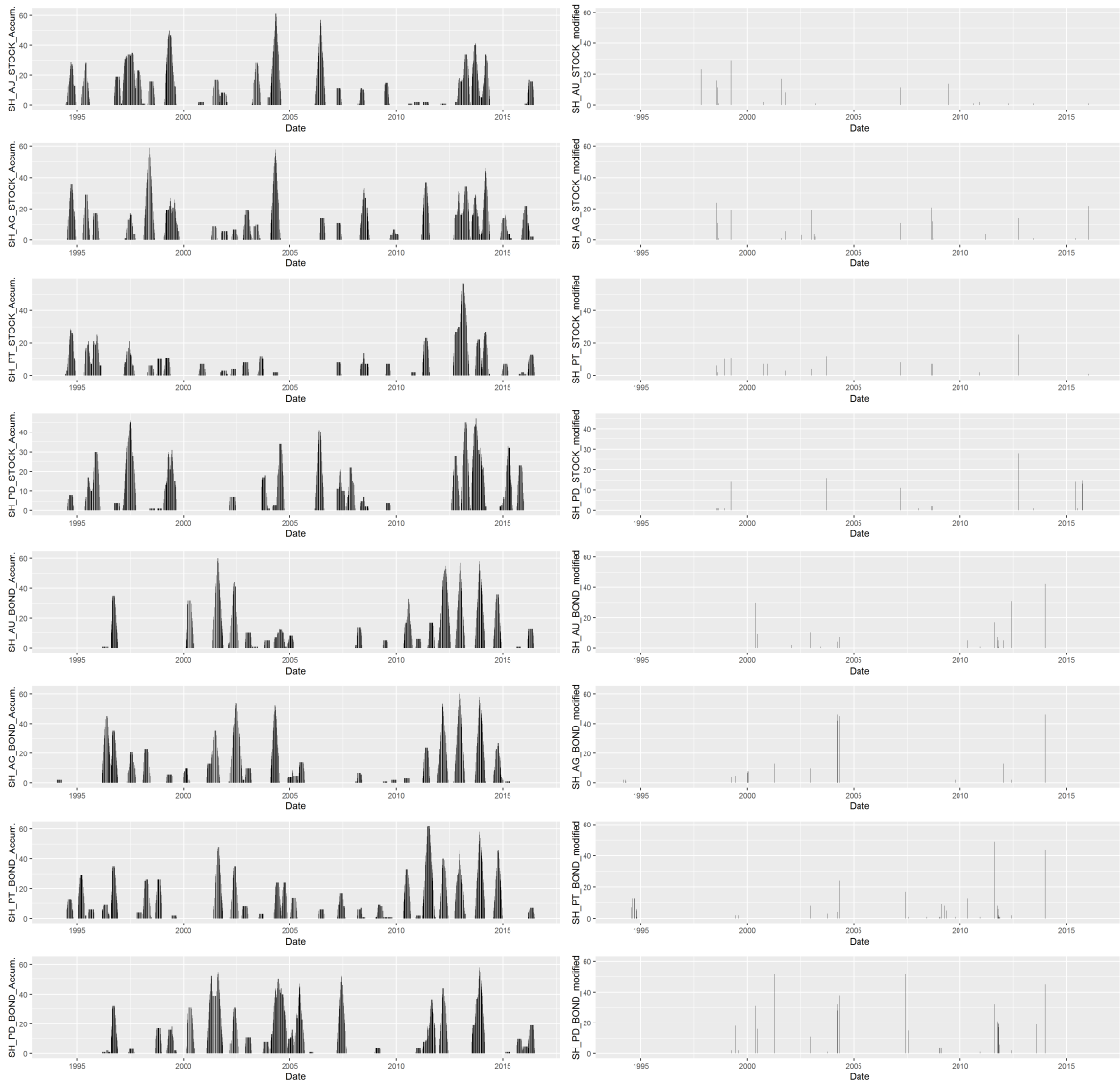


Figure 5.5: Weak safe haven results accumulated vs. modified — Italy

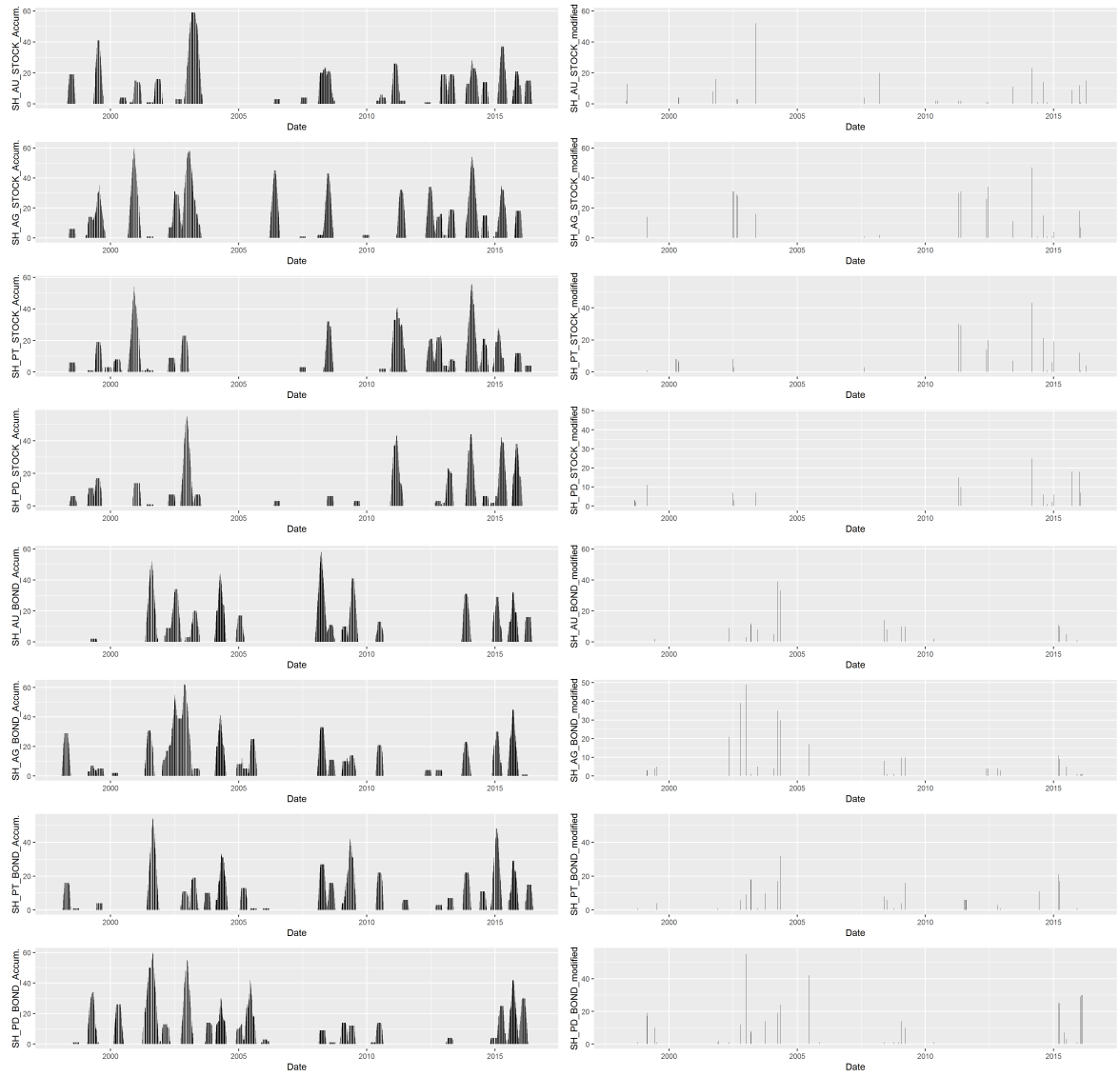


Figure 5.6: Weak safe haven results accumulated vs. modified — Switzerland

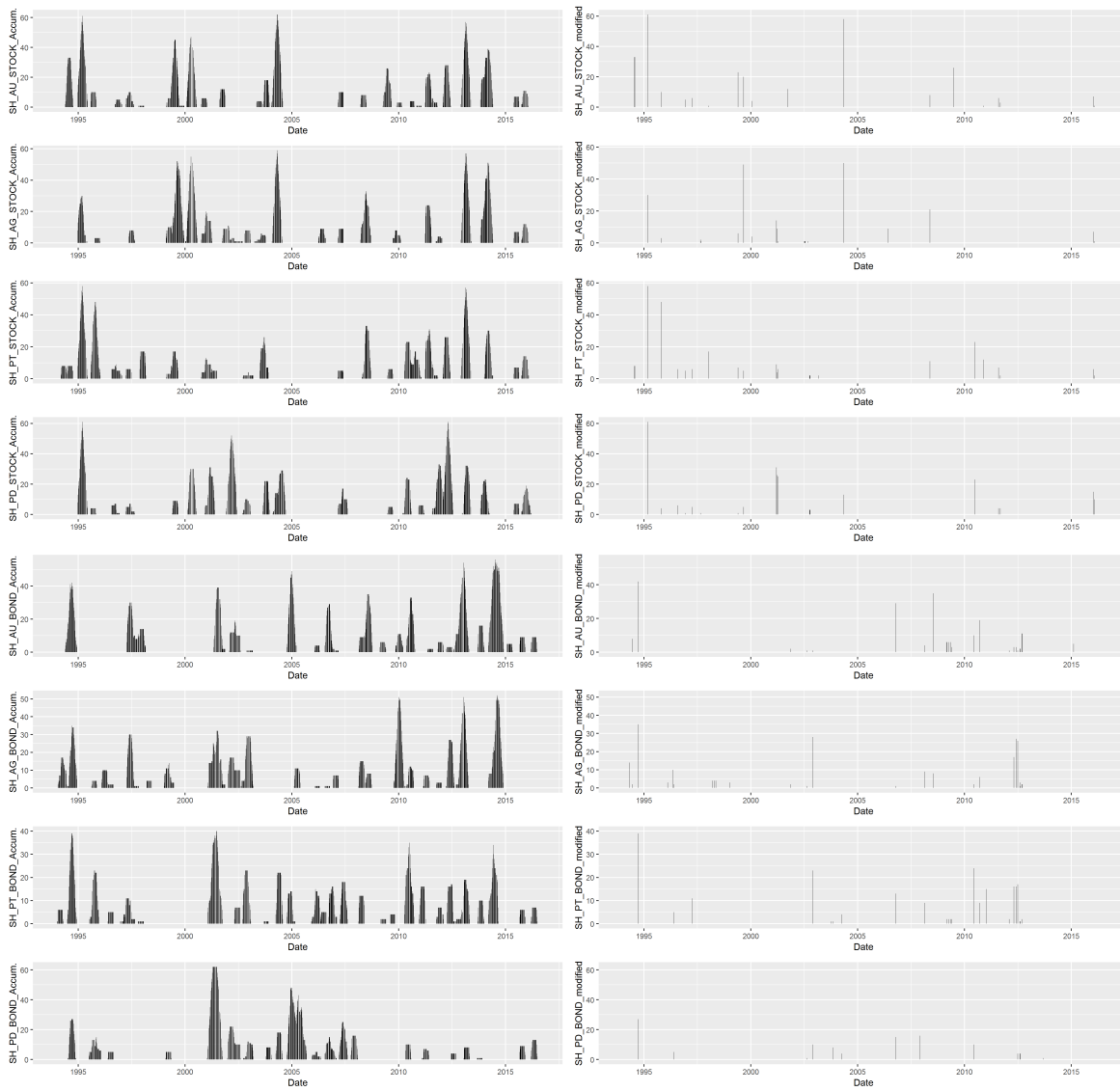


Figure 5.7: Weak safe haven results accumulated vs. modified — Canada

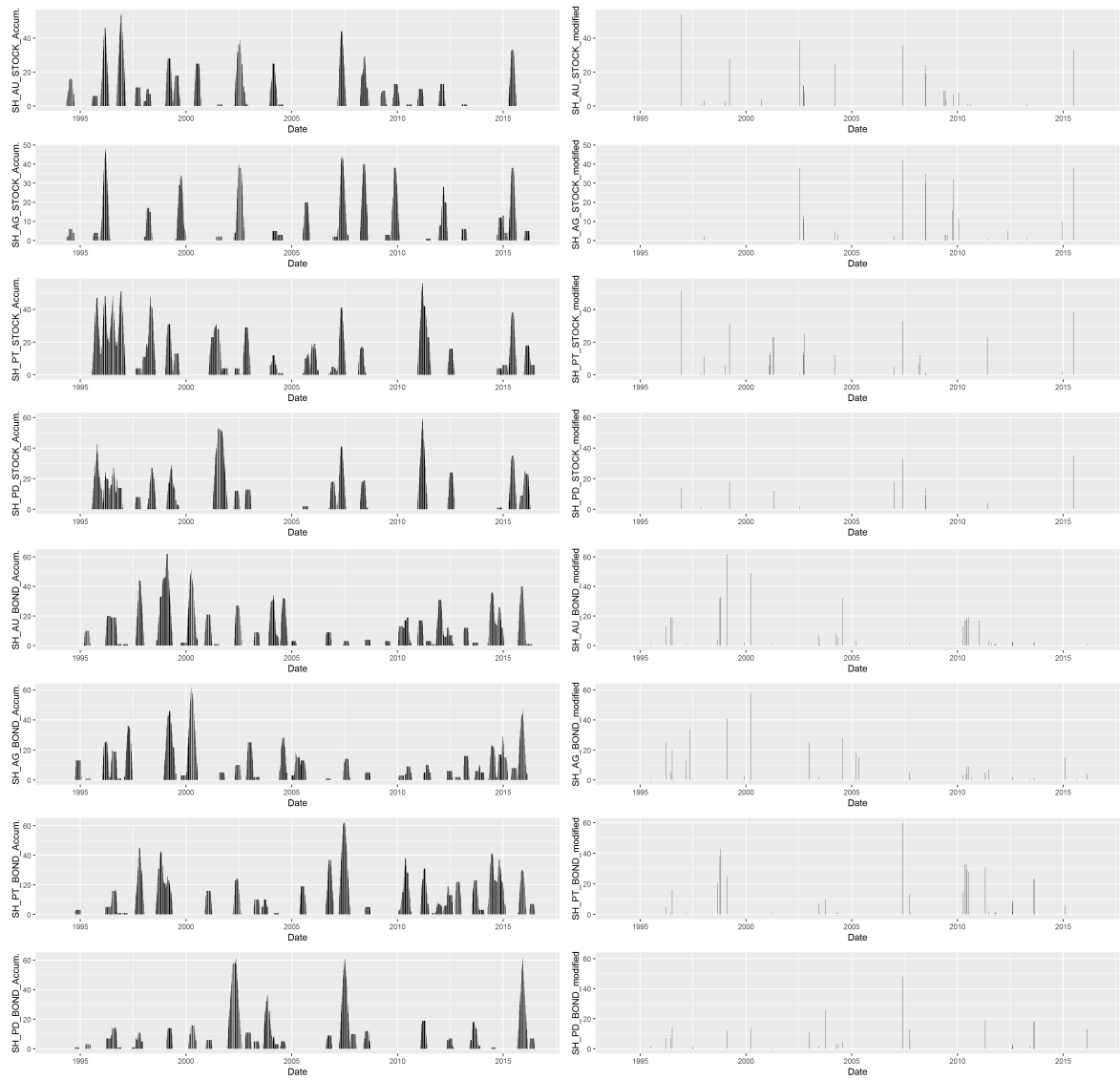


Figure 5.8: Weak safe haven results accumulated vs. modified — Japan

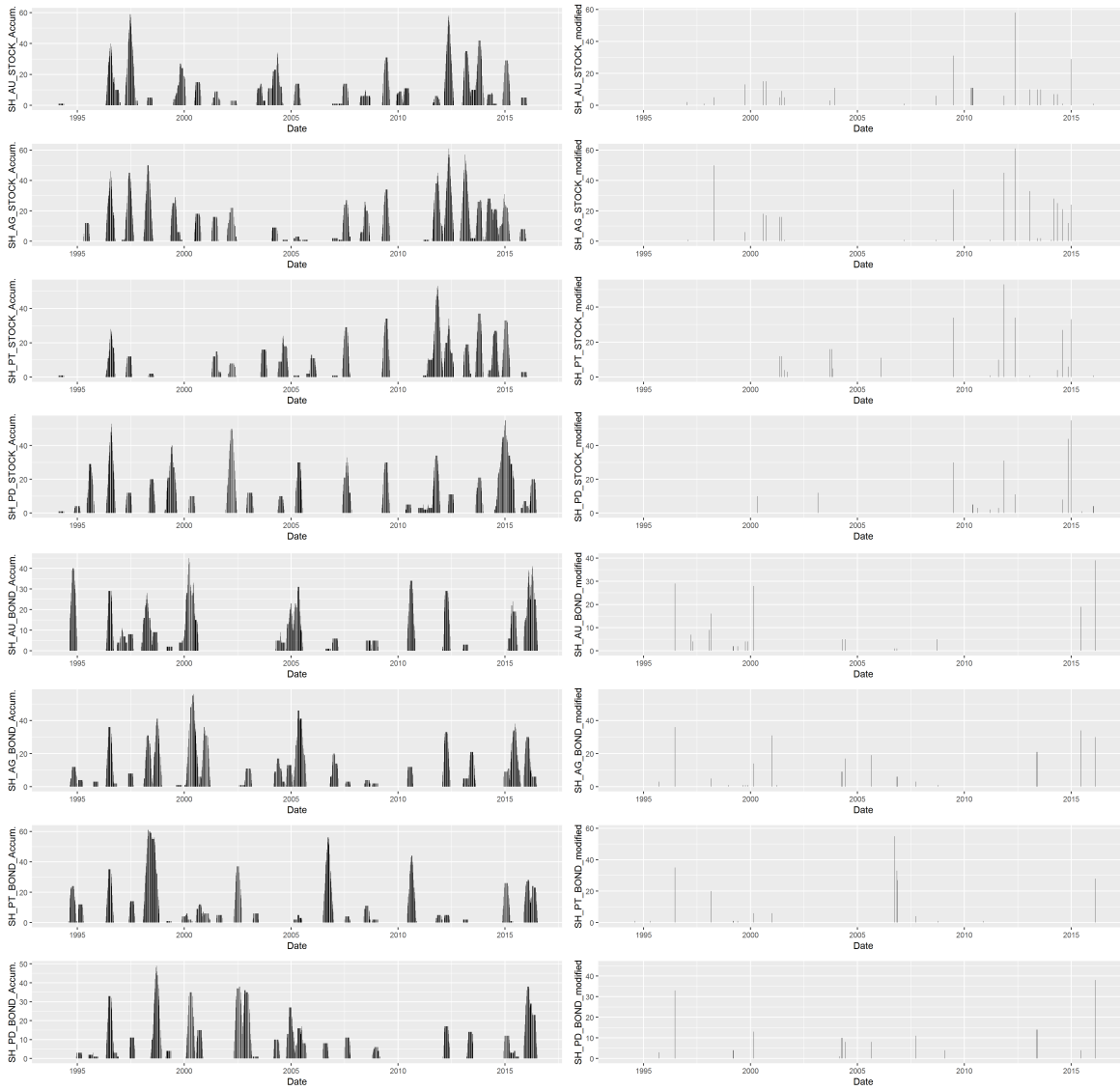


Figure 5.9: Weak safe haven results accumulated vs. modified — China

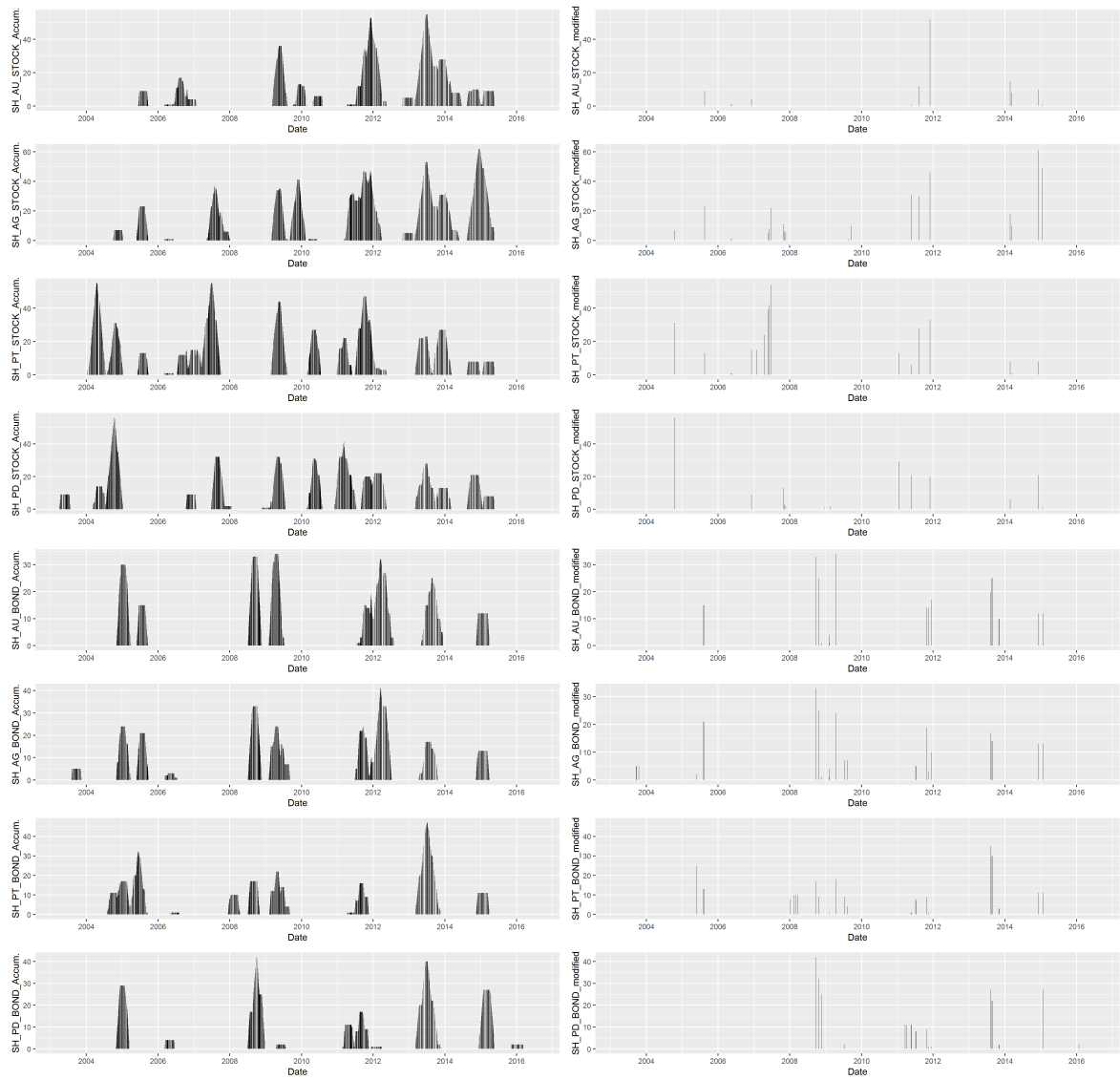


Figure 5.10: Weak safe haven results accumulated vs. modified — India

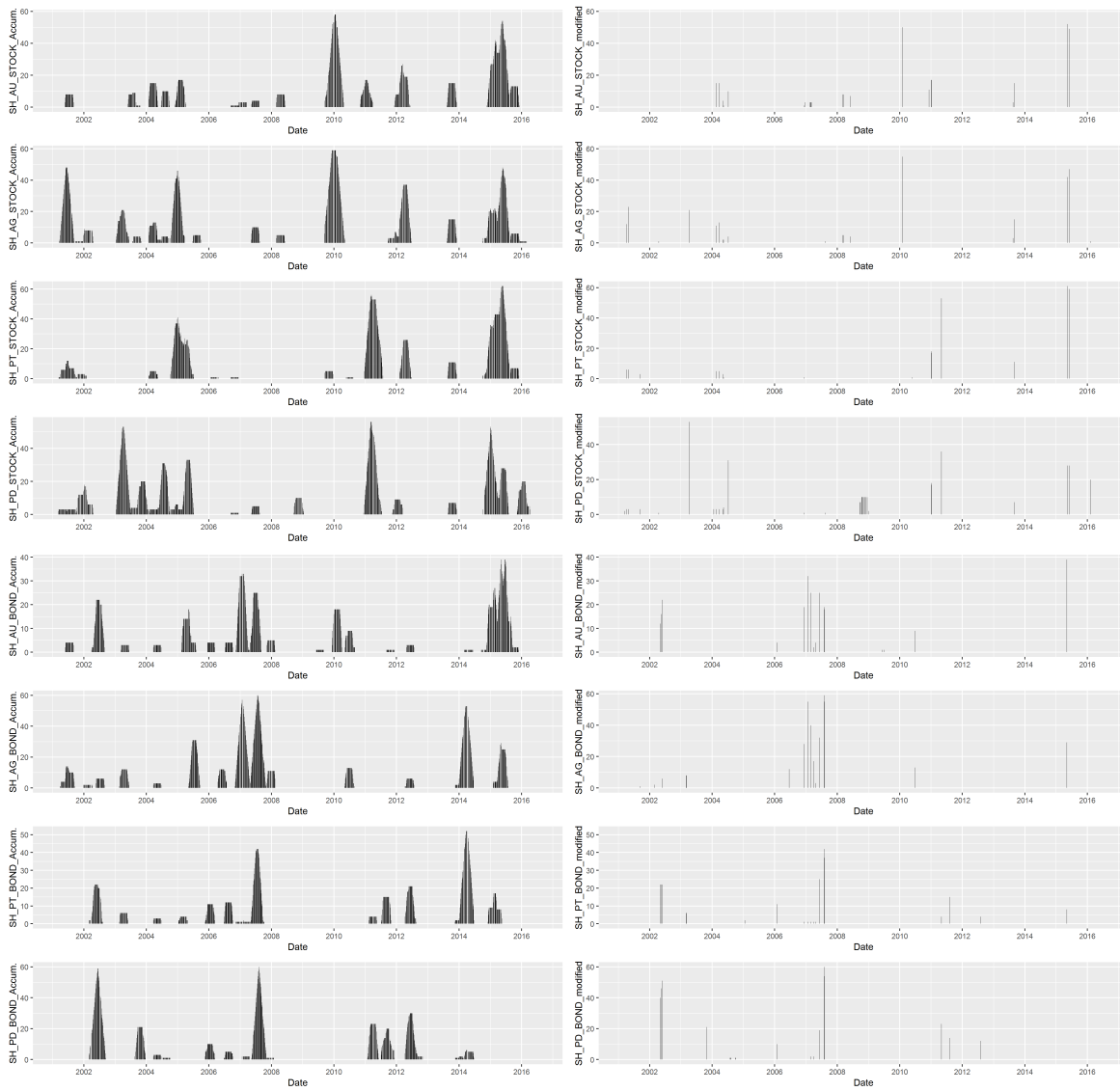


Figure 5.11: Weak safe haven results accumulated vs. modified — South Africa

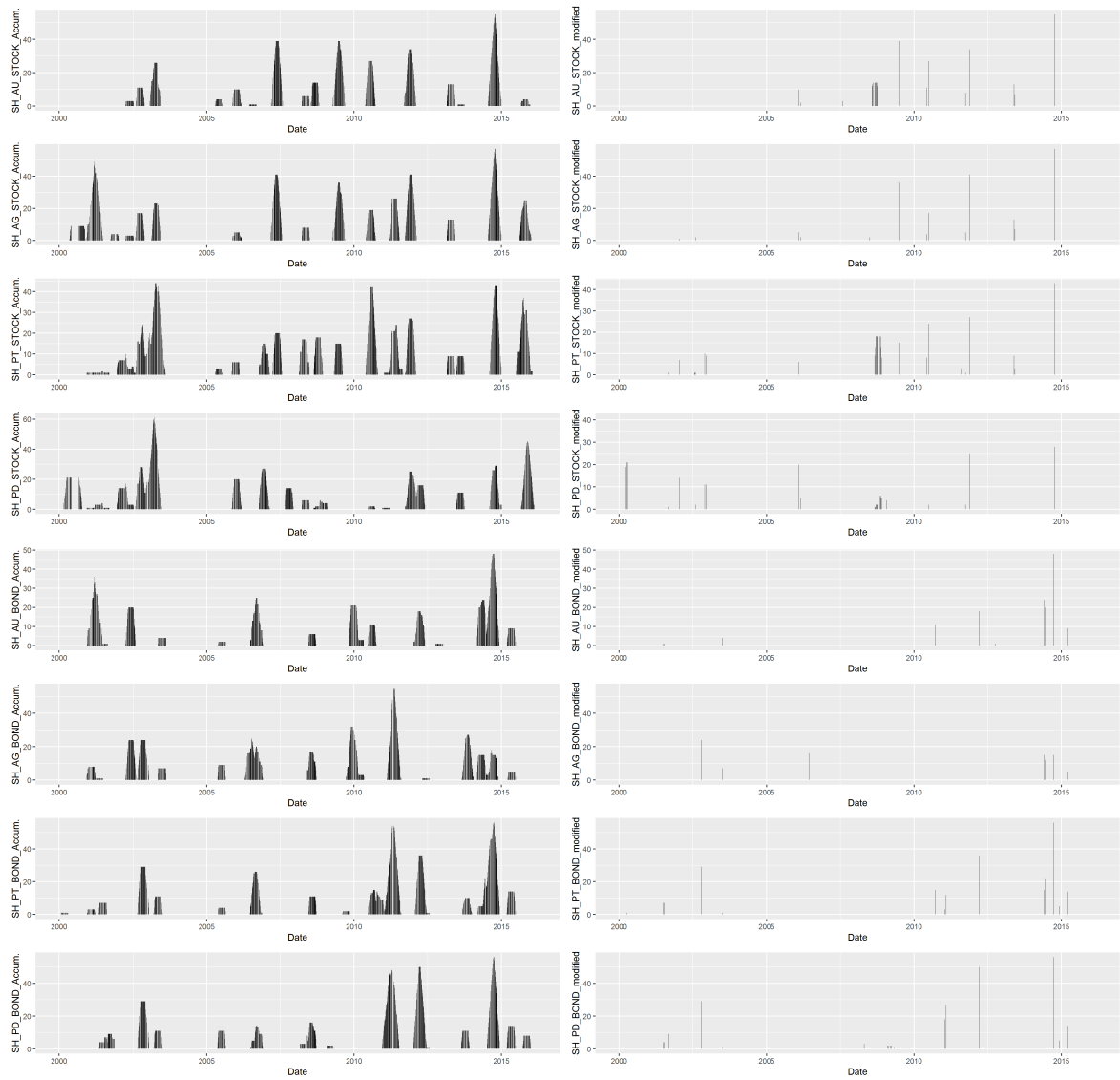


Table 5.2: Precious metals average weak safe havenness across countries

	AU.STOCK	AG.STOCK	PT.STOCK	PD.STOCK	Avg.%	AU.BOND	AG.BOND	PT.BOND	PD.BOND	Avg.%
US	31%	50%	26%	35%	35%	26%	28%	24%	19%	24%
UK	34%	25%	28%	26%	28%	36%	26%	21%	26%	27%
GERMANY	40%	37%	26%	40%	36%	23%	29%	25%	32%	27%
FRANCE	31%	38%	29%	28%	31%	30%	30%	47%	35%	35%
ITALY	40%	39%	35%	31%	36%	25%	43%	38%	36%	35%
SWISS	32%	38%	35%	32%	34%	33%	36%	32%	22%	31%
CANADA	29%	32%	31%	23%	29%	42%	39%	36%	32%	37%
JAPAN	36%	33%	24%	25%	30%	30%	39%	33%	33%	34%
CHINA	26%	36%	34%	30%	32%	29%	38%	43%	30%	35%
INDIA	30%	33%	23%	44%	32%	29%	25%	27%	24%	26%
SOUTHAFRICA	40%	34%	51%	47%	43%	20%	23%	30%	26%	25%
Avg.%	34%	36%	31%	33%	33%	29%	32%	32%	29%	31%

Notes:

1. Weak safe havenness is calculated as a percentage of time when precious metals are weak safe haven at extreme market events (i.e. when market return falls under 5% quantile of return distribution). For instance, gold has been a safe haven against S&P500 for 86 days among those about 278 days when the stock market crashed from January 4 to July 15 2016, hence $86/278 = 31\%$.
2. Bold indicates that the number is above average safe havenness across eleven countries.

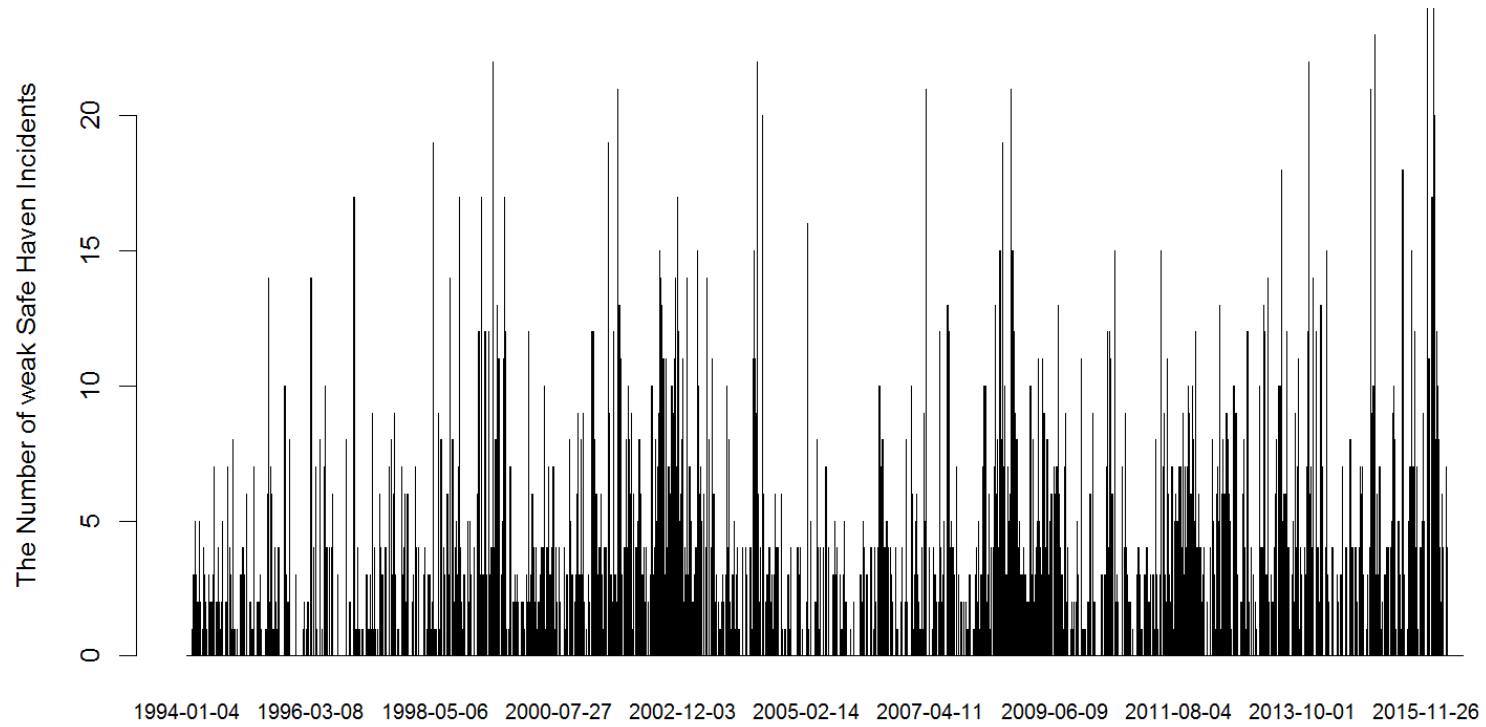
Table 5.3: Precious metals average strong safe havenness across countries

	AU_STOCK	AG_STOCK	PT_STOCK	PD_STOCK	Avg.%	AU_BOND	AG_BOND	PT_BOND	PD_BOND	Avg.%
US	1.1%	1.4%	0.7%	0.0%	0.8%	0.0%	0.4%	0.0%	0.0%	0.1%
UK	0.0%	1.4%	0.0%	0.4%	0.4%	2.1%	2.8%	1.8%	0.0%	1.7%
GERMANY	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
FRANCE	1.1%	1.1%	0.4%	0.4%	0.7%	2.8%	0.0%	1.8%	0.0%	1.2%
ITALY	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
SWISS	1.1%	1.1%	0.0%	1.1%	0.8%	0.4%	0.7%	0.7%	0.0%	0.4%
CANADA	0.0%	0.0%	0.7%	1.4%	0.5%	0.0%	0.4%	1.8%	0.0%	0.5%
JAPAN	0.4%	0.4%	2.6%	0.4%	0.9%	0.0%	1.5%	0.7%	0.0%	0.5%
CHINA	1.4%	2.8%	2.1%	0.0%	1.5%	0.0%	0.0%	0.7%	0.0%	0.2%
INDIA	1.6%	1.6%	1.6%	1.1%	1.5%	0.0%	0.0%	0.0%	0.0%	0.0%
SOUTHAFRICA	0.0%	2.8%	1.1%	1.7%	1.4%	0.6%	0.6%	1.1%	0.0%	0.6%
Avg.%	0.6%	1.1%	0.8%	0.6%	0.8%	0.5%	0.6%	0.8%	0.0%	0.5%

Notes:

1. Strong safe havenness is calculated as a percentage of times when precious metals are a strong safe haven at extreme market events (i.e. when market return falls under 5% quantile of return distribution). For instance, gold has been a safe haven against S&P500 for only 3 days among those about 278 days when the stock market crashed from January 4 to July 15 2016, hence $3/278 = 1.1\%$.
2. Bold indicates that the number is above average safe havenness across eleven countries.

Figure 5.12: Total number of incidents when precious metals as weak safe haven



Note: the aggregated number of weak safe haven incidents on a particular day is calculated as the sum of weak safe haven dummy indicating whether a precious metal acted as a weak safe haven on this day. For instance, on December 3 2015, there are 23 incidents, including gold, platinum and palladium as safe haven against US bond index (3 incidents), gold, silver, platinum and palladium as safe haven against FTSE100 (4 incidents), and so on. The full list can be found in Table 5.4.

Figure 5.13: Total number of incidents when precious metals as strong safe haven

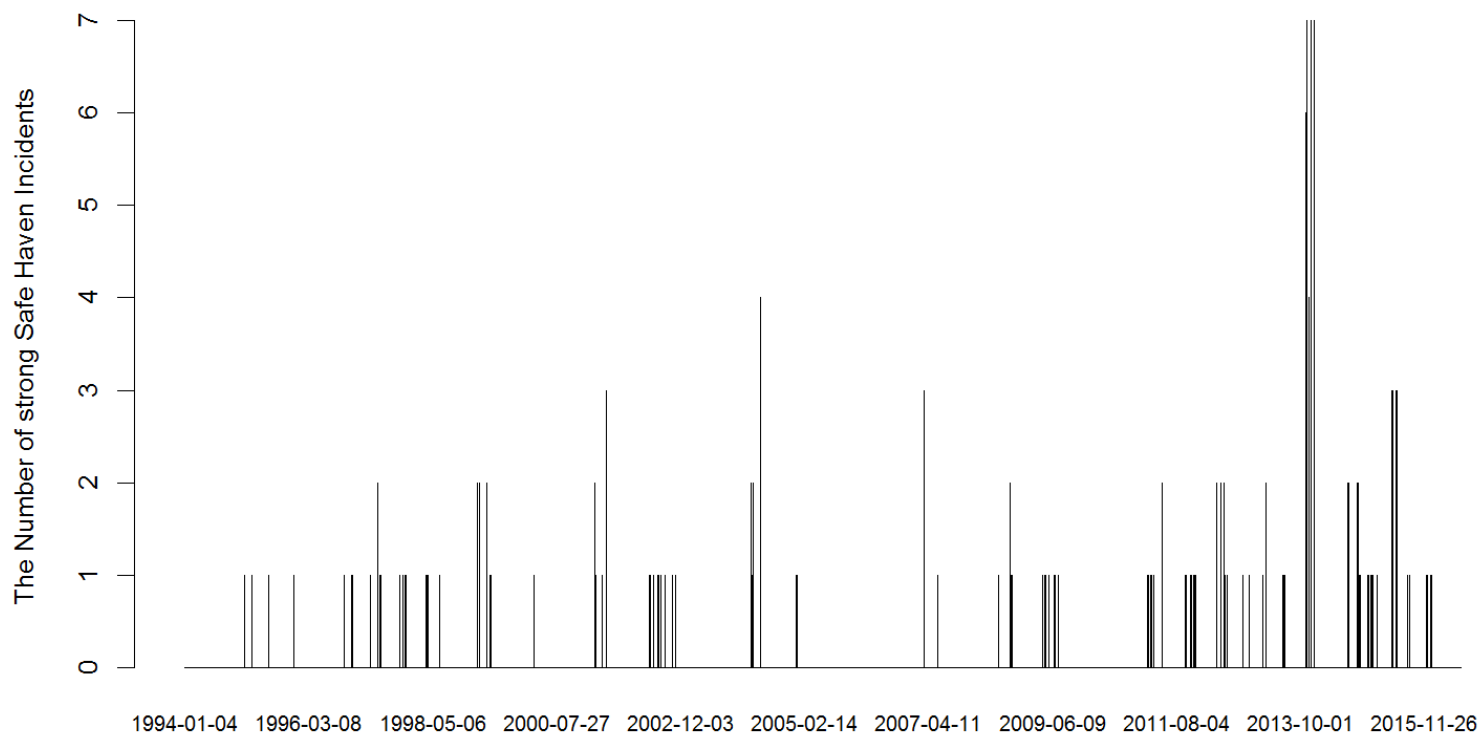


Table 5.4: Top ten dates with highest safe haven incidents

Sum	Date	Event		Stock				Bond			
				AU	AG	PT	PD	AU	AG	PT	PD
23	15/10/14	Fears of a global economic slowdown, tensions in the Middle East, uncertainty about the Federal Reserve and the spread of the Ebola virus	France	1		1	1	1	1	1	1
			UK	1	1	1	1	1		1	
			Switzerland	1	1	1	1				
			Germany			1	1		1		
			South Africa			1	1				
15	20/06/13	The chair of the Federal Reserve gave the clearest signal yet that America's huge stimulus pack1e will be slowed this year.	US							1	
			Germany	1	1	1	1				
			India	1	1	1	1				
			Italy	1	1	1	1				
			Canada			1	1				
14	14/05/12	Growing concerns about the eurozone debt crisis, and fears about a slowing U.S. economy.	France			1					
			China					1	1	1	1
			Canada	1		1	1				
			France			1	1				
			Germany						1	1	
12	11/08/10	Worries about European debt and slow of US economy.	Switzerland						1	1	
			UK			1					
			France	1	1	1	1		1	1	
			South Africa						1	1	
			Switzerland					1	1		
12	06/12/96	Federal Reserve Board Chairman Alan Greenspan gives a speech in which he suggests that "irrational exuberance" may have "unduly escalated asset values".	UK			1	1				
			UK	1	1	1	1				
			Germany	1	1	1	1				
			Japan		1	1	1				
			Switzerland			1					
10	16/09/08	Global Financial Crisis. After Lehman Brothers filed for bankruptcy protection and Merrill Lynch sold to Bank of America on 15th September	Japan		1	1	1		1	1	1
			India						1		1
			Italy			1	1				
10	15/12/14	Decline in oil prices and dismal economic data from China.	France		1	1					
			Germany		1	1					
			Italy		1	1					
			Switzerland		1	1					
			UK		1						
9	15/03/11	Japan's devastating earthquake and nuclear crisis.	Japan							1	
			France	1		1	1	1		1	1
			Germany	1		1	1		1		
9	23/04/12	Eurozone. economy was struggling to rebound from a fourth-quarter contraction and Dutch PM Mark Rutte resigned after austerity talks collapse.	Germany		1	1	1		1		
			UK		1	1	1				
			Switzerland		1				1		
8	27/10/97	Mini-crash caused by the economic crisis in Asia.	Canada			1				1	
			South Africa			1	1				
			UK			1	1				
			US							1	
			Switzerland	1							

Chapter 6

Determinants of Precious Metals as Safe Haven

6.1 Introduction

Built upon empirical evidence obtained from the previous chapter, this chapter attempts to identify robust economic and political determinants of precious metals safe haven properties applying zero-inflated Poisson regression (ZIP) and extreme bound analysis (EBA). In addition, a portfolio analysis is carried out testing whether precious metals add value to the stock or bond index portfolios with signals built from those exogenous determinants.

6.2 Model and data

Descriptive summary of the data for eleven countries can be found in Table 6.1 and data sources are listed in Appendix M. The potential determinant variables examined include three types of market stress indicators (i.e. financial market stress, political stress and consumer sentiment indicators) as discussed in Section 2.1.6, as well as six macroeconomic variables including nominal interest rate, inflation, exchange rate, industrial production, commodity market index and oil price.

The financial market stress measurements used include stock index volatility such as VIX

for the US published by the Chicago Board Options Exchange (CBOE), FTSE 100 Volatility Index for the UK published by FTSE, Vdax New Volatility Index for Germany published by the Deutsche Boerse, and so on; and comprehensive financial stress indices (FSI), including FSI index for the US published by the Federal Reserve Bank of Kansas City, the Euro Area Systemic Stress Indicator Composite Index for European countries (the UK, Germany, France, Italy) published by the European Central Bank and the Nomura China Stress Indicator published by Nomura Holdings, Inc.. For other countries, however, a composite financial stress indicator is either not available at all or published only recently and hence without enough history for this analysis. Political stress indicator collected is the Economic Policy Uncertainty Composite Index published by the Baker et al. [2013], it is available for all countries studied except for South Africa. Consumer sentiment data used are the University of Michigan Consumer Sentiment Index for the US, European Commission Economic Sentiment Indicator for the UK, Germany, France and Italy published by the European Commission, a separate Consumer Confidence EU Compatible for Switzerland published by European Commission as well, Canada Composite Leading Consumer Confidence Index published by OECD, and so on. Macroeconomic data collected are benchmarking nominal interest rate, such as the Federal Funds Target Rate for the US, Bank of England Official Bank Rate for the UK, etc.; inflation as measured by Consumer Price Index (CPI) and the ones published by the International Monetary Fund (IMF) are used for all countries; currency values as measured by its exchange rate with the US dollar and the Trade Weighted Broad Dollar value for the US dollar; industrial production indices published by IMF for all countries; credit spreads, published by Oxford Economics for all countries; finally the S&P GSCI Commodity Index and the Brent crude oil spot price for all countries. The above six economic variables normally have some empirical relationship with precious metals price or volatility movements (see studies of Batten et al. [2010] and Baur and Lucey [2010, 2017]), therefore it would be interesting to examine if these relationships also influence on precious metals safe havenness during market distress periods. Some of the explanatory variables have a shorter history. In order to examine all explanatory variables, the safe haven results are matched against it. The time period examined across countries are as follows: the US (January 1997 – March

2016), the UK (February 2000 – May 2016), Germany (February 2000 – May 2016), France (February 2000 – February 2016), Italy (April 2010 – March 2016), Switzerland (July 2005 – May 2016), Canada (October 2009 – April 2016), Japan (October 2000 – May 2016), China (February 2011 – December 2015), India (November 2011 – March 2016), South Africa (May 2007 – December 2015).

All the data are dis-aggregated into daily frequency¹. The Augmented Dickey-Fuller test is used to test stationary, and results are shown in Table 4.1. For those series which are not stationary, they are converted, via differences, to stationary series. Data is analysed firstly with Zero-inflated Poisson regression (ZIP) and then Extreme Bound Analysis (EBA). Zero-inflated Poisson regression rather than a basic Poisson regression is applied because the dependent variables, safe haven results, are overdispersed. By definition, safe haven results are obtained when market returns fall below 5% quantile, so it only happens less than 5% of the time. Nevertheless, overdispersion ratio is calculated (see Table G.1), which confirm that data are indeed overdispersed.

6.3 Results

6.3.1 ZIP

Results of ZIP are presented in Tables G.2 – G.12 in Appendix G. Similar patterns can be seen across countries for a few explanatory variables. For example, an increase of Economic Policy Uncertainty is found to be positively related to the likelihood of gold being a safe haven against stock market falls in France, Japan and India, and against bond market extreme events in the US, UK, Germany, France, Italy and India, albeit the coefficients are very small. The largest positive coefficient is 1.01 for Japan. This is consistent with previous literature which focus on the impact of political tension on the price of gold such as Ariovich [1983], Bilgin et al. [2018], Baur and Smales [2018]. It is also found to be significant for other precious metals such as silver against stock market crashes in the US, UK, France, Italy, Canada,

¹For example, to convert monthly Economic Policy Uncertainty Index into daily, the same value is applied to each day of the month. No other frequency conversion technique is used here.

Japan and China and so on. It suggests that precious metals are more likely to become safe haven during market distress triggered by policy instability across countries. The Economic Policy Uncertainty Index is not published for Switzerland or South Africa.

A Financial stress index is only available for the US and European countries. Results are quite mixed. Take gold as an example, Δfsi is a negative significant predictor of gold being a safe haven against the US stock market, but is a positive and significant predictor against the US bond market. It is, however, negative and significant for gold against both stock and bond markets in the UK. In Europe, it also shows different results across countries. When Δfsi increases, gold is more likely to be a safe haven against stock markets in Germany and Italy but negative in France. It has some quite large coefficients, especially as a positive determinant for gold against Italian stocks and German bonds, which is probably due to the small number of safe haven incidents. Similarly, stock volatility as measured by VIX in the US, VFTS in the UK, etc. also show mixed results across countries. $\Delta stockvolatility$ has a negative relationship with gold as safe haven against stock markets in the US, Germany, Italy, Switzerland and South Africa. However, it is a positive predictor for gold as safe haven in the UK, France, Canada, Japan and India. Furthermore, it is a positive predictor for gold as safe haven against bond markets in the US, Germany, France, Italy, Canada, Japan and South Africa. As to credit spreads, another indicator of economic uncertainty, its change is a negative predictor for gold, platinum and palladium as safe haven against the US stocks, however it is positive for silver. The change of consumer confidence is a significant predictor for gold as a safe haven against both stock and bond markets in the US and China. However it has opposite results, it is positive in the US but negative in China. Therefore given other variables remain the same level, a further decline of consumer sentiment is likely to have a negative impact on gold as safe haven in the US. In China, however, gold is more likely to be a safe haven when consumer confidence is further impaired.² Change of CPI, or inflation, is mainly a positive predictor for precious metals as a safe haven against stock market extreme

²The change of benchmark interest rate is rare relatively to other explanatory variables, possibly one of the reasons why it caused so many linear singularity problem in the Poisson regressions, which means that it almost perfectly separates or predicts the safe haven count results in some cases, such as Canada, China, India and South Africa. In other cases, despite not causing singularly problem, it has extreme large coefficients such as in the US, UK, Switzerland, Japan and China. It is mostly positive when it is significant.

events, suggesting that precious metals are more likely to be a safe haven against stock market declines under higher inflationary environment. However results are mixed for the bond markets. The currency value as measured by the trade weighted value of the US dollar or the exchange rate with the US dollar for other currencies shows an interesting divergence for stock and bond markets. It is a mainly positive determinant for precious metals as safe haven against stocks across countries, except for Germany and Canada. For bond markets, it is mostly positive for gold, however, for silver, platinum and palladium, it is positive only for the US, and in some cases for the UK, Germany, and South Africa, it has been mainly a negative predictor. Although we might expect the general commodity price environment to have more of an impact on the industrial metals — silver, platinum, and palladium — it is significant for gold as well. An increase of the oil price is a negative predictor for gold as safe haven against the US stocks but positive for bond markets. While it has opposite results for the UK and Germany in that it is positive as predictor for gold as safe haven against stock market and negative for bond market. For the Asian countries, the oil price is found to be a positive determinant for gold, platinum and palladium as a safe haven against China stock market, for platinum and palladium against the Indian stock market, and for gold as a safe haven against China and Indian bond markets declines.

6.3.2 EBA

The results of the ZIP analysis provide little consistent evidence on cross country determinants of safe haven status. Considering the relatively large number of potential determinants and potential various model specification, we attempt to isolate robust determinants. To do this we apply extreme bound analysis (EBA) in R with the package “ExtremeBounds”. The theory behind this has been discussed in the methodology chapter.

A naive extreme bounds analysis is conducted first, which considers all the combinations of potential determinants. Since the dependent variable is a safe haven count, the objective regression is further specified as a Generalized Linear Model. Although the results from naive extreme bounds analysis might be biased since it may not take into account the likely multicollinearity among the included variables as well as some variables measuring similar

concepts according to Hlavac [2004], they still provide valuable insights and are also used in the next step to set a more sophisticated extreme bound analysis³. In sophisticated EBA, those variables determined to be robust determinants in the previous naive analysis are set as *free* variables which are to be included in all regression models. Results from Sala-i-Martins version are considered and define a determinant as *robust* when its value of CDF (0) — the fraction of the variables cumulative distribution — is more than 85%. For example, VIX and EPU are robust variables for gold as safe haven against S&P500, which are then set as a free variable in the sophisticated version. The rest of the variables are set as focus variables, which enter as possible variables of interest. In addition we also specify variables which measure similar concepts as exclusive parameters, and thus not to be included in any regression at the same time. One set of mutually exclusive variables are specified: the financial stress indicators which include VIX and FSI for the US, FTSE and FSI for the UK, VDAX and FSI for Germany and so on. The *k* argument remains at its default value of 0:3, which means that rather than estimating all possible combinations of the doubtful variables in naive EBA, only up to three doubtful variables are added to the focus variable in each specification. Eventually however all focus variables are included in some specification. To further eliminate the influence of coefficient estimates from model specifications that suffer from high multicollinearity, a maximum acceptable variance inflation factor is set at 7. In addition, heteroscedasticity-robust standard error are used via the sandwich package and more weight is given to estimation results from regression models which provide a better fit. Finally the model remains set as general which does not assume any particular distribution of coefficient estimates across different model specifications.

Since EBA doesn't model excess zeros separately, results from which are expected to be different from zero-inflated Poisson regressions. Nevertheless, any common results from zero-inflated Poisson regression and Extreme Bound Analysis are more likely to indicate a robust determinant. In general, results from EBA show a more clear divergence between potential safe haven determinants across countries. Δ_{epu} is found to be a robust positive

³Although we do control for multicollinearity via selection only of those variables in each pass where the data pass a variance inflation test.

determinant for all four metals as safe haven against stock market crashes in the US, Japan and India. Coefficients tend to be very small though. Meanwhile, Δepu is a positive predictor for gold only but not other precious metals in Germany, France, Italy, Japan, China and India, however it is only robust in Germany and Japan. Results of stock volatility show a much clear picture from EBA, that it is dominantly a robust positive determinant for precious metals as safe haven against stock market, with two exceptions of India and Canada (positive but less robust). However results for bond markets show an interesting divergence that stock volatility has a negative impact on precious metals as safe haven in the US, UK, Germany, India and South Africa, however it has positive impact in Italy, Canada and Japan. However, results are quite mixed for composite financial stress indices Δfsi in the US, UK and European countries. An increase of $\Delta credit\ spreads$ is most of the time positively associated with gold, silver and platinum as safe haven against S&P500, however it is not robust as G.CDF, the value of the cumulative density function based on Sala-i-Martin's EBA, is less than 90%. G indicates that the objective regression is specified as a Generalized Linear Model, that it does not assume any particular distribution of regression coefficients across the estimated models. In Europe, it is a positive determinant for gold as safe haven against stock market crashes in UK, Germany and Italy, however it is negative in France and Switzerland. In Asia when gold is a safe haven against stocks, $\Delta credit\ spreads$ is more likely increasing in China and India, however decreasing in Japan and South Africa. $\Delta interest\ rate$ is more often to be a robust positive predictor for precious metals as safe haven against stock markets in the US, UK and European countries. However it is mainly a negative predictor for Asian countries.

6.4 Portfolio Analysis

As results show, economic policy uncertainty (EPU) and stock market volatility are positive and robust determinants when gold and sometimes other precious metals are safe haven against stock market crashes, and occasionally against bond market distress. In this section, a couple of trading strategies are designed using EPU and stock market volatility as indicators to examine how a portfolio of stock indices or government bonds with or without hedging from

precious metals would perform when trading off these two indicators. There are 7 countries with EPU and stock volatility data both available, which are the US, UK, Germany, France, Italy, Canada, and Japan. While China and India don't have stock volatility indices, Swiss and South Africa don't have EPU.

6.4.1 Setting up the Strategy

The hypothesis is that when EPU or stock market volatility increases, there could be downward pressure on stock or bond market indices returns, while there could be upward pressure on precious metals returns, and vice versa. Two types of indicators are used. One uses EPU or stock market volatility itself as the indicator. The other constructs the Moving-Average-Convergence-Divergence (MACD) from EPU or stock market volatilities respectively, which highlights the momentum and trend direction of the raw signal⁴. The long only and long short strategies are applied to both signals. The strategies are applied to a single asset portfolio first of stock index, bond index respectively, then they are applied to portfolios containing one stock or bond index and one precious metal, hence two assets portfolios. Take stock index portfolio as an example. Four trading strategies are set up against EPU index as follows:

- Long only: when EPU increases, buy stock index;
- Long short: when EPU increases(decreases), buy(sell) stock index;
- Long only with MACD indicator: when the MACD line crosses below the signal line, then it is a bullish sign for stocks, go long;
- Long short with MACD indicator: when the MACD line crosses below the signal line, then it is a bullish sign for stocks, go long; if the MACD line crosses above the signal line, it is a bearish sign for stocks, go short.

Take stock + gold portfolio as an example. Four trading strategies against EPU index are as follows:

⁴Two lines compose the MACD: the MACD line and the Signal line. Take MACD(12,26,9) as an example, the MACD line is calculated as 12day simple moving average (SMA) subtracted by 26day SMA, and the Signal line is 9day SMA of MACD line.

- Long only: when EPU increases, buy stock index, and when EPU drops, buy gold;
- Long short: when EPU increases(decreases), buy(sell) stock index and sell(buy) gold;
- Long only with MACD indicator: when the MACD line crosses below the signal line, long stocks, and when the MACD line crosses above the signal line, long gold;
- Long short with MACD indicator: when the MACD line crosses below the signal line, then long stocks and short gold; if the MACD line crosses above the signal line, short stocks and long gold.

6.4.2 Performance

Portfolio performance is measured by total return over the whole history, Sharpe Ratio and Annualized Sharpe Ratio. How performance evolves across time is plotted in Figures 6.1 - 6.4 for stock and bond portfolios with gold, and Figures I.1 - I.6 for stock and bond portfolios with silver, platinum and palladium. When a strategy is referred to as outperforming the other, the Sharpe Ratio is used as the reference metrics, and all results are obtained "in-sample", in the sense that the judgement of which strategy is better is based on seeing performance over the full history already⁵.

Stock Portfolios with EPU as Indicator

Stock portfolios with hedging from gold outperform those without in at least two strategies for all countries except the UK, and in all 4 strategies for Japan. Among four strategies, stock portfolios with gold outperform stock only with the MACD long only strategies in US (70% vs 36% Annualized Sharpe Ratio), UK (20% vs 19%), Germany (20% vs 10%), France (57% vs 22%), Italy (48% vs 19%), Canada (37% vs 12%) and Japan (53% vs 25%). On the contrary, gold doesn't provide extra alpha in China and India markets. In addition, MACD signals outperform signals based on EPU changes, which suggests that the impact from EPU

⁵In order to compare out-of-sample performance of each strategy, a simple method is to divide the sample into training set and testing set. The strategy which performs best in the training set will be ran again on the testing test to obtain the out-of-sample portfolio performance metrics. The idea is that information used to make strategy selection should not be included in performance measurement.

movement has a lagging impact that trading strategy follows that long term trend rather than daily movement could capture more value. Besides, the fact that EPU is converted from monthly frequency could be the other reason of it. Furthermore, MACD long only tends to outperform MACD long short strategy in most countries except Italy, France and China, that the short selling of shock index when EPU increases and gold when EPU drops doesn't provide extra alpha to the portfolio. This might be because that gold price increases more when political risk surges than it drops in response to political risk declines, which is in consistent with previous studies such as Bilgin et al. [2018] which find that rising economic and political uncertainty contributes to increases in the price of gold but gold prices are less likely to fall when economic policy conditions have improved. Compared with gold, other precious metals offer less alpha in hedging stock portfolios. Hedging with silver enhances stock portfolios in at least one strategy for Italy, France, Canada and China, platinum in Germany, Italy, Canada and China, and palladium for Italy and China only. Silver, platinum and palladium actually add more alpha than gold against some Chinese stock index portfolios, e.g. the portfolio of stocks and silver has an Annualized Sharpe Ratio of 47%, platinum 36%, palladium 60%, which are superior than gold (21%).

Stock Portfolios with Stock Market Volatility Index as Indicator

Stock portfolios with hedging from gold outperform those without in at least two strategies for six countries including the UK, Germany, France, Italy, Switzerland, and South Africa. However, it is not the case for US, Japan and Canada. Therefore, EPU seems to be a better signal given those four strategies settings. Portfolios trading off MACD signals perform better than those trading off stock volatility daily movement of the US, UK, Canada, Italy, Germany, France, and Japan, but not for South Africa and Switzerland. Similarly, long only strategy outperforms long short strategy in most countries except Italy and some portfolios of France. In general, performances are significantly worse across four strategies compared to portfolios trading off signals based on EPU.

Bond Portfolios with EPU as Indicator

When hedging with gold, bond portfolio performances improve in two out of four strategies in the US, Italy, India and China, and in all four strategies for Japan and Canada, while it only improves in one strategy in the UK, Germany and France. For example, portfolio with US government bond index and gold has an Annualized Sharpe Ratio of 71.9%, and the result is 40.8% without hedging. However, silver, platinum and palladium failed to provide additional value to the bond portfolio with Annualized Sharpe Ratios of 22.9%, 7.0%, and -4.8% respectively. Only occasionally, silver adds more value than gold in the portfolios such as the Indian bond portfolio with the EPU MACD long short strategy (43.9% Annualized Sharpe Ratio compared with 35.8% of bonds plus gold and 6.1% bonds only). Similar to the stock portfolios, bond portfolios trading off EPU MACD signals long only outperform others in most countries.

Bond Portfolios with Stock Market Volatility Index as Indicator

Precious metals don't seem to provide any extra benefits against bond portfolios in the US, UK and Germany when trading off signals based on stock market volatilities. Take the MACD long only strategy as an example, the bond index portfolios perform well in the US with an Annualized Sharpe Ratio of 79.9%, while the bond portfolio with hedging from gold only has an Annualized Sharpe Ratio of 36.9%. However, precious metals especially gold do add values in some portfolios for Japan, Italy and Switzerland. Portfolios long only stock volatility MACD signals outperform other three strategies in countries including the US, UK, Italy and France, but not always in Canada, South Africa, Germany, Japan and Switzerland when long only strategy works better overall. Some portfolios such as the US, UK, France, Canada, and South Africa perform poorly with long short strategies.

6.5 Conclusion

This chapter attempts to characterize those periods in which under certain political, economic and financial conditions, gold, silver, platinum and palladium are more likely to become safe

haven assets and hedge the risks of market declines. Political risk is found to be a positive and robust determinant across countries as of whether gold is safe haven against stock (except the UK, and Canada) and bond markets (except the US, Italy, Canada and Japan) tail events. Stock volatility also sees positive and robust results across countries (except India) but only against stock market stress. Exchange rate, interest rate and credit spreads tend to have large coefficient values but results are quite mixed for different markets and not robust. In addition, a portfolio analysis is carried out testing whether precious metals add value to the stock or bond index portfolios with four trading strategies, based on signals from political risk and stock market volatilities. Results show that in generally they do add alpha in the portfolio. In most cases, gold outperforms other three precious metals against both stock and bond portfolios and the MACD long only strategy performed better than others.

Table 6.1: Summary of Market Stress and Macroeconomic Data

	Mean	S.D	Kurt.	Skew.	Min.	Max.	ADF ⁶	P Value	Obs.
US									
gsci	392.73	186.99	-1.21	0.34	128.89	890.29	-1.76	0.68	4937
oil	57.22	35.27	-1.16	0.45	9.64	146.08	-1.53	0.64	4937
vix	20.91	8.30	7.09	2.02	9.89	80.86	-4.94	0.01	4937
fsi	0.10	1.09	9.85	2.74	-1.07	6.19	-3.49*	0.04	4937
sentiment	86.85	13.52	-0.62	-0.28	55.30	112.00	-2.14	0.52	4937
epu	111.18	43.15	1.65	1.25	44.78	283.67	-4.53*	0.01	4937
r	2.53	2.31	-1.62	0.28	0.13	6.50	-1.53	0.78	4937
cpi	91.30	12.28	-1.38	-0.07	70.81	109.45	-2.20	0.49	4937
USD	109.39	9.41	-1.02	0.33	93.73	130.24	-1.56	0.76	4937
ind_production	101.73	7.88	0.12	-0.64	79.50	114.30	-2.32	0.44	4937
credit spread	1.30	0.86	8.27	2.54	0.34	5.26	-2.39	0.41	4937
UK									
gsci	445.58	170.86	-1.16	0.09	161.96	890.29	-1.76	0.68	3917
oil	67.00	32.52	-1.24	0.24	17.68	146.08	-1.84	0.64	3917
vfts	20.26	8.77	5.40	1.90	9.10	78.69	-4.65*	0.01	3917
fsi	0.21	0.18	1.71	1.50	0.02	0.84	-2.39	0.42	3917
sentiment	101.04	10.00	1.83	-1.12	64.30	119.10	-3.12	0.11	3917
epu	151.62	90.56	0.55	0.95	29.03	479.33	-1.85	0.64	3917
r	2.79	2.17	-1.77	0.03	0.50	6.00	-0.97	0.94	3917
cpi	95.79	10.86	-1.44	0.24	80.45	112.28	-1.86	0.64	3917
GBP	1.66	0.17	-0.56	0.68	1.37	2.11	-1.36	0.85	3917
ind_production	103.76	5.69	-1.63	-0.11	93.80	112.90	-1.59	0.75	3917
credit spread	0.26	0.23	1.96	1.03	-0.08	1.02	-1.44	0.81	3917
Germany									
gsci	446.40	171.16	-1.16	0.08	161.96	890.29	-1.76	0.68	3927
oil	67.17	32.58	-1.25	0.23	17.68	146.08	-1.84	0.64	3927
v1x	24.48	9.90	3.74	1.77	11.65	83.23	-4.17*	0.01	3927
fsi	0.21	0.18	1.68	1.49	0.02	0.84	-2.39	0.42	3927
sentiment	99.47	9.63	0.21	-0.70	71.10	117.50	-3.77	0.02	3927
epu	123.58	56.73	2.02	1.15	28.43	377.84	-4.36*	0.01	3927
r	2.10	1.30	-1.01	0.47	0.28	4.72	-2.32	0.44	3927
cpi	97.02	6.92	-1.32	-0.04	85.21	107.21	-1.49	0.79	3927
EUR	1.23	0.18	-0.38	-0.58	0.83	1.60	-2.90	0.20	3927
ind_production	100.24	8.92	-1.64	-0.10	84.80	114.20	-3.02	0.15	3927

⁶* denotes statistical significance at 1% level.

credit spread	1.21	0.79	0.64	0.58	-0.33	3.71	-4.06*	0.01	3927
France									
gsci	447.03	171.50	-1.17	0.07	161.96	890.29	-2.69	0.29	3923
oil	67.31	32.63	-1.26	0.21	17.68	146.08	-2.83	0.23	3923
vcac	23.51	9.04	3.82	1.66	9.24	78.05	-4.35*	0.01	3923
fsi	0.21	0.18	1.66	1.49	0.02	0.84	-2.39	0.42	3923
sentiment	-17.80	8.18	0.02	0.27	-37.00	3.30	-3.27	0.08	3923
epu	157.42	84.68	-0.62	0.49	16.59	380.18	-2.03	0.56	3923
r	2.54	1.05	-0.58	0.83	1.14	5.10	-2.66	0.30	3923
cpi	96.62	6.96	-1.22	-0.24	83.63	106.14	-0.21	0.99	3923
EUR	1.23	0.18	-0.37	-0.59	0.83	1.60	-2.90	0.20	3923
ind_production	106.93	6.63	-1.56	-0.14	94.00	116.90	-2.52	0.36	3923
credit spread	0.30	0.10	1.16	-0.07	0.01	0.57	-3.63*	0.03	3923
Italy									
gsci	572.27	117.19	-0.28	-0.97	271.81	760.33	-2.69	0.29	1480
oil	92.48	25.27	-0.45	-0.91	27.88	126.65	-2.83	0.23	1480
mibivi	27.91	7.26	1.97	1.45	16.57	64.17	-4.42*	0.01	1480
fsi	0.20	0.14	-0.01	0.93	0.02	0.66	-2.39	0.42	1480
sentiment	96.85	8.85	-0.98	-0.61	79.80	109.60	-2.75	0.26	1480
epu	131.69	35.28	0.39	0.76	54.13	241.04	-3.37	0.06	1480
r	1.88	0.68	-0.80	0.62	0.95	3.46	-2.88	0.21	1480
cpi	105.40	2.62	-0.55	-0.99	99.79	107.89	-0.04	0.99	1480
EUR	1.28	0.10	-0.53	-0.68	1.05	1.48	-2.90	0.20	1480
ind_production	95.27	4.09	-1.01	0.73	90.60	104.00	-3.11	0.11	1480
credit spread	-1.73	0.48	2.13	-1.49	-3.25	-1.17	-2.43	0.40	1480
Switzerland									
gsci	535.17	123.39	-0.86	0.04	271.81	890.29	-1.76	0.68	2669
oil	83.29	25.41	-1.17	0.02	27.88	146.08	-1.84	0.64	2669
vsmi	18.73	8.15	11.05	2.76	9.24	86.13	-3.8*	0.02	2669
sentiment	-6.44	15.26	0.14	-0.64	-49.00	16.00	-3.16	0.09	2669
r	0.60	1.05	-0.28	0.92	-0.75	2.75	-1.79	0.67	2669
cpi	98.74	1.39	-0.47	-0.69	95.22	101.05	-3.34	0.06	2669
CHF	1.04	0.13	-1.01	0.47	0.76	1.33	-2.31	0.45	2669
ind_production	2.59	5.06	-0.07	0.05	-8.80	13.60	-3.68*	0.04	2669
credit spread	0.52	0.35	-1.14	0.26	0.05	1.16	-3.37	0.06	2669
Canada									
gsci	565.36	116.42	-0.43	-0.84	271.81	760.33	-2.69	0.29	1600

oil	90.86	25.16	-0.63	-0.77	27.88	126.65	-2.83	0.23	1600
vixc	17.31	4.68	1.04	1.04	8.40	36.71	-3.99*	0.01	1600
sentiment	97.19	6.58	-0.30	-0.14	80.65	113.90	-2.91	0.20	1600
epu	184.98	60.91	1.90	1.31	97.12	399.85	-3.74*	0.02	1600
r	0.83	0.26	-0.05	-1.22	0.25	1.00	-2.18	0.50	1600
cpi	104.83	3.20	-0.88	-0.32	98.40	110.16	-2.24	0.48	1600
CAD	1.08	0.12	0.54	1.30	0.94	1.46	-1.3	0.87	1600
ind.productrion	106.26	4.38	-1.01	-0.34	96.90	112.60	-2.59	0.33	1600
credit spread	0.18	0.22	-0.50	-0.34	-0.31	0.53	-6.78*	0.01	1600
Japan									
gsci	448.49	170.60	-1.15	0.07	161.96	890.29	-2.69	0.29	3722
oil	67.53	32.54	-1.25	0.22	17.68	146.08	-2.83	0.23	3722
vxj	25.71	9.44	11.46	2.63	10.97	97.27	-5.59*	0.01	3722
sentiment	-37.82	25.01	-1.19	-0.21	-88.90	6.10	-2.47	0.39	3722
epu	103.09	35.21	-0.36	0.51	43.31	196.05	-3.71*	0.02	3722
r	0.11	0.15	2.01	1.78	-0.01	0.72	-1.66	0.72	3722
cpi	101.08	1.25	-0.38	0.80	99.20	104.00	-1.86	0.63	3722
YEN	105.58	14.55	-0.83	-0.47	75.82	134.71	-1.58	0.75	3722
ind_production	103.09	35.21	-0.36	0.51	43.31	196.05	-3.11	0.11	3722
credit spreads	0.22	0.07	1.07	0.40	0.09	0.45	-2.82	0.24	3722
China									
gsci	606.06	101.71	1.20	-1.51	305.01	760.33	-2.69	0.29	967
oil	100.44	21.82	1.21	-1.57	36.11	126.65	-2.83	0.23	967
sentiment	103.28	3.29	-0.72	-0.22	97.00	109.90	-3.43	0.05	967
epu	167.98	87.87	-0.47	0.54	26.14	393.23	-2.79	0.24	967
r	5.99	0.52	2.25	-1.49	4.35	6.56	0.375	0.99	967
cpi	110.05	3.32	-1.24	-0.02	103.50	115.60	-2.63	0.32	967
CNY	132.68	20.75	-0.55	0.03	84.60	185.10	-2.72	0.27	967
ind_production	132.68	20.75	-0.55	0.03	84.60	185.10	-3.93*	0.02	967
credits preads	2.16	0.40	0.10	-0.02	1.27	2.93	-2.08	0.54	967
India									
gsci	558.87	126.03	-0.82	-0.88	271.81	715.52	-2.69	0.29	1024
oil	90.82	27.66	-0.88	-0.85	27.88	126.22	-2.83	0.23	1024
nselv	5437.37	1343.97	-1.48	0.38	3461.97	7726.58	-1.3	0.87	1024
sentiment	44.00	2.67	-1.00	-0.09	39.00	50.10	-1.61	0.73	1024
epu	126.64	56.57	0.09	0.79	45.60	283.69	-2.11	0.53	1024
r	6.71	0.49	-0.50	-0.44	5.75	7.50	-2.69	0.29	1024
cpi	134.12	12.48	-1.17	-0.33	111.98	151.85	0.821	0.99	1024

INR	59.43	5.05	-0.97	-0.28	48.70	68.85	-2.14	0.52	1024
ind_production	107.69	5.36	-0.26	0.53	97.60	122.10	-2.64	0.31	1024
credits preads	2.13	0.29	-1.47	-0.11	1.75	2.57	-2.82	0.24	1024
South Africa									
gsci	557.31	119.89	-0.63	-0.14	305.94	890.29	-2.69	0.29	1828
oil	87.53	24.11	-1.00	-0.21	36.35	146.08	-2.83	0.23	1828
savit40	23.36	7.49	3.38	1.61	11.88	57.97	-3.63*	0.03	1828
sentiment	4.01	9.70	-0.88	0.34	-15.10	23.00	-2.21	0.49	1828
r	7.15	2.35	-0.58	0.99	5.00	12.00	-1.42	0.82	1828
cpi	105.82	15.52	-1.16	0.10	78.89	132.14	0.585	0.99	1828
ZAR	8.96	1.97	-0.09	0.85	6.50	15.90	-2.02	0.57	1828
ind_production	90.66	4.76	0.00	0.00	80.72	101.30	-2.76	0.26	1828
credit spreads	12.04	2.80	-0.51	1.09	9.45	18.15	-3.3	0.07	1828

Table 6.2: Summary of sophisticated extreme bound analysis — the US

	Stock Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)	Bond Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)
(Intercept)	free	0.20* (100%)	free	0.39* (100%)	free	0.24* (100%)	free	0.16* (100%)	free	0.17* (100%)	free	0.17* (100%)	free	0.19* (100%)	free	0.11* (100%)
Δvix	free	0.18* (100%)	free	0.37* (100%)	free	0.25* (100%)	free	0.15* (100%)	focus	-0.01 (74%)	focus	-0.01 (84%)	free	-0.05* (100%)	focus	-0.01* (93%)
Δfsi	focus	-0.04 (68%)	focus	-0.02 (56%)	free	0.08 (75%)	free	0.02 (60%)	focus	0.15* (98%)	focus	0.16* (98%)	free	0.14* (95%)	focus	0.02 (67%)
Δepu	free	0.23* (98%)	free	0.19* (92%)	free	0.63* (99%)	free	0.14* (93%)	focus	-0.01 (51%)	free	-0.20 (83%)	focus	0.05 (62%)	free	0.10 (85%)
$\Delta sentiment$	focus	0.01* (92%)	focus	0.01 (79%)	focus	0.00 (59%)	focus	-0.01* (93%)	free	0.02* (94%)	focus	0.00 (77%)	focus	0.00 (68%)	focus	-0.01* (92%)
$\Delta creditspreads$	focus	0.03 (70%)	focus	0.07 (81%)	focus	0.00 (51%)	focus	-0.04 (84%)	focus	0.04 (83%)	focus	0.03 (81%)	focus	0.02 (68%)	focus	-0.05* (99%)
Δr	focus	0.06 (61%)	focus	0.09 (59%)	free	-1.74 (84%)	free	-0.24 (82%)	focus	0.05 (69%)	focus	0.07 (74%)	focus	-0.97 (82%)	focus	-0.07 (69%)
Δcpi	focus	-0.08 (82%)	focus	0.02 (56%)	focus	0.02 (55%)	focus	-0.07 (77%)	focus	-0.08 (85%)	free	-0.18* (99%)	focus	0.07 (77%)	free	-0.13* (100%)
ΔUSD	focus	-0.09 (81%)	focus	0.06 (66%)	focus	-0.02 (58%)	focus	0.06 (80%)	free	0.18* (95%)	focus	0.14* (91%)	free	0.27* (99%)	free	0.10* (90%)
$\Delta ind\_production$	focus	-0.04* (91%)	free	-0.09* (94%)	focus	-0.06* (91%)	focus	-0.02 (71%)	focus	0.07* (98%)	focus	0.02 (78%)	focus	-0.04 (86%)	focus	0.03* (91%)
$\Delta gsci$	focus	0.03* (100%)	focus	0.02* (96%)	focus	0.01 (84%)	focus	0.01 (73%)	focus	0.01 (87%)	free	0.01* (93%)	focus	0.00 (66%)	focus	0.00* (91%)
Δoil	free	-0.07 (76%)	focus	-0.01 (45%)	focus	-0.04 (61%)	focus	-0.04 (73%)	focus	0.01 (72%)	focus	0.00 (51%)	focus	0.02 (72%)	focus	0.01 (75%)

Notes:

1. * denotes a robust determinant when the G.CDF is above 90%.

2. coefficients for EPU is multiplied by 100 for illustration purpose.

Table 6.3: Summary of sophisticated extreme bound analysis — the UK

	Stock Gold		Silver		Platinum		Palladium		Bond Gold		Silver		Platinum		Palladium	
	type	Coef. (G.CDF)	type	Coef. (G.CDF)	type	Coef. (G.CDF)	type	Coef. (G.CDF)	type	Coef. (G.CDF)	type	Coef. (G.CDF)	type	Coef. (G.CDF)	type	Coef. (G.CDF)
(Intercept)	free	0.40* (100%)	free	0.24* (100%)	free	0.15* (100%)	free	0.10* (100%)	free	0.18* (93%)	free	0.22* (99%)	free	0.13* (99%)	free	0.27* (100%)
$\Delta vfts$	free	0.51* (100%)	free	0.23* (100%)	focus	0.13* (100%)	free	0.14* (100%)	focus	-0.07* (100%)	focus	-0.09* (98%)	free	-0.03* (95%)	free	-0.04* (98%)
Δfsi	focus	0.33 (87%)	free	-0.25* (95%)	focus	-0.10 (74%)	focus	-0.21* (97%)	focus	-0.62* (99%)	focus	-0.63* (100%)	free	-0.56* (99%)	free	-0.59* (100%)
Δepu	focus	-0.06* (93%)	focus	0.03 (88%)	focus	-0.02 (89%)	free	0.06* (100%)	focus	0.11* (99%)	focus	0.09* (96%)	free	0.07* (99%)	focus	0.01 (69%)
$\Delta sentiment$	free	-0.05* (99%)	focus	-0.01 (69%)	focus	-0.02* (98%)	focus	0.00 (52%)	focus	0.00 (54%)	focus	0.01* (91%)	focus	-0.01* (90%)	focus	0.00 (70%)
$\Delta creditspreads$	focus	0.69* (94%)	free	0.50* (94%)	focus	0.12 (70%)	free	0.46* (97%)	focus	-0.10 (60%)	focus	0.00 (51%)	focus	0.07 (68%)	focus	0.02 (59%)
Δr	focus	1.26 (89%)	focus	0.42 (80%)	focus	0.35* (95%)	focus	0.28 (83%)	focus	0.89 (80%)	focus	1.03 (83%)	focus	-0.23* (96%)	focus	1.07 (78%)
Δcpi	free	0.25* (98%)	focus	-0.01 (53%)	focus	0.02 (56%)	free	-0.20* (98%)	focus	0.07 (72%)	focus	0.08 (75%)	free	0.17* (97%)	focus	0.11* (94%)
ΔGBP	free	15.80* (98%)	focus	5.06* (92%)	focus	3.68 (86%)	free	4.82* (96%)	focus	0.15 (51%)	focus	-0.25 (50%)	focus	0.32 (53%)	focus	-0.59 (56%)
$\Delta ind\_production$	focus	-0.07 (84%)	focus	0.02 (73%)	focus	-0.02* (91%)	focus	0.00 (52%)	focus	0.03 (78%)	focus	0.03 (74%)	focus	-0.01 (63%)	focus	0.02 (80%)
$\Delta gsci$	focus	0.01 (71%)	focus	0.00 (57%)	focus	0.00 (38%)	focus	0.00 (76%)	focus	0.02* (91%)	focus	0.02* (95%)	free	0.02* (96%)	focus	0.01 (69%)
Δoil	focus	0.08 (86%)	focus	-0.03 (81%)	focus	0.01 (45%)	focus	-0.02 (85%)	focus	-0.05 (65%)	focus	-0.05 (44%)	focus	-0.14* (91%)	focus	-0.05 (79%)

Notes:

1. * denotes a robust determinant when the G.CDF is above 90%.

2. coefficients for EPU is multiplied by 100 for illustration purpose.

Table 6.4: Summary of sophisticated extreme bound analysis — Germany

	Stock Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)	Bond Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)
(Intercept)	free	0.26* (99%)	free	0.05 (79%)	free	0.01 (59%)	free	0.39* (100%)	free	0.16* (100%)	free	0.21* (100%)	free	0.14* (100%)	free	0.31* (100%)
$\Delta v1x$	free	0.44* (100%)	free	0.23* (100%)	free	0.13* (100%)	free	0.32* (100%)	free	-0.05* (93%)	free	-0.09* (99%)	free	-0.04* (99%)	free	-0.07* (99%)
Δfsi	focus	-0.52 (65%)	free	-1.46* (92%)	focus	-0.70 (75%)	focus	-1.55* (96%)	focus	0.85 (89%)	focus	-0.40 (69%)	focus	0.71 (89%)	focus	-0.03 (51%)
Δepu	free	0.14* (91%)	focus	-0.03 (62%)	focus	0.03 (68%)	focus	0.06 (79%)	focus	0.08 (73%)	focus	0.02 (60%)	free	0.13* (92%)	focus	0.10 (80%)
$\Delta sentiment$	free	-0.05* (96%)	free	-0.04* (98%)	free	-0.04* (96%)	free	-0.09* (100%)	focus	-0.01 (62%)	focus	0.00 (51%)	focus	0.01 (61%)	focus	-0.02* (94%)
$\Delta creditspreads$	free	0.12* (92%)	free	0.14* (99%)	free	0.09* (96%)	free	-0.04 (77%)	focus	0.05 (86%)	focus	0.00 (52%)	focus	0.01 (61%)	free	-0.08* (90%)
Δr	focus	0.01 (51%)	free	0.64* (97%)	free	0.59* (97%)	free	0.60* (97%)	focus	-0.16 (74%)	focus	-0.07 (65%)	focus	-0.12 (68%)	focus	-0.28 (78%)
Δcpi	free	-0.20* (93%)	focus	-0.01 (54%)	focus	0.06 (74%)	focus	-0.29* (93%)	focus	-0.12 (87%)	focus	-0.12 (84%)	free	-0.19* (95%)	focus	0.05 (74%)
ΔEUR	focus	-0.08 (51%)	focus	-4.99 (78%)	focus	-3.02 (77%)	focus	12.51* (98%)	focus	-3.06 (70%)	focus	-6.48 (79%)	focus	-1.70 (61%)	free	- (96%)
$\Delta ind\_production$	focus	0.01 (68%)	focus	0.02* (93%)	focus	0.01 (70%)	focus	0.00 (56%)	focus	0.00 (52%)	focus	-0.01 (69%)	focus	-0.01 (80%)	focus	0.01 (73%)
$\Delta gsci$	focus	0.02 (87%)	focus	0.02* (95%)	free	0.02* (94%)	free	0.02* (98%)	free	0.01* (92%)	free	0.01 (88%)	focus	0.00 (86%)	focus	0.01* (96%)
Δoil	focus	0.04 (74%)	focus	0.09* (95%)	focus	-0.06 (87%)	focus	-0.11* (93%)	focus	-0.07 (85%)	focus	-0.12* (94%)	focus	0.00 (44%)	focus	-0.01 (41%)

Notes:

1. * denotes a robust determinant when the G.CDF is above 90%.

2. coefficients for EPU is multiplied by 100 for illustration purpose.

Table 6.5: Summary of sophisticated extreme bound analysis — France

	Stock Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)	Bond Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)
(Intercept)	free	0.21* (100%)	free	0.29* (100%)	free	0.13* (100%)	free	0.19* (100%)	free	0.30* (100%)	free	0.25* (100%)	free	0.27* (100%)	free	0.32* (100%)
Δvac	free	0.06* (99%)	focus	0.01 (62%)	focus	0.02 (88%)	focus	0.02 (88%)	free	0.04* (97%)	focus	0.00 (56%)	focus	0.02 (77%)	focus	0.00 (53%)
Δfsi	focus	-0.75 (79%)	focus	-1.00* (91%)	focus	0.10 (60%)	focus	0.15 (57%)	focus	1.35* (90%)	focus	-0.71 (82%)	free	1.37* (91%)	focus	1.13 (87%)
Δepu	focus	0.02 (64%)	free	0.19* (100%)	focus	0.02 (63%)	focus	0.07 (86%)	free	0.13* (91%)	focus	0.09 (88%)	focus	0.08 (77%)	focus	0.07 (81%)
$\Delta sentiment$	focus	0.02* (94%)	free	-0.02* (96%)	focus	0.00 (62%)	focus	0.02* (93%)	focus	-0.02 (77%)	focus	-0.01 (68%)	free	-0.03 (87%)	focus	-0.01 (63%)
$\Delta creditspreads$	focus	-0.77* (95%)	focus	-0.74* (97%)	free	-0.82* (98%)	focus	0.39 (76%)	free	1.93* (94%)	focus	0.41 (67%)	focus	0.85 (88%)	focus	0.90 (77%)
Δr	focus	-0.09 (68%)	focus	-0.09 (68%)	focus	0.06 (75%)	focus	0.22 (83%)	focus	-0.21 (72%)	focus	-0.35* (92%)	free	-0.47* (97%)	focus	0.06 (58%)
Δcpi	focus	0.11 (85%)	free	-0.21* (92%)	focus	-0.09 (86%)	focus	-0.01 (54%)	focus	-0.11 (75%)	focus	-0.09 (71%)	focus	0.00 (52%)	free	0.24* (97%)
ΔEUR	focus	-3.63 (72%)	focus	1.35 (60%)	free	-7.13* (96%)	focus	1.43 (62%)	focus	-3.56 (71%)	focus	-4.93 (77%)	focus	0.12 (51%)	free	- 10.44* (90%)
$\Delta ind\_production$	focus	0.03 (89%)	focus	0.01 (62%)	focus	0.00 (52%)	focus	0.01 (60%)	focus	-0.03* (93%)	focus	-0.03* (96%)	focus	-0.04* (94%)	free	-0.03 (89%)
$\Delta gsci$	focus	0.00 (53%)	focus	-0.01 (86%)	focus	0.00 (78%)	focus	-0.01 (75%)	focus	0.00 (55%)	focus	0.00 (58%)	focus	0.00 (66%)	focus	0.00 (59%)
Δoil	focus	0.00 (54%)	focus	0.01 (48%)	focus	0.02 (62%)	focus	-0.03 (75%)	focus	-0.04 (82%)	focus	-0.02 (71%)	focus	-0.06 (85%)	focus	-0.03 (69%)

Notes:

1. * denotes a robust determinant when the G.CDF is above 90%.
2. coefficients for EPU is amplified by 100 for illustration purpose.

Table 6.6: Summary of sophisticated extreme bound analysis — Italy

	Stock Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)	Bond Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)
(Intercept)	free	0.21* (97%)	free	0.49* (100%)	free	0.71* (100%)	free	0.26* (97%)	free	0.22* (99%)	free	0.28* (96%)	free	0.29* (96%)	free	0.92* (100%)
$\Delta mibivi$	free	0.08* (100%)	free	0.20* (100%)	free	0.18* (100%)	free	0.13* (100%)	free	0.04* (93%)	free	0.05* (93%)	free	0.11* (99%)	free	0.13* (100%)
Δfsi	focus	0.74 (85%)	focus	-1.28 (79%)	focus	-0.67 (70%)	focus	0.84 (78%)	focus	0.72* (90%)	focus	0.42 (72%)	focus	1.83* (96%)	focus	0.39 (64%)
Δepu	focus	0.03 (63%)	focus	-0.17* (93%)	free	-0.27* (99%)	focus	0.02 (58%)	focus	-0.09 (81%)	focus	-0.05 (65%)	focus	-0.04 (60%)	free	-0.42* (98%)
$\Delta sentiment$	focus	0.01 (69%)	focus	-0.01 (57%)	focus	0.01 (61%)	focus	0.02 (84%)	focus	0.02 (87%)	focus	0.01 (64%)	focus	0.03 (84%)	focus	-0.01 (74%)
$\Delta creditspreads$	focus	0.12 (83%)	focus	-0.01 (55%)	focus	-0.02 (60%)	focus	0.03 (66%)	focus	-0.05 (87%)	focus	0.05 (78%)	focus	0.13* (98%)	focus	-0.08* (96%)
Δr	focus	-0.32* (93%)	focus	0.29 (75%)	focus	0.39 (88%)	focus	-0.29 (88%)	focus	0.34 (89%)	focus	0.46 (89%)	free	0.66* (95%)	focus	0.15 (70%)
Δcpi	free	-0.30* (98%)	focus	-0.09 (63%)	focus	-0.26 (82%)	focus	-0.71* (100%)	free	-0.36* (93%)	free	-0.34* (93%)	focus	-0.30 (81%)	free	-0.55* (97%)
ΔEUR	focus	0.94 (58%)	free	- (99%)	free	- (98%)	focus	-4.41 (77%)	focus	0.48 (55%)	focus	-1.28 (61%)	focus	-5.48 (81%)	free	20.92* (99%)
$\Delta ind\_production$	focus	0.03 (80%)	focus	-0.04 (66%)	focus	-0.09 (89%)	focus	0.02 (69%)	free	0.07* (96%)	free	0.07* (90%)	free	0.10* (94%)	focus	0.05 (82%)
$\Delta gsci$	focus	0.00 (73%)	focus	-0.02 (82%)	focus	-0.02 (69%)	focus	-0.01 (77%)	focus	0.01 (78%)	focus	0.01 (76%)	focus	0.01 (78%)	focus	0.00 (51%)
Δoil	focus	0.01 (54%)	focus	0.05 (57%)	focus	0.09 (77%)	focus	0.05 (76%)	focus	-0.01 (53%)	focus	-0.01 (50%)	focus	0.00 (55%)	focus	-0.02 (62%)

Notes:

1. * denotes a robust determinant when the G.CDF is above 90%.

2. coefficients for EPU is multiplied by 100 for illustration purpose.

Table 6.7: Summary of sophisticated extreme bound analysis — Switzerland

	Stock Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)	Bond Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)
(Intercept)	free	0.46 (82%)	free	0.41* (98%)	free	0.64* (96%)	free	0.40 (68%)	free	0.46* (98%)	free	0.50* (100%)	free	0.14 (84%)	free	-0.23 (36%)
$\Delta vsmi$	focus	0.01* (98%)	focus	0.00 (67%)	focus	0.01* (95%)	free	0.01* (99%)	focus	0.00 (57%)	focus	0.00 (86%)	focus	0.00 (57%)	focus	0.00 (61%)
$\Delta sentiment$	focus	0.00 (81%)	focus	0.00 (78%)	focus	0.02 (88%)	focus	0.02 (89%)	focus	0.01 (85%)	focus	0.00 (78%)	focus	0.00 (74%)	focus	0.00 (70%)
$\Delta creditspreads$	free	-0.56* (91%)	focus	-0.38* (90%)	focus	0.49* (91%)	focus	0.36 (82%)	focus	0.18 (71%)	focus	0.08 (58%)	focus	0.19 (81%)	focus	0.11* (93%)
Δr	focus	0.25 (85%)	focus	0.00 (51%)	focus	0.40* (95%)	focus	0.75* (100%)	focus	0.12 (72%)	focus	-0.09 (68%)	focus	-0.04 (58%)	focus	0.00 (40%)
Δcpi	focus	0.02 (58%)	focus	0.06 (74%)	focus	-0.06 (74%)	focus	-0.13* (94%)	focus	-0.05 (69%)	focus	-0.01 (55%)	focus	-0.03 (64%)	focus	0.01 (61%)
ΔCHF	focus	-0.72* (100%)	focus	-0.49* (95%)	focus	-0.83* (100%)	focus	-0.84* (100%)	focus	-0.41* (90%)	focus	-0.57* (99%)	focus	0.12 (69%)	focus	0.45* (100%)
$\Delta ind\_production$	focus	-0.01* (90%)	focus	-0.01* (90%)	focus	0.01 (78%)	focus	0.02 (87%)	focus	-0.01 (84%)	focus	-0.01 (68%)	focus	0.01 (71%)	focus	0.01 (83%)
$\Delta gsci$	focus	0.00 (52%)	free	0.01 (84%)	focus	0.01 (67%)	focus	-0.02* (99%)	free	0.01* (96%)	free	0.02* (98%)	free	0.02* (99%)	focus	0.01* (95%)
Δoil	free	-0.07* (91%)	focus	-0.08 (85%)	free	-0.06 (84%)	focus	-0.04 (76%)	focus	-0.06 (80%)	focus	-0.04 (74%)	focus	-0.02 (70%)	focus	0.01 (76%)

Notes:

1. * denotes a robust determinant when the G.CDF is above 90%.
2. coefficients for EPU is multiplied by 100 for illustration purpose.

Table 6.8: Summary of sophisticated extreme bound analysis — Canada

	Stock Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)	Bond Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)
(Intercept)	free	0.01* (93%)	free	0.14* (100%)	free	0.15* (100%)	free	0.17* (100%)	free	0.29* (100%)	free	0.30* (100%)	free	0.37* (100%)	free	0.23* (100%)
$\Delta vixc$	focus	0.02 (86%)	focus	-0.01 (62%)	focus	0.02 (70%)	focus	0.02 (66%)	focus	0.01 (61%)	focus	0.03 (72%)	focus	0.00 (55%)	free	0.06 (89%)
Δepu	focus	-0.02 (84%)	focus	0.00 (53%)	focus	0.04 (77%)	focus	0.03 (74%)	focus	-0.02 (63%)	focus	-0.14* (94%)	focus	-0.02 (58%)	focus	-0.05* (90%)
$\Delta sentiment$	focus	0.00* (93%)	focus	0.00 (55%)	focus	-0.01 (84%)	focus	-0.02 (89%)	focus	0.00 (61%)	focus	0.00 (67%)	focus	0.00 (62%)	focus	0.00 (65%)
$\Delta creditspreads$	focus	-0.03 (62%)	focus	-0.34 (82%)	focus	-0.24 (85%)	focus	-0.17 (75%)	free	1.02* (96%)	focus	0.03 (57%)	free	1.53* (97%)	focus	0.02 (55%)
Δr	focus	-0.39 (78%)	focus	-0.28 (71%)	focus	0.33 (68%)	focus	0.53 (72%)	focus	0.01 (51%)	free	-0.11 (54%)	focus	0.32 (63%)	focus	-0.13 (56%)
Δcpi	focus	0.08* (94%)	free	-0.13* (92%)	free	0.23 (79%)	free	0.24 (81%)	free	-0.34* (98%)	focus	-0.12 (70%)	focus	-0.21* (90%)	free	-0.24* (91%)
ΔCAD	free	-7.11 (80%)	focus	-6.46 (74%)	focus	6.10 (64%)	focus	10.55 (72%)	focus	-2.65 (60%)	focus	-6.32 (70%)	focus	-5.54 (69%)	focus	-5.11 (66%)
$\Delta ind\_production$	free	0.12* (91%)	focus	0.05 (65%)	focus	-0.01 (52%)	focus	0.04 (58%)	focus	0.05 (64%)	focus	-0.22* (94%)	focus	0.08 (69%)	focus	-0.02 (57%)
$\Delta gsci$	focus	-0.01 (78%)	focus	0.00 (53%)	focus	0.01 (71%)	focus	0.01 (66%)	focus	0.00 (57%)	focus	0.01 (71%)	focus	-0.01 (75%)	focus	0.00 (64%)
Δoil	focus	-0.03 (78%)	focus	-0.01 (61%)	focus	-0.01 (49%)	focus	0.01 (56%)	focus	-0.02 (68%)	focus	0.02 (65%)	focus	0.00 (57%)	focus	-0.01 (56%)

Notes:

1. * denotes a robust determinant when the G.CDF is above 90%.

2. coefficients for EPU is multiplied by 100 for illustration purpose.

Table 6.9: Summary of sophisticated extreme bound analysis — Japan

	Stock Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)	Bond Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)
(Intercept)	free	0.24* (100%)	free	0.24* (100%)	free	0.20* (100%)	free	0.21* (100%)	free	0.12* (100%)	free	0.23* (100%)	free	0.15* (100%)	free	0.16* (100%)
Δvxj	free	0.18* (100%)	free	0.18* (100%)	free	0.16* (100%)	free	0.16* (100%)	focus	0.01 (67%)	focus	0.01 (75%)	focus	0.01 (73%)	free	0.02 (87%)
Δepu	free	0.26* (96%)	free	0.36* (98%)	free	0.25* (96%)	free	0.21* (91%)	focus	-0.08 (84%)	focus	-0.11 (84%)	focus	-0.07 (71%)	focus	-0.12 (83%)
$\Delta sentiment$	focus	0.00 (56%)	free	-0.01* (100%)	free	-0.01* (99%)	focus	-0.01* (100%)	free	0.00* (95%)	free	0.01* (100%)	focus	0.00 (83%)	free	0.01* (100%)
$\Delta creditspreads$	free	-2.12* (100%)	free	-2.27* (99%)	free	-1.91* (98%)	focus	-1.05 (87%)	focus	-0.06 (63%)	focus	0.90* (99%)	focus	0.25 (76%)	focus	0.48 (89%)
Δr	focus	-3.62* (99%)	focus	-5.42* (97%)	focus	-4.30* (97%)	focus	-2.12* (97%)	focus	0.39 (71%)	focus	0.23 (57%)	free	-4.85 (84%)	focus	-0.17 (61%)
Δcpi	focus	0.14* (94%)	free	0.24* (93%)	focus	0.07 (79%)	focus	0.00 (50%)	focus	0.04 (67%)	focus	0.12 (88%)	focus	-0.03 (62%)	focus	0.08 (87%)
ΔYEN	focus	0.03 (69%)	focus	0.05 (84%)	focus	0.03 (70%)	focus	0.02 (61%)	free	0.06* (92%)	focus	0.04 (71%)	focus	0.05 (89%)	focus	0.05 (82%)
$\Delta ind\_production$	free	0.02* (94%)	focus	0.01 (68%)	free	0.03* (99%)	free	0.04* (100%)	focus	0.00 (57%)	focus	0.00 (58%)	focus	0.01 (88%)	focus	0.01 (66%)
$\Delta gsci$	focus	0.03* (94%)	focus	0.01 (66%)	focus	0.01 (73%)	focus	0.01 (75%)	focus	0.01 (80%)	focus	0.01 (75%)	focus	0.00 (78%)	focus	0.00 (83%)
Δoil	free	-0.10* (93%)	focus	-0.04 (70%)	focus	-0.05 (81%)	focus	-0.03 (71%)	focus	-0.01 (41%)	focus	-0.02 (49%)	focus	0.04 (88%)	focus	0.01 (72%)

Notes:

1. * denotes a robust determinant when the G.CDF is above 90%.
2. coefficients for EPU is multiplied by 100 for illustration purpose.

Table 6.10: Summary of sophisticated extreme bound analysis — China

	Stock Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)	Bond Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)
(Intercept)	free	0.31* (100%)	free	0.50* (100%)	free	0.22* (100%)	free	0.18* (100%)	free	0.35* (100%)	free	0.27* (100%)	free	0.34* (100%)	free	0.38* (100%)
Δepu	focus	0.04 (62%)	focus	-0.04 (58%)	free	0.12 (86%)	focus	-0.05 (75%)	focus	0.01 (54%)	focus	-0.03 (64%)	focus	-0.01 (53%)	focus	0.05 (73%)
$\Delta sentiment$	focus	-0.08* (97%)	focus	-0.04 (77%)	free	-0.03 (85%)	focus	-0.03 (86%)	focus	0.02 (86%)	focus	0.01 (61%)	focus	-0.01 (64%)	focus	0.00 (54%)
$\Delta creditspreads$	focus	0.83* (93%)	focus	0.36 (66%)	free	0.48 (82%)	focus	0.28 (79%)	focus	0.54 (88%)	focus	0.25 (73%)	focus	0.03 (55%)	focus	0.43* (97%)
Δr	focus	-0.57 (54%)	focus	-0.86 (54%)	focus	-0.57 (80%)	focus	-0.45 (79%)	focus	-0.90* (90%)	focus	-0.92* (93%)	focus	-0.74 (81%)	focus	-1.00 (88%)
Δcpi	focus	0.03 (56%)	focus	0.44* (91%)	focus	0.11 (74%)	focus	0.04 (67%)	focus	0.08 (74%)	focus	0.11 (87%)	focus	0.24* (97%)	focus	0.13* (90%)
ΔCNY	focus	16.12 (89%)	focus	35.83* (97%)	focus	5.31 (77%)	free	14.14* (97%)	focus	2.13 (58%)	focus	1.70 (58%)	focus	6.57 (79%)	focus	-5.61 (81%)
$\Delta ind\_production$	focus	0.00 (60%)	focus	-0.01 (75%)	focus	0.00 (66%)	focus	0.00 (58%)	focus	0.00 (78%)	focus	0.00 (52%)	focus	0.00 (60%)	focus	0.00 (65%)
$\Delta gsci$	focus	-0.01 (61%)	focus	0.00 (51%)	focus	0.00 (60%)	focus	0.00 (49%)	free	0.03* (98%)	free	0.03* (97%)	focus	0.02* (91%)	free	0.04* (96%)
Δoil	focus	0.01 (51%)	focus	0.00 (50%)	focus	0.02 (61%)	focus	-0.02 (63%)	focus	-0.07 (76%)	focus	-0.06 (80%)	focus	0.02 (73%)	focus	-0.15 (89%)

Notes:

1. * denotes a robust determinant when the G.CDF is above 90%.

2. coefficients for EPU is multiplied by 100 for illustration purpose.

Table 6.11: Summary of sophisticated extreme bound analysis — India

	Stock Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)	Bond Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)
(Intercept)	free	0.35* (100%)	free	0.33* (100%)	free	0.37* (99%)	free	0.24* (99%)	free	0.12* (96%)	free	0.10* (93%)	free	0.10* (97%)	free	0.05* (94%)
$\Delta nselv$	free	-0.02* (100%)	free	-0.01* (99%)	free	-0.02* (99%)	free	-0.01* (99%)	free	0.00* (94%)	focus	0.00* (90%)	focus	0.00* (95%)	focus	0.00 (84%)
Δepu	focus	0.28* (91%)	focus	0.32* (94%)	focus	0.34* (96%)	focus	0.12 (87%)	focus	0.11* (91%)	focus	0.00 (53%)	focus	0.04 (59%)	focus	0.08 (64%)
$\Delta sentiment$	focus	0.08* (96%)	focus	0.09* (97%)	focus	0.10* (97%)	focus	0.07* (92%)	focus	-0.03 (84%)	focus	0.00 (52%)	focus	-0.02 (83%)	focus	-0.02 (82%)
$\Delta creditspreads$	focus	0.60* (95%)	free	0.74* (95%)	focus	0.47* (91%)	focus	-0.10 (65%)	focus	0.07 (76%)	focus	0.00 (52%)	focus	-0.21 (85%)	focus	-0.28 (84%)
Δr	focus	-0.13 (62%)	focus	-0.07 (57%)	focus	-0.21 (67%)	focus	-0.03 (55%)	focus	0.10* (90%)	free	0.56 (87%)	free	0.56 (87%)	focus	0.09* (93%)
Δcpi	focus	-0.11 (89%)	focus	-0.10* (90%)	focus	-0.15* (92%)	focus	-0.13* (93%)	focus	-0.07* (92%)	focus	0.00 (67%)	focus	0.04 (84%)	focus	0.03 (87%)
ΔINR	free	-0.03 (53%)	focus	0.17 (69%)	focus	-0.18 (70%)	focus	-0.22 (84%)	free	0.23 (82%)	focus	0.20 (86%)	focus	0.16* (95%)	focus	0.10 (82%)
$\Delta ind\_production$	free	-0.04* (93%)	free	-0.03* (93%)	free	-0.04* (91%)	free	-0.01 (76%)	free	-0.01 (85%)	focus	0.01 (66%)	free	0.02 (85%)	focus	0.01* (96%)
$\Delta gsci$	focus	0.02 (86%)	focus	0.02 (81%)	focus	0.02 (86%)	focus	0.01 (76%)	focus	-0.01* (90%)	focus	-0.02* (91%)	focus	-0.02* (90%)	focus	-0.01 (85%)
Δoil	focus	0.05 (72%)	focus	0.04 (67%)	focus	0.05 (69%)	focus	-0.02 (56%)	focus	0.00 (32%)	focus	-0.01 (65%)	focus	-0.02 (71%)	focus	0.02 (32%)

Notes:

1. * denotes a robust determinant when the G.CDF is above 90%.

2. coefficients for EPU is multiplied by 100 for illustration purpose.

Table 6.12: Summary of sophisticated extreme bound analysis — South Africa

	Stock Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)	Bond Gold type	Coef. (G.CDF)	Silver type	Coef. (G.CDF)	Platinum type	Coef. (G.CDF)	Palladium type	Coef. (G.CDF)
(Intercept)	free	0.33* (100%)	free	0.24* (100%)	free	0.45* (100%)	free	0.15* (100%)	free	0.09* (99%)	free	0.14* (100%)	free	0.21* (100%)	free	0.16* (100%)
$\Delta savit40$	free	0.91* (100%)	free	0.59* (100%)	free	1.05* (100%)	free	0.26* (100%)	focus	-0.03 (79%)	focus	0.00 (54%)	focus	-0.06* (90%)	focus	-0.01 (63%)
$\Delta sentiment$	focus	-0.01 (89%)	focus	-0.01 (78%)	focus	-0.01 (71%)	focus	0.00 (67%)	free	0.01 (87%)	free	-0.02* (98%)	focus	0.00 (55%)	focus	0.00 (68%)
$\Delta creditspreads$	free	-0.21* (90%)	free	-0.26* (96%)	focus	0.04 (69%)	free	0.05* (99%)	focus	0.04* (98%)	focus	-0.01 (78%)	focus	0.02 (82%)	focus	0.00 (49%)
Δr	focus	-0.15 (66%)	focus	0.18 (72%)	focus	-0.75* (98%)	focus	-0.25* (99%)	focus	-0.05 (78%)	focus	-0.07 (82%)	focus	-0.07 (79%)	focus	-0.42 (86%)
Δcpi	focus	0.05 (69%)	focus	0.05 (69%)	focus	-0.13 (89%)	focus	-0.10* (99%)	focus	0.00 (55%)	focus	-0.08* (91%)	focus	-0.12* (98%)	focus	0.01 (62%)
ΔZAR	free	1.97* (99%)	free	0.77* (90%)	free	3.97* (100%)	free	0.90* (100%)	free	0.55* (98%)	free	0.67* (97%)	free	1.19* (99%)	free	1.03* (98%)
$\Delta ind\_production$	free	-0.05* (100%)	focus	-0.02 (84%)	free	-0.09* (100%)	focus	-0.03* (99%)	free	0.03 (82%)	free	0.03 (80%)	free	0.03 (80%)	free	0.05* (91%)
$\Delta gsci$	focus	0.01 (71%)	focus	0.01 (58%)	focus	0.01 (59%)	focus	0.00 (54%)	focus	0.00 (68%)	focus	0.01 (76%)	focus	0.01 (76%)	focus	0.00 (74%)
Δoil	focus	-0.08 (81%)	focus	-0.08 (87%)	focus	-0.04 (66%)	focus	-0.03 (85%)	focus	0.02 (81%)	focus	-0.03 (74%)	focus	0.02 (69%)	focus	0.05 (89%)

Notes:

1. * denotes a robust determinant when the G.CDF is above 90%.
2. coefficients for EPU is amplified by 100 for illustration purpose.

Table 6.13: Stock Portfolio Performance - Signal Built from EPU

Portfolio	long only			macd long only			long short			macd long short		
	r	s.r.	a.s.r.	r	s.r.	a.s.r.	r	s.r.	a.s.r.	r	s.r.	a.s.r.
USA S.	28%	3%	41%	178%	3%	36%	43%	3%	44%	216%	2%	21%
USA S.+AG	35%	2%	23%	777%	3%	31%	45%	2%	22%	888%	2%	19%
USA S.+AU	29%	2%	32%	1277%	5%	70%	35%	2%	25%	2081%	4%	51%
USA S.+PD	8%	0%	4%	189%	1%	5%	-7%	0%	-9%	18%	0%	-16%
USA S.+PT	25%	2%	23%	227%	2%	19%	27%	1%	18%	85%	1%	-2%
GBR S.	22%	3%	41%	56%	2%	19%	33%	3%	41%	152%	2%	21%
GBR S.+AG	7%	0%	3%	69%	1%	-2%	0%	0%	-4%	-8%	0%	-18%
GBR S.+AU	26%	2%	32%	126%	2%	20%	32%	2%	29%	23%	0%	-8%
GBR S.+PD	-6%	0%	-10%	-25%	0%	-20%	-14%	-1%	-19%	-30%	0%	-23%
GBR S.+PT	13%	1%	12%	-8%	0%	-13%	16%	1%	13%	-50%	-1%	-29%
JPN S.	-11%	-2%	-26%	111%	2%	25%	-23%	-2%	-37%	223%	2%	20%
JPN S.+AG	-2%	0%	-6%	124%	1%	3%	16%	1%	6%	-9%	0%	-20%
JPN S.+AU	-2%	0%	-6%	537%	4%	53%	2%	0%	-1%	508%	3%	26%
JPN S.+PD	0%	0%	-4%	-5%	0%	-16%	-28%	-2%	-34%	-15%	0%	-22%
JPN S.+PT	-10%	-1%	-17%	102%	1%	9%	-20%	-1%	-27%	68%	1%	-4%
ITA S.	-14%	-3%	-54%	36%	2%	19%	2%	0%	2%	105%	3%	35%
ITA S.+AG	-22%	-4%	-65%	122%	3%	34%	-11%	-1%	-27%	532%	5%	73%
ITA S.+AU	-20%	-4%	-70%	111%	4%	48%	-9%	-1%	-24%	388%	5%	79%
ITA S.+PD	-26%	-5%	-85%	95%	3%	31%	-10%	-2%	-31%	258%	4%	59%
ITA S.+PT	-18%	-4%	-64%	46%	2%	16%	4%	1%	7%	263%	5%	68%
IND S.	3%	2%	34%	11%	1%	19%	9%	3%	50%	-18%	-2%	-38%
IND S.+AG	7%	2%	34%	5%	0%	-6%	13%	3%	41%	46%	2%	17%
IND S.+AU	8%	3%	51%	11%	1%	8%	15%	3%	51%	10%	1%	-1%
IND S.+PD	-1%	0%	-8%	-19%	-2%	-35%	-7%	-2%	-29%	-49%	-4%	-67%
IND S.+PT	5%	2%	31%	-11%	-1%	-25%	9%	2%	31%	-14%	-1%	-28%
DEU S.	9%	1%	11%	57%	1%	10%	48%	3%	43%	68%	1%	1%
DEU S.+AG	14%	1%	7%	136%	1%	6%	69%	2%	33%	19%	0%	-15%
DEU S.+AU	18%	1%	18%	171%	2%	20%	66%	3%	42%	18%	0%	-12%
DEU S.+PD	15%	1%	11%	-14%	0%	-17%	85%	3%	48%	-39%	-1%	-26%
DEU S.+PT	5%	0%	2%	-9%	0%	-14%	47%	2%	30%	-69%	-2%	-37%
FRA S.	-5%	-1%	-10%	121%	2%	22%	24%	2%	23%	627%	3%	43%
FRA S.+AG	-1%	0%	-4%	455%	2%	26%	31%	1%	15%	1428%	3%	31%
FRA S.+AU	-7%	-1%	-13%	745%	4%	57%	7%	0%	3%	2328%	4%	57%
FRA S.+PD	-23%	-2%	-31%	-36%	-1%	-24%	-11%	-1%	-14%	-18%	0%	-21%
FRA S.+PT	-13%	-1%	-19%	119%	1%	10%	10%	1%	5%	324%	2%	16%
CHN S.	-8%	-3%	-48%	112%	7%	104%	-29%	-9%	-137%	256%	8%	127%
CHN S.+AG	15%	3%	47%	-7%	0%	-21%	-3%	0%	-12%	77%	2%	18%
CHN S.+AU	5%	2%	21%	52%	3%	38%	-15%	-4%	-58%	170%	5%	68%
CHN S.+PD	19%	4%	60%	86%	4%	49%	9%	2%	20%	273%	6%	92%
CHN S.+PT	9%	2%	36%	17%	1%	6%	-10%	-2%	-40%	111%	4%	48%
CAN S.	0%	0%	-3%	10%	1%	12%	5%	2%	28%	4%	0%	-2%
CAN S.+AG	3%	1%	7%	58%	2%	21%	19%	3%	43%	106%	3%	27%
CAN S.+AU	1%	0%	6%	55%	3%	37%	9%	2%	34%	79%	3%	40%
CAN S.+PD	-16%	-4%	-64%	68%	2%	28%	-6%	-1%	-21%	83%	2%	27%
CAN S.+PT	-5%	-2%	-28%	-10%	-1%	-18%	2%	1%	7%	2%	0%	-7%

Three performance metrics are presented here: total returns (r.), the Sharpe Ratio (s.r.) and the Annualized Sharpe Ratio (a.s.r.).

Two lines compose the MACD: the MACD line and the Signal line. Here MACD(25,75,20) is applied, which means that the MACD line is calculated as 25day simple moving average (SMA) subtracted by 75day SMA, and the Signal line is 20day SMA of MACD line.

Table 6.14: Stock Portfolio Performance - Signal Built from Stock Market Volatility

Portfolio	long only			macd long only			long short			macd long short		
	r	s.r.	a.s.r.	r	s.r.	a.s.r.	r	s.r.	a.s.r.	r	s.r.	a.s.r.
USA S.	64%	1%	13%	19%	1%	2%	-41%	-1%	-24%	-41%	-1%	-24%
USA S.+AG	-69%	-2%	-36%	101%	1%	2%	-99%	-4%	-76%	-48%	-1%	-26%
USA S.+AU	3%	0%	-8%	94%	1%	11%	-88%	-3%	-52%	-57%	-1%	-29%
USA S.+PD	-67%	-1%	-33%	120%	1%	0%	-99%	-4%	-74%	-31%	0%	-23%
USA S.+PT	-59%	-1%	-32%	42%	1%	-2%	-98%	-5%	-77%	-65%	-1%	-33%
GBR S.	-58%	-3%	-46%	-36%	-2%	-31%	-58%	-2%	-37%	-58%	-2%	-37%
GBR S.+AG	-52%	-1%	-30%	85%	1%	3%	-92%	-3%	-57%	10%	0%	-15%
GBR S.+AU	-36%	-1%	-24%	54%	1%	7%	-90%	-3%	-63%	-43%	-1%	-26%
GBR S.+PD	-66%	-2%	-37%	-11%	0%	-16%	-88%	-2%	-51%	0%	0%	-17%
GBR S.+PT	-57%	-2%	-35%	-18%	0%	-16%	-90%	-3%	-61%	-60%	-1%	-34%
CAN S.	40%	3%	49%	8%	1%	10%	1%	0%	-5%	1%	0%	-5%
CAN S.+AG	-18%	-1%	-24%	-34%	-2%	-38%	-44%	-2%	-44%	-64%	-4%	-65%
CAN S.+AU	46%	2%	29%	-5%	0%	-12%	47%	2%	22%	-32%	-2%	-40%
CAN S.+PD	3%	0%	-10%	-48%	-3%	-54%	-53%	-3%	-55%	-82%	-7%	-106%
CAN S.+PT	-27%	-2%	-36%	-53%	-5%	-77%	-44%	-3%	-56%	-71%	-7%	-109%
ITA S.	-39%	-3%	-53%	33%	2%	19%	96%	3%	32%	96%	3%	32%
ITA S.+AG	-30%	-1%	-34%	99%	3%	32%	-26%	-1%	-31%	410%	5%	61%
ITA S.+AU	-22%	-1%	-30%	67%	3%	32%	-26%	-1%	-31%	207%	4%	49%
ITA S.+PD	-29%	-1%	-33%	150%	4%	52%	-40%	-2%	-40%	492%	6%	94%
ITA S.+PT	-44%	-3%	-53%	-5%	0%	-15%	-29%	-1%	-33%	53%	2%	11%
SAF S.	40%	2%	17%	10%	1%	2%	-28%	-1%	-29%	-28%	-1%	-29%
SAF S.+AG	122%	2%	20%	-51%	-2%	-42%	112%	2%	9%	-86%	-4%	-76%
SAF S.+AU	118%	3%	35%	-9%	0%	-16%	54%	1%	5%	-66%	-3%	-58%
SAF S.+PD	-26%	-1%	-27%	10%	0%	-10%	-76%	-3%	-64%	-55%	-2%	-44%
SAF S.+PT	-24%	-1%	-26%	-33%	-1%	-33%	-51%	-2%	-45%	-59%	-3%	-52%
DEU S.	-26%	-1%	-20%	46%	1%	9%	47%	1%	-2%	47%	1%	-2%
DEU S.+AG	-9%	0%	-16%	158%	1%	9%	-80%	-2%	-42%	43%	0%	-12%
DEU S.+AU	7%	0%	-9%	195%	2%	24%	-80%	-2%	-45%	40%	0%	-8%
DEU S.+PD	-56%	-1%	-31%	-6%	0%	-15%	-87%	-2%	-48%	-27%	0%	-23%
DEU S.+PT	-51%	-1%	-30%	86%	1%	6%	-91%	-3%	-58%	31%	0%	-10%
FRA S.	-65%	-3%	-47%	6%	0%	-5%	68%	1%	2%	68%	1%	2%
FRA S.+AG	-60%	-1%	-34%	44%	1%	-5%	-92%	-3%	-57%	3%	0%	-17%
FRA S.+AU	-58%	-2%	-35%	144%	2%	19%	-94%	-4%	-68%	102%	1%	0%
FRA S.+PD	-79%	-2%	-46%	-18%	0%	-18%	-94%	-3%	-60%	35%	0%	-13%
FRA S.+PT	-75%	-2%	-47%	29%	0%	-4%	-96%	-4%	-71%	46%	1%	-7%
JPN S.	-37%	-1%	-26%	9%	0%	-3%	-13%	0%	-16%	-13%	0%	-16%
JPN S.+AG	88%	1%	1%	184%	2%	13%	5%	0%	-18%	45%	0%	-12%
JPN S.+AU	33%	1%	-2%	142%	2%	20%	-62%	-1%	-35%	-12%	0%	-18%
JPN S.+PD	-89%	-3%	-59%	27%	0%	-9%	-99%	-5%	-79%	51%	0%	-12%
JPN S.+PT	-48%	-1%	-30%	62%	1%	3%	-85%	-3%	-53%	7%	0%	-14%
CHE S.	73%	3%	35%	-21%	-1%	-27%	-44%	-2%	-37%	-44%	-2%	-37%
CHE S.+AG	323%	3%	37%	47%	1%	-2%	501%	3%	29%	0%	0%	-18%
CHE S.+AU	273%	4%	59%	63%	2%	17%	292%	3%	35%	-2%	0%	-14%
CHE S.+PD	44%	1%	-1%	84%	1%	9%	-39%	-1%	-29%	42%	1%	-6%
CHE S.+PT	79%	2%	16%	-18%	-1%	-19%	135%	2%	17%	-38%	-1%	-29%

Three performance metrics are presented here: total returns (r.), the Sharpe Ratio (s.r.) and the Annualized Sharpe Ratio (a.s.r.).

Two lines compose the MACD: the MACD line and the Signal line. Here MACD(25,75,20) is applied, which means that the MACD line is calculated as 25day simple moving average (SMA) subtracted by 75day SMA, and the Signal line is 20day SMA of MACD line.

Table 6.15: Bond Portfolio Performance - Signal Built from EPU

Portfolio	long only			macd long only			long short			macd long short		
	r	s.r.	a.s.r.	r	s.r.	a.s.r.	r	s.r.	a.s.r.	r	s.r.	a.s.r.
Portfolio	r	s.r.	a.s.r.	r	s.r.	a.s.r.	r	s.r.	a.s.r.	r	s.r.	a.s.r.
USA B.	0%	0%	-1%	43%	3%	41%	-2%	-1%	-9%	-36%	-2%	-39%
USA B.+AG	5%	0%	2%	351%	2%	23%	-1%	0%	-4%	100%	1%	-4%
USA B.+AU	0%	0%	-1%	608%	5%	72%	-7%	-1%	-12%	342%	3%	35%
USA B.+PD	-15%	-1%	-19%	48%	1%	-5%	-36%	-2%	-37%	-76%	-1%	-37%
USA B.+PT	-2%	0%	-5%	68%	1%	7%	-13%	-1%	-16%	-62%	-1%	-32%
GBR B.	-2%	-1%	-20%	55%	5%	80%	3%	1%	15%	-4%	0%	-8%
GBR B.+AG	-15%	-1%	-20%	68%	1%	0%	-23%	-1%	-24%	-65%	-1%	-35%
GBR B.+AU	0%	0%	-1%	126%	2%	29%	3%	0%	2%	-53%	-2%	-34%
GBR B.+PD	-25%	-2%	-39%	-26%	0%	-20%	-34%	-2%	-40%	-74%	-2%	-39%
GBR B.+PT	-9%	-1%	-16%	-8%	0%	-12%	-10%	-1%	-14%	-81%	-3%	-53%
JPN B.	-3%	-2%	-35%	14%	2%	35%	-6%	-3%	-51%	-11%	-2%	-26%
JPN B.+AG	6%	1%	6%	21%	0%	-8%	41%	2%	23%	-75%	-2%	-43%
JPN B.+AU	6%	1%	11%	244%	4%	55%	25%	2%	31%	67%	1%	9%
JPN B.+PD	8%	1%	7%	-49%	-1%	-30%	-12%	-1%	-16%	-77%	-2%	-43%
JPN B.+PT	-2%	0%	-6%	9%	0%	-5%	-3%	0%	-6%	-54%	-1%	-33%
ITA B.	1%	1%	7%	23%	3%	49%	2%	1%	12%	-2%	0%	-8%
ITA B.+AG	-9%	-2%	-34%	99%	3%	43%	-12%	-2%	-33%	203%	4%	47%
ITA B.+AU	-6%	-2%	-40%	89%	5%	77%	-9%	-2%	-39%	134%	5%	71%
ITA B.+PD	-13%	-4%	-64%	75%	3%	41%	-10%	-2%	-35%	72%	2%	20%
ITA B.+PT	-4%	-2%	-27%	31%	2%	23%	3%	1%	11%	74%	3%	39%
IND B.	3%	6%	93%	17%	7%	115%	0%	0%	-3%	2%	1%	6%
IND B.+AG	7%	2%	38%	10%	1%	3%	4%	1%	15%	81%	3%	44%
IND B.+AU	8%	4%	60%	17%	2%	24%	6%	2%	28%	36%	3%	36%
IND B.+PD	-1%	0%	-8%	-15%	-1%	-31%	-14%	-3%	-55%	-36%	-3%	-53%
IND B.+PT	5%	2%	35%	-6%	-1%	-18%	0%	0%	-2%	6%	0%	-2%
DEU B.	1%	0%	5%	58%	5%	83%	-1%	0%	-4%	-5%	0%	-9%
DEU B.+AG	5%	0%	2%	138%	2%	13%	13%	1%	6%	-33%	0%	-23%
DEU B.+AU	9%	1%	16%	173%	3%	40%	11%	1%	14%	-34%	-1%	-23%
DEU B.+PD	6%	0%	5%	-13%	0%	-16%	24%	1%	16%	-66%	-1%	-35%
DEU B.+PT	-3%	0%	-7%	-8%	0%	-12%	-2%	0%	-5%	-82%	-3%	-55%
FRA B.	-1%	0%	-8%	65%	6%	92%	-2%	-1%	-11%	0%	0%	-2%
FRA B.+AG	3%	0%	2%	315%	3%	30%	3%	0%	-1%	110%	1%	-1%
FRA B.+AU	-4%	-1%	-10%	532%	6%	86%	-15%	-2%	-27%	234%	3%	34%
FRA B.+PD	-20%	-2%	-33%	-52%	-1%	-31%	-30%	-2%	-37%	-89%	-3%	-53%
FRA B.+PT	-9%	-1%	-17%	64%	1%	11%	-13%	-1%	-18%	-42%	-1%	-26%
CHN B.	0%	-1%	-17%	3%	1%	21%	-3%	-4%	-62%	-4%	-1%	-21%
CHN B.+AG	24%	6%	95%	-55%	-6%	-95%	33%	5%	85%	-52%	-4%	-66%
CHN B.+AU	13%	6%	98%	-26%	-4%	-62%	16%	5%	83%	-27%	-3%	-48%
CHN B.+PD	28%	7%	113%	-10%	-1%	-23%	49%	8%	134%	1%	0%	-13%
CHN B.+PT	17%	7%	114%	-43%	-7%	-106%	24%	7%	115%	-43%	-4%	-73%
CAN B.	-7%	-8%	-126%	10%	3%	39%	-10%	-9%	-137%	-14%	-3%	-47%
CAN B.+AG	-4%	-1%	-14%	56%	2%	24%	2%	0%	1%	70%	2%	12%
CAN B.+AU	-6%	-2%	-37%	54%	3%	47%	-6%	-2%	-32%	48%	2%	29%
CAN B.+PD	-22%	-6%	-93%	67%	3%	31%	-19%	-3%	-57%	52%	1%	7%
CAN B.+PT	-12%	-4%	-69%	-11%	-1%	-20%	-12%	-3%	-50%	-15%	-1%	-23%

Three performance metrics are presented here: total returns (r.), the Sharpe Ratio (s.r.) and the Annualized Sharpe Ratio (a.s.r.).

Two lines compose the MACD: the MACD line and the Signal line. Here MACD(25,75,20) is applied, which means that the MACD line is calculated as 25day simple moving average (SMA) subtracted by 75day SMA, and the Signal line is 20day SMA of MACD line.

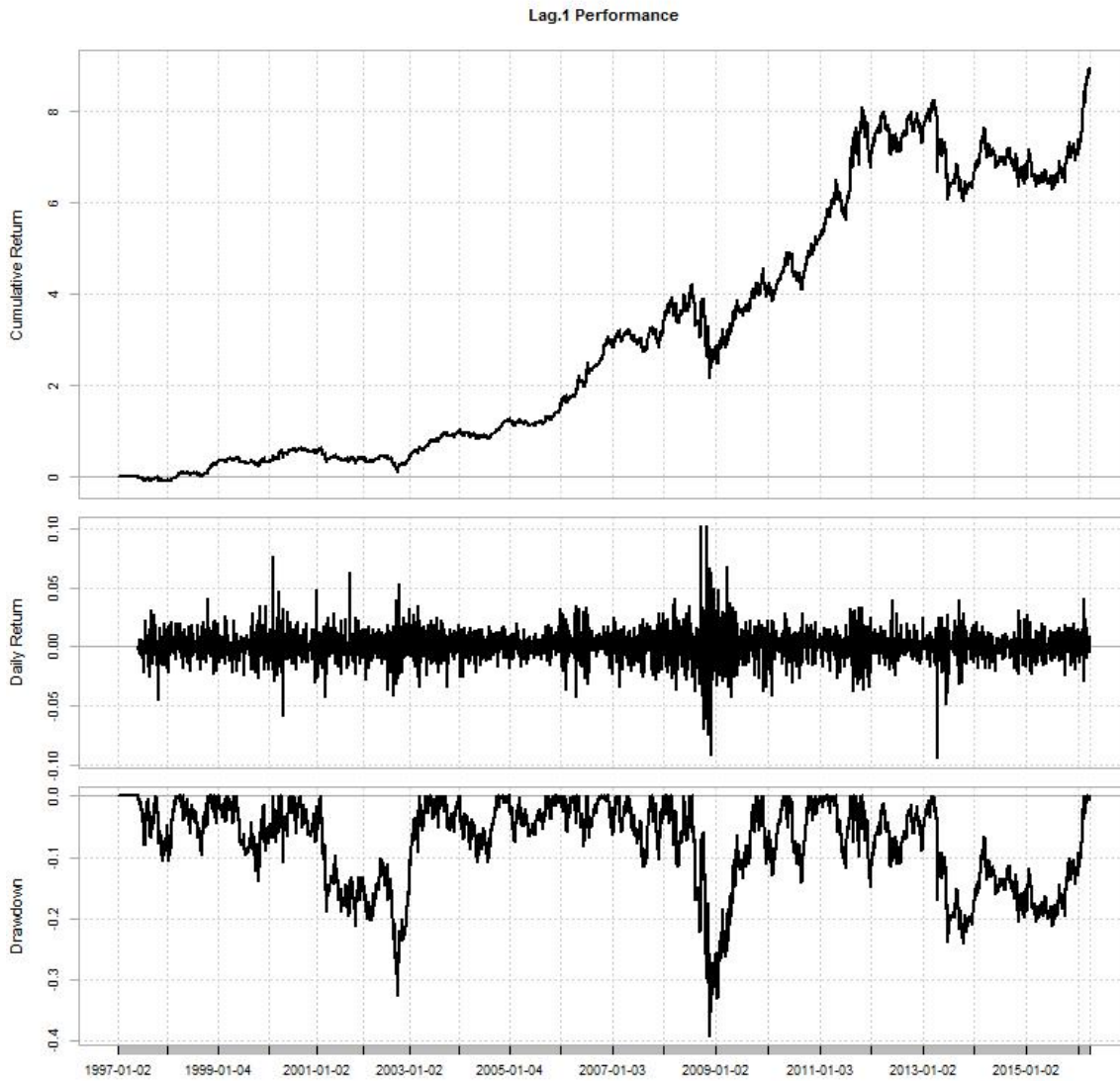
Table 6.16: Bond Portfolio Performance - Signal Built from Stock Market Volatility

Portfolio	long only			macd long only			long short			macd long short		
	r	s.r.	a.s.r.	r	s.r.	a.s.r.	r	s.r.	a.s.r.	r	s.r.	a.s.r.
USA B.	122%	6%	87%	92%	5%	80%	16%	1%	9%	16%	1%	9%
USA B.+AG	-59%	-1%	-31%	224%	2%	17%	-98%	-4%	-75%	3%	0%	-15%
USA B.+AU	40%	1%	7%	212%	3%	37%	-81%	-3%	-54%	-14%	0%	-14%
USA B.+PD	-55%	-1%	-28%	254%	2%	12%	-99%	-4%	-70%	36%	0%	-14%
USA B.+PT	-44%	-1%	-26%	128%	2%	16%	-96%	-5%	-76%	-31%	-1%	-20%
GBR B.	72%	5%	86%	64%	6%	87%	7%	0%	5%	7%	0%	5%
GBR B.+AG	95%	1%	8%	376%	3%	33%	-49%	-1%	-28%	179%	1%	4%
GBR B.+AU	159%	3%	40%	297%	4%	58%	-37%	-1%	-25%	44%	1%	3%
GBR B.+PD	36%	1%	-5%	130%	1%	9%	-28%	0%	-23%	154%	1%	0%
GBR B.+PT	74%	1%	13%	111%	2%	19%	-39%	-1%	-24%	1%	0%	-11%
CAN B.	38%	8%	134%	8%	2%	31%	-16%	-3%	-56%	-16%	-3%	-56%
CAN B.+AG	-19%	-1%	-25%	-35%	-2%	-39%	-54%	-2%	-50%	-70%	-4%	-69%
CAN B.+AU	44%	3%	37%	-5%	0%	-13%	22%	1%	9%	-44%	-3%	-59%
CAN B.+PD	2%	0%	-10%	-48%	-3%	-57%	-61%	-3%	-58%	-85%	-6%	-99%
CAN B.+PT	-28%	-2%	-41%	-53%	-5%	-88%	-54%	-4%	-64%	-76%	-7%	-111%
ITA B.	38%	6%	87%	40%	5%	82%	28%	3%	41%	28%	3%	41%
ITA B.+AG	57%	2%	24%	109%	4%	51%	84%	2%	16%	233%	4%	53%
ITA B.+AU	76%	4%	68%	76%	4%	66%	84%	3%	45%	101%	4%	56%
ITA B.+PD	60%	2%	28%	163%	5%	80%	50%	2%	9%	287%	5%	78%
ITA B.+PT	26%	2%	19%	-1%	0%	-8%	76%	3%	38%	0%	0%	-10%
SAF B.	22%	3%	42%	19%	3%	41%	-24%	-3%	-50%	-24%	-3%	-50%
SAF B.+AG	92%	2%	21%	-47%	-2%	-41%	45%	1%	-4%	-86%	-4%	-75%
SAF B.+AU	89%	3%	47%	-1%	0%	-9%	6%	0%	-7%	-64%	-4%	-69%
SAF B.+PD	-36%	-1%	-34%	19%	1%	-4%	-83%	-4%	-74%	-53%	-2%	-42%
SAF B.+PT	-35%	-2%	-37%	-28%	-1%	-30%	-67%	-4%	-63%	-57%	-3%	-52%
DEU B.	124%	9%	139%	62%	6%	89%	0%	0%	-3%	0%	0%	-3%
DEU B.+AG	175%	2%	17%	186%	2%	18%	-13%	0%	-18%	-3%	0%	-16%
DEU B.+AU	224%	4%	50%	227%	3%	48%	-14%	0%	-14%	-5%	0%	-11%
DEU B.+PD	33%	0%	-5%	4%	0%	-11%	-43%	-1%	-26%	-50%	-1%	-29%
DEU B.+PT	49%	1%	7%	106%	2%	18%	-61%	-2%	-35%	-11%	0%	-15%
FRA B.	119%	9%	141%	63%	6%	93%	-3%	0%	-6%	-3%	0%	-6%
FRA B.+AG	151%	2%	15%	121%	1%	11%	-21%	0%	-20%	-40%	-1%	-25%
FRA B.+AU	166%	3%	42%	273%	4%	55%	-42%	-1%	-27%	17%	0%	-4%
FRA B.+PD	29%	0%	-5%	25%	0%	-6%	-41%	-1%	-26%	-22%	0%	-21%
FRA B.+PT	56%	1%	9%	97%	2%	18%	-54%	-1%	-32%	-16%	0%	-16%
JPN B.	43%	6%	96%	14%	2%	37%	-12%	-2%	-26%	-12%	-2%	-26%
JPN B.+AG	326%	3%	37%	195%	2%	22%	251%	2%	10%	48%	1%	-8%
JPN B.+AU	203%	4%	52%	152%	3%	39%	26%	1%	-1%	-10%	0%	-13%
JPN B.+PD	-74%	-2%	-48%	32%	0%	-5%	-95%	-4%	-68%	54%	1%	-8%
JPN B.+PT	17%	0%	-1%	69%	1%	12%	-50%	-1%	-31%	9%	0%	-9%
CHE B.	25%	5%	74%	18%	4%	66%	-7%	-1%	-21%	-7%	-1%	-21%
CHE B.+AG	205%	3%	31%	121%	2%	15%	168%	2%	8%	64%	1%	-5%
CHE B.+AU	170%	4%	60%	146%	4%	50%	75%	2%	16%	62%	1%	13%
CHE B.+PD	4%	0%	-10%	177%	3%	29%	-73%	-2%	-49%	135%	2%	8%
CHE B.+PT	29%	1%	6%	24%	1%	2%	5%	0%	-10%	1%	0%	-12%

Three performance metrics are presented here: total returns (r.), the Sharpe Ratio (s.r.) and the Annualized Sharpe Ratio (a.s.r.).

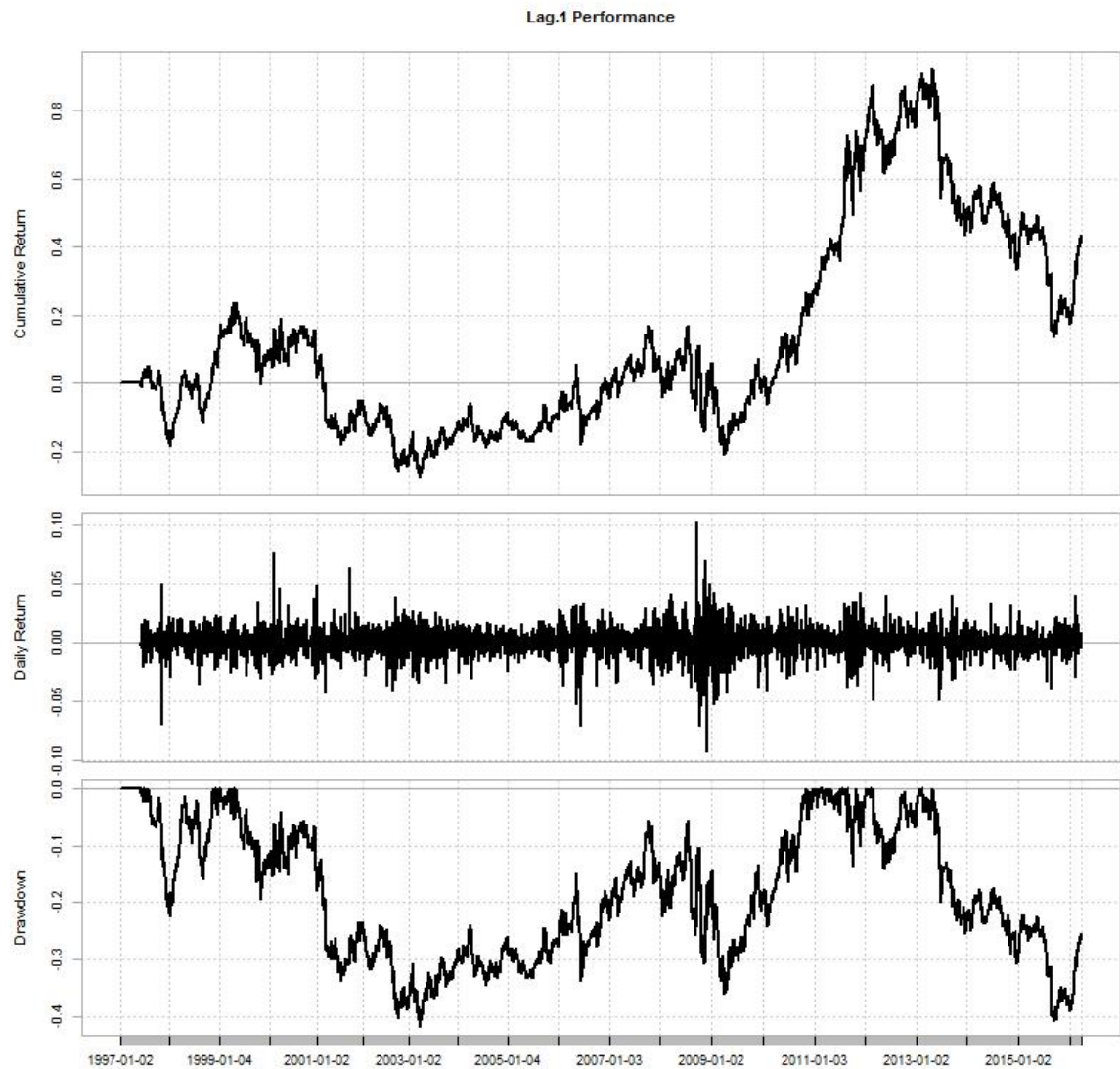
Two lines compose the MACD: the MACD line and the Signal line. Here MACD(25,75,20) is applied, which means that the MACD line is calculated as 25day simple moving average (SMA) subtracted by 75day SMA, and the Signal line is 20day SMA of MACD line.

Figure 6.1: US Stock and Gold Portfolio Performance Summary - EPU Long Only MACD Strategy



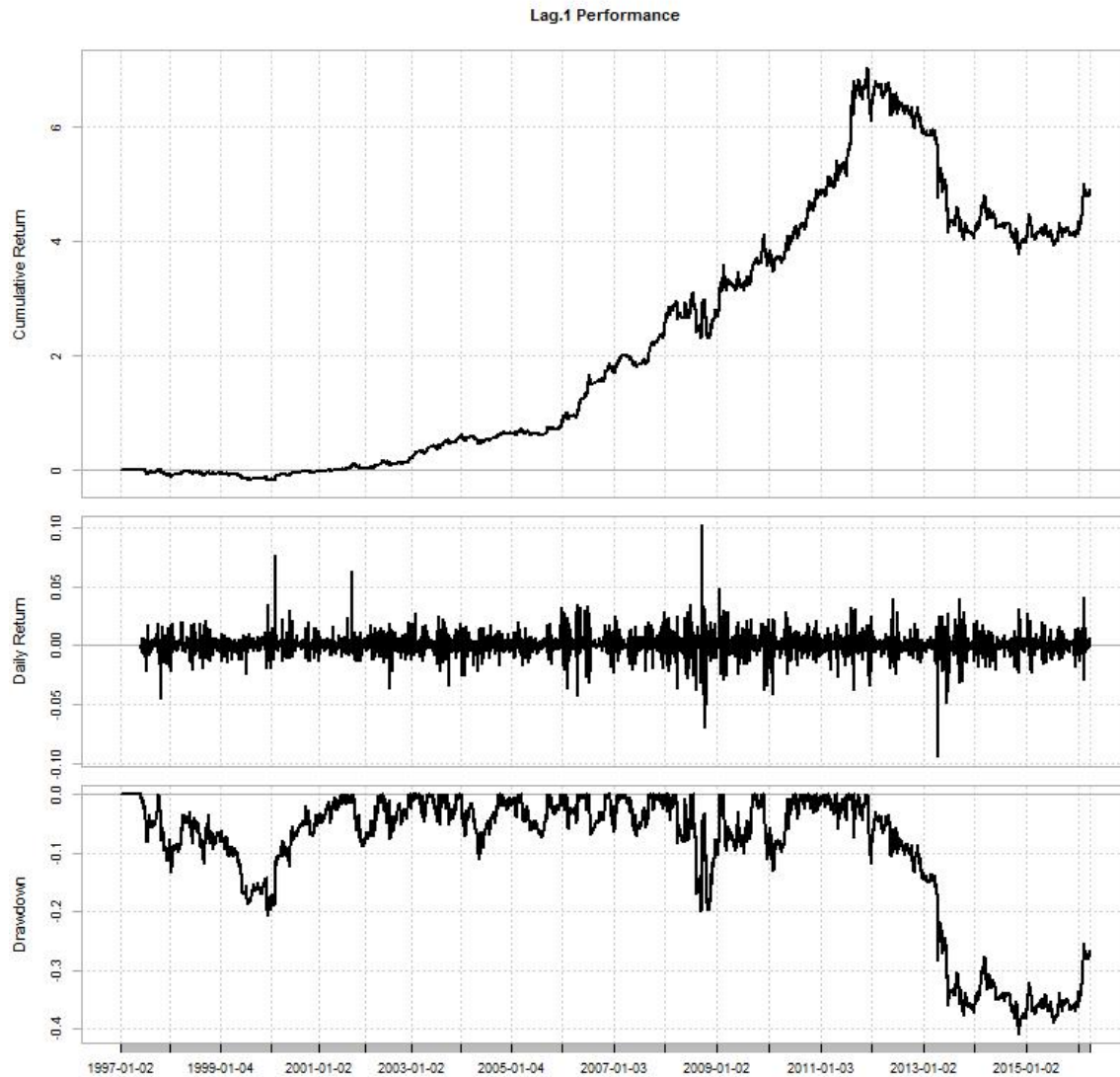
- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure 6.2: US Stock and Gold Portfolio Performance Summary - Stock Volatility Long Only MACD Strategy



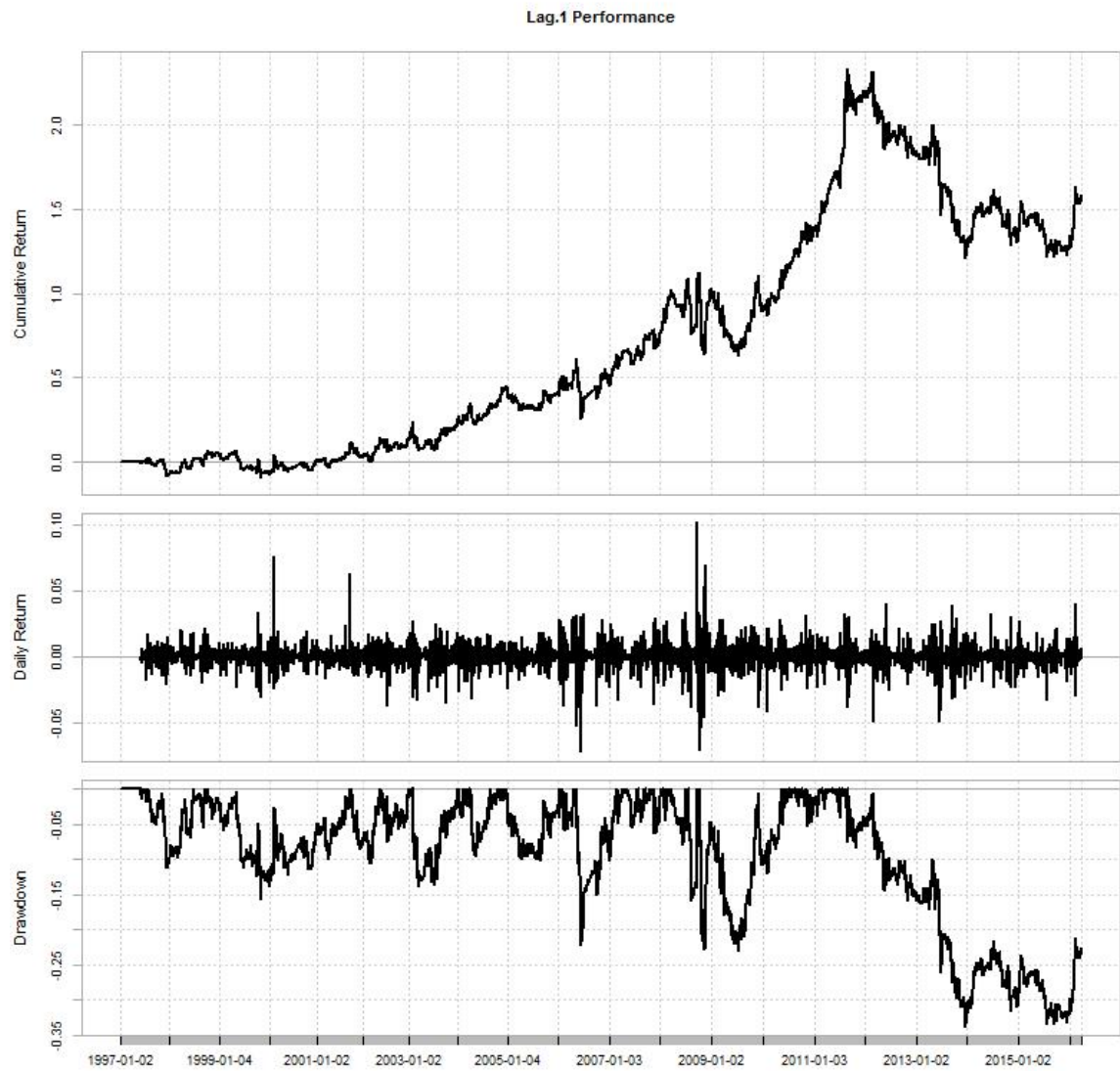
- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure 6.3: US Bond and Gold Portfolio Performance Summary - EPU Long Only MACD Strategy



- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure 6.4: US Bond and Gold Portfolio Performance Summary - Stock Volatility Long Only MACD Strategy



- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Chapter 7

In Search of Safe Haven Assets

7.1 Introduction

This chapter uses online search data to gauge retail investors' sentiment and attention on a number of considered safe haven assets or currencies, including gold, the US dollar, Swiss Franc and Japanese Yen. Those three currencies are selected since there are a large number of studies on their role as safe haven currencies such as Ranaldo and Soderlind [2010] as discussed in the literature review section 2.1.3.

Search data from Google (i.e. Google Trends) are collected on a global coverage as well as specifying sources as only from the US, UK and Germany. In addition, search data from Baidu (i.e. Baidu Index) is collected to measure public interests in China. Spillover analysis is applied to assess any causal and dynamic relationships between safe haven assets price movement and related search activities.

7.2 Model and data

7.2.1 Search Data

Google search volume indices (i.e. Google Trends) from the US, UK, Germany and worldwide are used, as Google is the dominant search engines in those regions. The region is specified on the Google Trends platform. The Baidu Index is used to analyse Chinese search interests.

Although both Google Trends and Baidu Index are measuring a similar concept, Google Trends measures relative search popularity and the data is constantly rescaled (with the range of 0–100) and re-sampled whilst the Baidu Index is weighted on absolute search volume and it is not rescaled or re-sampled^{1 2}.

Two groups of search terms are selected for spillover analysis in each market, one related to searches on safe haven asset or safe investments, the other specifically on considered safe haven assets/currencies (i.e. “gold”, “the US dollar” and so on.) A few of relevant search terms are evaluated for each topic in each market, and the most representative one is selected considering its relative popularity³ and consistency⁴. For China, the term “safe haven” has only been indexed since the end of 2016. Since, therefore, it does not have sufficient historical volume I, instead, use the term “economic crisis” as this reflects public concerns on the economic situations, hence a similar context when people are searching for safe haven assets. Search data is obtained with full history, i.e. Google Trends from January 2004 to March 2017, and Baidu Index from January 2011 to March 2017. Only monthly frequency is available from Google Trends for the whole history, therefore Baidu Index is obtained as monthly as well. Terms considered and selected can be found in Table 7.1 and Figure 7.1.

7.2.2 Financial market data

For each market, prices are converted to local currencies, hence in US dollars for the US, Pound for the UK, Euro for Germany and RMB for China. Prices in the US dollar are

¹More information on how the indices are calculated can be found on websites: support.google.com/trends and index.baidu.com/Helper.

²Both Google Trends and Baidu Index are as proxies for the number of searches, and do not distinguish whether the query is made from the same IP or not. Therefore 1000 search queries submitted from one IP and 200 identical queries submitted from 5 IPs in the same region will contribute to the final index of this region in the same way. Because of this nature in the data, this chapter attempts to explore the relationship between search interests with asset returns without adjusting the IP sources of the searches.

³Absolute search volumes are compared by downloading data for multiple search terms at the same time.

⁴For example, the term “safe investment” is used for worldwide and the US analysis, while “safe haven” is used for the UK and Germany, because searches of “safe haven” worldwide and in the US are significantly skewed in February 2013 due to the release of a movie called “Safe Haven”, and its influence cannot be removed by specifying search category as “Finance”. Searches for Swiss Franc also see an abrupt jump in January 2015 when the Swiss National Bank unexpectedly ended its minimum exchange rate which led to an immediately devaluation of the currency. However, I do not remove this extreme value as it is relevant search interest responding to the abrupt policy change.

also used with worldwide Google Trends data for a worldwide analysis. Financial data are all sourced from the Bloomberg, and the history matched against search data. In addition, considering most time series are non-stationary, arithmetic returns are used for spillover analysis. Summary descriptive statistics of search data and financial data can be found in Table 7.2, Table 7.3. They are also plotted in Figures D.24 – D.41 in the Appendix D.

Diebold and Yilmaz [2009] proposed spillover index is applied to assess the intensity of return spillovers between safe haven assets and their corresponding search activities. In this analysis, for each safe haven asset in each market, a 3-variable Vector Autoregressive model (VAR) is applied. For example, to examine spillovers between gold and its related search activities in the US, VAR has gold price in the US dollar, search volume of “gold” and “safe haven” in the US respectively. This analysis only investigates spillovers between gold price and related search volumes, therefore only those three variables are selected as endogenous variables. In assessing how the spillover evolves across time, VAR is applied to data over a rolling window of 24 months or two years (i.e. spillover index at time T is determined by spillover results over the time $T-23$ to T)⁵.

7.3 Results

The rolling spillover indices from growth rate of searches activities to asset returns, and from asset returns to searches are shown in Figures 7.2 – 7.5. The full return spillover analysis results for each country are included in Appendix J, which include, for instance, spillover indices from asset return to itself.

7.3.1 Spillovers from searches to asset return

Figures 7.2 and 7.3 show spillovers from growth rate of searches on the *asset/currency*, and growth rate of searches on “*safe haven*” to asset return respectively. Search data for China has a shorter history, so spillover indices only start from 2013. It is worth noting that spillover

⁵Only spillovers on returns are examined but not on volatilities, considering that the data is obtained at monthly frequency while volatility spillover between asset price and online searches is likely to be a short term phenomenon

index at time T is obtained from VAR over previous two-years window.

Spillover from searches on “gold” to gold return in local currencies show strikingly similar patterns across countries, in that it increases during market stress times such as the 2007–2008 Global Financial Crisis, 2009–2012 European sovereign debt crisis, and during the recent political uncertainty of the Brexit and the US election in 2016. It reaches the highest point, around 70, at the end of 2011 in the US and Germany. There is a spike at 80 for China, which drops significantly since then. For US dollars, spillovers are more volatile. There are some similar results across countries such as increasing spillovers in the end of 2016. However there are also diverging patterns, for instance, from 2008 to 2010 spillovers in the US is declining while it is at a relatively high level in the UK and Germany; besides spillover in China is increasing rapidly in 2017, while it is not in other countries. CHF has seen a much clear picture that spillovers from searches to its return has been extremely low before 2012. There have been increasing impacts in 2012, and it increases dramatically in January 2015. This is probably due to the unexpected devaluation of the currency as the Swiss National Bank abandoning the cap of exchange rate with the Euro. Germany saw the biggest spillovers from searches in from 2015 to 2016, while China saw the smallest impact. Spillovers from searches on “Japanese Yen” to Yen’s return are relatively more volatile. However, I can see a general upward trend in the end of 2008 and 2014 across countries. Next I look at spillovers from searches on “safe haven” to each asset/currency in Figure 7.3. Searches on “safe haven” have some similar impact to gold return across markets such as increasing spillover in 2009, 2011 and in the end of 2016, as well as quite a small spillover from the end of 2015 to 2016; however, I also observe some unique patterns for individual markets, such as a relatively high spillover in the UK from 2006 to 2008, similarly in China and Germany in 2014, but not in other markets. Spillovers to the US dollars remain at a relatively low level across countries most of the time, except from 2009 to the end of 2010 in the UK, Germany and worldwide. Spillovers from searches on “safe haven” to Swiss Franc have more variations across countries. Spillovers are seen going up in the end of 2007 in the US, UK and Germany, in the end of 2010 in Germany, the US and worldwide, in 2012 in the UK and worldwide. There is not really much impact from searches on “safe haven” to Yen in most times across countries. The

only exceptions are Germany in the end of 2009, the US and worldwide in the middle of 2013.

7.3.2 Spillovers from asset returns to related search activities

Figures 7.4 and 7.5 show spillovers from asset returns to related search activities, including searches on the “*asset/currency*” itself (Figure 7.4) and searches just on “*safe haven*” (Figure 7.5). Figure 7.4 shows that spillovers from asset returns to searches on the asset share similar results across countries, especially for gold, the US dollar, and Swiss Franc. Spillovers jump during market stress periods such as 2008, 2010, 2012 and end of 2016, although the values do not exceed 50 in any case. Spillovers to gold, the US dollar and Swiss Franc peaked at the same time in the end of 2008 in the US, while spillovers to Swiss Franc had a record high level again later in 2014. Returns of Yen also have impacts on its search volume in 2008 but only at a relatively high level in the UK and to a lesser extent in other countries. Figure 19 shows spillover results from asset returns to searches on “safe haven” across countries, which have more variations across countries compared with Figure 7.4. Gold return has increasing impact on searches on “safe haven” in the UK in the end of 2006 and 2012, in the US in the end of 2010, and in China and Germany in the middle of 2016. To the US dollar, Swiss Franc and Japanese Yen, I see more variations than similar patterns across countries.

7.4 Conclusion

In this study, online search data is used to gauge retail investors’ sentiment and attention on a number of considered safe haven assets or currencies, including gold, the US dollar, Swiss Franc and Japanese Yen. Google Trends is used for the US, UK, Germany and worldwide, while Baidu Index is used for China. On average, I find that spillovers from search volumes to returns are higher than spillovers from returns to search activities in the US, UK, Germany, China and worldwide. In general, the spillovers from searches to returns increase during market stress times such as the 2007–2008 Global Financial Crisis, 2009–2012 European sovereign debt crisis, and during recent political uncertainty in 2016–2017. Besides, I see that in the US, Germany and worldwide, searches on “gold” has a bigger spillover effect on

gold returns than currencies in 2008 and 2012, however searches on “safe haven” tend to have a higher spillover on the US dollar than gold returns especially during 2009 to 2011.

Table 7.1: Search term selection

Topic	Worldwide	the US	the UK	Germany
safe haven	safe haven safe investment safe investments	safe haven safe investment safe investments	safe haven safe investment safe investments	safe haven safe investment safe investments
gold	gold price gold prices price of gold gold	gold price gold prices price of gold gold	gold prices gold price price of gold gold	gold prices gold price price of gold gold
US dollar	USD US dollar	USD US dollar	USD US dollar	USD US dollar
Swiss Franc	Swiss Franc CHF CHF to USD	Swiss Franc CHF CHF to USD	Swiss Franc CHF CHF to USD	Swiss Franc CHF CHF to USD
Japanese yen	Japanese Yen Yen Yen to USD	Japanese Yen Yen Yen to USD	Japanese Yen Yen Yen to USD	Japanese Yen Yen Yen to USD

Figure 7.1: Baidu search term selection (in Chinese and English translation)

Topic	Safe Haven	Gold	US dollar	Swiss franc	Japanese Yen
Term Selected (in bold)	避险 safe haven	投资黄金 Invest in gold	美元 US dollar	瑞士法郎 Swiss franc	日元 Japanese Yen
	经济危机 economic crisis	黄金 Gold			

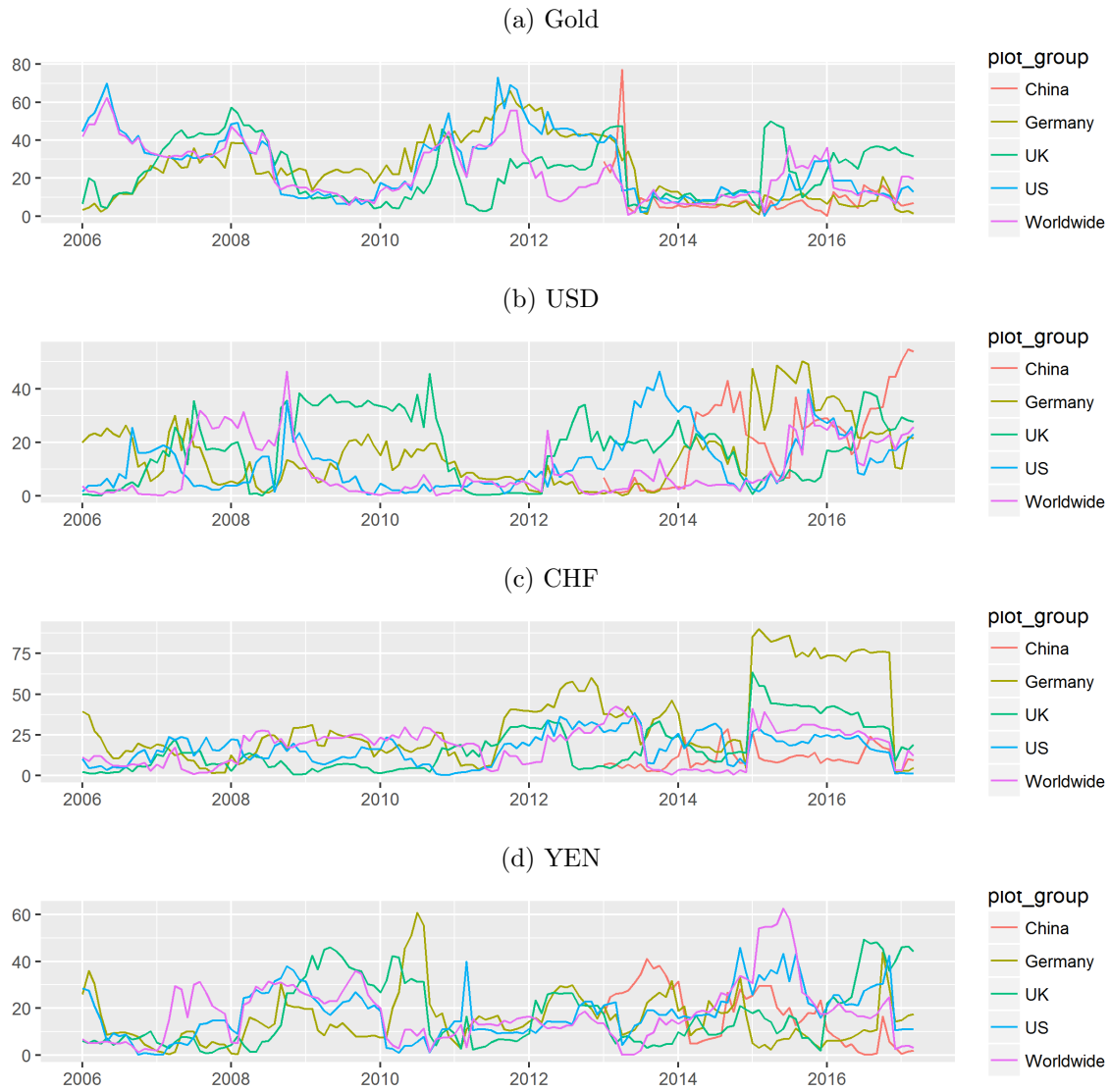
Table 7.2: Summary of data — level

	Mean	S.D.	Kurt.	Skew.	Min.	Max.	ADF ⁶	Obs.
AU	1046.0	402.8	-1.1	-0.1	384.5	1772.0	-1.09	159
USD	107.0	8.2	-0.4	0.7	94.6	127.7	-1.40	159
CHF	1.0	0.1	-1.1	-0.1	0.8	1.3	-1.93	159
YEN	0.0	0.0	-0.6	0.7	0.0	0.0	-1.12	159
AU_GBP	654.1	288.3	-1.4	-0.1	214.2	1123.4	-1.53	159
USD_GBP	0.6	0.1	0.4	0.5	0.5	0.8	-2.43	159
CHF_GBP	0.6	0.1	-1.4	-0.2	0.4	0.8	-1.85	159
YEN_GBP	0.0	0.0	-1.3	0.2	0.0	0.0	-1.50	159
AU_EUR	814.8	321.2	-1.4	-0.1	319.7	1356.1	-1.61	159
USD_EUR	0.8	0.1	-0.3	0.5	0.6	0.9	-2.27	159
CHF_EUR	0.7	0.1	-1.4	0.3	0.6	1.0	-2.54	159
YEN_EUR	0.0	0.0	-0.2	0.5	0.0	0.0	-1.92	159
AU_RMB	8774.8	1298.5	-1.1	0.5	6896.2	11323.3	-1.50	75
USD_RMB	6.4	0.2	0.3	1.0	6.1	6.9	0.18	75
CHF_RMB	6.8	0.3	5.7	2.0	6.3	8.2	-2.95	75
YEN_RMB	0.1	0.0	-1.3	0.4	0.1	0.1	-1.35	75
safe haven: (Worldwide)	20.1	7.3	12.5	2.9	9.0	62.0	-3.23	159
gold: (Worldwide)	38.3	13.1	3.2	1.2	19.0	100.0	-4.36*	159
USD: (Worldwide)	30.9	23.9	-0.1	1.0	4.0	100.0	-0.95	159
CHF: (Worldwide)	30.0	10.8	11.0	1.9	13.0	100.0	-3.22	159
Yen: (Worldwide)	55.1	16.8	0.4	1.1	29.0	100.0	-1.60	159
safe haven: (US)	27.0	12.1	13.2	2.7	0.0	100.0	-4.64*	159
gold: (US)	40.1	11.5	5.3	1.6	22.0	100.0	-2.81	159
USD: (US)	30.0	22.1	-0.1	0.9	4.0	100.0	-1.46	159
CHF: (US)	42.2	11.6	3.3	0.8	13.0	100.0	-3.74	159
Yen: (US)	56.9	16.4	0.4	1.2	33.0	100.0	-1.51	159
safe haven: (UK)	9.5	11.8	22.3	3.6	0.0	100.0	-6.85*	159
gold: (UK)	46.6	14.6	0.3	0.3	21.0	100.0	-2.66	159
USD: (UK)	22.5	20.6	0.3	1.1	2.0	100.0	-2.08	159
CHF: (UK)	26.2	16.4	1.7	1.2	5.0	100.0	-2.43	159
Yen: (UK)	39.2	18.5	1.0	1.3	13.0	100.0	-0.98	159
safe haven: (Germany)	5.2	10.2	49.5	6.0	0.0	100.0	-4.73*	159
gold: (Germany)	45.4	15.4	-0.3	0.4	19.0	100.0	-4.02*	159
USD: (Germany)	51.7	26.8	-1.1	-0.2	7.0	100.0	-2.09	159
CHF: (Germany)	36.2	10.8	8.4	1.6	17.0	100.0	-2.56	159
Yen: (Germany)	54.8	13.2	0.2	0.5	27.0	100.0	-3.66	159
safe haven: (China)	703.1	209.3	-0.1	0.8	357.2	1247.0	-2.48	75
gold: (China)	11906.5	5468.7	26.5	4.1	4334.4	48427.3	-3.59	75
USD: (China)	9208.6	6315.2	2.2	1.4	1897.8	32506.0	-0.47	75
CHF: (China)	731.2	257.3	0.3	0.8	248.4	1471.5	-2.49	75
Yen: (China)	9528.0	6894.9	-0.6	0.8	1427.2	25394.6	-2.34	75

Table 7.3: Summary of data — first difference

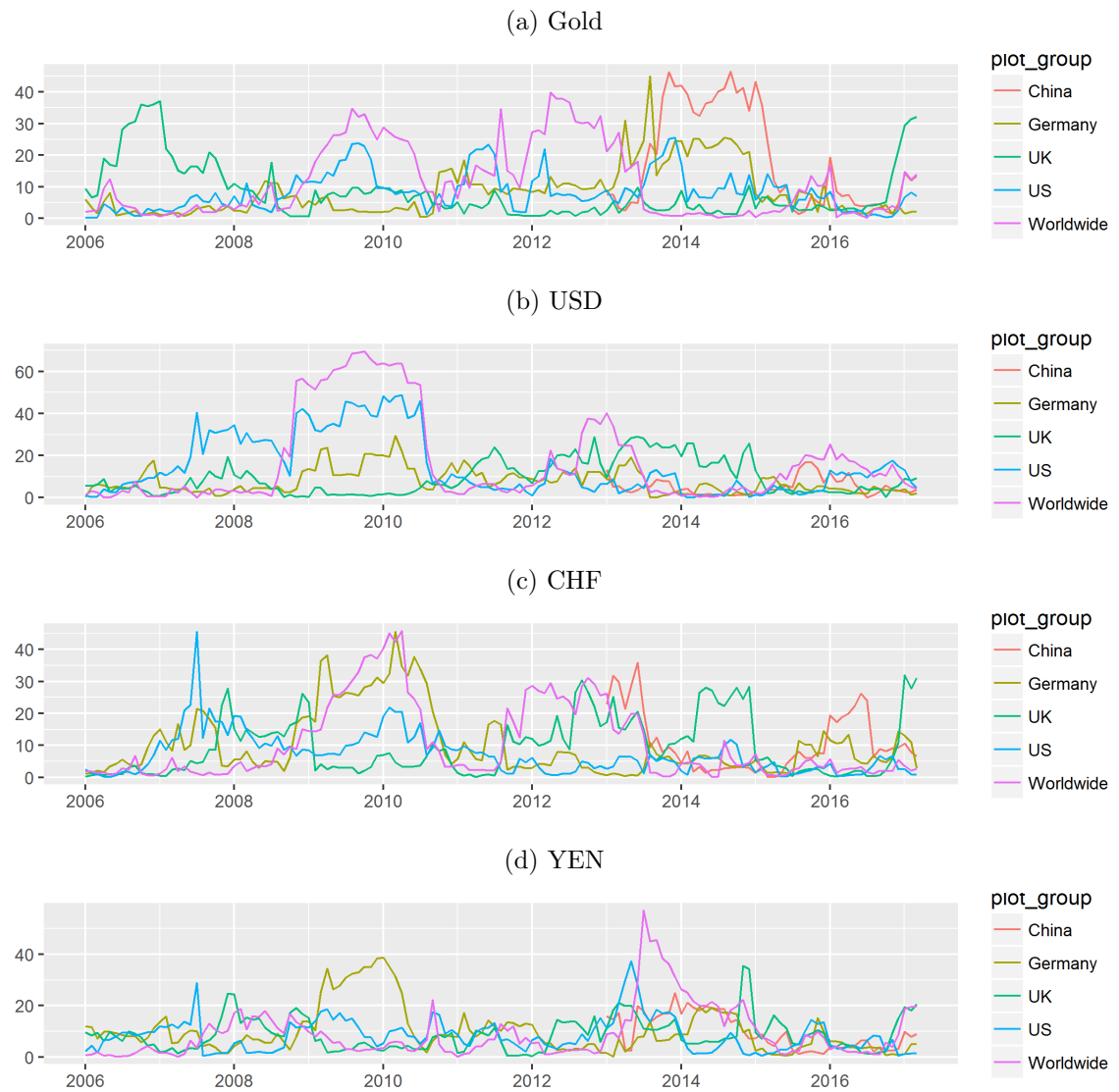
	Mean	S.D.	Kurt.	Skew.	Min.	Max.	ADF ⁷	Obs.
ΔAU	0.01	0.04	0.29	0.07	-0.11	0.12	-4.7*	158
ΔUSD	0.00	0.01	3.26	0.85	-0.03	0.07	-4.7*	158
Δchf	0.00	0.02	2.29	-0.24	-0.11	0.08	-5.0*	158
ΔYEN	0.00	0.02	0.53	-0.04	-0.07	0.06	-5.5*	158
ΔAU_GBP	0.01	0.04	0.40	0.23	-0.10	0.13	-4.7*	158
ΔUSD_GBP	0.00	0.02	2.97	0.92	-0.06	0.10	-5.3*	158
ΔCHF_GBP	0.00	0.02	1.42	0.63	-0.07	0.08	-5.0*	158
ΔYEN_GBP	0.00	0.03	3.29	1.17	-0.07	0.14	-5.0*	158
ΔAU_EUR	0.01	0.04	0.90	0.25	-0.11	0.13	-4.5*	158
ΔUSD_EUR	0.00	0.02	0.89	0.40	-0.06	0.08	-4.7*	158
ΔCHF_EUR	0.00	0.02	11.22	1.49	-0.07	0.10	-5.0*	158
ΔYEN_EUR	0.00	0.03	4.71	1.04	-0.07	0.15	-5.3*	158
ΔAU_RMB	0.00	0.04	0.17	0.39	-0.07	0.11	-3.0	74
ΔUSD_RMB	0.00	0.01	1.01	1.19	-0.01	0.02	-4.2*	74
ΔCHF_RMB	0.00	0.02	5.81	-1.42	-0.11	0.04	-5.4*	74
ΔYEN_RMB	0.00	0.02	0.09	-0.49	-0.07	0.05	-3.4	74
$\Delta safehaven : (Worldwide)$	0.06	0.37	3.33	1.32	-0.71	1.65	-5.8*	158
$\Delta gold : (Worldwide)$	0.00	0.18	5.98	1.32	-0.49	0.94	-6.7*	158
$\Delta USD : (Worldwide)$	0.02	0.10	3.94	0.89	-0.22	0.47	-5.8*	158
$\Delta CHF : (Worldwide)$	0.01	0.14	26.30	2.82	-0.58	1.14	-6.6*	158
$\Delta Yen : (Worldwide)$	0.01	0.14	22.36	2.28	-0.61	1.01	-6.4*	158
$\Delta safehaven : (US)$	0.11	0.59	8.83	2.28	-1.00	3.18	-5.2*	158
$\Delta gold : (US)$	0.00	0.17	2.30	0.87	-0.40	0.65	-6.1*	158
$\Delta USD : (US)$	0.02	0.10	3.27	0.94	-0.22	0.49	-6.3*	158
$\Delta CHF : (US)$	0.01	0.15	6.31	0.62	-0.51	0.82	-7.6*	158
$\Delta Yen : (US)$	0.01	0.11	7.07	0.68	-0.50	0.62	-7.2*	158
$\Delta safehaven : (UK)$	0.01	0.51	2.83	0.24	-1.61	1.69	-7.5*	158
$\Delta gold : (UK)$	0.00	0.13	2.40	0.23	-0.44	0.47	-7.3*	158
$\Delta USD : (UK)$	0.02	0.16	4.42	0.67	-0.41	0.69	-7.0*	158
$\Delta CHF : (UK)$	0.01	0.22	2.13	0.48	-0.62	0.84	-8.1*	158
$\Delta Yen : (UK)$	0.01	0.14	2.31	-0.31	-0.54	0.51	-7.3*	158
$\Delta safehaven : (Germany)$	0.00	0.27	8.12	0.56	-1.04	1.45	-5.7*	158
$\Delta gold : (Germany)$	0.00	0.16	2.48	0.26	-0.60	0.57	-6.9*	158
$\Delta USD : (Germany)$	0.01	0.16	4.93	-0.03	-0.69	0.56	-4.5*	158
$\Delta CHF : (Germany)$	0.00	0.15	11.32	1.56	-0.53	0.94	-6.5*	158
$\Delta Yen : (Germany)$	0.00	0.16	3.59	-0.14	-0.60	0.67	-7.1*	158
$\Delta safehaven : (China)$	0.03	0.21	1.49	0.32	-0.52	0.72	-6.3*	74
$\Delta gold : (China)$	0.09	0.62	50.73	6.59	-0.57	4.88	-4.3*	74
$\Delta USD : (China)$	0.05	0.17	2.09	0.99	-0.29	0.63	-4.5*	74
$\Delta CHF : (China)$	0.04	0.24	11.60	2.58	-0.48	1.28	-4.3*	74
$\Delta Yen : (China)$	0.05	0.17	0.49	0.77	-0.27	0.59	-4.7*	74

Figure 7.2: Spillover from searches of the asset to the asset return



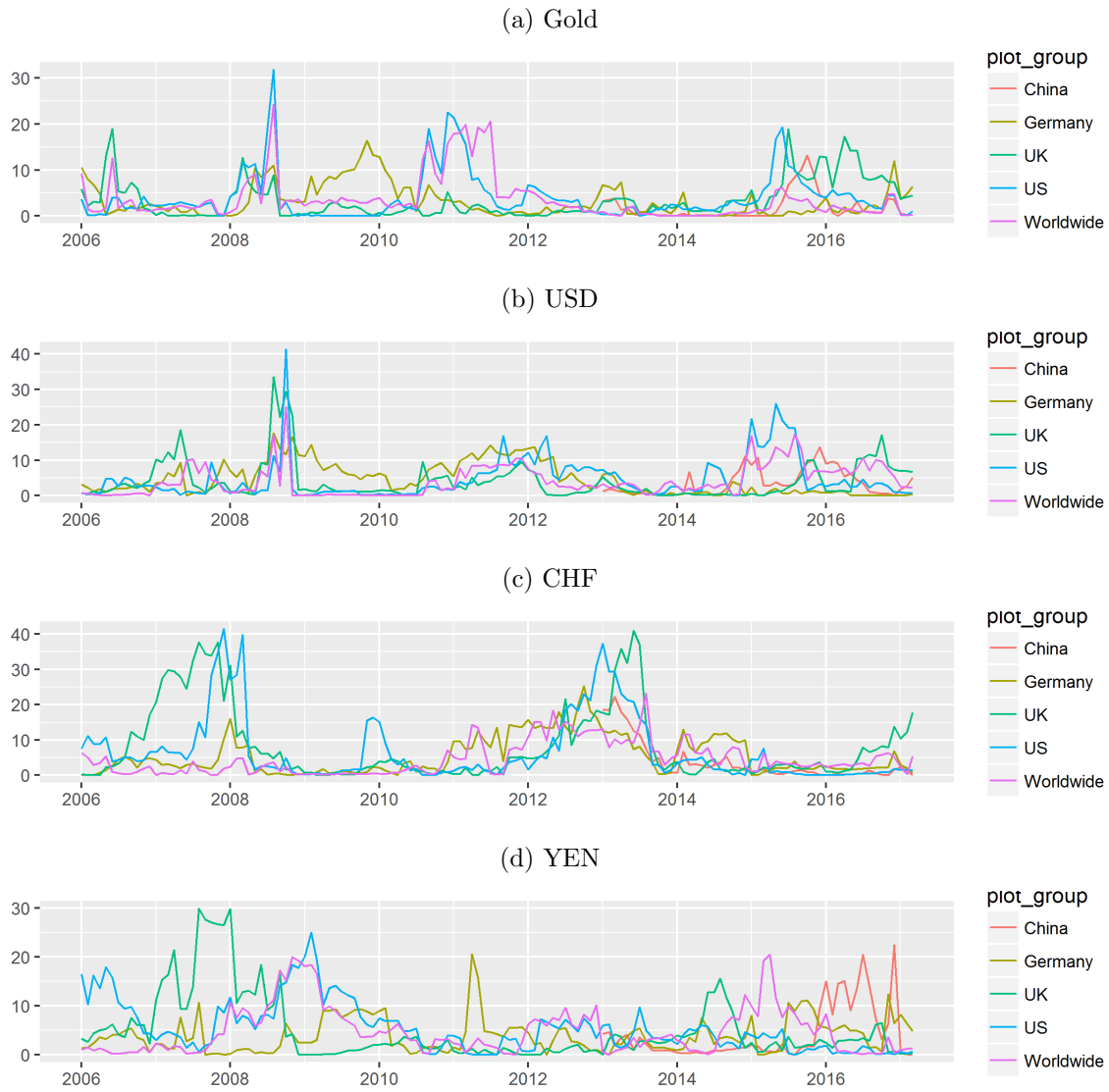
Note: spillover indices at a given time T is obtained from a previous two-year window.

Figure 7.3: Spillover from searches of “safe haven” asset to the asset return



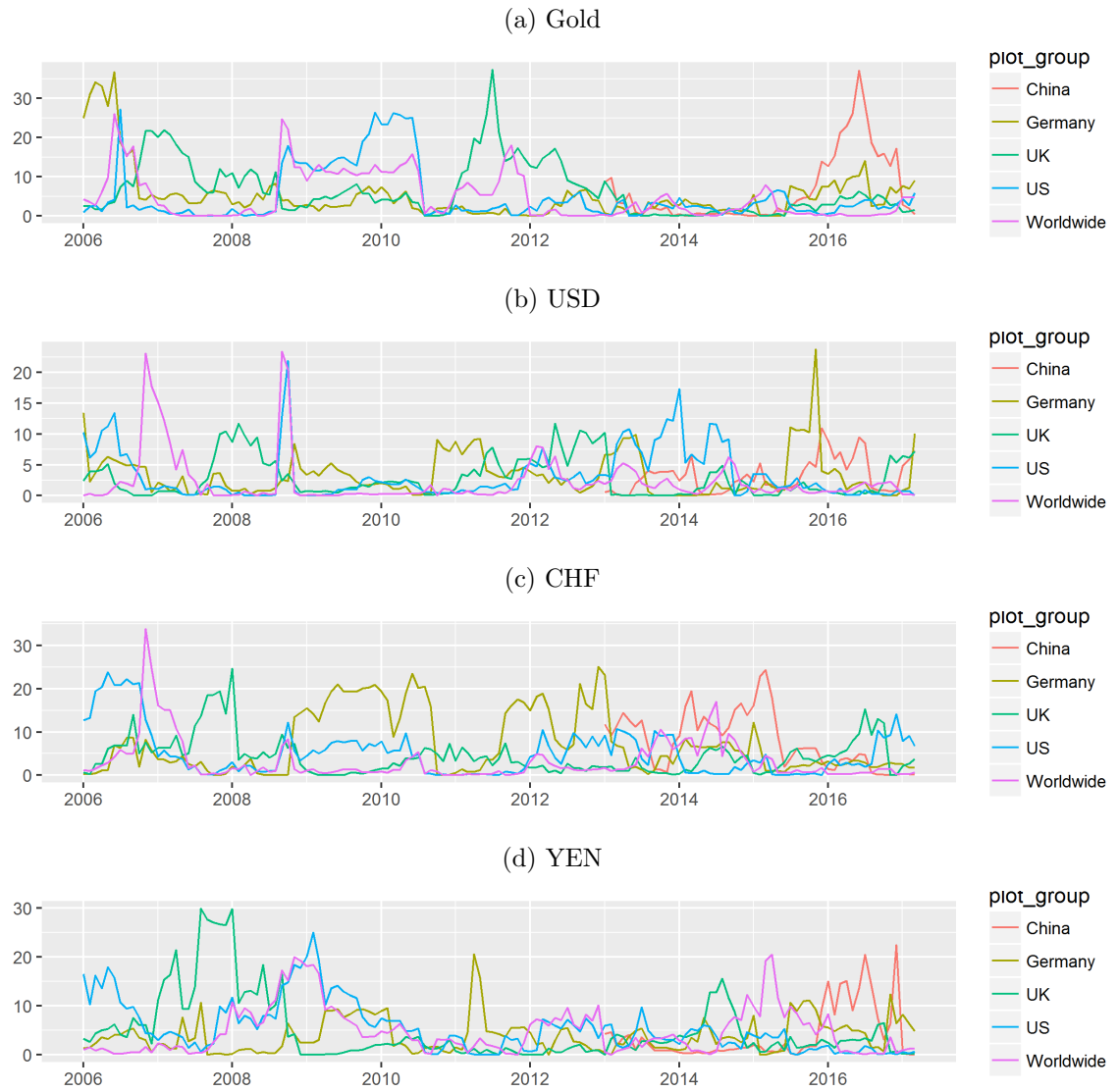
Note: spillover indices at a given time T is obtained from a previous two-year window.

Figure 7.4: Spillover from asset returns to searches of the asset



Note: spillover indices at a given time T is obtained from a previous two-year window.

Figure 7.5: Spillover from asset returns to searches of “safe haven” asset



Note: spillover indices at a given time T is obtained from a previous two-year window.

Chapter 8

Conclusions and Future Work

8.1 Introduction

The last chapter concludes the main findings from this thesis, its limitations and suggestions for future work.

8.2 Main Findings and Contributions

This thesis firstly overviews conceptual and theoretical aspects of safe haven assets, flight-to-safety phenomenon and related topics such as theoretical aspects of the safe asset, empirical findings of flight-to-safety episodes across countries as well as asset classes, analytical framework of market linkages during crisis periods, and historical economic crises triggered by various reasons and different types of market stress measurements. It identifies that gold's role as safe haven has motivated studies on silver, platinum, and palladium's potential as safe haven assets. Then it reviews studies on the economics of precious metal markets including the demand, supply and above-ground stock statistics for gold, silver, platinum and palladium, the price and volatility determinants of each metal, the inter-linkages between them, and previous findings of studies on metals as safe haven assets. The final section of the literature review is on the sentiment aspect of safe haven assets, mainly sentiment as

measured by investor attention. It firstly reviews the theoretical background of sentiment analysis on asset pricing, then it reviews studies on how investor attention may influence the price discovery process, next it discusses how investor attention could be measured by online search data, how data is collected and how an index is constructed, and finally it looks at its applications in economics and financial research.

The first empirical analysis in this study explores dynamic dependence with Dynamic Conditional Correlation (DCC) between precious metals market, equity and bond markets across eleven countries including the US, UK, Germany, France, Italy, Switzerland, Canada, Japan, China, India and South Africa over the period from January 1994 to July 2016. The decoupling between equity and bond markets is observed across markets, which is consistent with previous studies. Similar patterns are also obtained across metals and countries such as negative correlations between gold and stock market during the 2007-2009 Global Financial crisis, which suggests a need for further investigation of gold and other precious metals as safe haven across countries.

The second part of the analysis examines precious metals time-varying safe haven status across eleven countries. Mostly applying existing modelling procedures, however, a few modifications are made to generate a series of daily weak and strong safe haven incidents for each metal. In addition, results are aggregated to calculate the average weak and strong safe havenness for each metal in each country, which refers to the proportion of time when a metal functions as a weak or strong safe haven over the examined time frame. Results show that precious metals could provide weak safe haven hedge about 33% of the time against stocks and 31% of the time against bonds, when the asset return fall is in the lower 5% region. On average, gold is not the most frequent safe haven across eleven countries. In general, precious metals provided protection at different times across countries. No precious metal provides safe haven status consistently, over time or across asset classes. And, finally, strong safe haven status is rare.

The analysis then goes on to characterize those periods in which, under certain political, economic and financial conditions, gold, silver, platinum and palladium are more likely to become safe haven assets and hedge the risks of market tail events. Zero-inflated Pois-

son regression is applied first, then considering the large number of potential determinants and various model specifications, model sensitivity is considered in particular by applying Extreme Bound Analysis (EBA). EBA identifies robust variables with the safe haven incidences. Political risk is found to be a positive and robust determinant in most countries when gold is safe haven against stock and bond markets tail events. Stock volatility also sees positive and robust results across countries but only against stock market stress. Exchange rate, interest rate and credit spreads tend to have large coefficient values but results are quite mixed for different markets and not robust. In addition, a portfolio analysis is carried out testing whether precious metals add value to the stock or bond index portfolios with four trading strategies, based on signals from political risk and stock market volatilities. Results show that in generally they do add alpha in the portfolio. In most cases, gold outperforms other three precious metals against both stock and bond portfolios and the MACD long only strategy performs better than others.

The last part of the analysis looks into the sentiment aspect of safe haven assets, in particular on investor attention as measured by online search interests. It goes beyond precious metals and includes considered safe haven currencies including the US dollar, Japanese Yen, and Swiss Franc. Spillover analysis is applied to assess any causal and dynamic relationships between safe haven assets price movement and related search activities. Online search interests are collected from worldwide, the US, UK, Germany, and China, combining data from Google and Baidu. On average, we find that spillovers from search volumes to returns are higher than spillovers from returns to search activities in the US, UK, Germany, China and worldwide. In general, the spillovers from searches to returns increase during market stress times such as the 2007–2008 Global Financial Crisis, 2009–2012 European sovereign debt crisis, and during recent political uncertainty of Brexit and the US presidential election in 2016–2017. Besides, we see that in the US, Germany and worldwide, searches on “gold” have a bigger spillover effect on gold returns than currencies in 2008 and 2012, however searches on “safe haven” tend to have a higher spillover on the US dollar than gold returns especially during 2009 to 2011.

8.3 Limitations and Future Work

Market return dependence as measured by Copula

Future work could apply copula to measure market return dependence under extreme scenarios. Copula came from the theory of probabilities in statistics and it has only become more popular in the finance domain since 1999 (e.g. Embrechts et al. [1999]), one hundred years after the introduction of bivariate correlation. Essentially, copula is a function that links univariate marginals to their multivariate distribution. Copula can measure market return dependence by their joint density function. It gives the probability that multiple assets will all be at their extreme lows or highs at the same time according to Engle [2009], therefore it has been applied to the study of extreme market co-movements such as contagion (e.g. Rodriguez [2007]). It has recently been applied in safe haven studies such as Liu et al. [2016], Nguyen and Liu [2017] and Bekiros et al. [2017]. Different from correlation, which measures linear dependence and invariant to non-linear transformations, copula can examine non-linear dependencies as discussed in Engle [2009]. Therefore, it would be interesting to examine precious metals time-varying safe haven properties with the copula approach and compare results obtained from this study.

Macroeconomic determinants in a global environment

This research only analyses domestic macroeconomic determinants for precious metals as safe haven against local stock or bond markets. However, as a globally traded large asset class, macroeconomic variables in some big economies are likely to influence precious metals performance across countries. Therefore, future work could examine potential determinants in a global environment by compiling the panel data of safe haven incidences across countries.

Model sensitivity analysis with Bayesian Model Averaging

As discussed in the methodology chapter, in the section titled Model Uncertainty, sensitivity analysis can also be referred to model averaging in the Bayesian manner. However, Bayesianism differs from frequentism in a fundamental way, in that they see probability differently.

Frequentists see probability as fundamentally related to the frequency of repeated events; while Bayesians see it as related to our own certainty or uncertainty of events. So, frequentists are talking about variation of data given a fixed model, whilst Bayesians are talking about given observed data, what is the model variations as argued by Koop [2003]. Bayesian Model Averaging (BMA) has been applied recently in Baur et al. [2014] and Baur and Lucey [2017] in examining how gold price determinants change by time. Therefore, it would be interesting to apply BMA to safe haven determinants, and see whether results are consistent with EBA in this study.

Appendix A

Arrow-Debreu Security

An **Arrow-Debreu Security** for state i is an asset that pays off one dollar in state i and zero in all other states. For instance, for a three possible states, the payoffs in a year from now are as follows:

Table A.1: Arrow-Debreu securities and complete markets

State	AD1	AD2	AD3
S_1	1	0	0
S_2	0	1	0
S_3	0	0	1
Price	S_1	S_2	S_3

AD1, AD2, and AD3 are Arrow-Debreu securities for states 1, 2, and 3 respectively. If an Arrow-Debreu security exists for each possible state i then we say that markets are complete, which means that any possible payoff could be recreated from a simple linear combination of Arrow-Debreu securities.

Table A.2: Complete markets

State	AD1	AD2	AD3	AssetX
S_1	1	0	0	X_1
S_2	0	1	0	X_2
S_3	0	0	1	X_3
Price	S_1	S_2	S_3	$P_X = X_1S_1 + X_2S_2 + X_3S_3$

Appendix B

A List of Safe Haven Assets in Academic Publications

Author and year	SH Assets, currencies or countries	Time period
Thomas and Michael [1987]	the US dollar-denominated assets	1980-1985
Ayanian [1989]	the US dollar	1973-1986
Throop et al. [1991]	the US dollar	1974-1984
Kumah [1995]	DM denominated assets	1974-1992
Citak [1999]	Gold	Middle 1980s
Doroodian and Caporale [2000]	the US dollar-denominated assets	1973-1996
Upper [2000]	Ten year German government bonds	1998
Kaul and Sapp [2006]	the US dollar and Swiss Franc	December 1999-December 2000
Ranaldo and Soderlind [2010]	Swiss Franc, Japanese Yen and Euro	1993-2008
Cairns et al. [2007]	Swiss Franc, Japanese Yen, Euro, etc.	1998-2006
Mora [2007]	Bank deposits	2007-2009 financial crisis
Beck and Rahbari [2008]	the US dollar and Euro	
Bleaney and Li [2009]	the US dollar	

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Aleksashenko [2009]	Russian Assets	before 2008
Roache and Rossi [2009]	Gold	1997-2009
Gómez-Puig [2009]	Government bonds from EMU countries	1998-2005
Mccauley and Mcguire [2009]	the US dollar	Late 2008
Hammoudeh et al. [2010]	Gold, Oil, silver and copper	1990-2006
Kiohos and Sariannidis [2010]	Gold	1999-2009
Sumner et al. [2010]	Gold	1970-2009
Baur and Lucey [2010]	Gold	Nov 1995 Nov 2005
Baur and K.J.McDermott [2010]	Gold	1979-2009
Beckmann and Scheiber [2010]	Euro in Southeastern Europe	Survey in 2011
Schuknecht and Hagen [2010]	German bonds	after the crisis
Coudert and Raymond [2010]	Gold as safe haven against stocks	1978-2009
Kohler [2010]	the US dollar, the Japanese Yen and Swiss franc	Asian financial crisis 1997-98; Russian debt default Aug 98; Global financial crisis 07-09
Hoffmann and Suter [2010]	the Swiss Franc	1990-2009
Lai and Tseng [2010]	The Chinese stock market	1993-1999; 2000-2008
Kim and Dilts [2011]	Gold and Oil	1970-2008
Filis et al. [2011]	Oil	2007-2009
Bartolini et al. [2010]	US T-bills	1999-2006
Lam and Tokuoka [2011]	Japanese Government Bonds	European sovereign debt crisis
Baudszus et al. [2012]	Equity REITs	1999-2010
Ejsing and Grothe [2012]	Germany and French government bonds	2008-2009, 2010-2011
Santis [2012]	German Bund	2007 Global financial crisis
Aizenman and Inoue [2013]	Gold	2007 Global financial crisis
Bernoth and Erdogan [2012]	German assets	Q4/2006-Q1/2010
Hsieh et al. [2012]	Investments in past long-term losers	1999-2009

Baele et al. [2013]	the Swiss Franc, the Japanese Yen, the US dollar
Wong and Fong [2013]	The Japanese Yen and the Hong Kong dollar 2001-2012

Appendix C

Data Sources

Data sources for empirical analysis of each country are listed as follow:

Oil price

Crude Oil Brent Cur. Month FOB \$/BBL, daily

Source: ICIS

GSCI

S&P GSCI Commodity Total Return, daily

Source: S&P Dow Jones Indices

Gold Spot \$/Oz Curncy, daily

The Gold Spot price is quoted as US dollars per Troy Ounce.

Silver Spot \$/Oz Curncy, daily

The Silver Spot price is quoted as US dollars per Troy Ounce.

Platinum Spot \$/Oz Curncy, daily

The per Troy ounce spot price for Platinum, in plate or ingot form, with a minimum purity of 99.95%.

Palladium Spot \$/Oz Curncy, daily

The per Troy ounce spot price for Palladium, in plate or ingot form, with a minimum purity of 99.95%.

The US

S&P500 index, daily

Source: Bloomberg

Bloomberg/EFFAS Bond Indices US Govt 7-10 Yr TR, daily

Source: Bloomberg

VIX

Chicago Board Options Exchange SPX Volatility Index, daily

Source: Chicago Board Options

FSI

United States Financial Stress Index, monthly

Source: Federal Reserve Bank of Kansas City

sentiment

University of Michigan Consumer Sentiment Index, monthly

Source: University of Michigan

EPU

US Economic Policy Uncertainty Composite Index, monthly

Source: Baker, Bloom & Davis

r

Federal Funds Target Rate - Upper Bound (NSA, Percent), daily

Source: Federal Reserve

CPI

IMF US CPI, monthly

Source: IMF

USD

US Trade Weighted Broad Dollar January 1997=100, daily

Source: Federal Reserve

Industrial production

IMF US Industrial Production SA, monthly

Source: IMF

Credit spreads

US Credit Spreads, period average NADJ, quarterly

Source: Oxford Economics

The UK

FTSE100 index, daily

Source: Bloomberg

Bloomberg/EFFAS Bond Indices UK Govt 7-10 Yr TR, daily

Source: Bloomberg

VFTS

FTSE 100 Volatility Index, daily

Source: FTSE

FSI

Euro Area Systemic Stress Indicator Composite Index NSA, weekly

Source: European Central Bank

sentiment

European Commission Economic Sentiment Indicator UK (SA), monthly

Source: European Commission

EPU

UK Economic Policy Uncertainty Composite Index, monthly

Source: Baker, Bloom & Davis

r

UK Bank of England Official Bank Rate, daily

Source: Bank of England

CPI

IMF UK CPI, monthly

Source: IMF

GBP

GBPUSD Spot Exchange Rate - Price of 1 GBP in USD, daily

Source: Bloomberg

Industrial production

IMF UK Industrial Production SA, monthly

Source: IMF

Credit spreads

UK Credit Spreads, period average NADJ, quarterly

Source: Oxford Economics

Germany**DAX30 index, daily**

Source: Bloomberg

Bloomberg/EFFAS Bond Indices Germany Govt 7-10 Yr TR, daily

Source: Bloomberg

V1X

Vdax New Volatility Index, daily

Source: Deutsche Boerse

FSI

Euro Area Systemic Stress Indicator Composite Index NSA, weekly

Source: European Central Bank

sentiment

European Commission Economic Sentiment Indicator Germany (SA), monthly

Source: European Commission

EPU

Germany Economic Policy Uncertainty Composite Index, monthly

Source: Baker, Bloom & Davis

r

Germany Households Interest Rate: New Agreed Mat ;1 Year Deposits, daily

Source: European Central Bank

CPI

IMF Germany CPI, monthly

Source: IMF

EUR

EURUSD Spot Exchange Rate - Price of 1 EUR in USD, daily

Source: Bloomberg

Industrial production

IMF Germany Industrial Production SA, monthly

Source: IMF

Credit spreads

Germany Credit Spreads, period average NADJ, quarterly

Source: Oxford Economics

France

CAC40 index, daily

Source: Bloomberg

Bloomberg/EFFAS Bond Indices France Govt 7-10 Yr TR, daily

Source: Bloomberg

VCAC

CAC 40 Volatility Index, daily

Source: Bloomberg

FSI

Euro Area Systemic Stress Indicator Composite Index NSA, weekly

Source: European Central Bank

sentiment

European Commission Economic Sentiment Indicator Germany (SA), monthly

Source: European Commission

EPU

France Economic Policy Uncertainty Composite Index, monthly

Source: Baker, Bloom & Davis

r

France Households Interest Rate: New Agreed Mat 1 Year Deposits, daily

Source: European Central Bank

CPI

IMF France CPI, monthly

Source: IMF

EUR

EURUSD Spot Exchange Rate - Price of 1 EUR in USD, daily

Source: Bloomberg

Industrial production

IMF France Industrial Production SA, monthly

Source: IMF

Credit spreads

France Credit Spreads, period average NADJ, quarterly

Source: Oxford Economics

Italy**FTSE MIB index, daily**

Source: Bloomberg

Bloomberg/EFFAS Bond Indices Italy Govt 7-10 Yr TR, daily

Source: Bloomberg

MIBIVI

30 Days Implied Volatility for FTSEMIB Index, daily

Source: Bloomberg

FSI

Euro Area Systemic Stress Indicator Composite Index NSA, weekly

Source: European Central Bank

sentiment

European Commission Economic Sentiment Indicator Germany (SA), monthly

Source: European Commission

EPU

Italy Economic Policy Uncertainty Composite Index, monthly

Source: Baker, Bloom & Davis

r

Italy Households Interest Rate: New Agreed Mat 1 Year Deposits, daily

Source: European Central Bank

CPI

IMF Italy CPI, monthly

Source: IMF

EUR

EURUSD Spot Exchange Rate - Price of 1 EUR in USD, daily

Source: Bloomberg

Industrial production

IMF Italy Industrial Production SA, monthly

Source: IMF

Credit spreads

Italy Credit Spreads, period average NADJ, quarterly

Source: Oxford Economics

Switzerland**Swiss Market Index index, daily**

Source: Bloomberg

Bloomberg/EFFAS Bond Indices Switzerland Govt 7-10 Yr TR, daily

Source: Bloomberg

VSMI

VSMIO Vol Index for SMI, daily

Source: Bloomberg

sentiment

Switzerland Consumer Confidence EU Compatible, monthly

Source: European Commission

EPU

Switzerland Economic Policy Uncertainty Composite Index, monthly

Source: Baker, Bloom & Davis

r

Switzerland National Bank Libor Target, daily

Source: Switzerland National Bank

CPI

IMF Switzerland CPI, monthly

Source: IMF

CHF

Swiss Franc Spot Currency, daily

Source: Bloomberg

Industrial production

IMF Switzerland Industrial Production SA, monthly

Source: IMF

Credit spreads

Switzerland Credit Spreads, period average NADJ, quarterly

Source: Oxford Economics

Canada**S&P/TSX index, daily**

Source: Bloomberg

Bloomberg/EFFAS Bond Indices Canada Govt 7-10 Yr TR, daily

Source: Bloomberg

VIXC

S&P/TSX 60 VIX, daily

Source: Bloomberg

sentiment

OECD Canada Composite Leading Indicator Consumer Confidence SA 2000Y, monthly

Source: OECD

EPU

Canada Economic Policy Uncertainty Composite Index, monthly

Source: Baker, Bloom & Davis

r

Bank of Canada Overnight Lending Rate, daily

Source: Bank of Canada

CPI

IMF Canada CPI, monthly

Source: IMF

CAD

Canadian Dollar Spot Currency, daily

Source: Bloomberg

Industrial production

IMF Canada Industrial Production SA, monthly

Source: IMF

Credit spreads

Canada Credit Spreads, period average NADJ, quarterly

Source: Oxford Economics

Japan

NIKKEI225 index, daily

Source: Bloomberg

Bloomberg/EFFAS Bond Indices Japan Govt 7-10 Yr TR, daily

Source: Bloomberg

VXJ

The VXJ index, daily

Source: Bloomberg

sentiment

BoJ Consumer Sentiment Present Economic Condition (NSA), monthly

Source: Bank of Japan

EPU

Japan Economic Policy Uncertainty Composite Index, monthly

Source: Baker, Bloom & Davis

r

Bank of Japan Result Unsecured Overnight Call Rate, daily

Source: Bank of Japan

CPI

IMF Japan CPI, monthly

Source: IMF

YEN

Japanese Yen Spot Currency, daily

Source: Bloomberg

Industrial production

IMF Japan Industrial Production SA, monthly

Source: IMF

Credit spreads

Japan Credit Spreads, period average NADJ, quarterly

Source: Oxford Economics

China**Shanghai Stock Exchange Composite Index (SHCOMP), daily**

Source: Bloomberg

FTSE China Govt Price 7 to 10 Yr, daily

Source: Bloomberg

FSI

The Nomura China Stress Indicator, monthly

Source: Nomura Holdings, Inc.

sentiment

China Consumer Confidence December 1997=100, monthly

Source: National Bureau of Statistics of China

EPU

China - HK Economic Policy Uncertainty News-Based Index, monthly

Source: Baker, Bloom & Davis

r

China 1 Year Benchmark Lending Rates, daily

Source: The People's Bank of China

CPI

IMF China CPI, monthly

Source: IMF

CNY

USDCNY Spot Exchange Rate - Price of 1 USD in CNY, daily

Source: Bloomberg

Industrial production

IMF China Industrial Production SA, monthly

Source: IMF

Credit spreads

China Credit Spreads, period average NADJ, quarterly

Source: Oxford Economics

India**NIFTY50 index, daily**

Source: Bloomberg

Bloomberg india Govt Bond 10YR Total Return, daily

Source: Bloomberg

NSELV

The NSE Nifty Low Volatility 50 Index, monthly

Source: Bloomberg

EPU

India Economic Policy Uncertainty News-Based Index, monthly

Source: Baker, Bloom & Davis

r

India Reserve Bank Reverse Repo Rate Policy Announcement, daily

Source: Reserve Bank of India

CPI

IMF India CPI, monthly

Source: IMF

INR

USDINR Spot Exchange Rate - Price of 1 USD in INR, daily

Source: Bloomberg

Industrial production

IMF India Industrial Production SA, monthly

Source: IMF

Credit spreads

India Credit Spreads, period average NADJ, quarterly

Source: Oxford Economics

South Africa**FTSE/JSE Africa Top40 index, daily**

Source: Bloomberg

Bloomberg/EFFAS Bond Indices S Africa Govt 7-10 Yr TR, daily

Source: Bloomberg

SAVIT40

The JSE Securities South African Volatility Index, monthly

Source: Bloomberg

r

South Africa Repo Avg Rate, daily

Source: South African Reserve Bank

CPI

IMF South Africa CPI, monthly

Source: IMF

ZAR

USDZAR Spot Exchange Rate - Price of 1 USD in ZAR, daily

Source: Bloomberg

Industrial production

Industrial Production South Africa SA, monthly

Source: IMF

Credit spreads

South Africa Credit Spreads, period average NADJ, quarterly

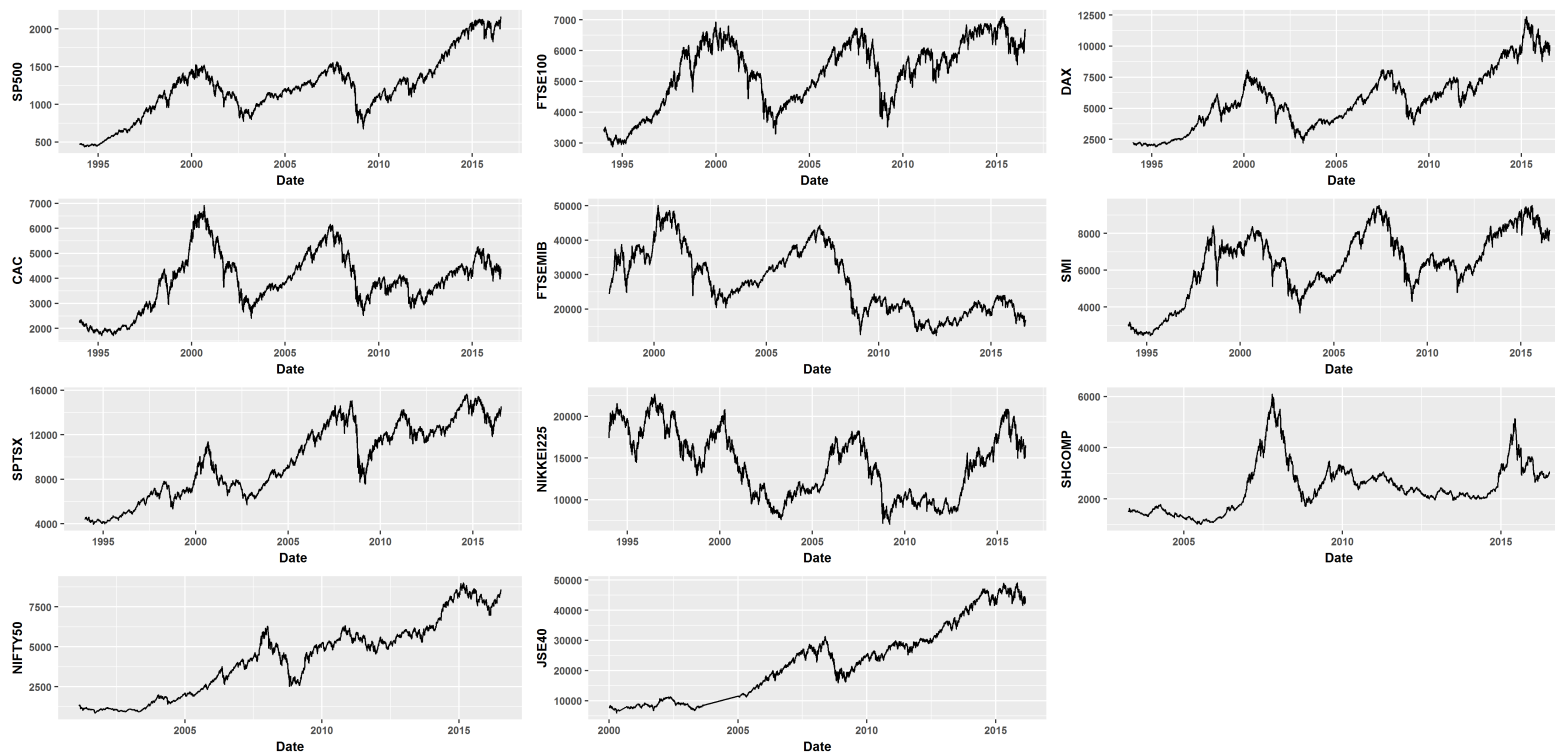
Source: Oxford Economics

Appendix D

Plots of Input Data

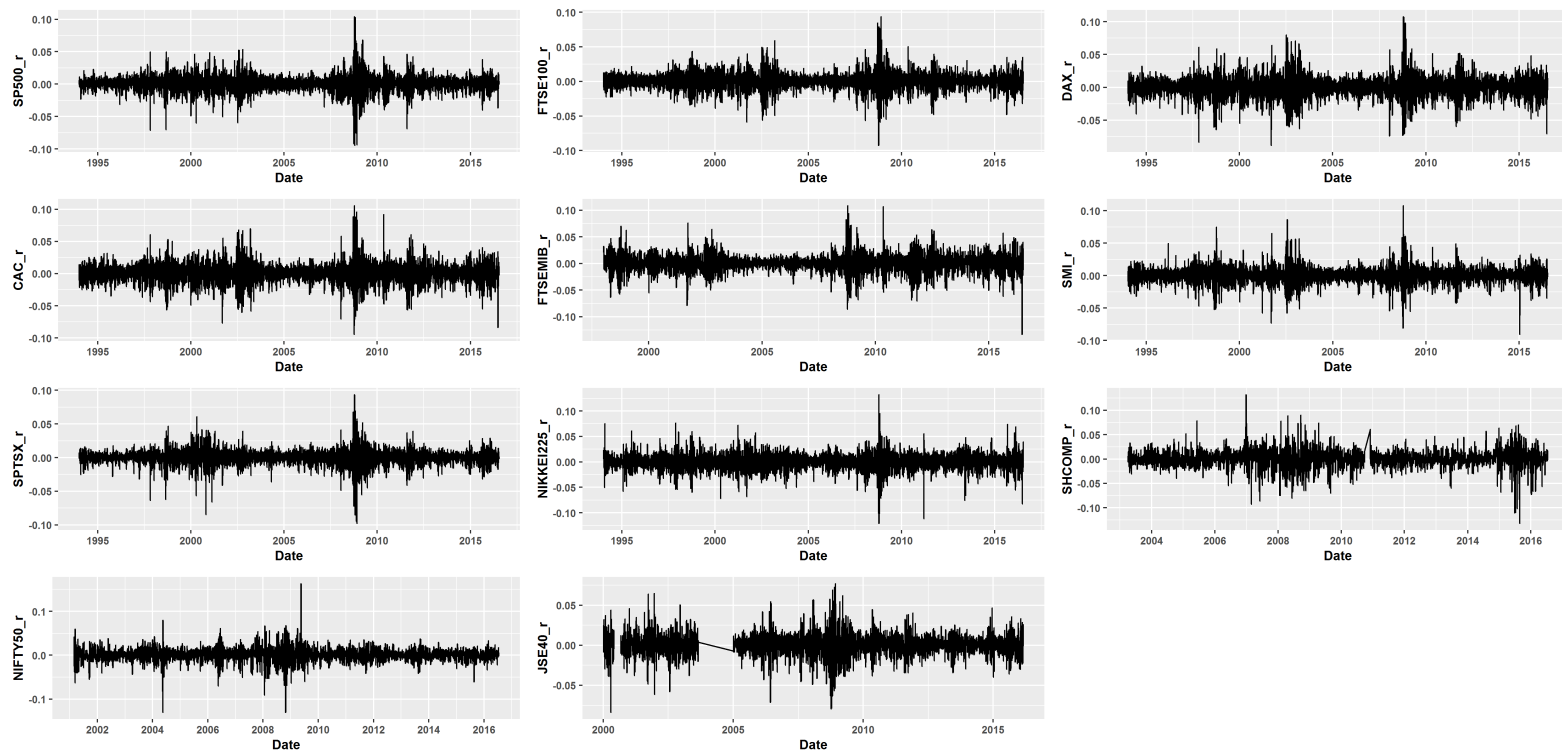
D.1 Precious Metals, Stock and Bond Indices Used in Chapters 4 and 5

Figure D.1: Stock market indices — level



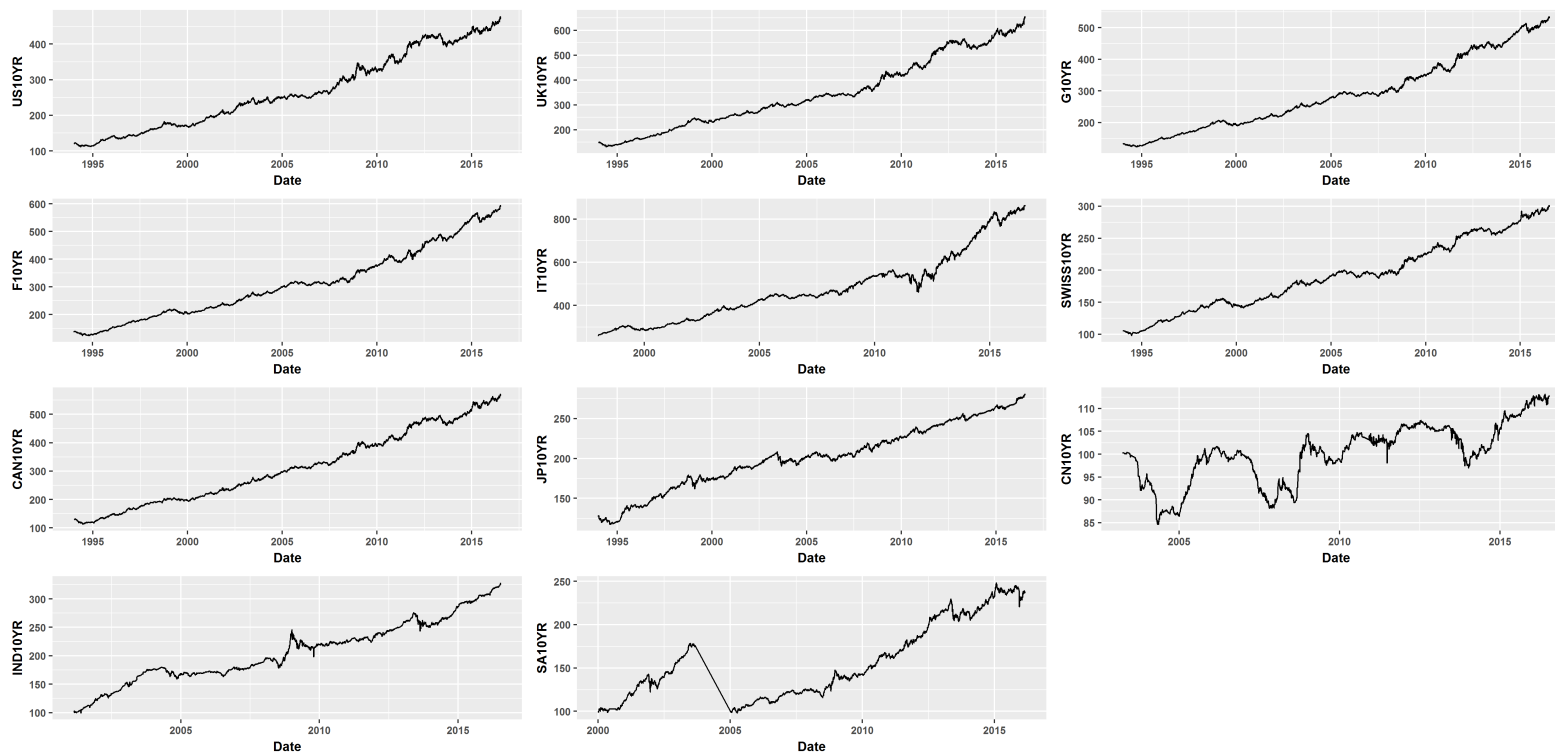
Note that data for China and South Africa are not continuous. There is missing data of government 10 year bond indices for both countries, which are from October 7 2010 to December 1 2010 for China, and from August 29 2003 to January 3 2005 for South Africa.

Figure D.2: Stock market indices — log return



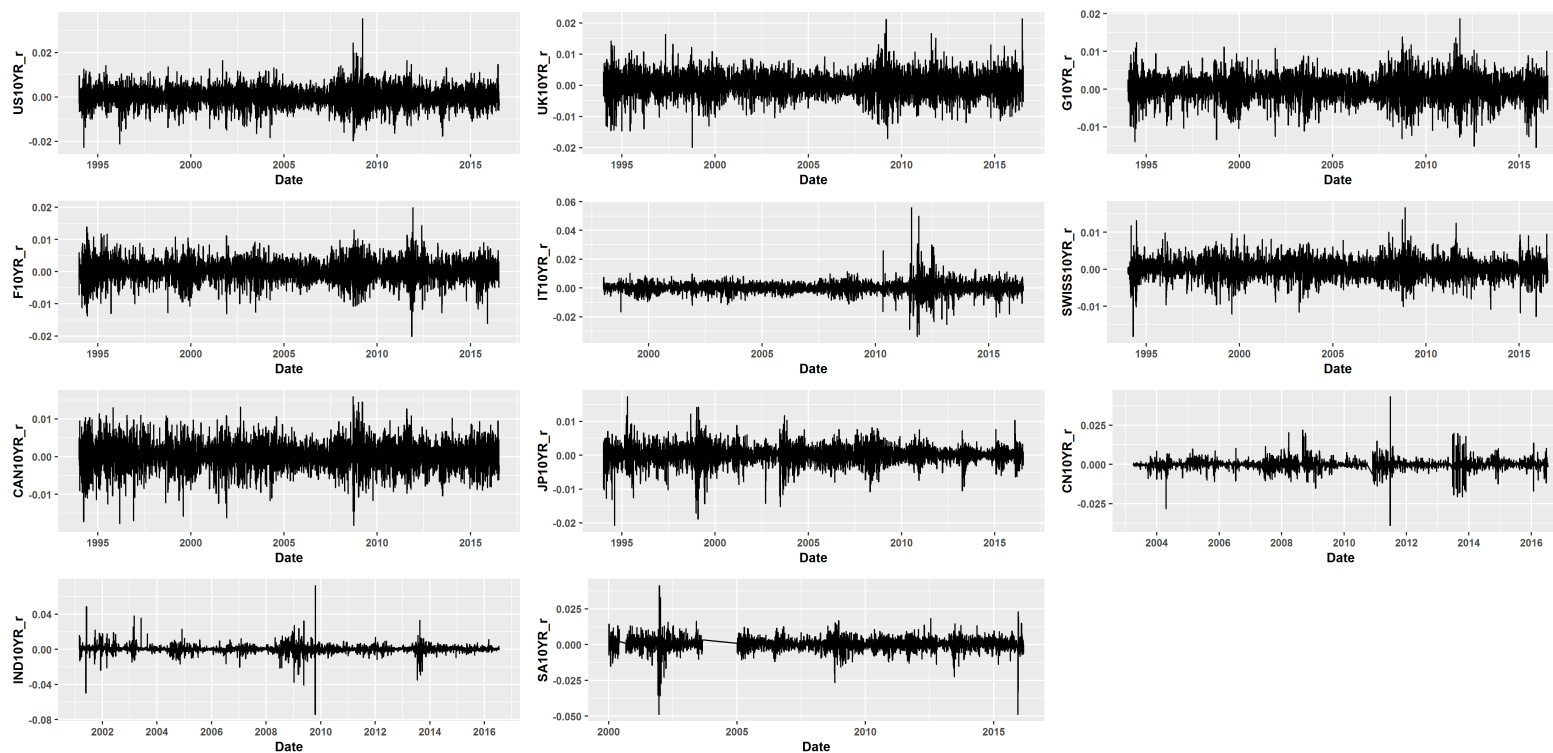
Note that data for China and South Africa are not continuous. There is missing data of government 10 year bond indices for both countries, which are from October 7 2010 to December 1 2010 for China, and from August 29 2003 to January 3 2005 for South Africa.

Figure D.3: Bond market indices — level



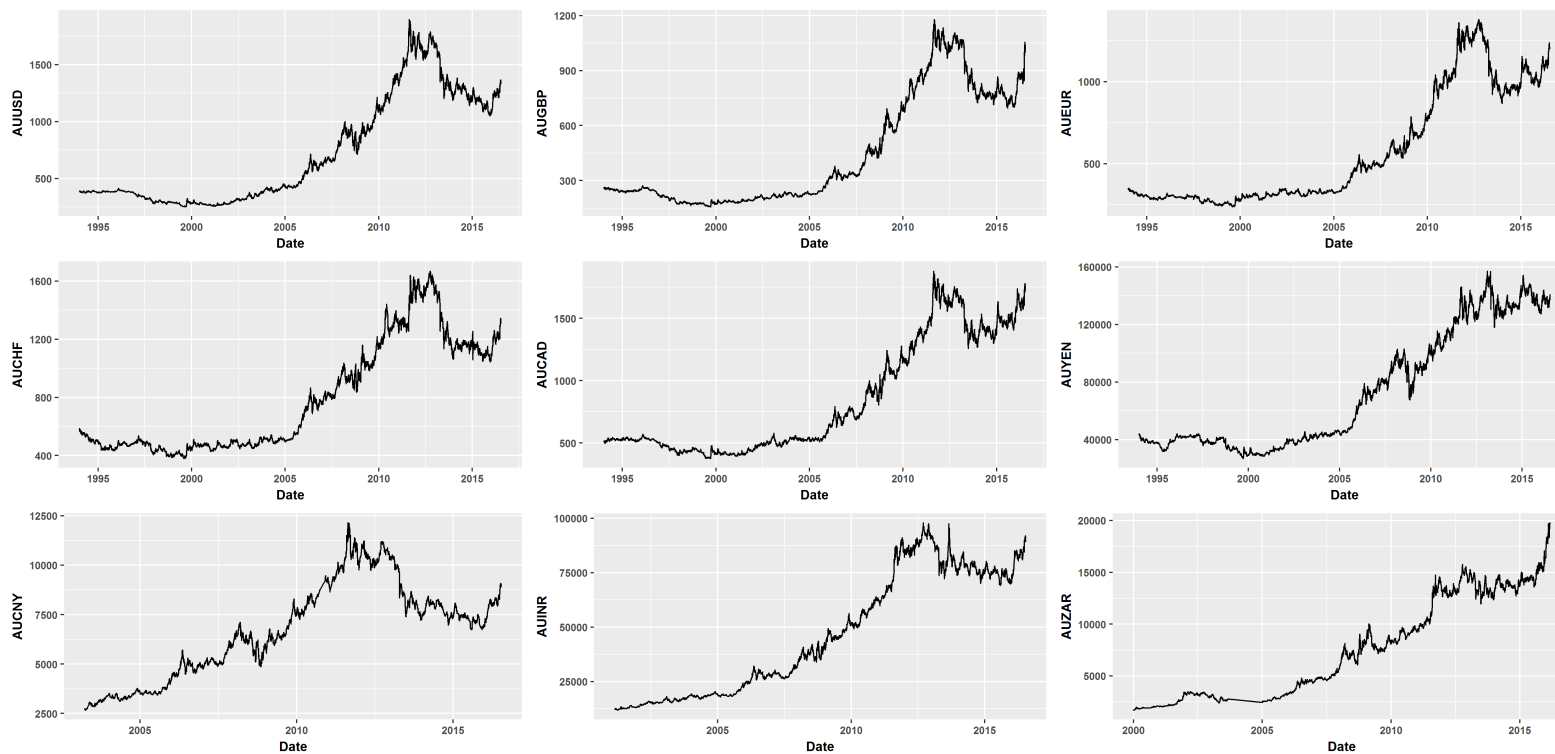
Note that data for China and South Africa are not continuous. There is missing data of government 10 year bond indices for both countries, which are from October 7 2010 to December 1 2010 for China, and from August 29 2003 to January 3 2005 for South Africa.

Figure D.4: Bond market indices — log return



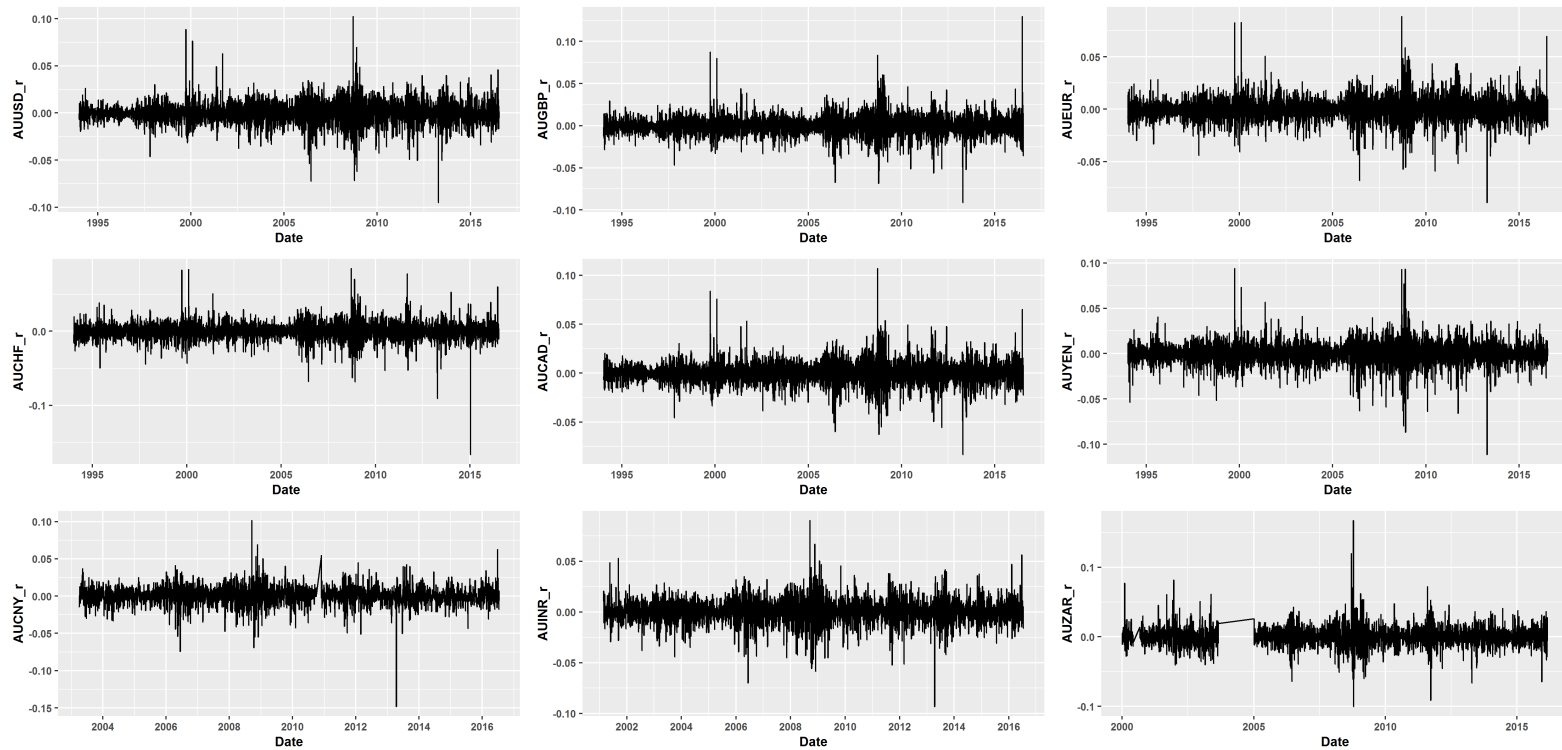
Note that data for China and South Africa are not continuous. There is missing data of government 10 year bond indices for both countries, which are from October 7 2010 to December 1 2010 for China, and from August 29 2003 to January 3 2005 for South Africa.

Figure D.5: Gold price in local currency — level



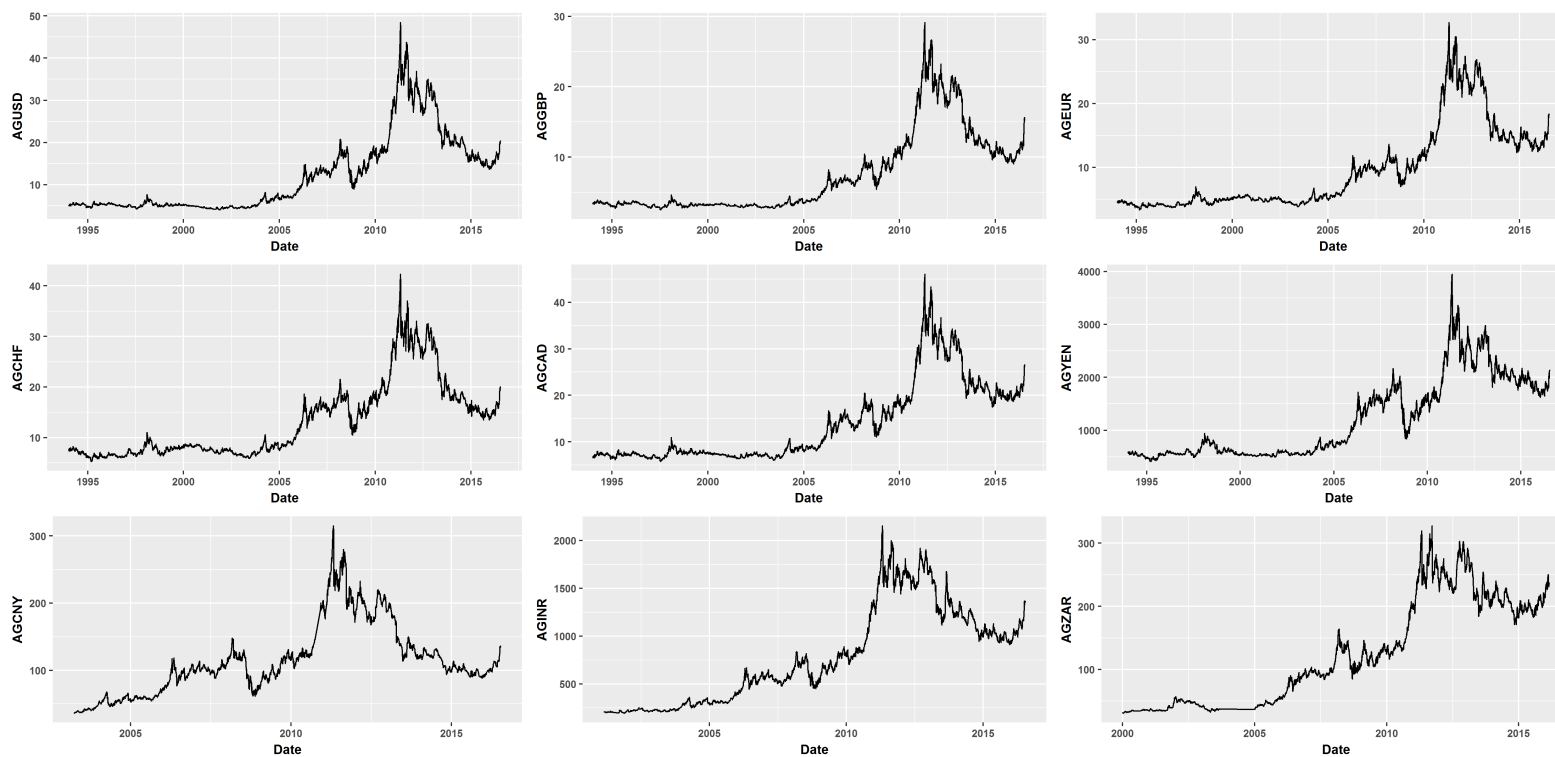
Note that data for China and South Africa are not continuous. There is missing data of government 10 year bond indices for both countries, which are from October 7 2010 to December 1 2010 for China, and from August 29 2003 to January 3 2005 for South Africa..

Figure D.6: Gold price in local currency — log return



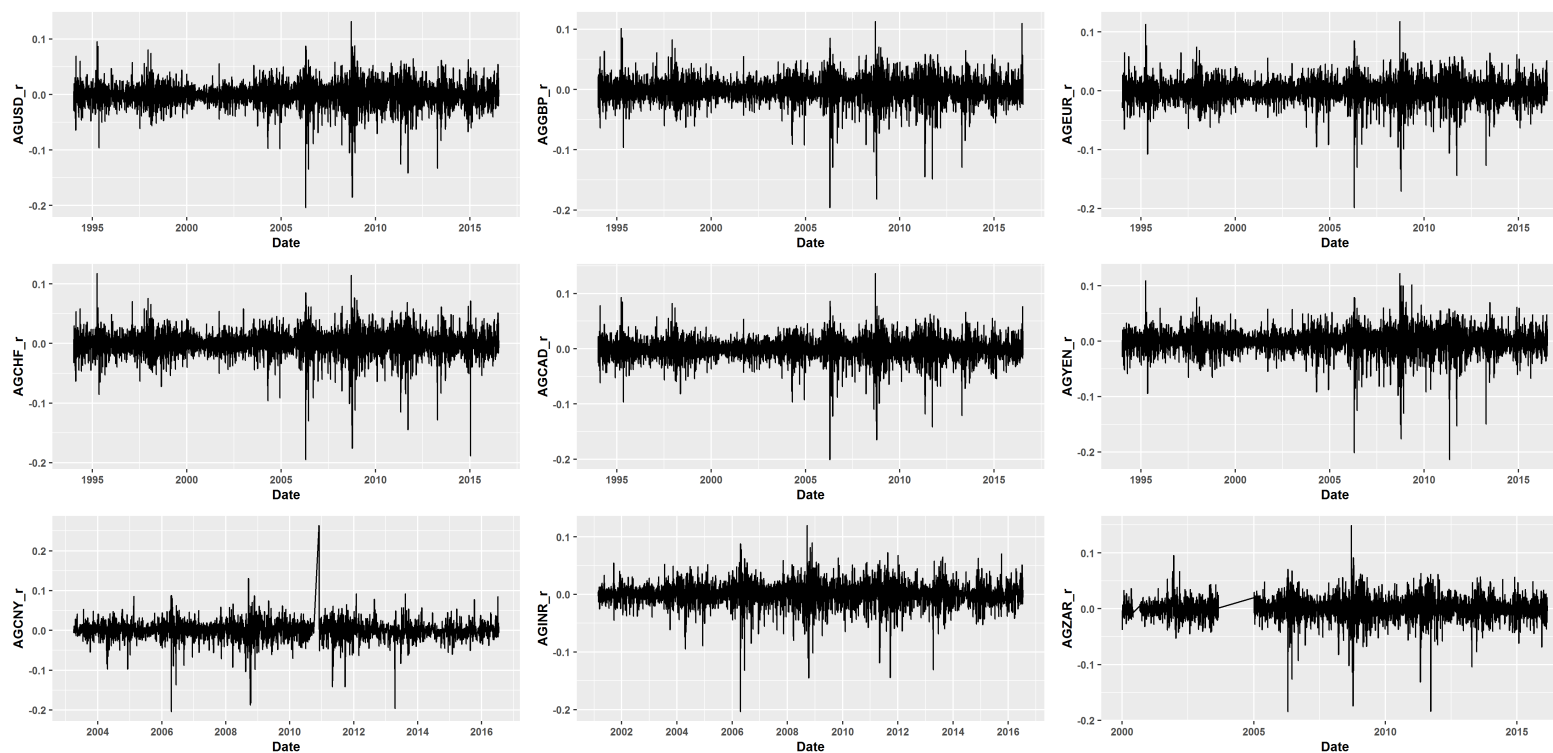
Note that data for China and South Africa are not continuous. There is missing data of government 10 year bond indices for both countries, which are from October 7 2010 to December 1 2010 for China, and from August 29 2003 to January 3 2005 for South Africa..

Figure D.7: Silver price in local currency — level



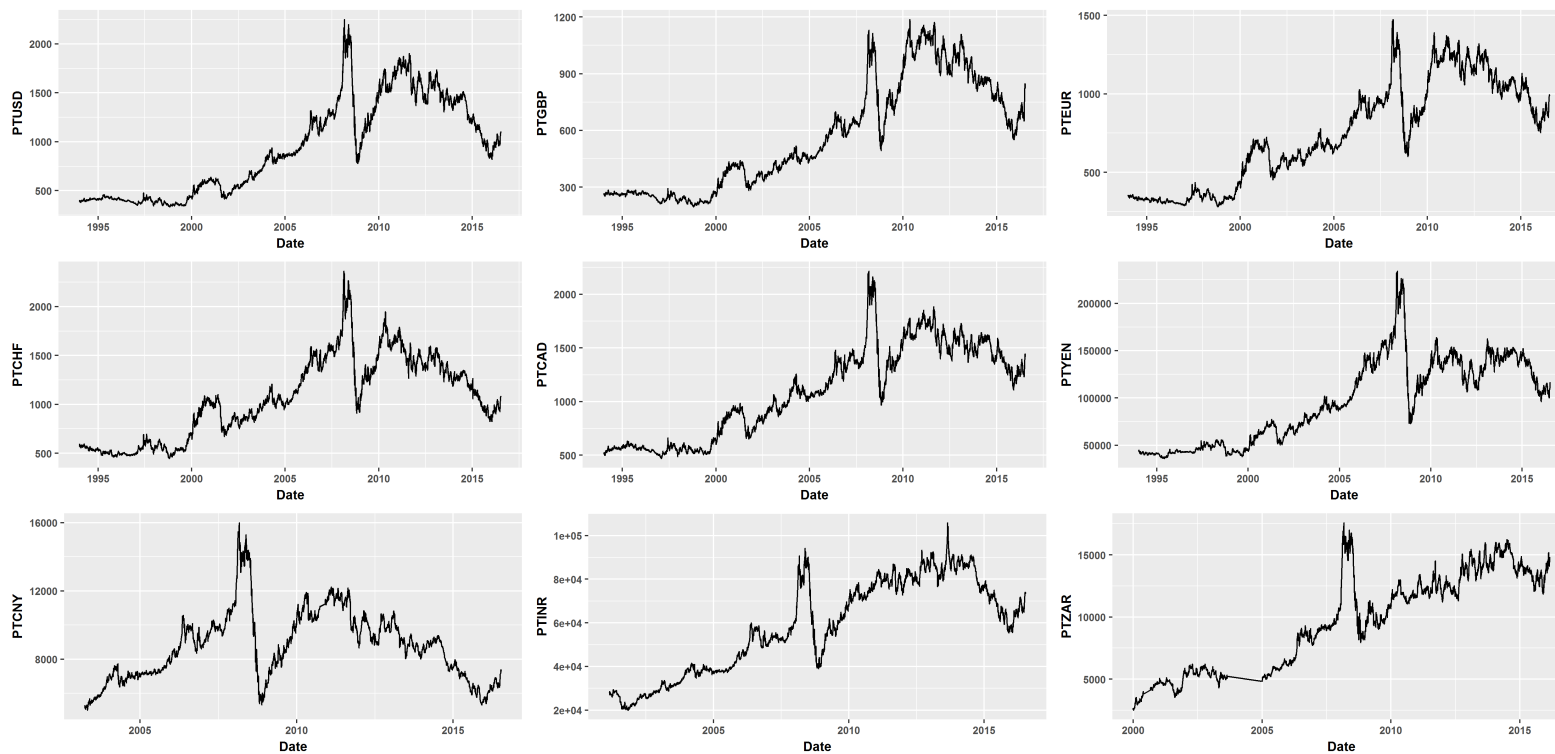
Note that data for China and South Africa are not continuous. There is missing data of government 10 year bond indices for both countries, which are from October 7 2010 to December 1 2010 for China, and from August 29 2003 to January 3 2005 for South Africa.

Figure D.8: Silver price in local currency — log return



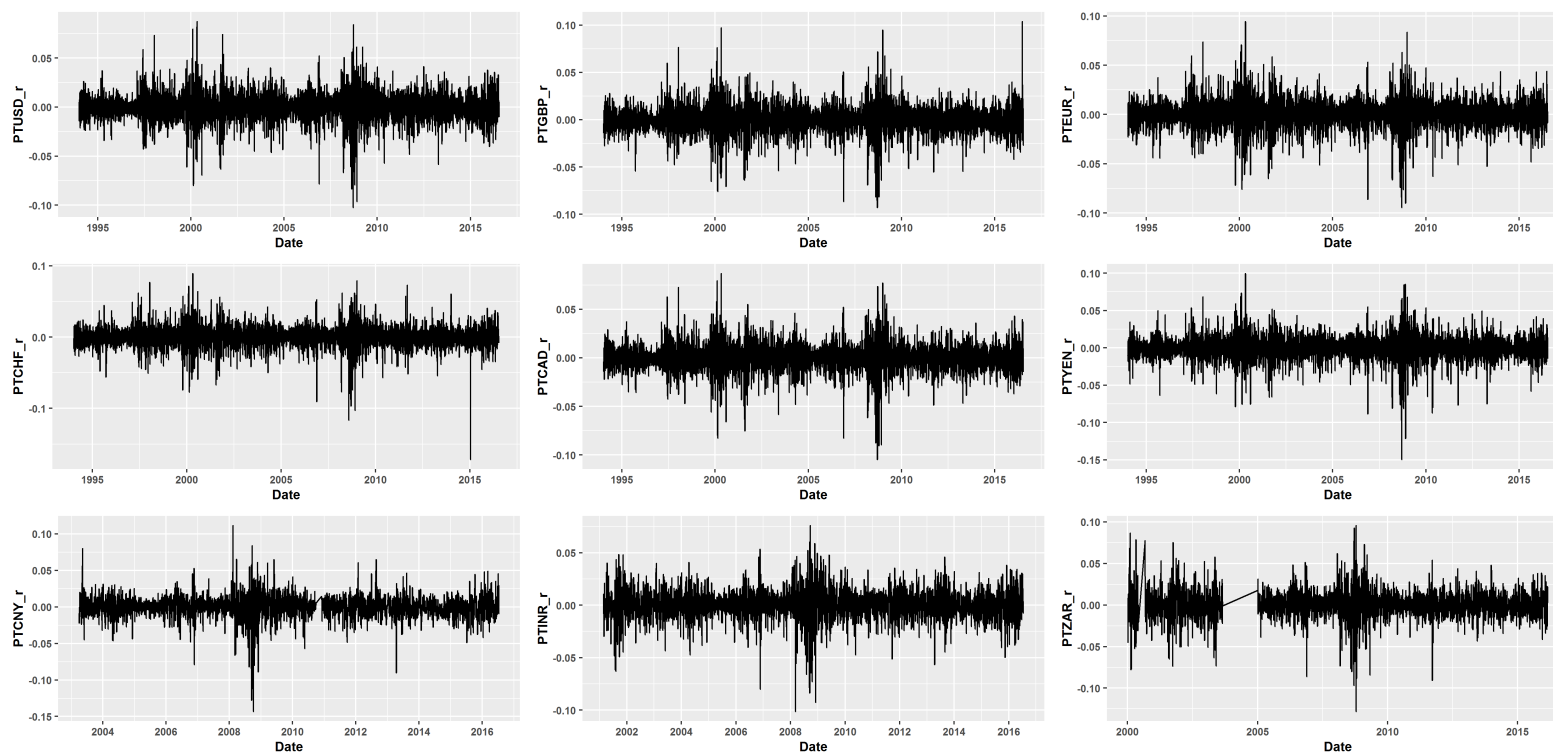
Note that data for China and South Africa are not continuous. There is missing data of government 10 year bond indices for both countries, which are from October 7 2010 to December 1 2010 for China, and from August 29 2003 to January 3 2005 for South Africa.

Figure D.9: Platinum price in local currency — level



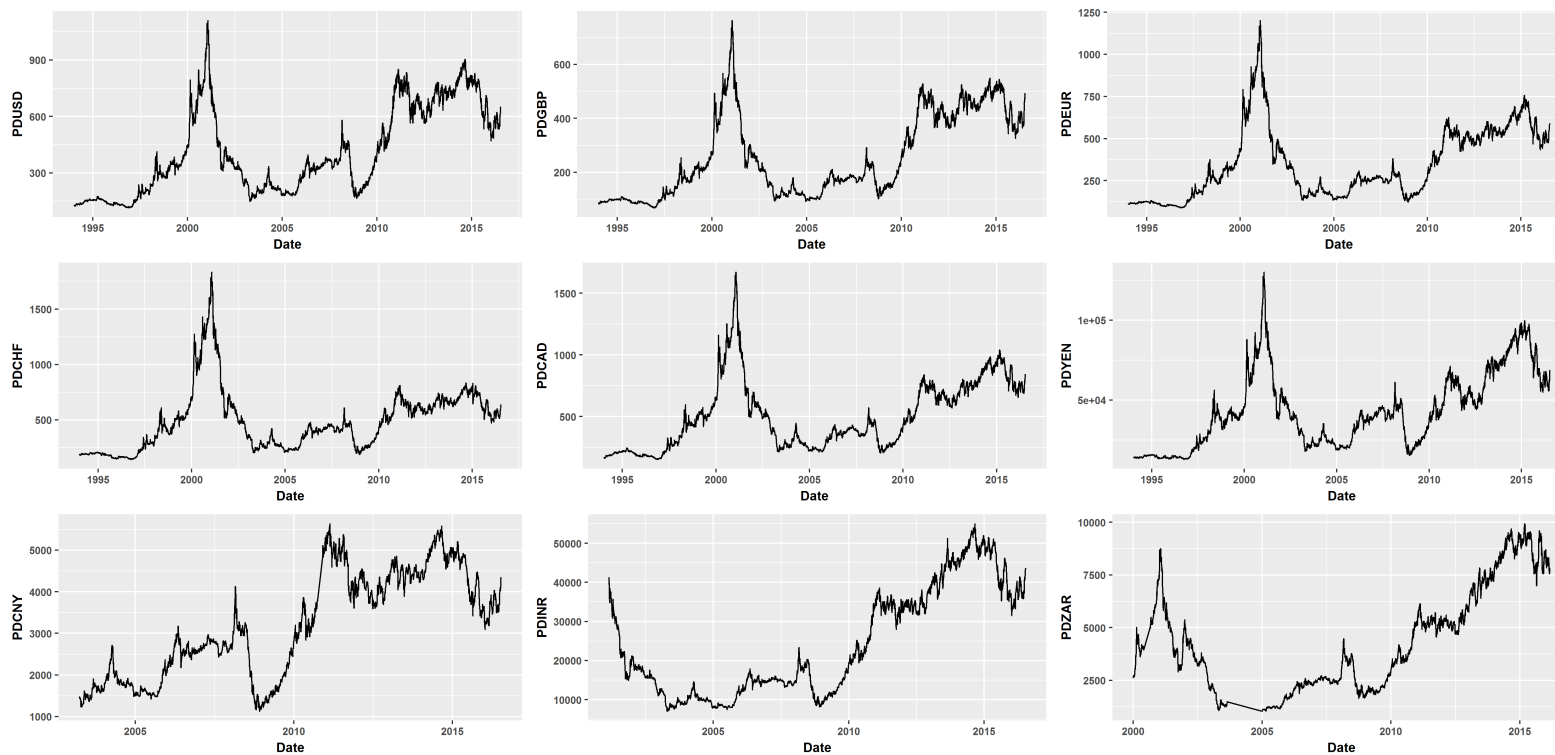
Note that data for China and South Africa are not continuous. There is missing data of government 10 year bond indices for both countries, which are from October 7 2010 to December 1 2010 for China, and from August 29 2003 to January 3 2005 for South Africa.

Figure D.10: Platinum price in local currency — log return



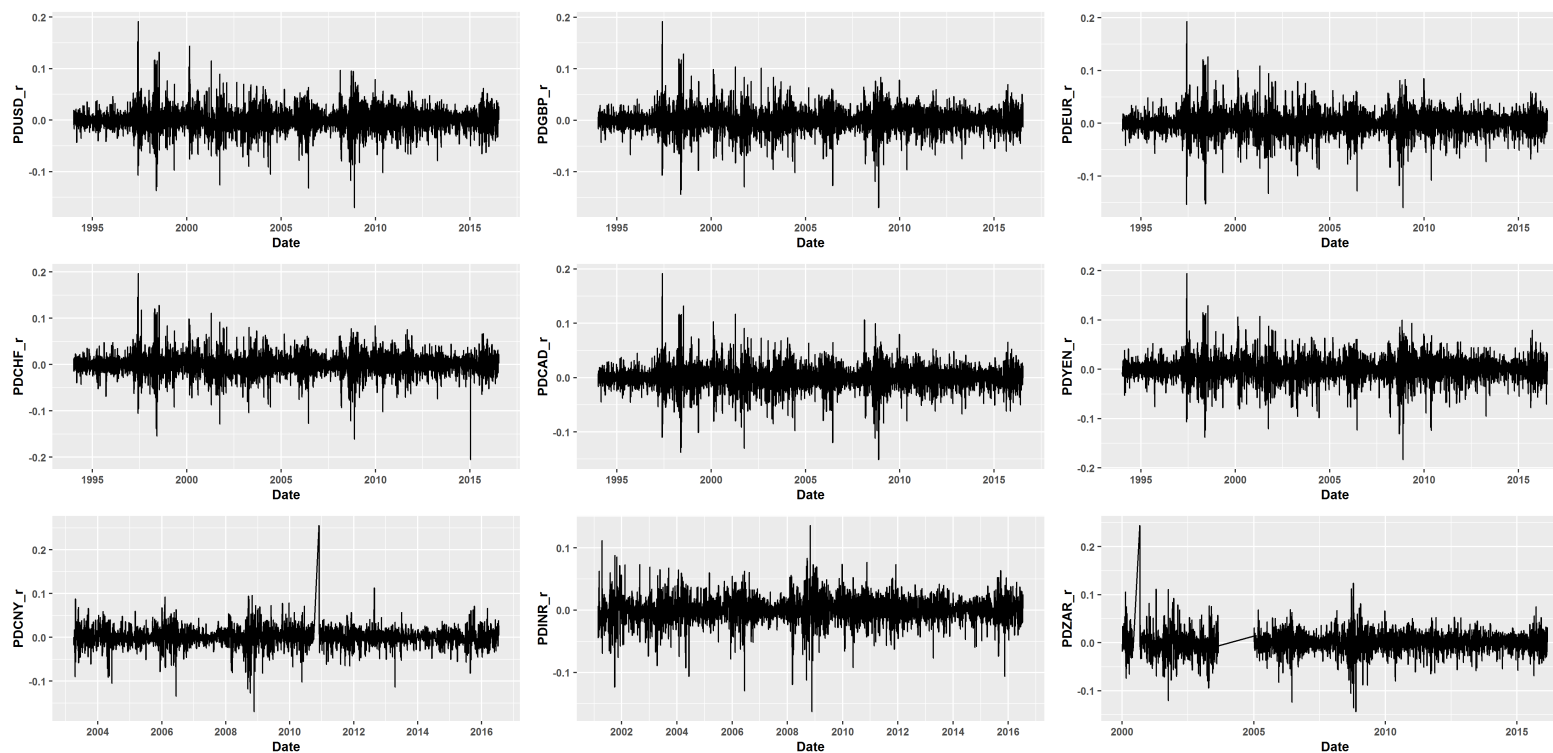
Note that data for China and South Africa are not continuous. There is missing data of government 10 year bond indices for both countries, which are from October 7 2010 to December 1 2010 for China, and from August 29 2003 to January 3 2005 for South Africa.

Figure D.11: Palladium price in local currency — level



Note that data for China and South Africa are not continuous. There is missing data of government 10 year bond indices for both countries, which are from October 7 2010 to December 1 2010 for China, and from August 29 2003 to January 3 2005 for South Africa.

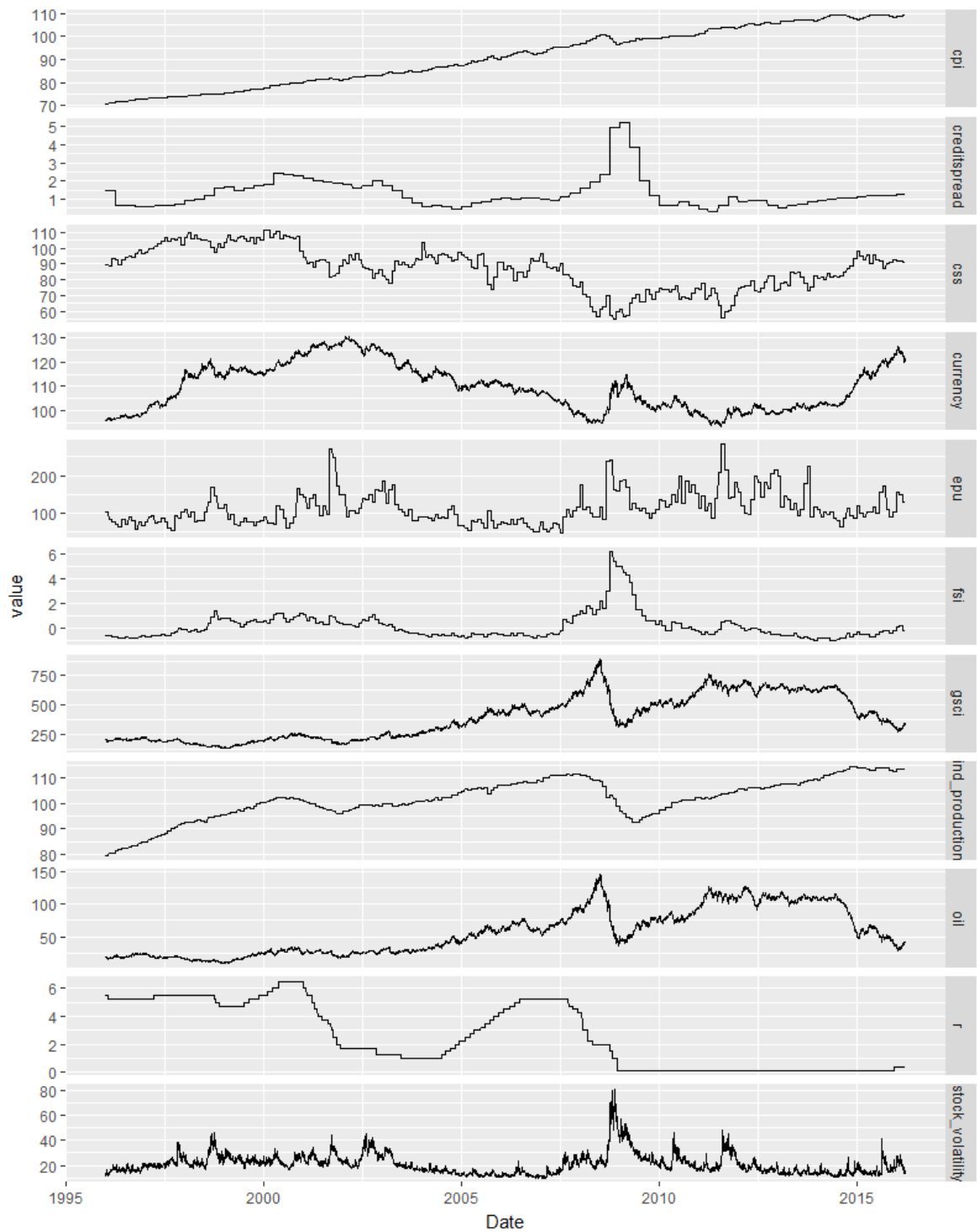
Figure D.12: Palladium price in local currency — log return



Note that data for China and South Africa are not continuous. There is missing data of government 10 year bond indices for both countries, which are from October 7 2010 to December 1 2010 for China, and from August 29 2003 to January 3 2005 for South Africa.

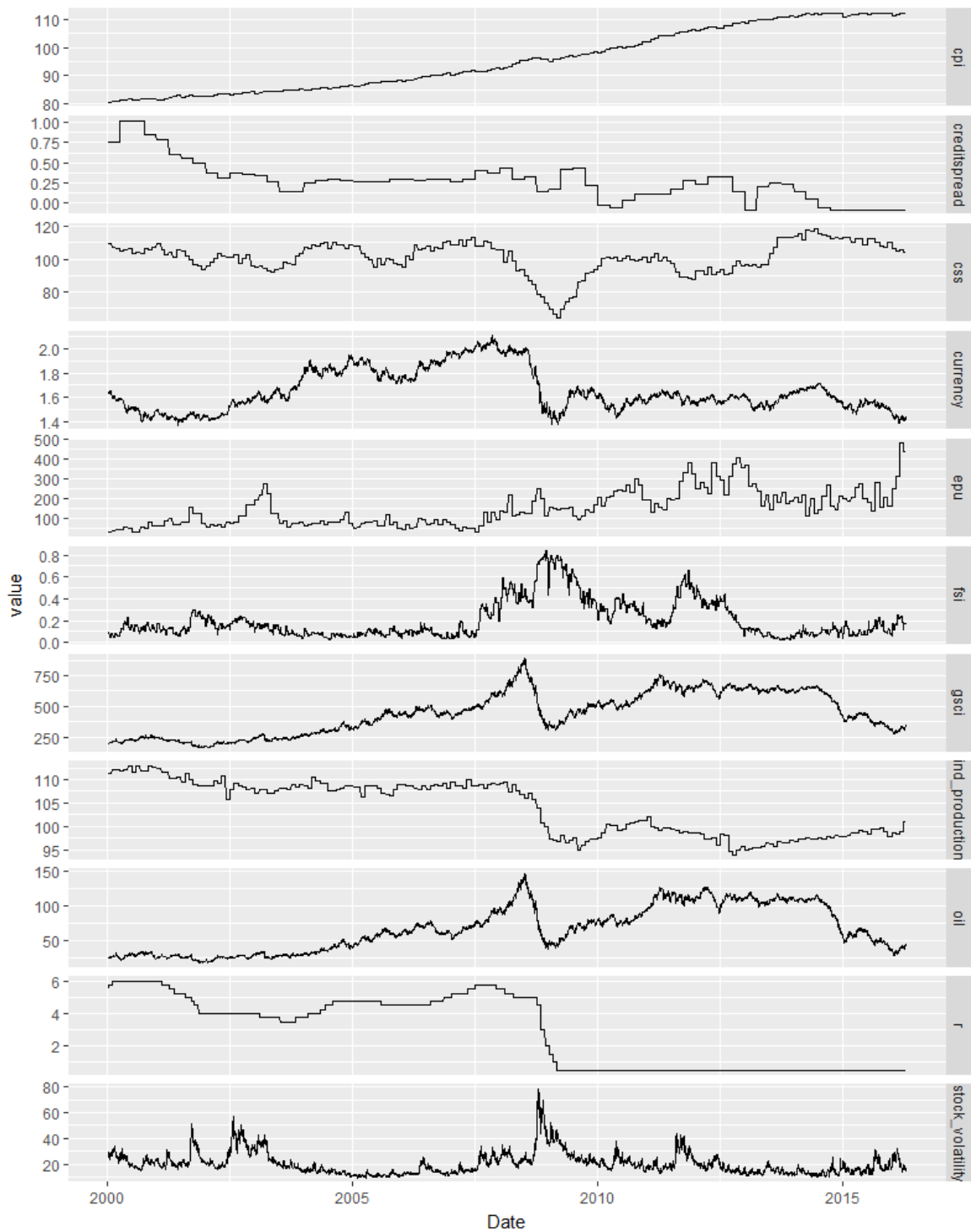
D.2 Explanatory Variables Used in Chapter 6

Figure D.13: Explanatory Variables - US



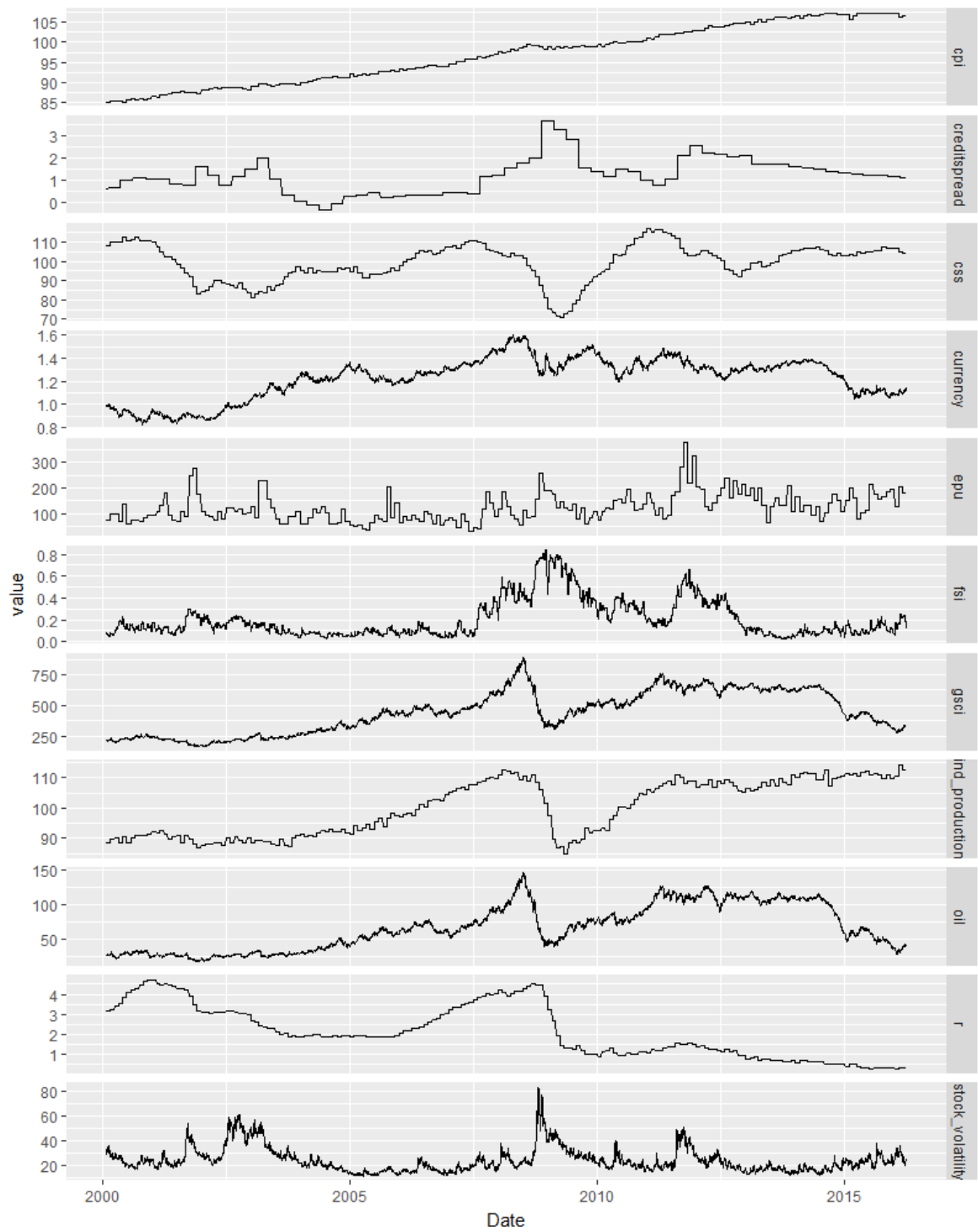
All the data are dis-aggregated into daily frequency. For example, to convert monthly Economic Policy Uncertainty Index into daily, the same value is applied to each day of the month. No other frequency conversion technique is used here.

Figure D.14: Explanatory Variables - UK



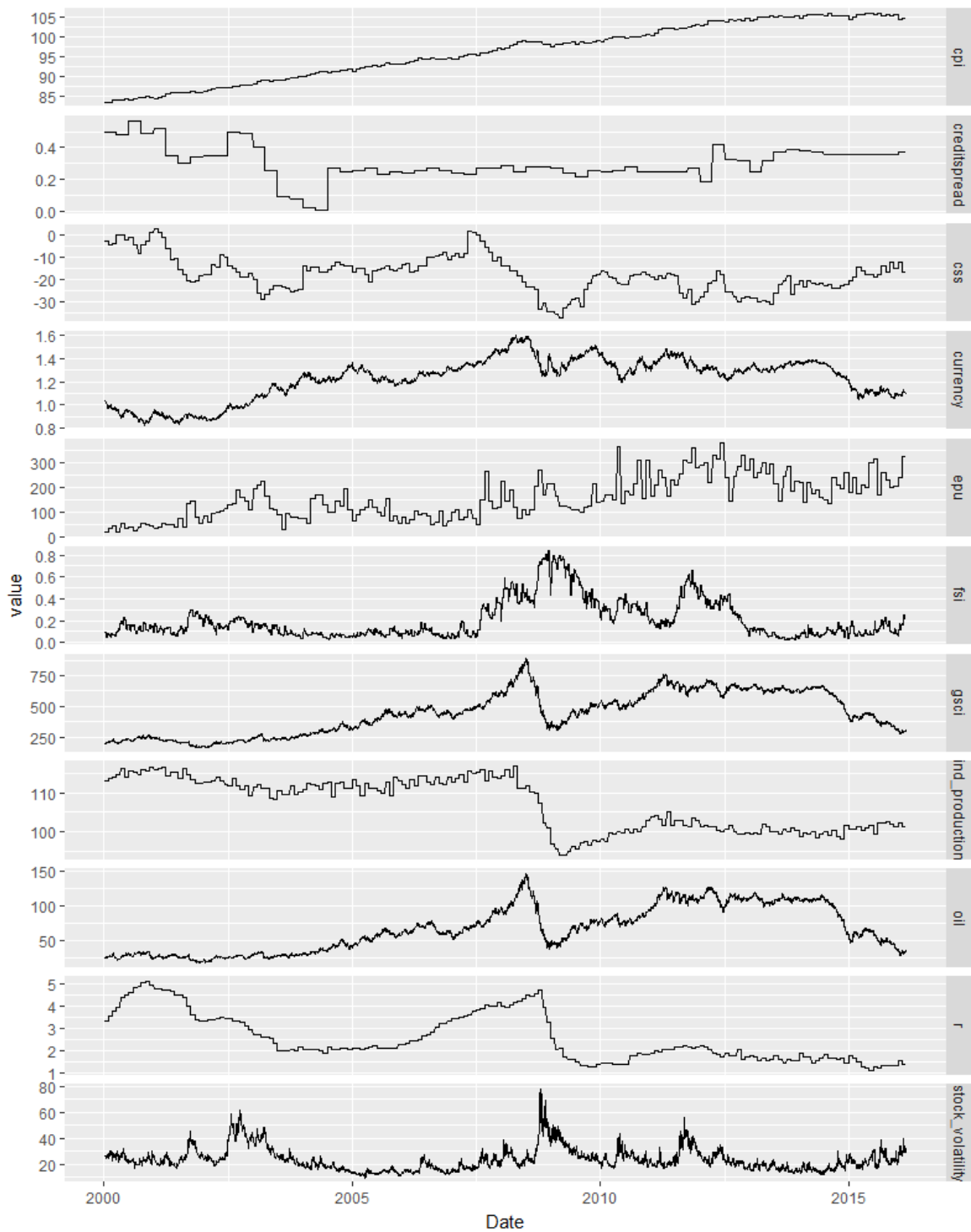
All the data are dis-aggregated into daily frequency. For example, to convert monthly Economic Policy Uncertainty Index into daily, the same value is applied to each day of the month. No other frequency conversion technique is used here.

Figure D.15: Explanatory Variables - Germany



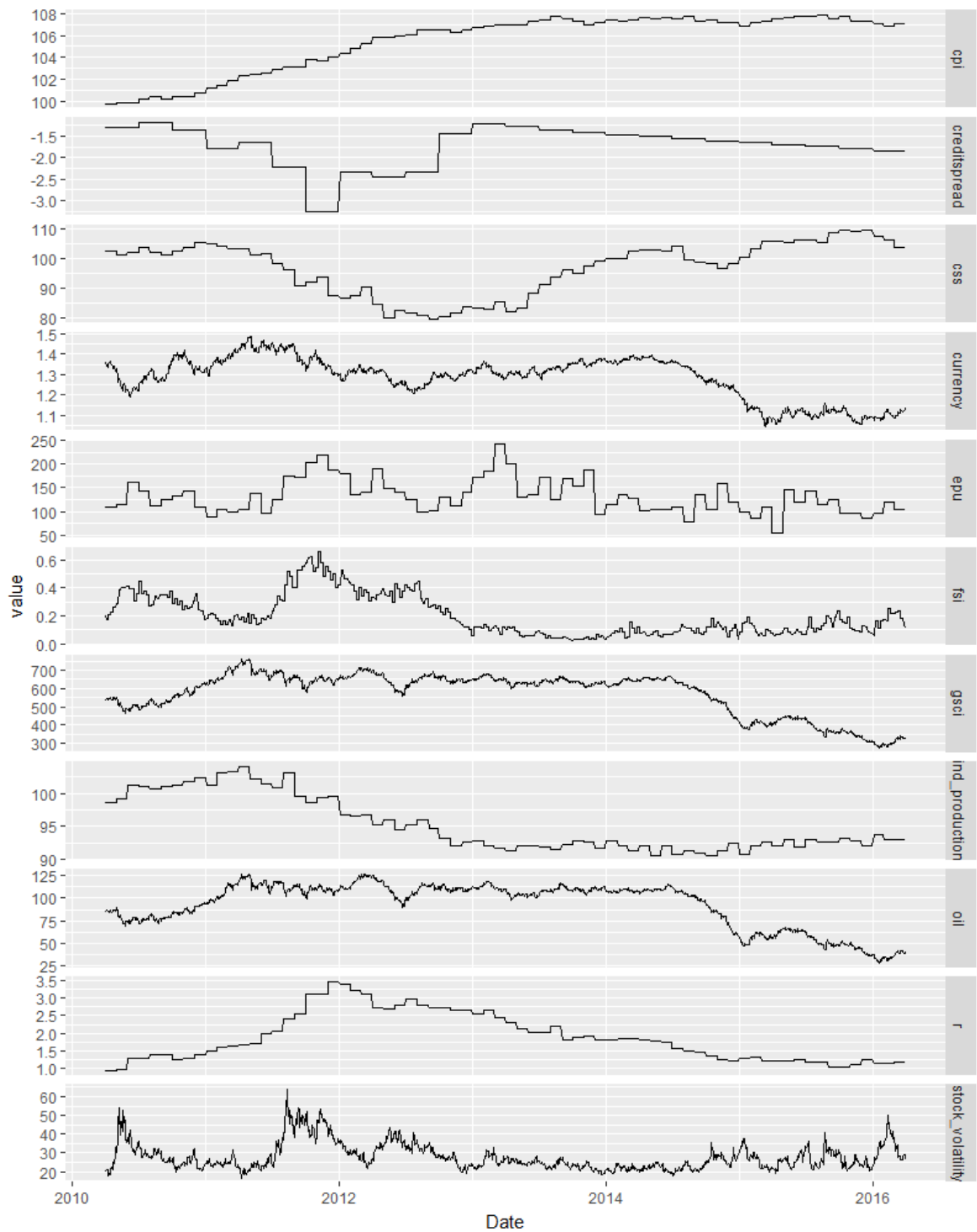
All the data are dis-aggregated into daily frequency. For example, to convert monthly Economic Policy Uncertainty Index into daily, the same value is applied to each day of the month. No other frequency conversion technique is used here.

Figure D.16: Explanatory Variables - France



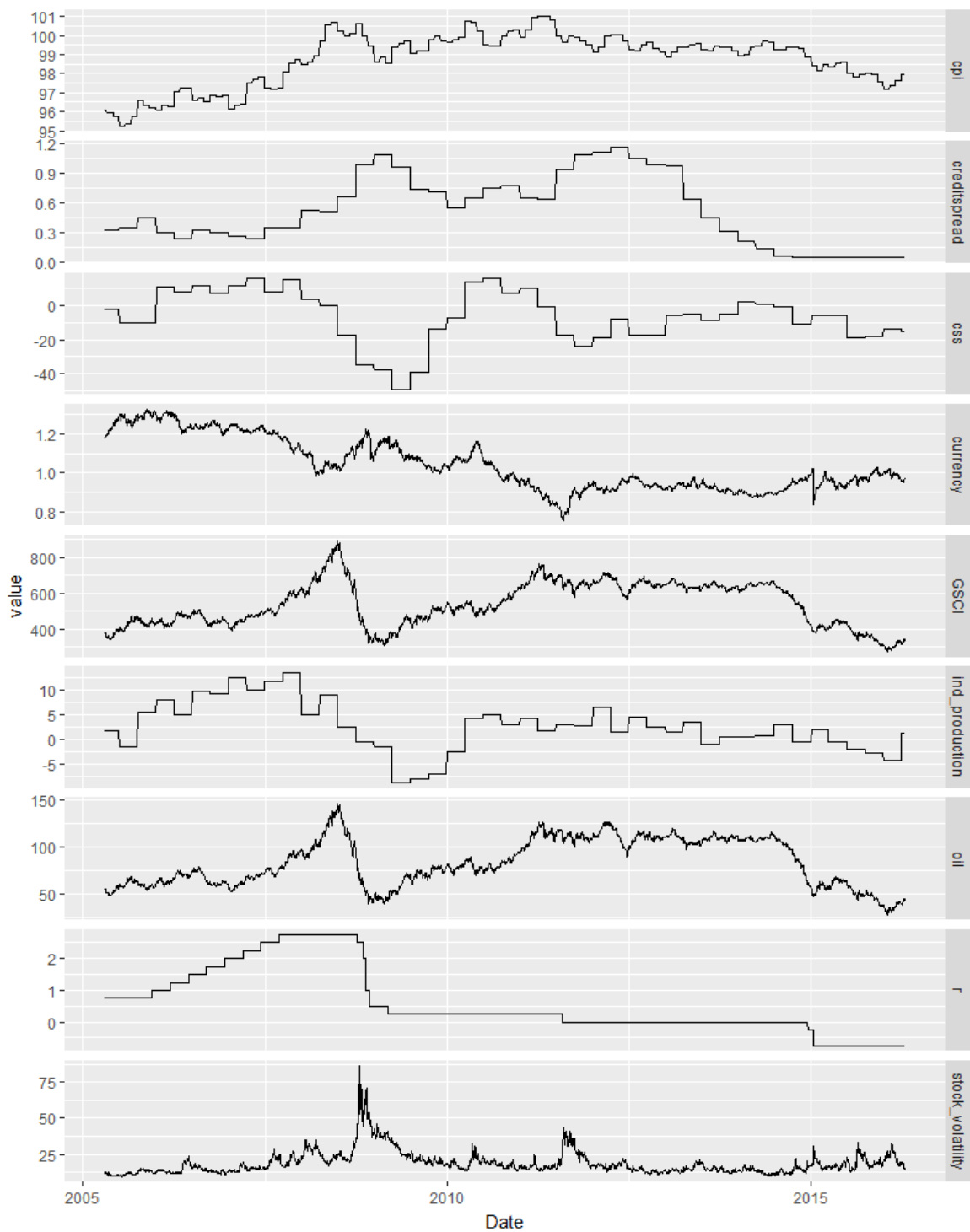
All the data are dis-aggregated into daily frequency. For example, to convert monthly Economic Policy Uncertainty Index into daily, the same value is applied to each day of the month. No other frequency conversion technique is used here.

Figure D.17: Explanatory Variables - Italy



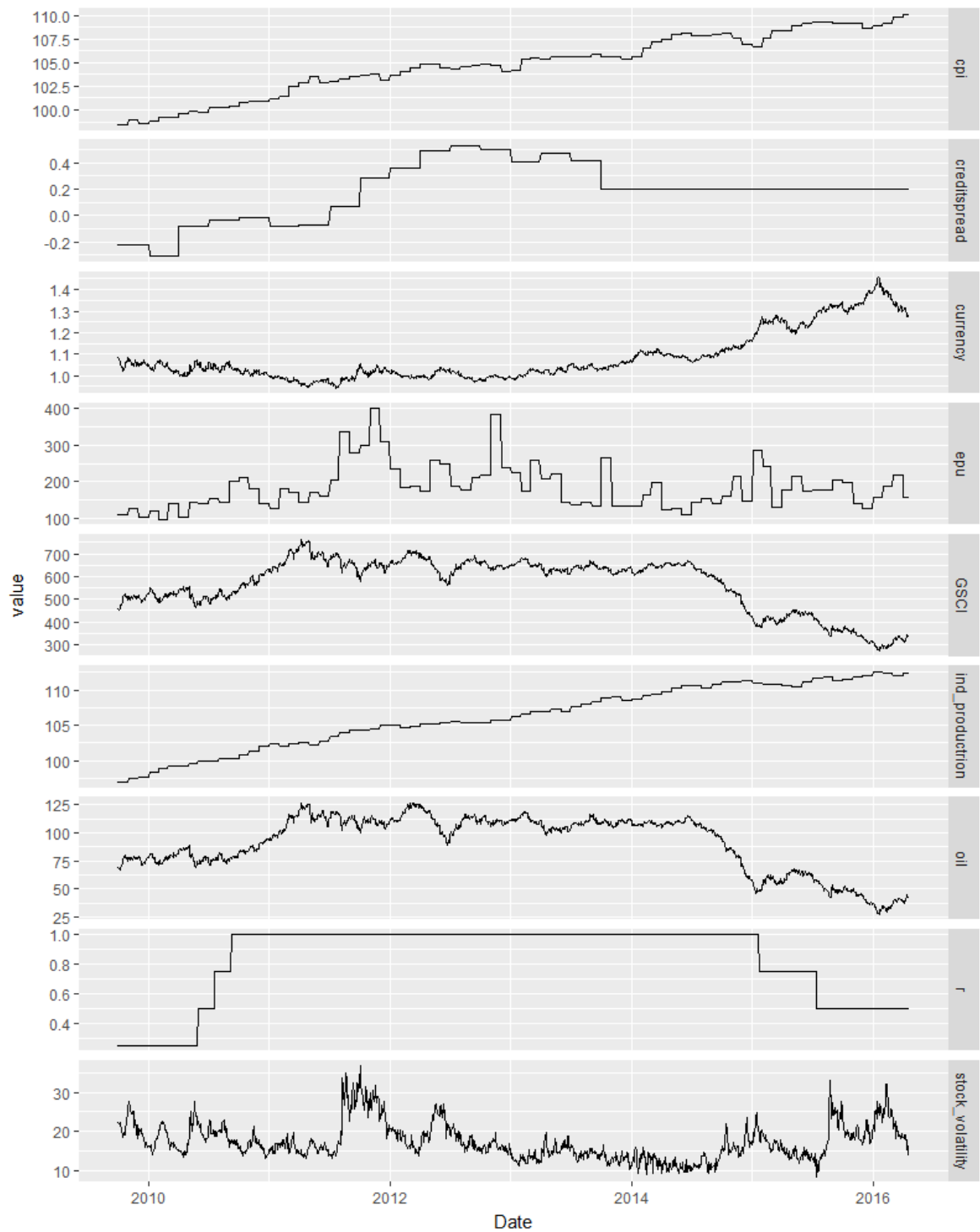
All the data are dis-aggregated into daily frequency. For example, to convert monthly Economic Policy Uncertainty Index into daily, the same value is applied to each day of the month. No other frequency conversion technique is used here.

Figure D.18: Explanatory Variables - Switzerland



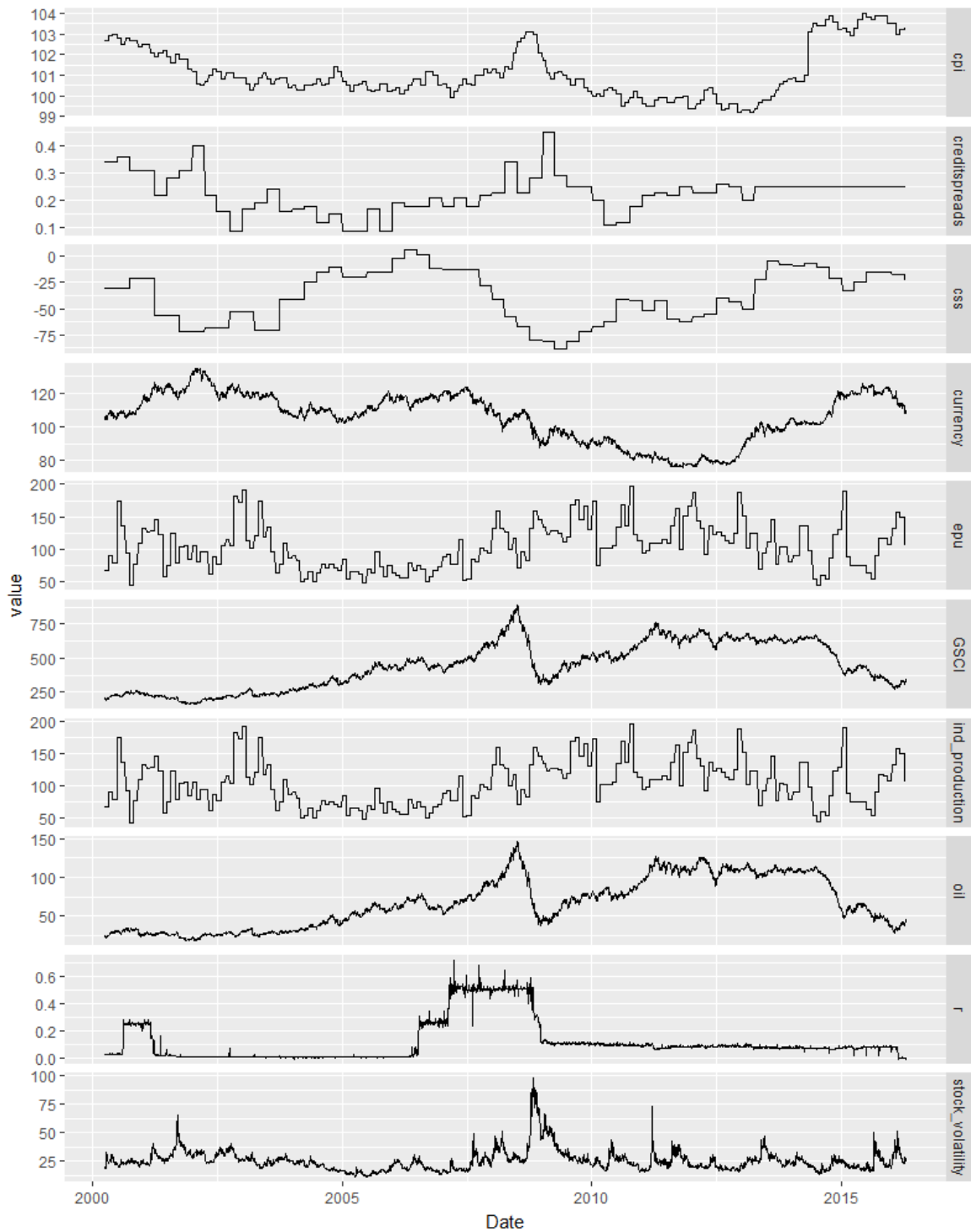
All the data are dis-aggregated into daily frequency. For example, to convert monthly Economic Policy Uncertainty Index into daily, the same value is applied to each day of the month. No other frequency conversion technique is used here.

Figure D.19: Explanatory Variables - Canada



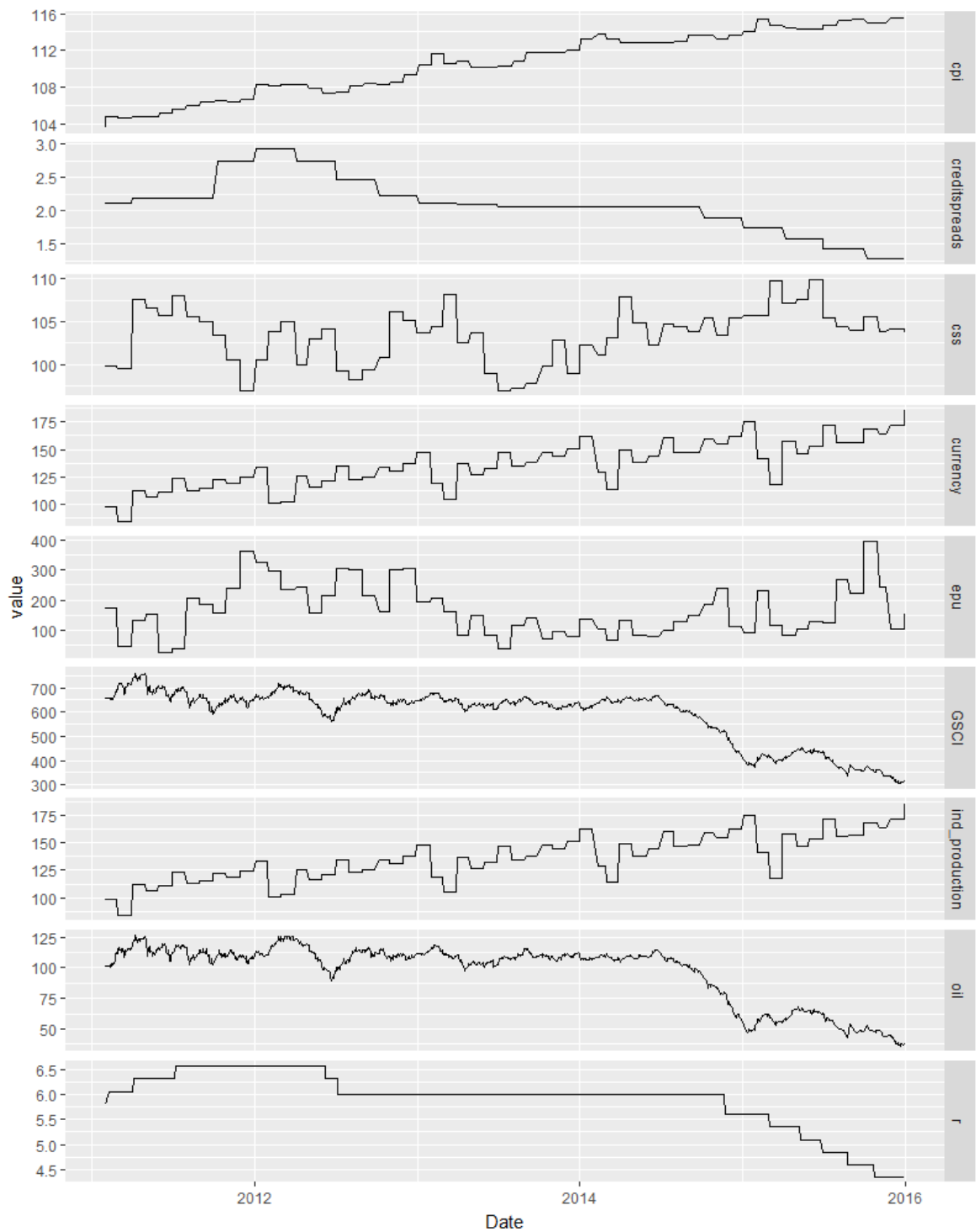
All the data are dis-aggregated into daily frequency. For example, to convert monthly Economic Policy Uncertainty Index into daily, the same value is applied to each day of the month. No other frequency conversion technique is used here.

Figure D.20: Explanatory Variables - Japan



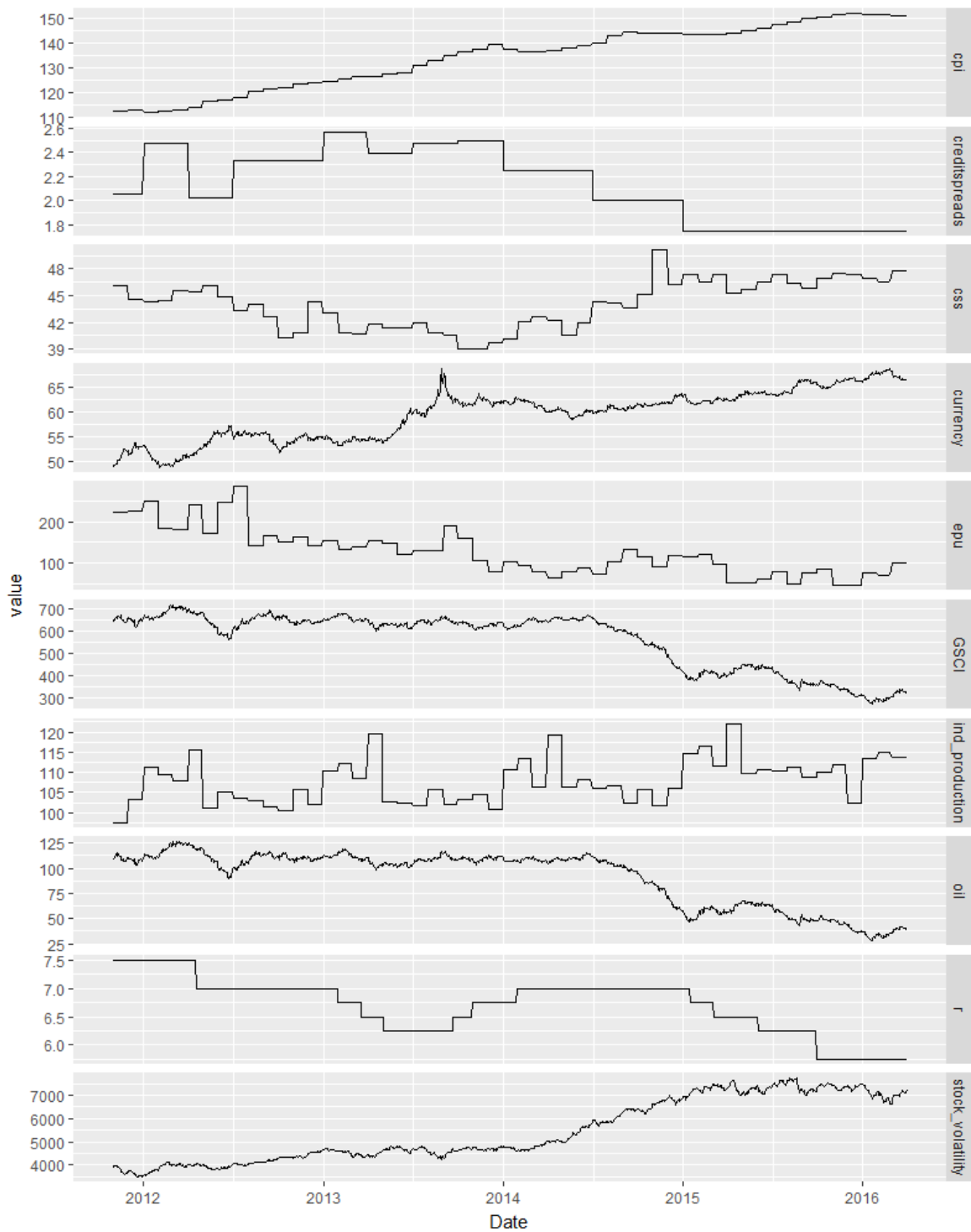
All the data are dis-aggregated into daily frequency. For example, to convert monthly Economic Policy Uncertainty Index into daily, the same value is applied to each day of the month. No other frequency conversion technique is used here.

Figure D.21: Explanatory Variables - China



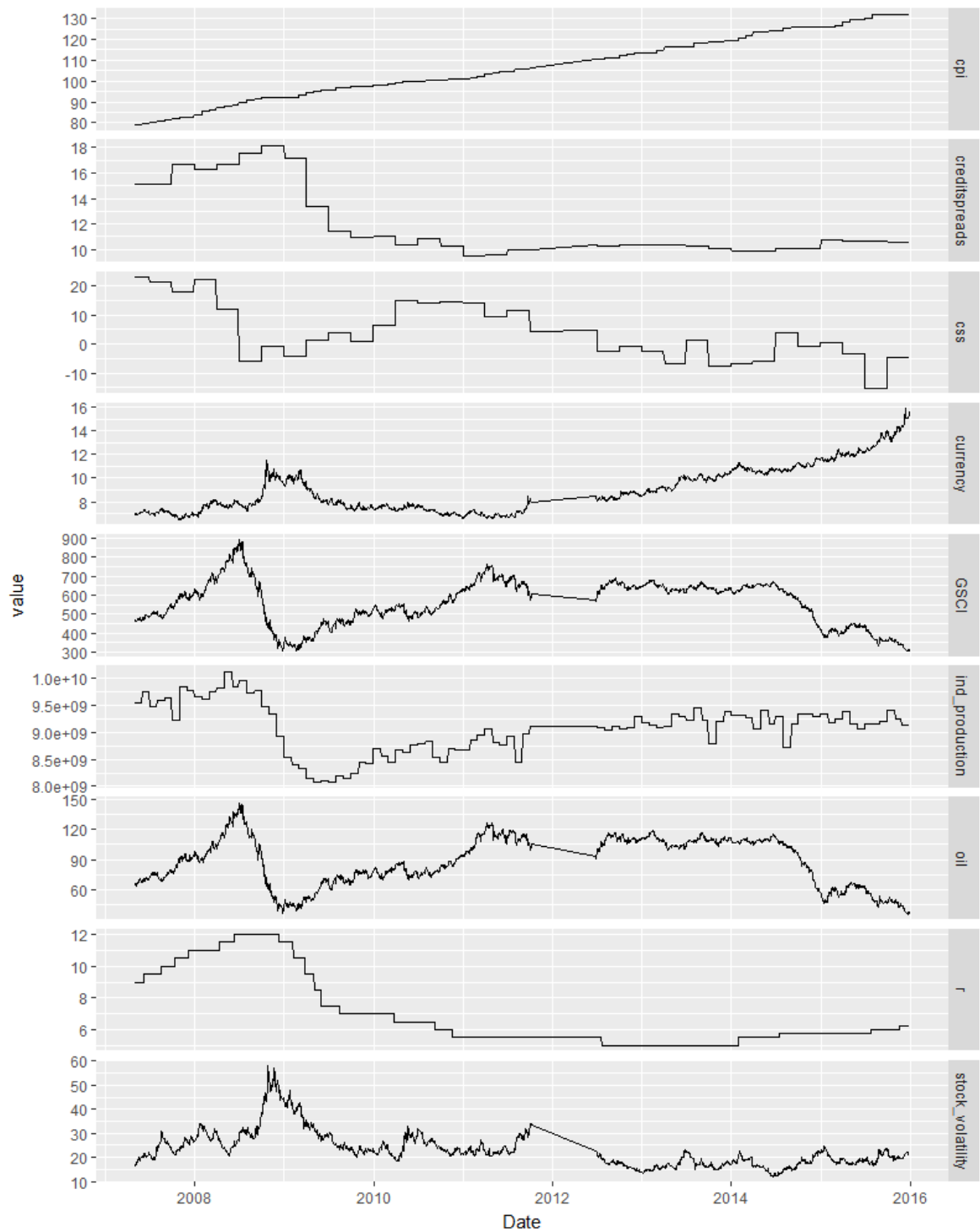
All the data are dis-aggregated into daily frequency. For example, to convert monthly Economic Policy Uncertainty Index into daily, the same value is applied to each day of the month. No other frequency conversion technique is used here.

Figure D.22: Explanatory Variables - India



All the data are dis-aggregated into daily frequency. For example, to convert monthly Economic Policy Uncertainty Index into daily, the same value is applied to each day of the month. No other frequency conversion technique is used here.

Figure D.23: Explanatory Variables - South Africa



All the data are dis-aggregated into daily frequency. For example, to convert monthly Economic Policy Uncertainty Index into daily, the same value is applied to each day of the month. No other frequency conversion technique is used here.

D.3 Safe Haven Assets and Search Data Used in Chapter 7

Figure D.24: Price in the US dollar

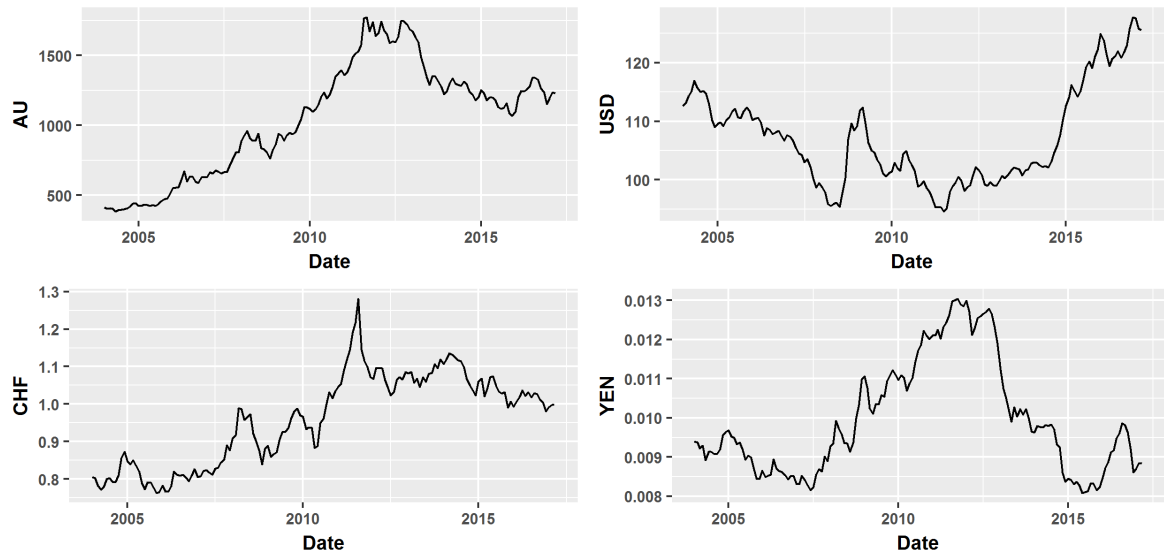


Figure D.25: Return from prices in the US dollar

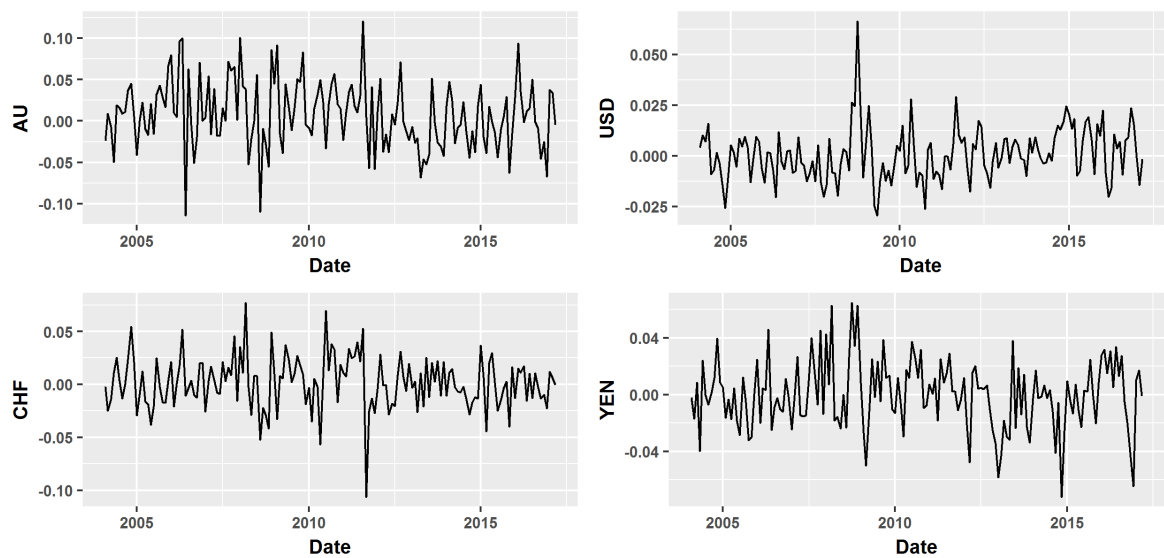


Figure D.26: Price in British pound

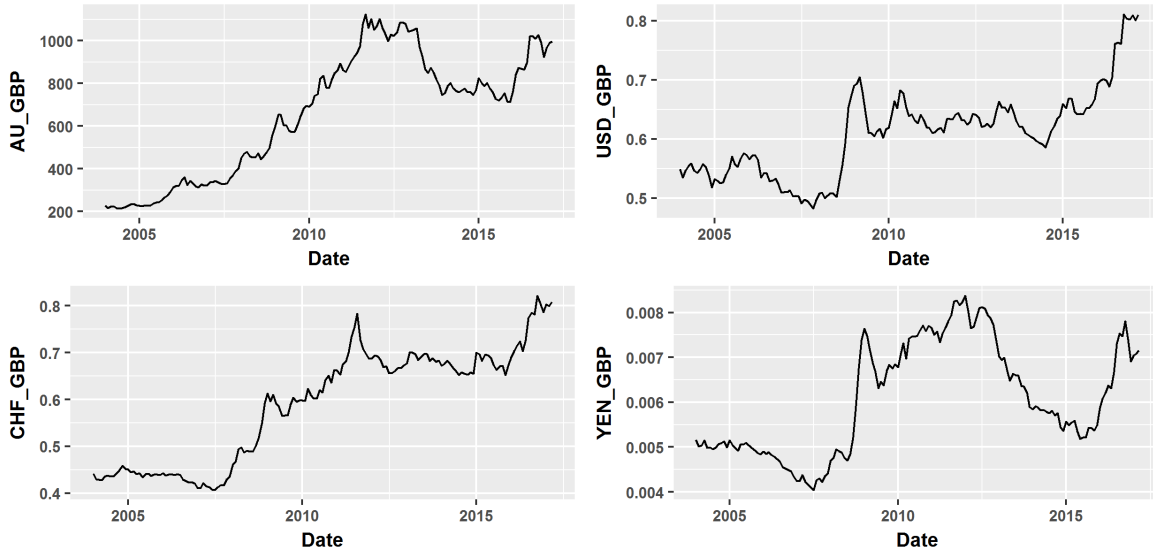


Figure D.27: Return from prices in British pound

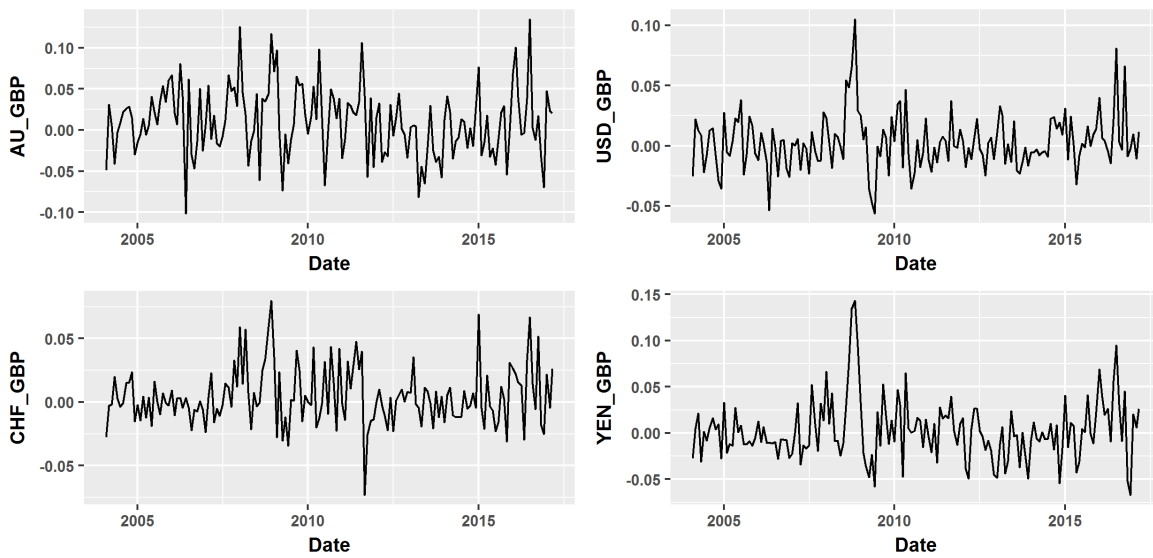


Figure D.28: Price in Euro

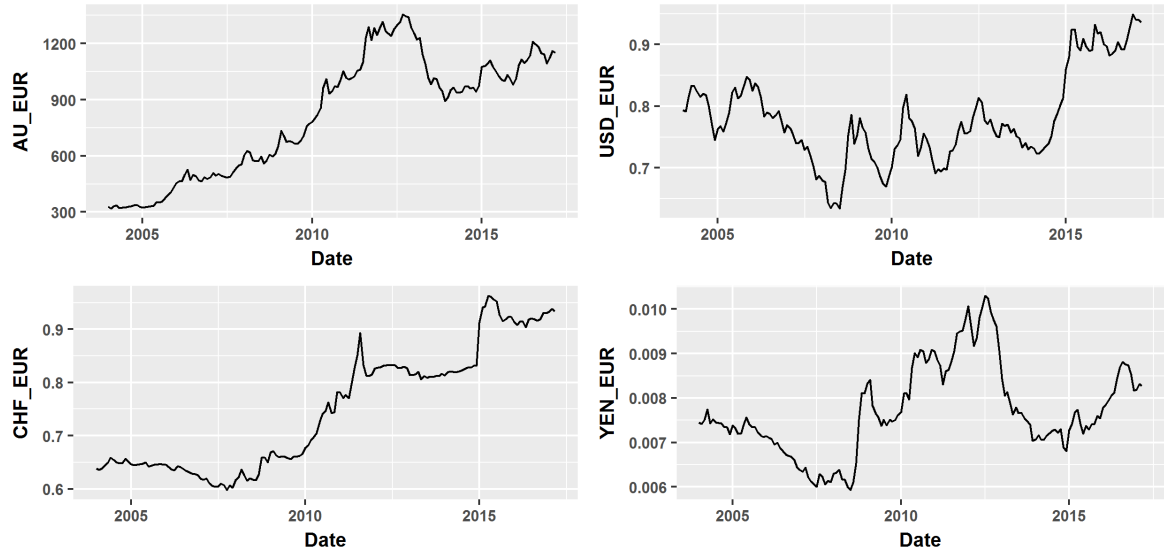


Figure D.29: Return from prices in Euro

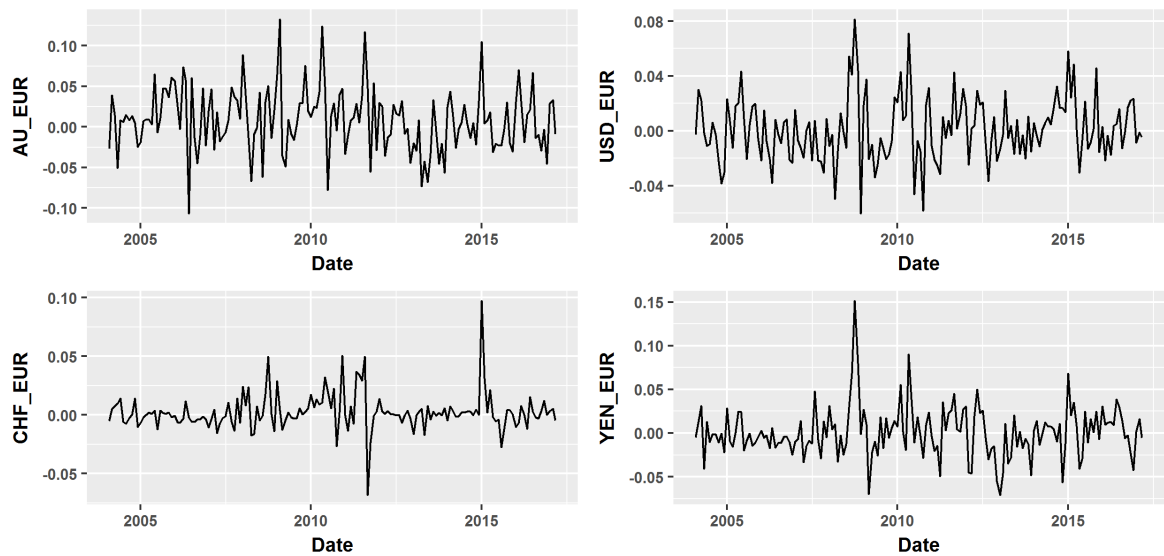


Figure D.30: Price in RMB

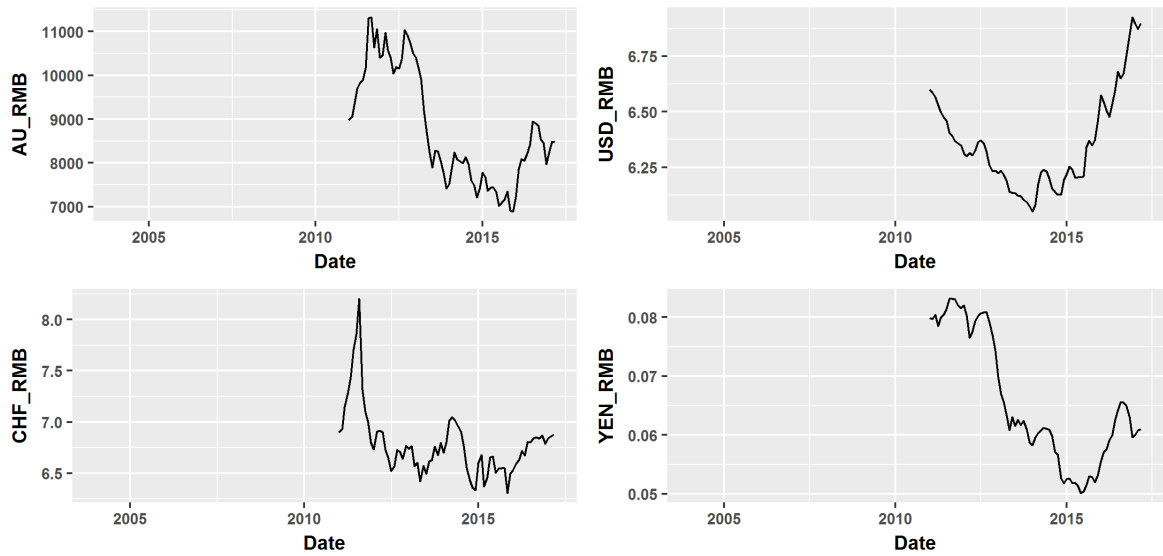


Figure D.31: Return from prices in RMB

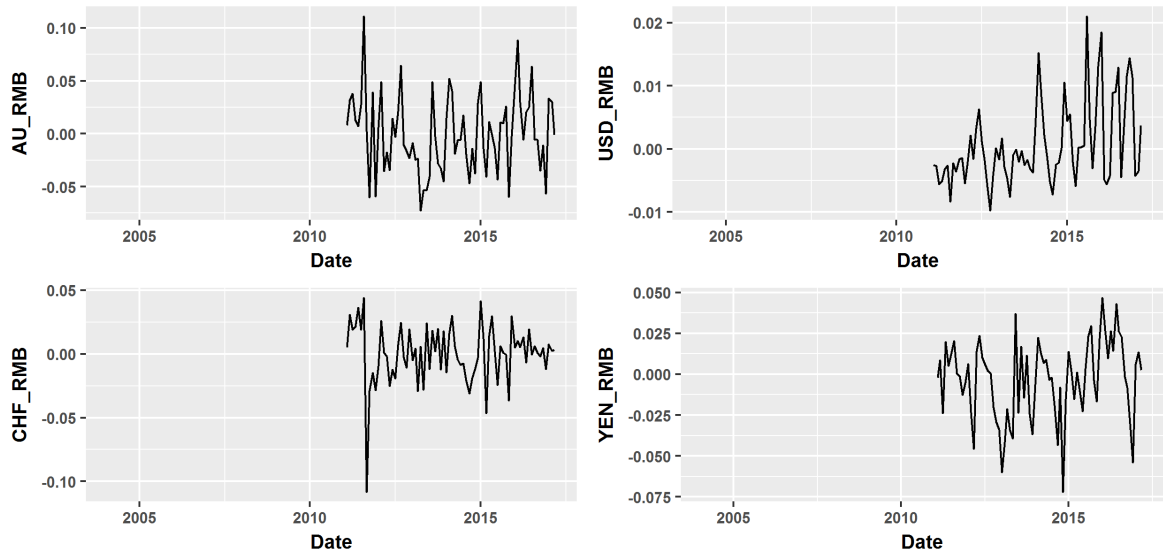


Figure D.32: Google Trends of “safe haven” — level

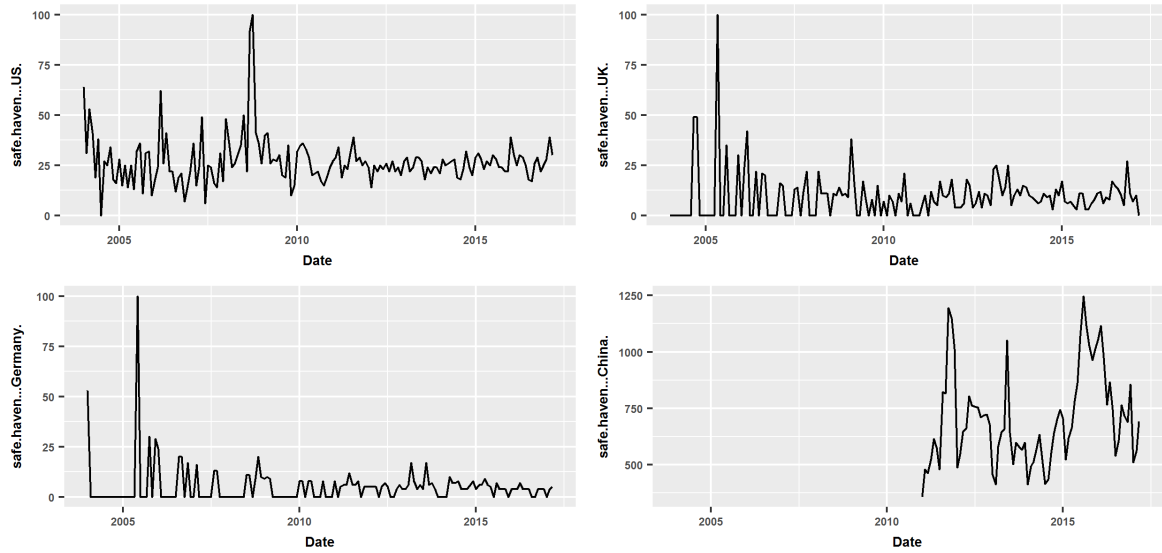


Figure D.33: Google Trends of “safe haven” — first difference

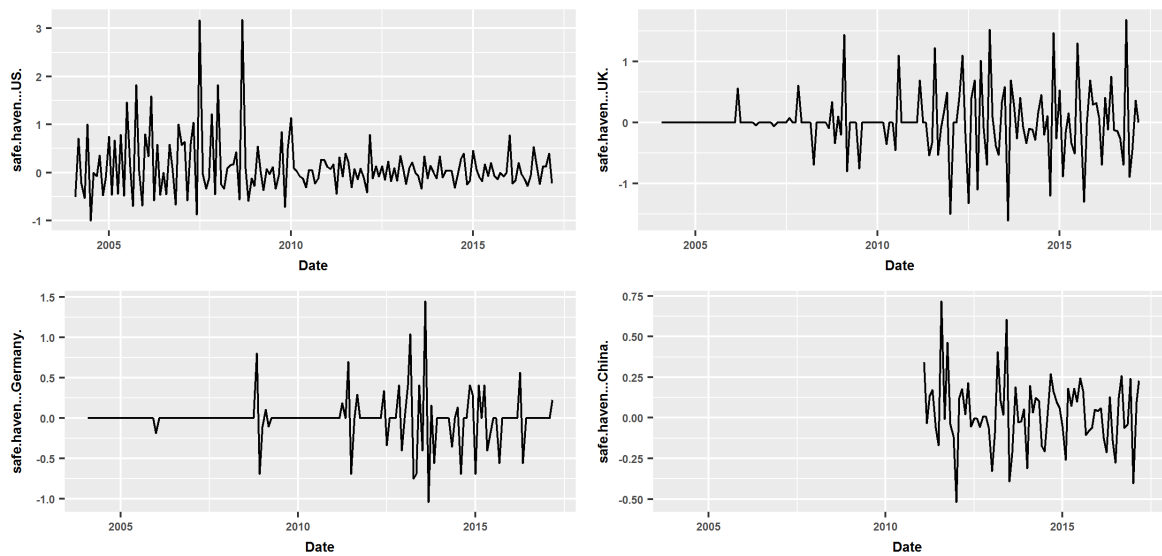


Figure D.34: Google Trends of “gold” — level

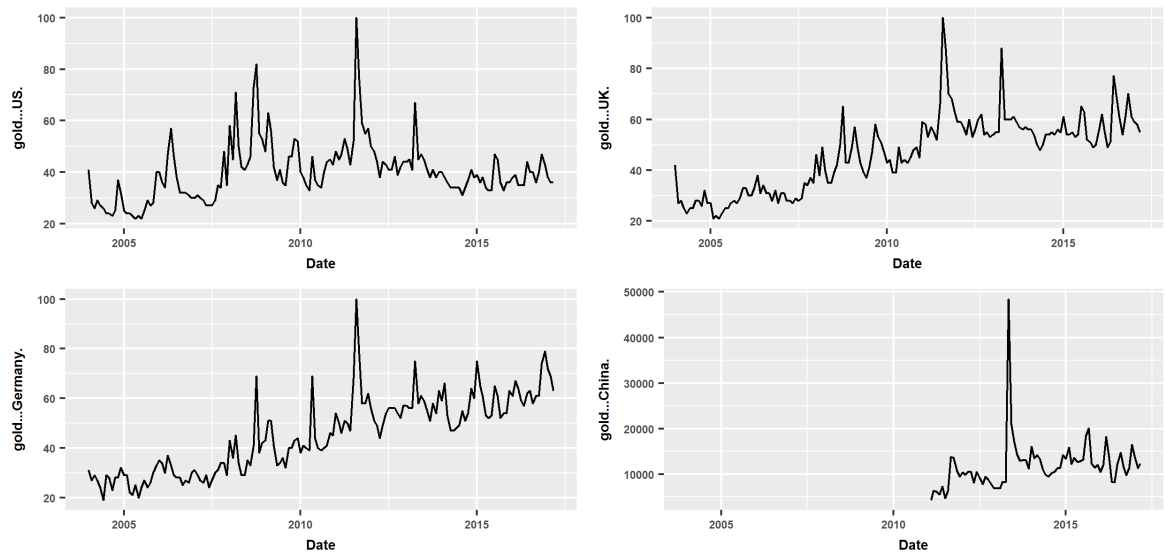


Figure D.35: Google Trends of “gold” — first difference

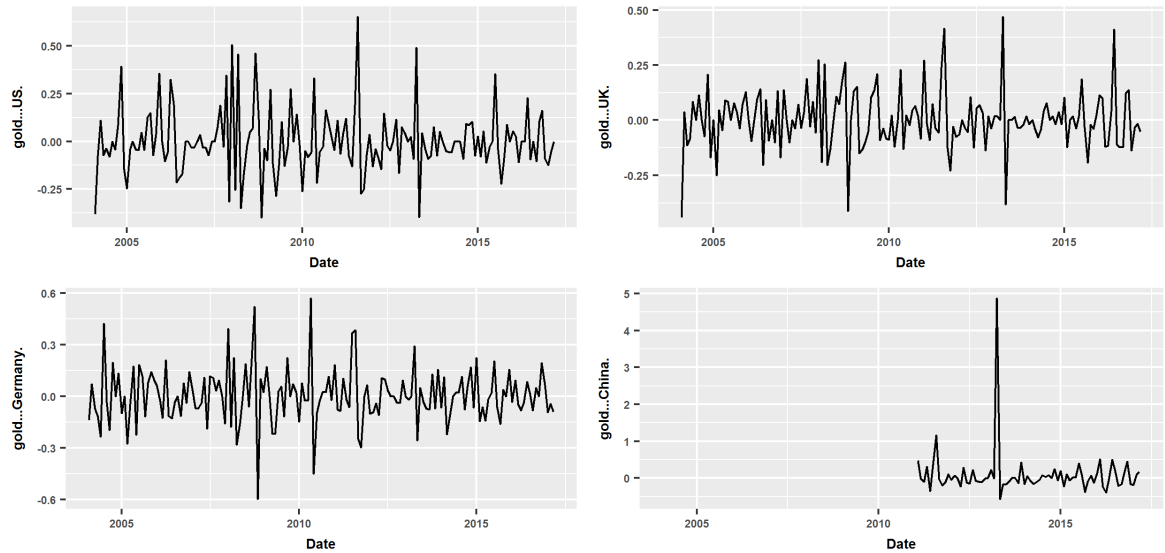


Figure D.36: Google Trends of “USD” — level

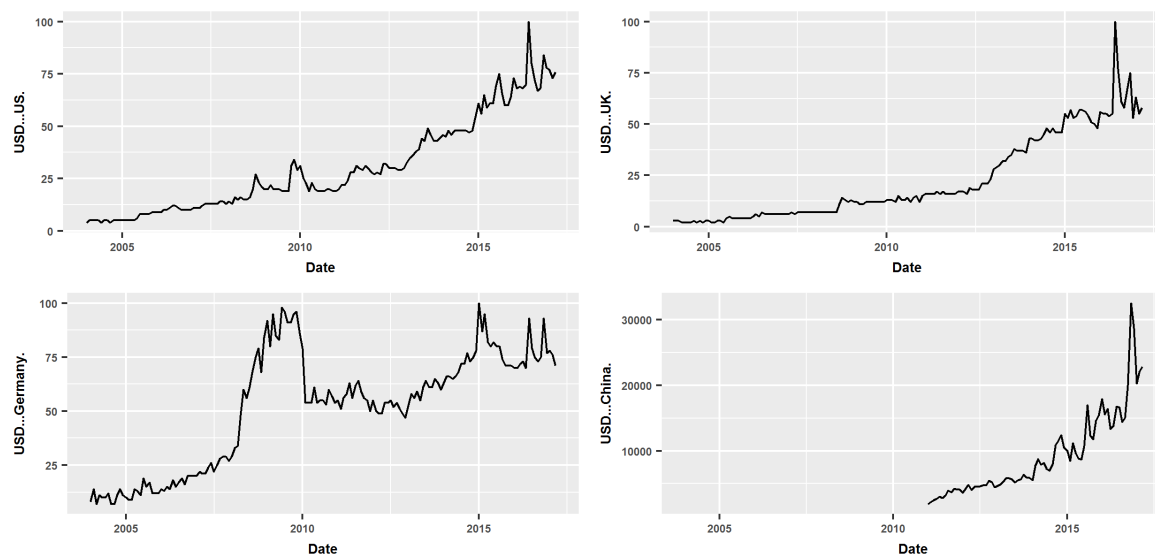


Figure D.37: Google Trends of “USD” — first difference

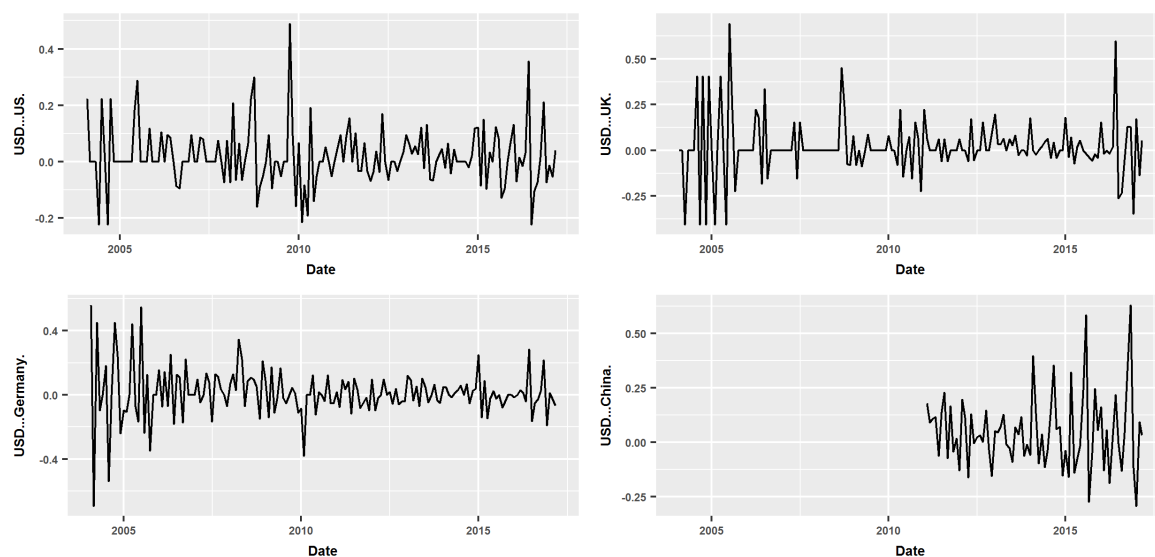


Figure D.38: Google Trends of “CHF” — level

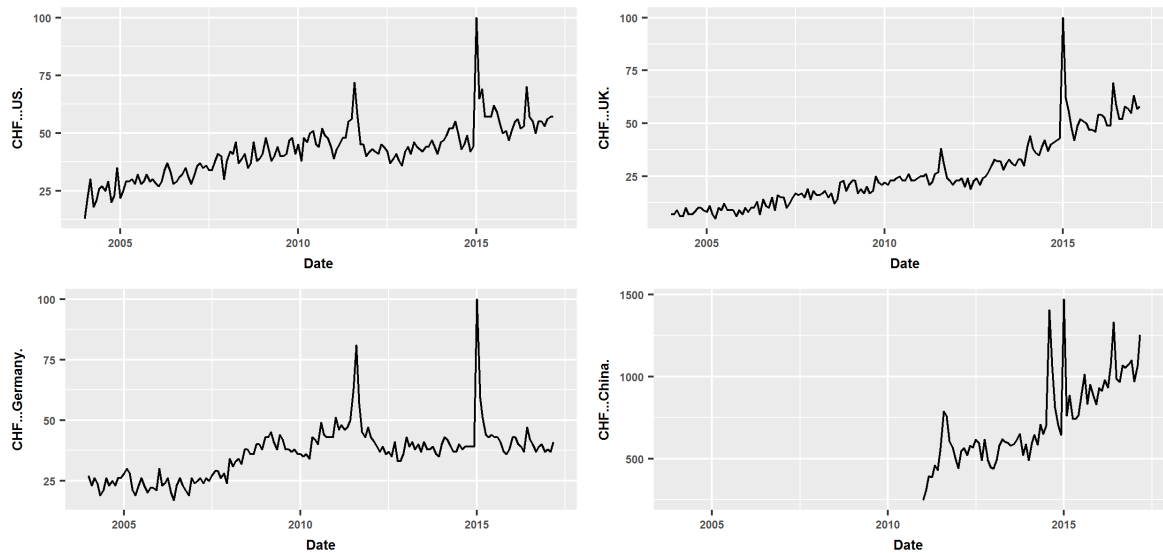


Figure D.39: Google Trends of “CHF” — first difference

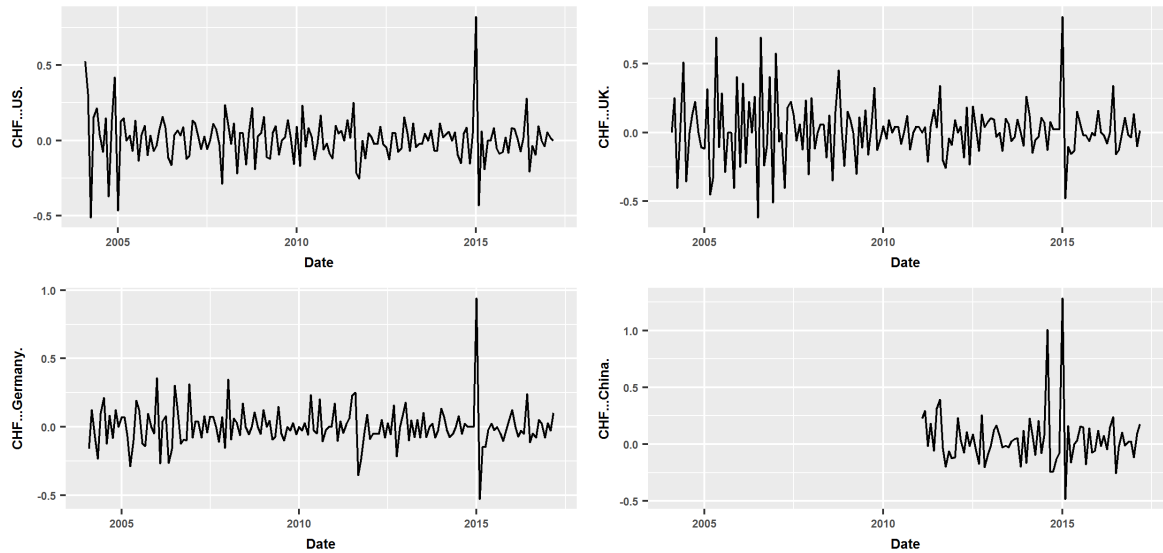


Figure D.40: Google Trends of “YEN” — level

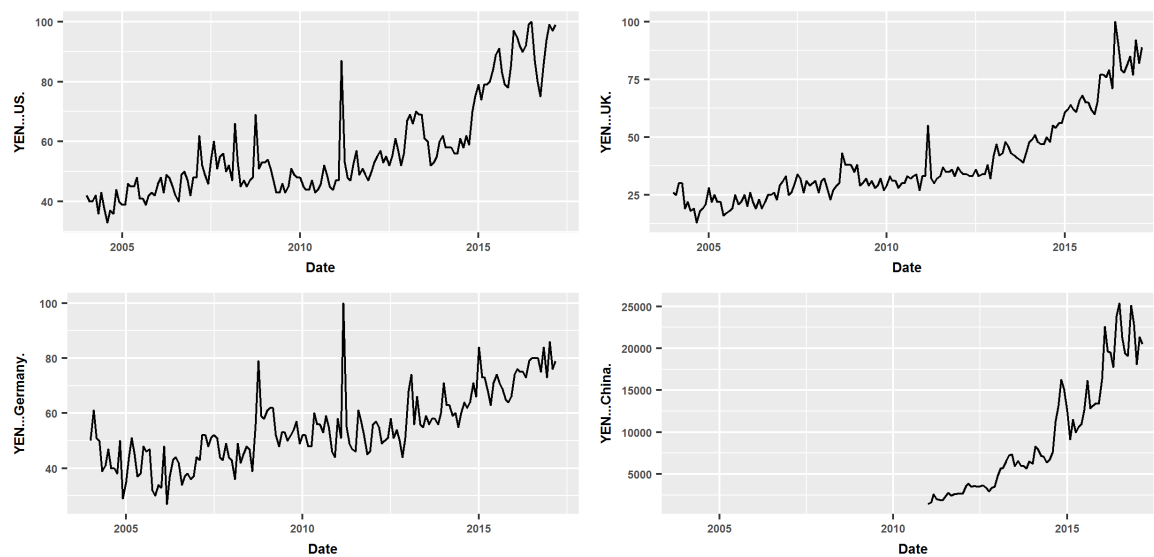
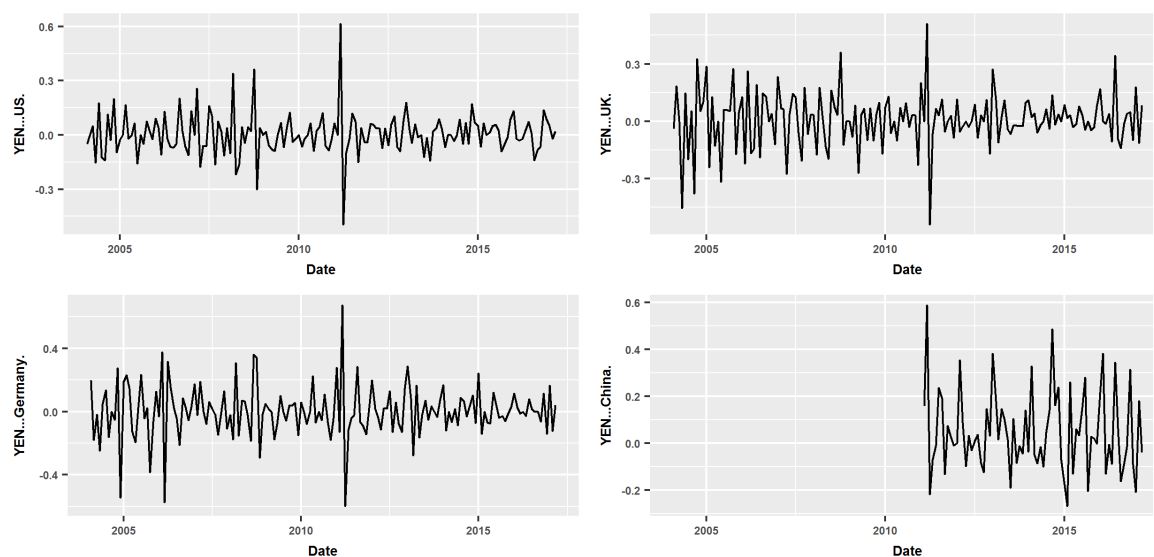


Figure D.41: Google Trends of “YEN” — first difference



Appendix E

Market Dependence as Measured by Correlations

The following plots first show rolling 1-quarter correlation coefficients between market returns, and then more smoothed results with 1-year window.

Figure E.1: 1-Quarter Rolling Correlation Coefficients — the US

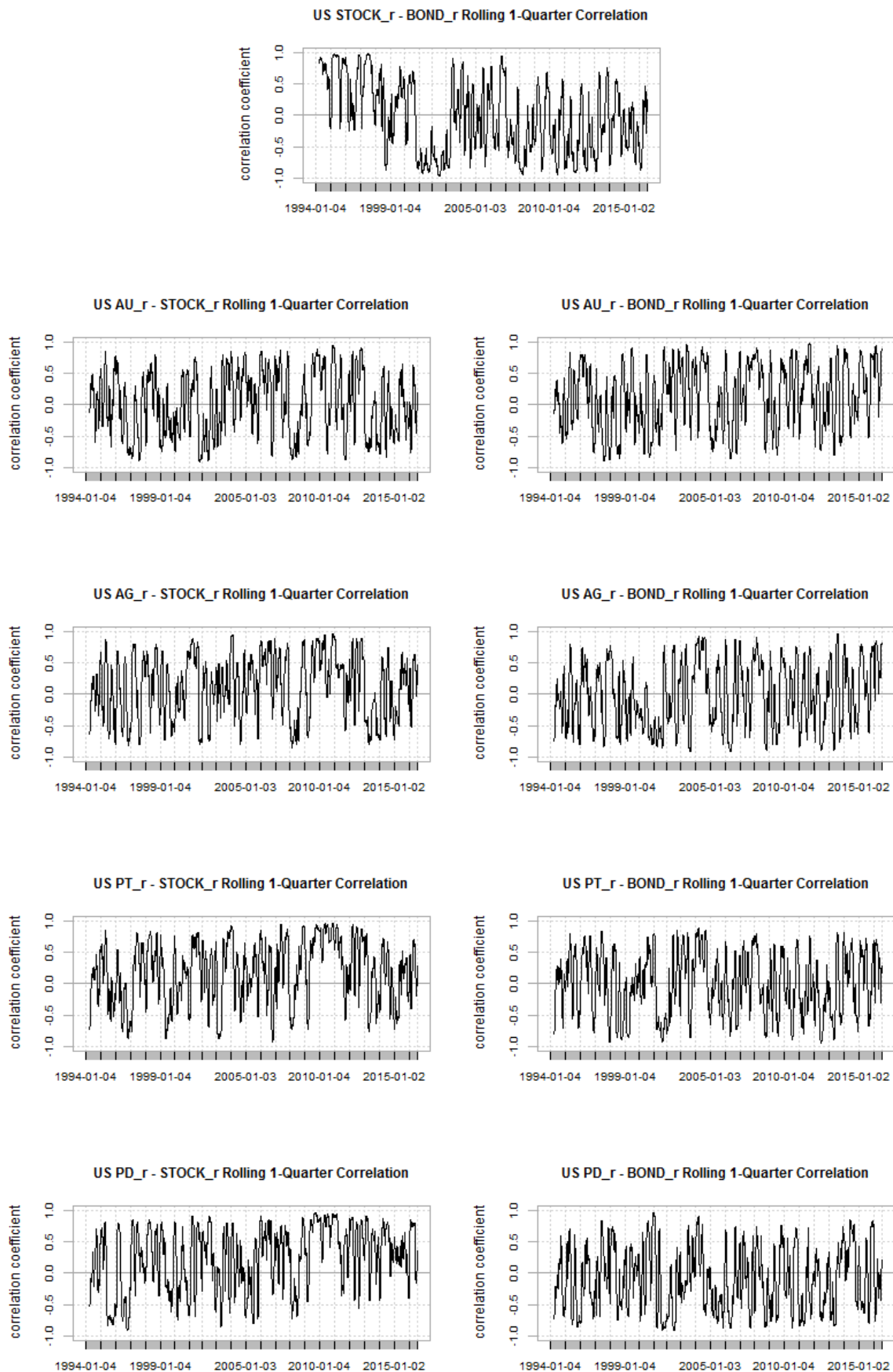


Figure E.2: 1-Quarter Rolling Correlation Coefficients — the UK

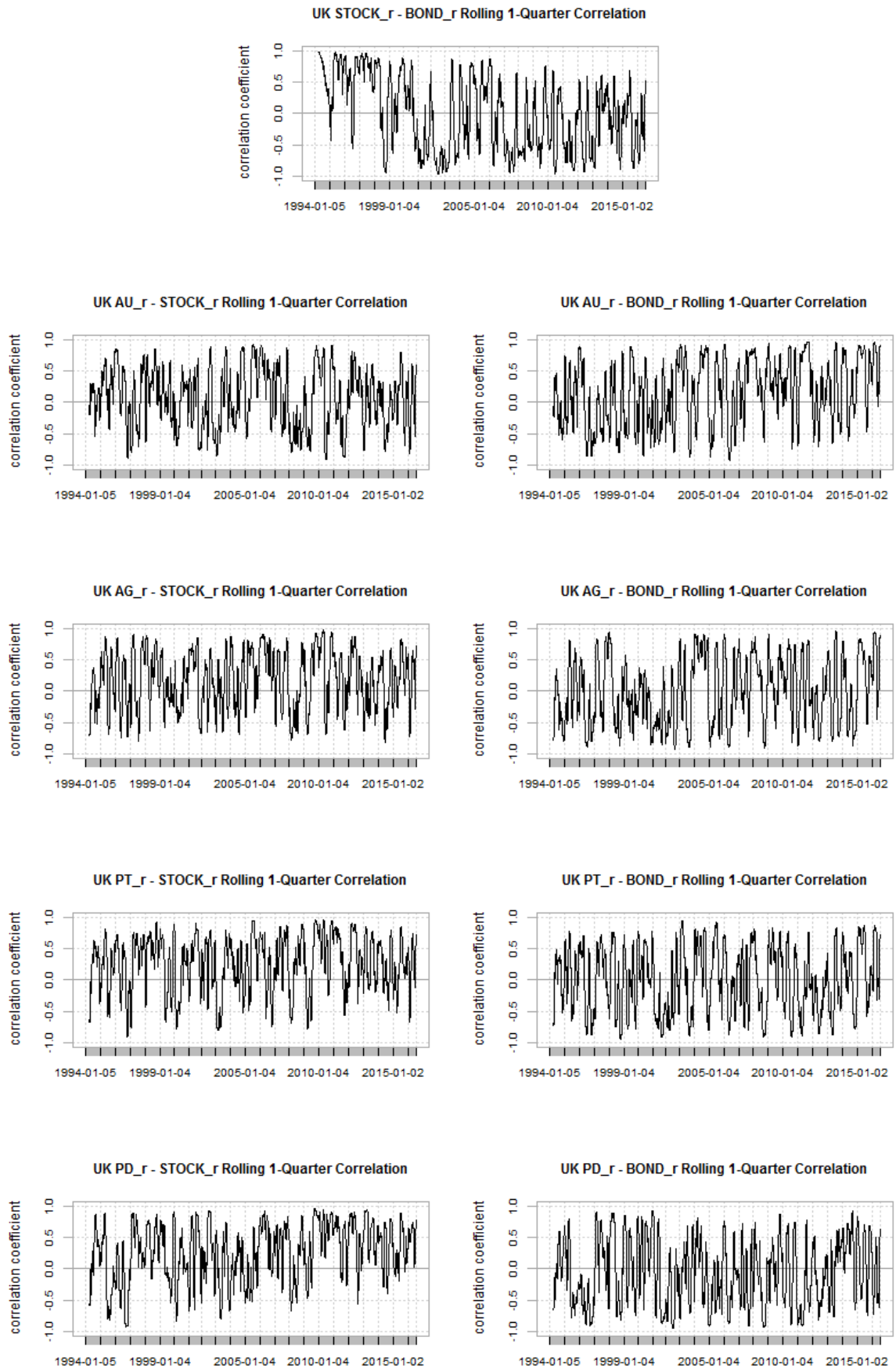


Figure E.3: 1-Quarter Rolling Correlation Coefficients — Germany

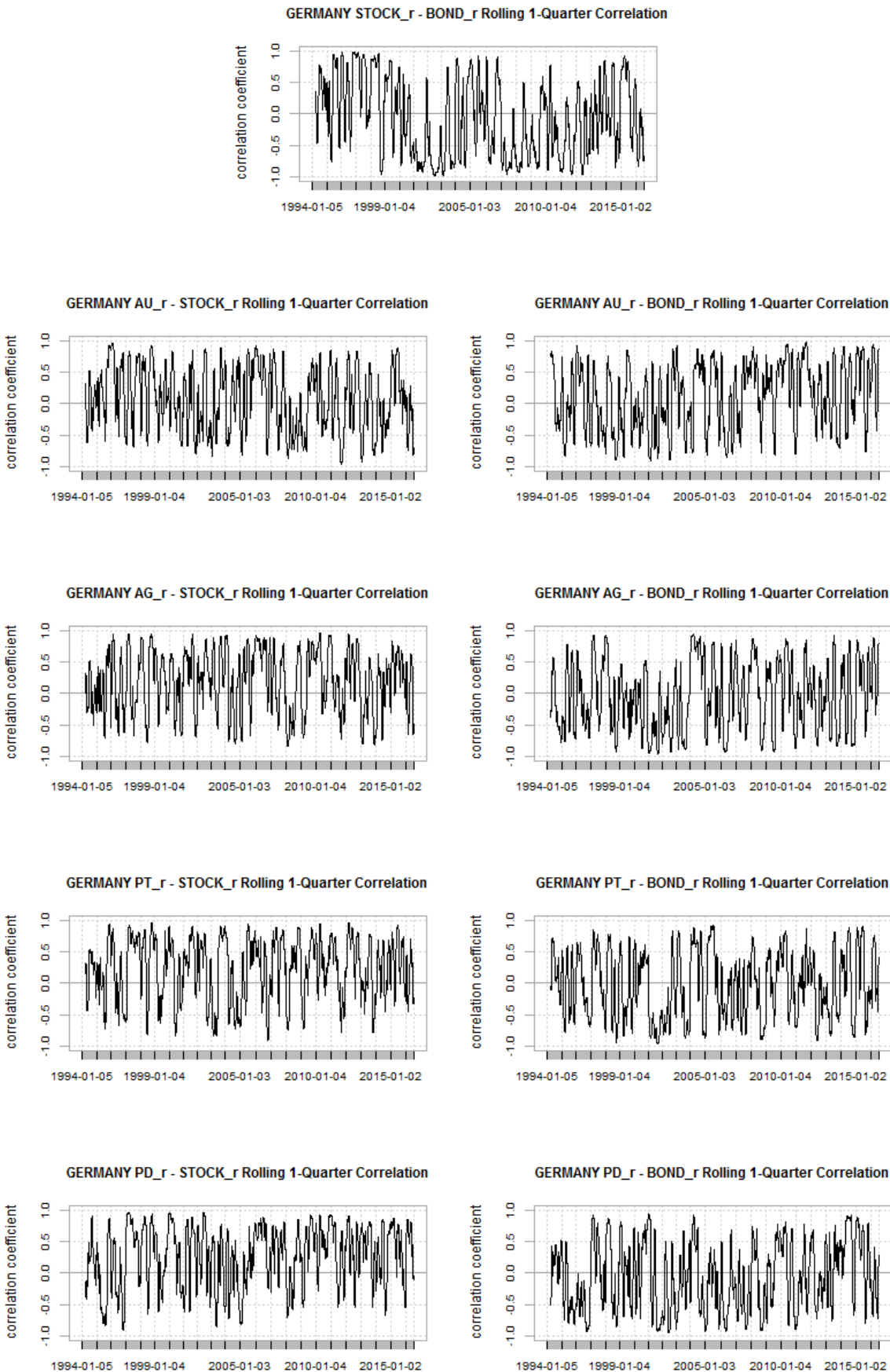


Figure E.4: 1-Quarter Rolling Correlation Coefficients — France

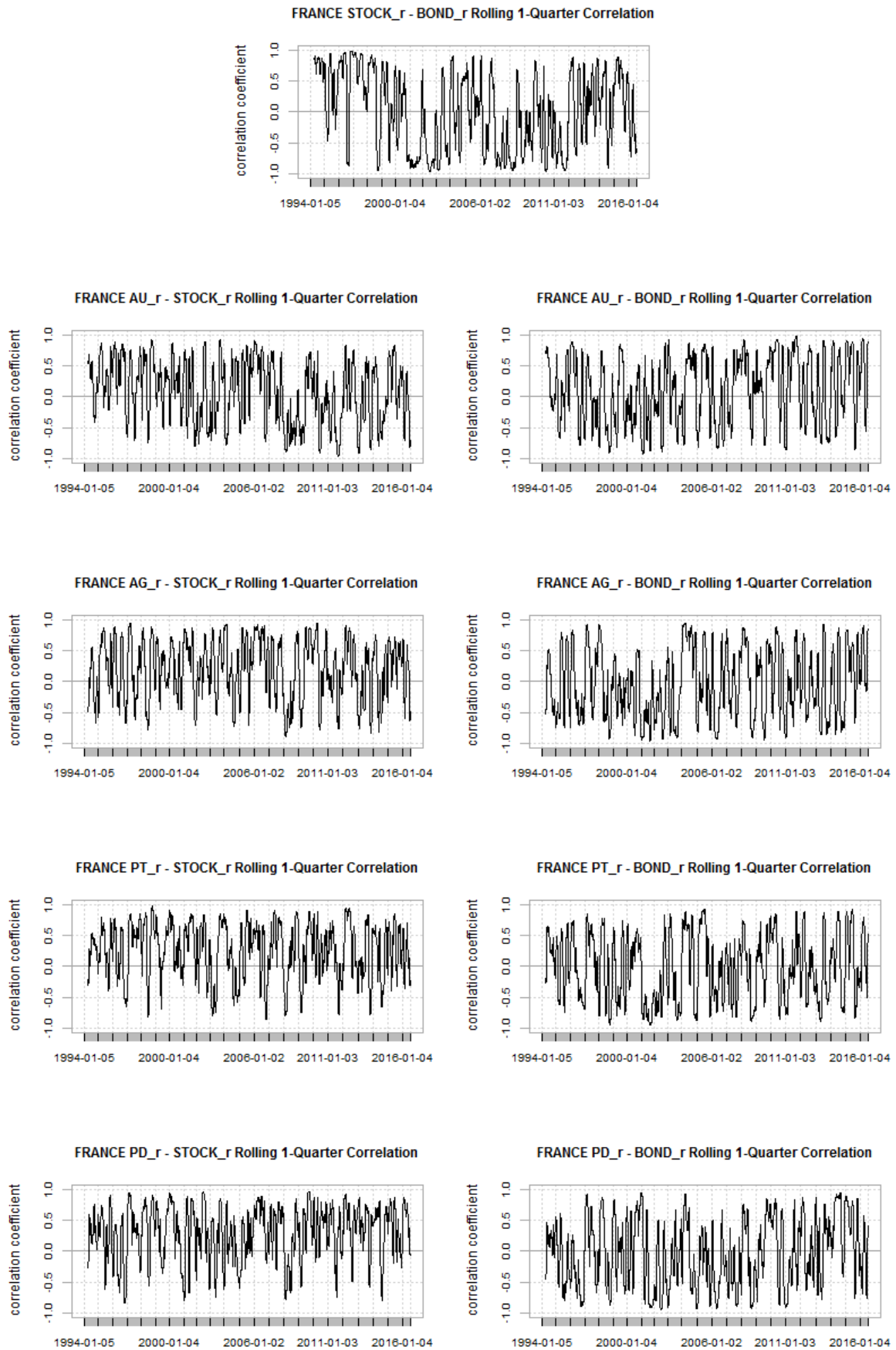


Figure E.5: 1-Quarter Rolling Correlation Coefficients — Italy

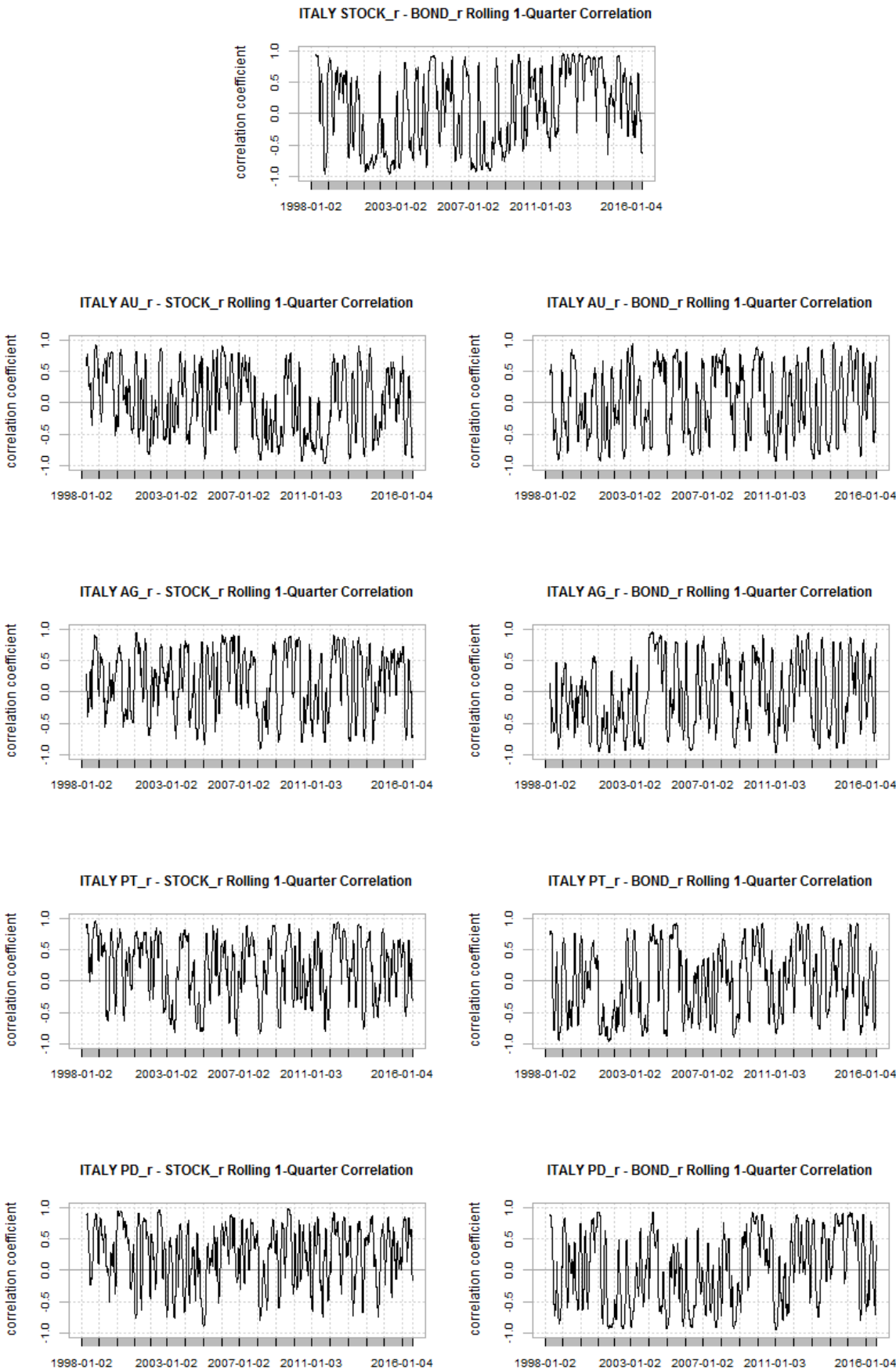


Figure E.6: 1-Quarter Rolling Correlation Coefficients — Switzerland

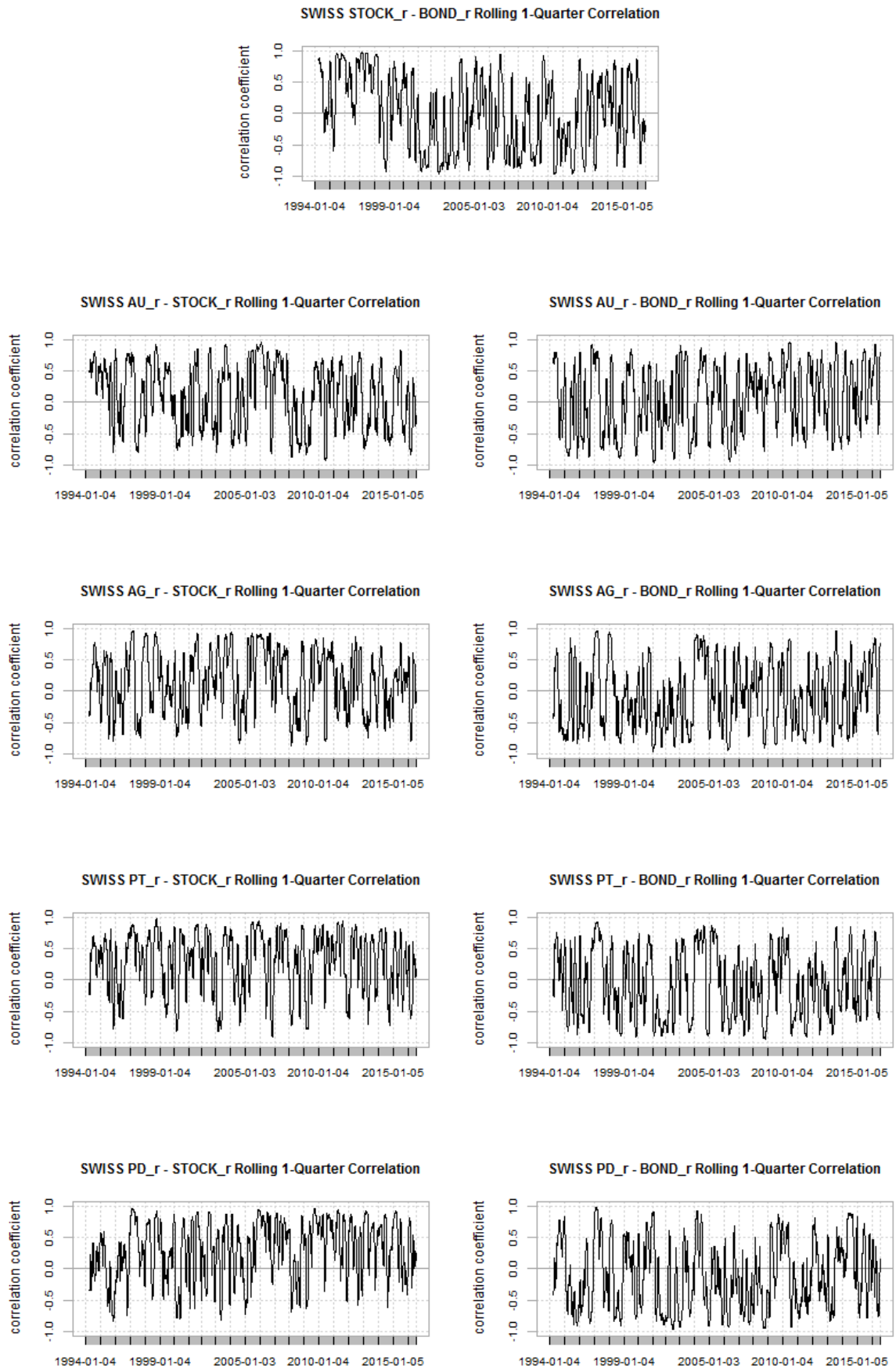


Figure E.7: 1-Quarter Rolling Correlation Coefficients — Canada

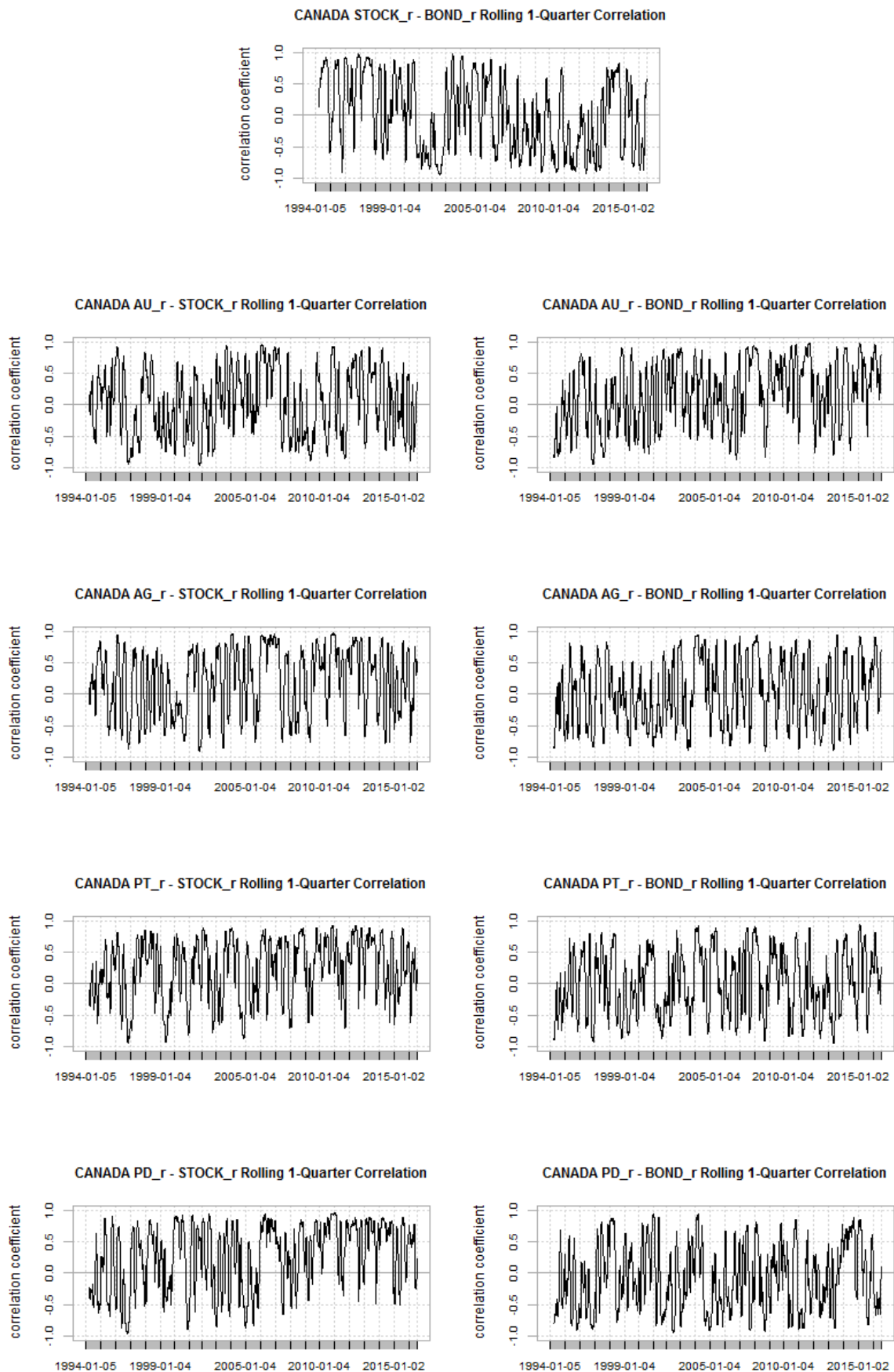


Figure E.8: 1-Quarter Rolling Correlation Coefficients — Japan

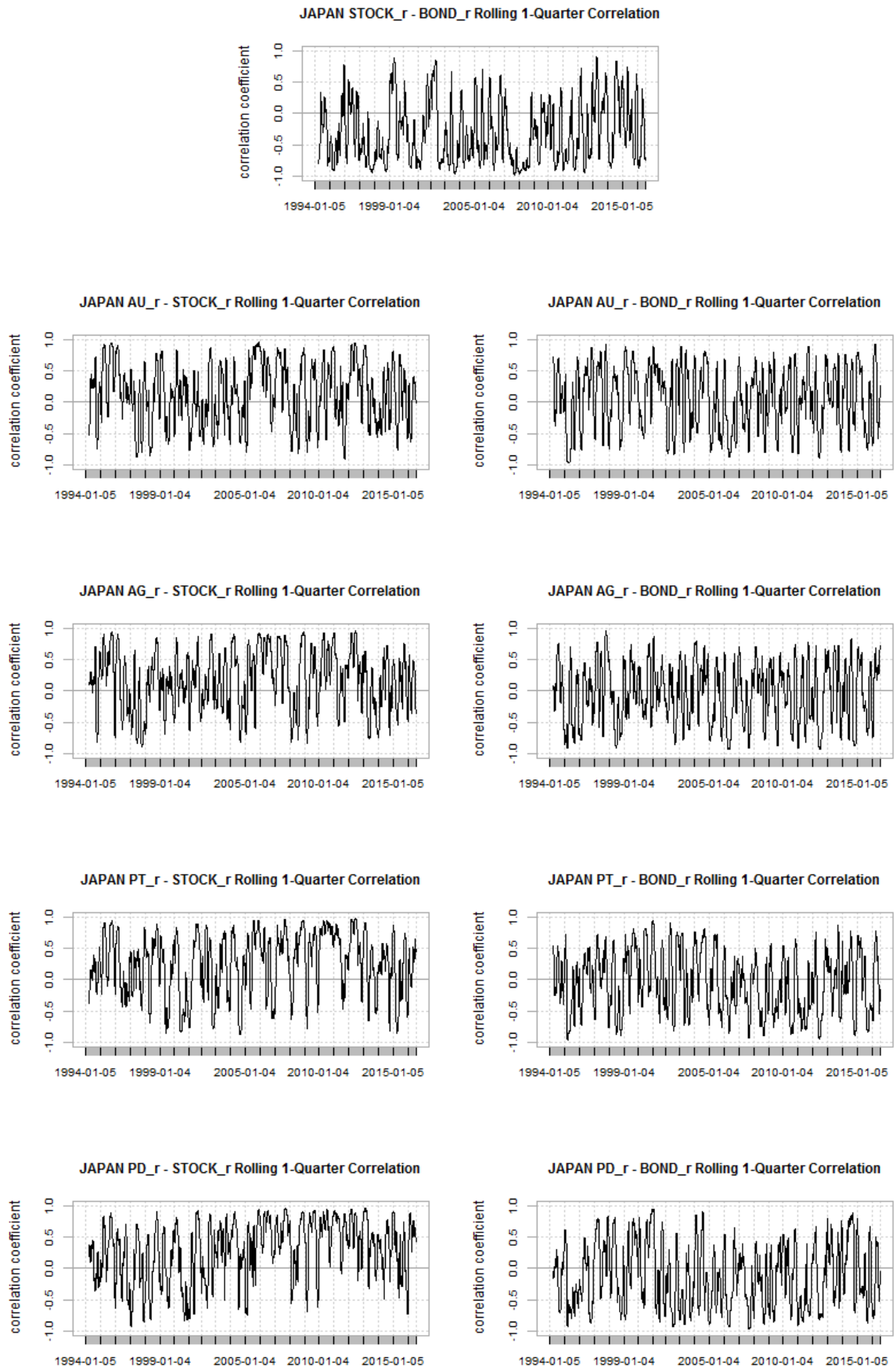


Figure E.9: 1-Quarter Rolling Correlation Coefficients — China

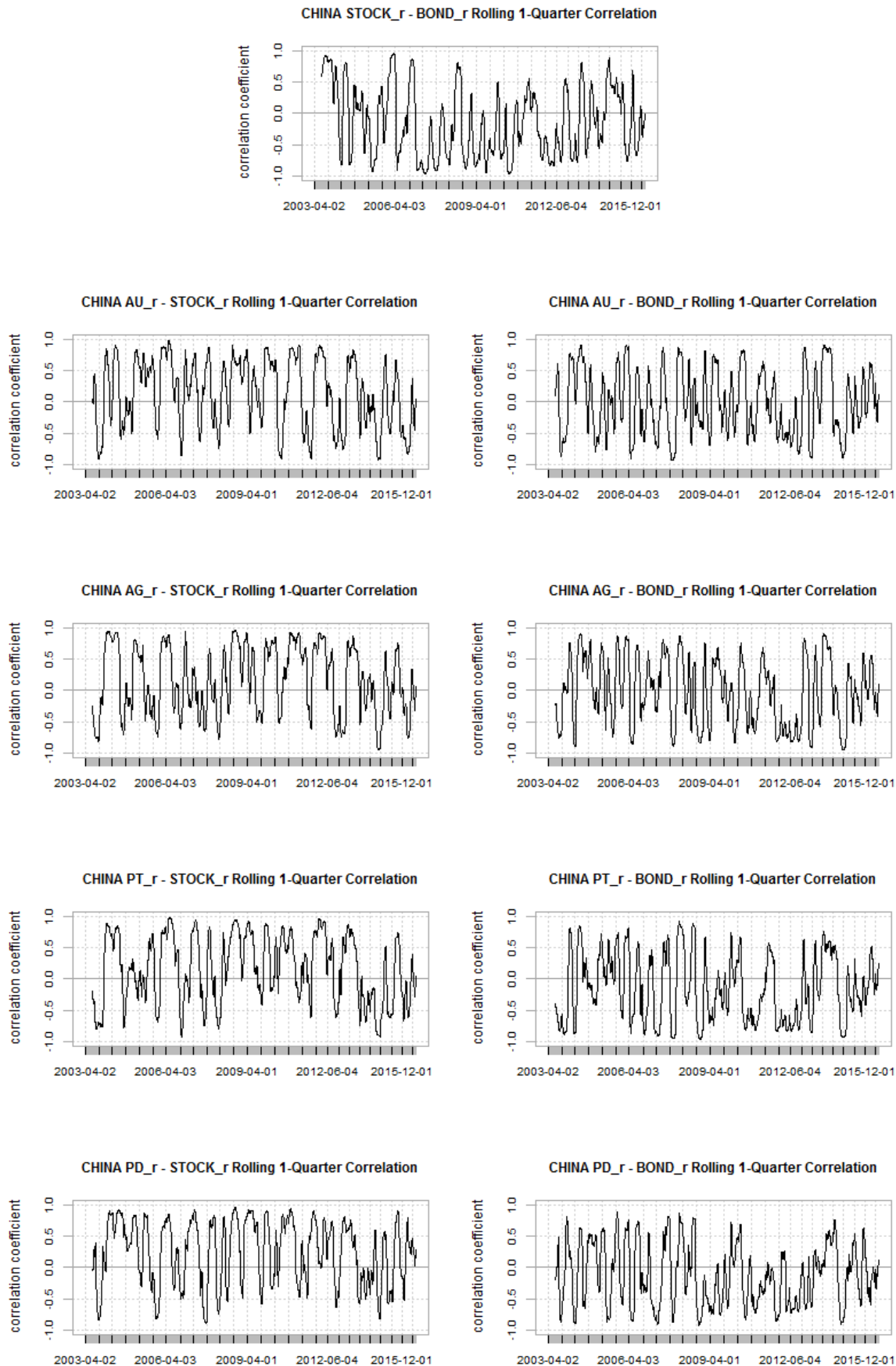


Figure E.10: 1-Quarter Rolling Correlation Coefficients — India

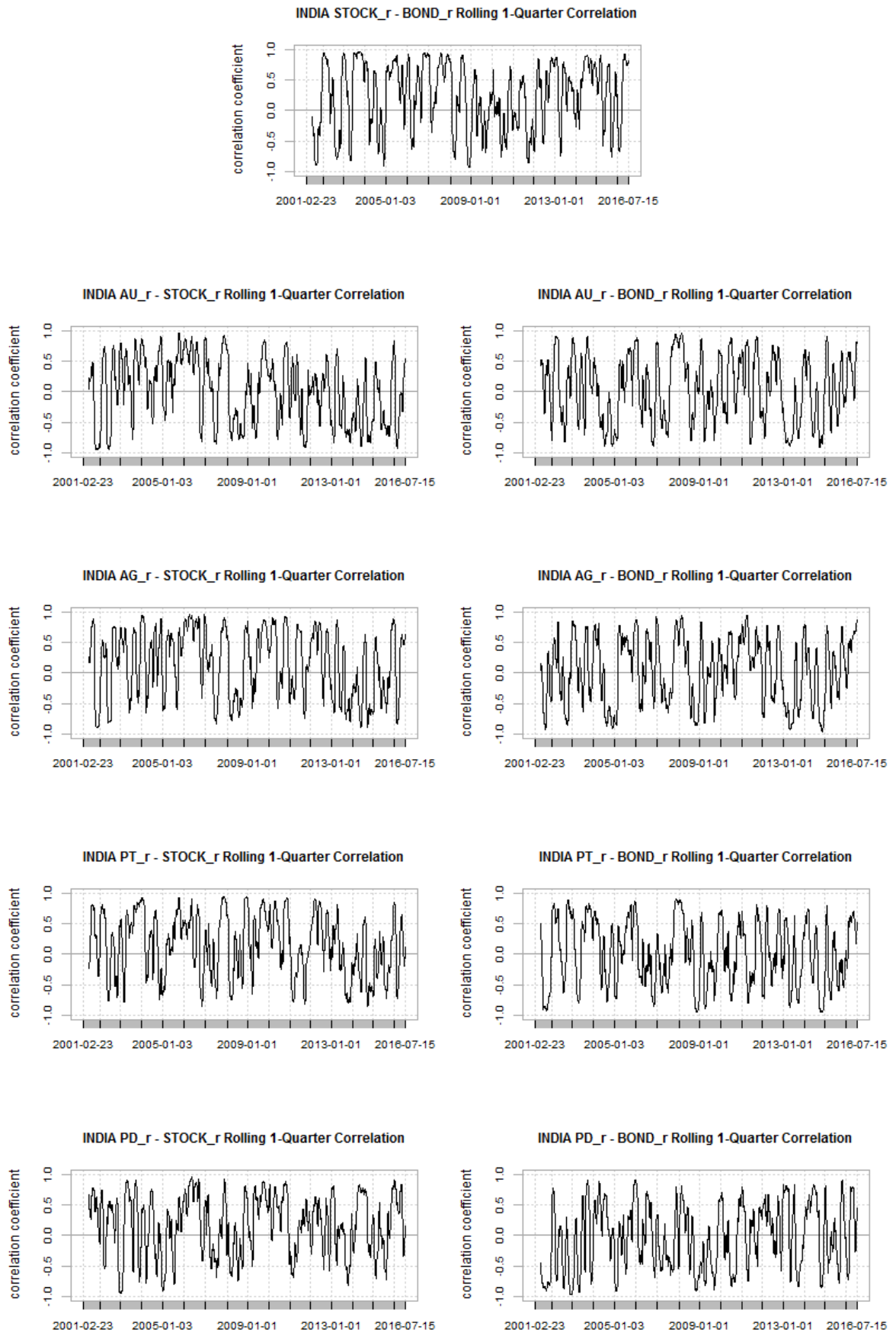


Figure E.11: 1-Quarter Rolling Correlation Coefficients — South Africa

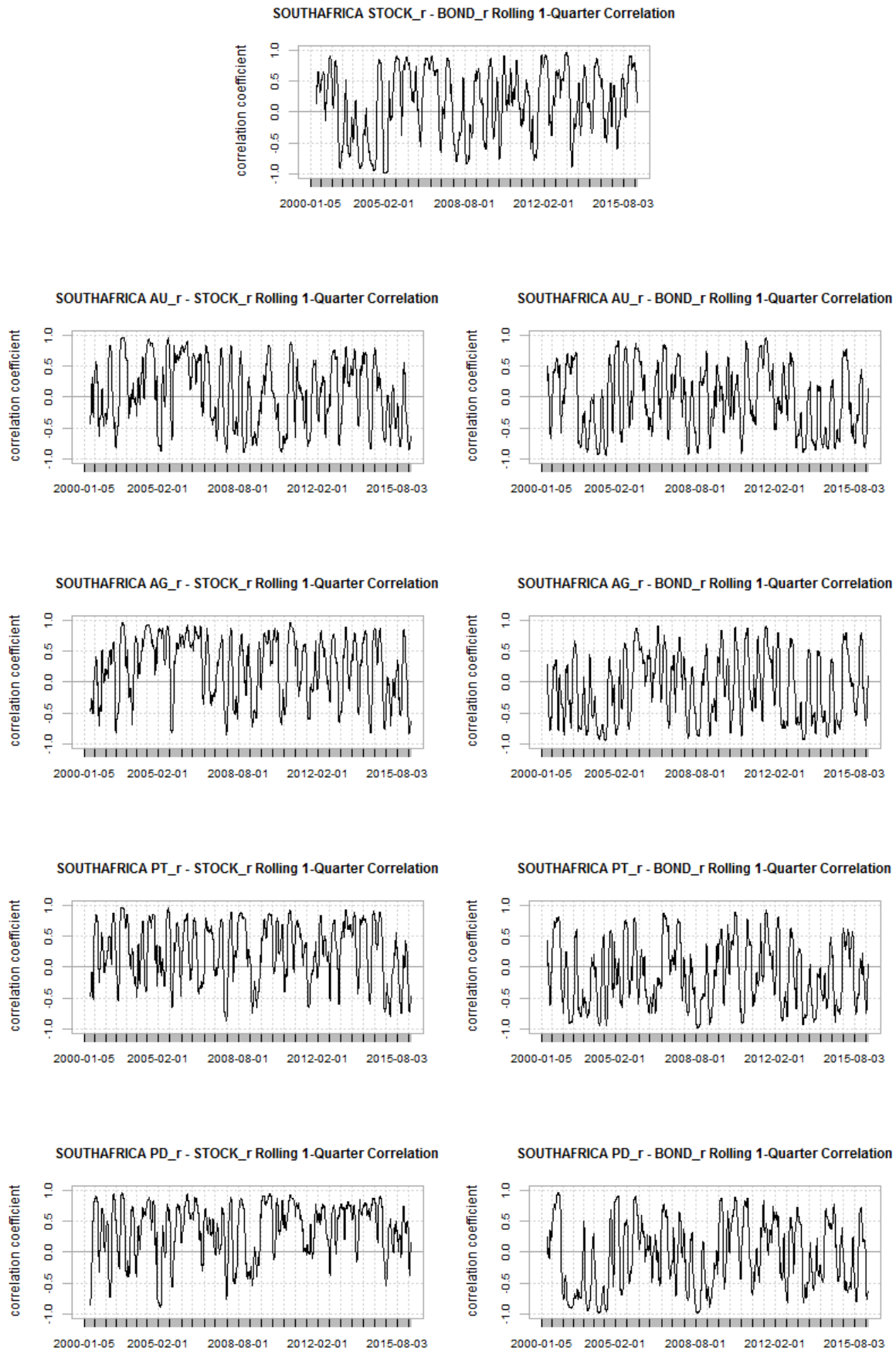


Figure E.12: 1-Year Rolling Correlation Coefficients — the US

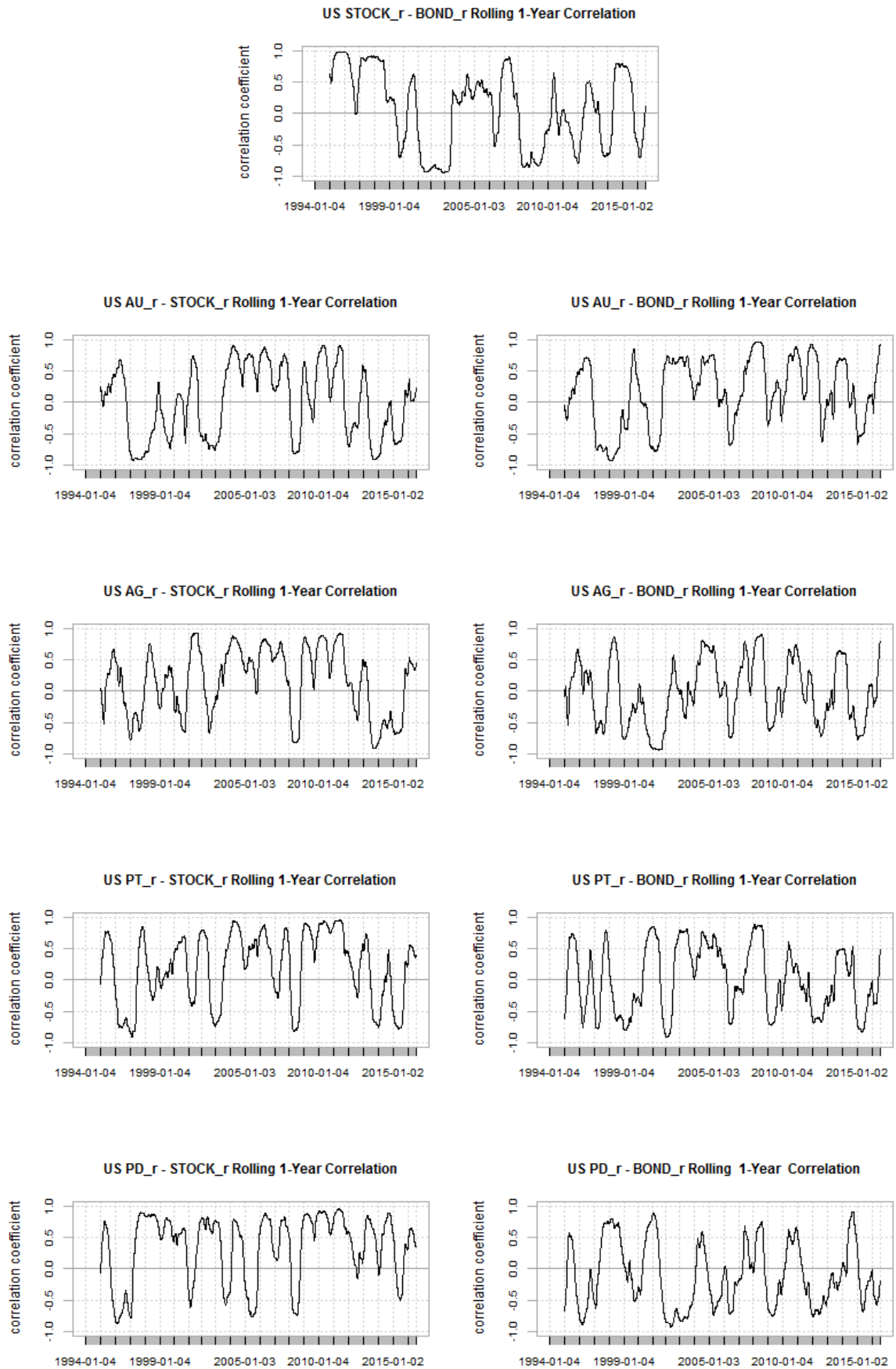


Figure E.13: 1-Year Rolling Correlation Coefficients — the UK

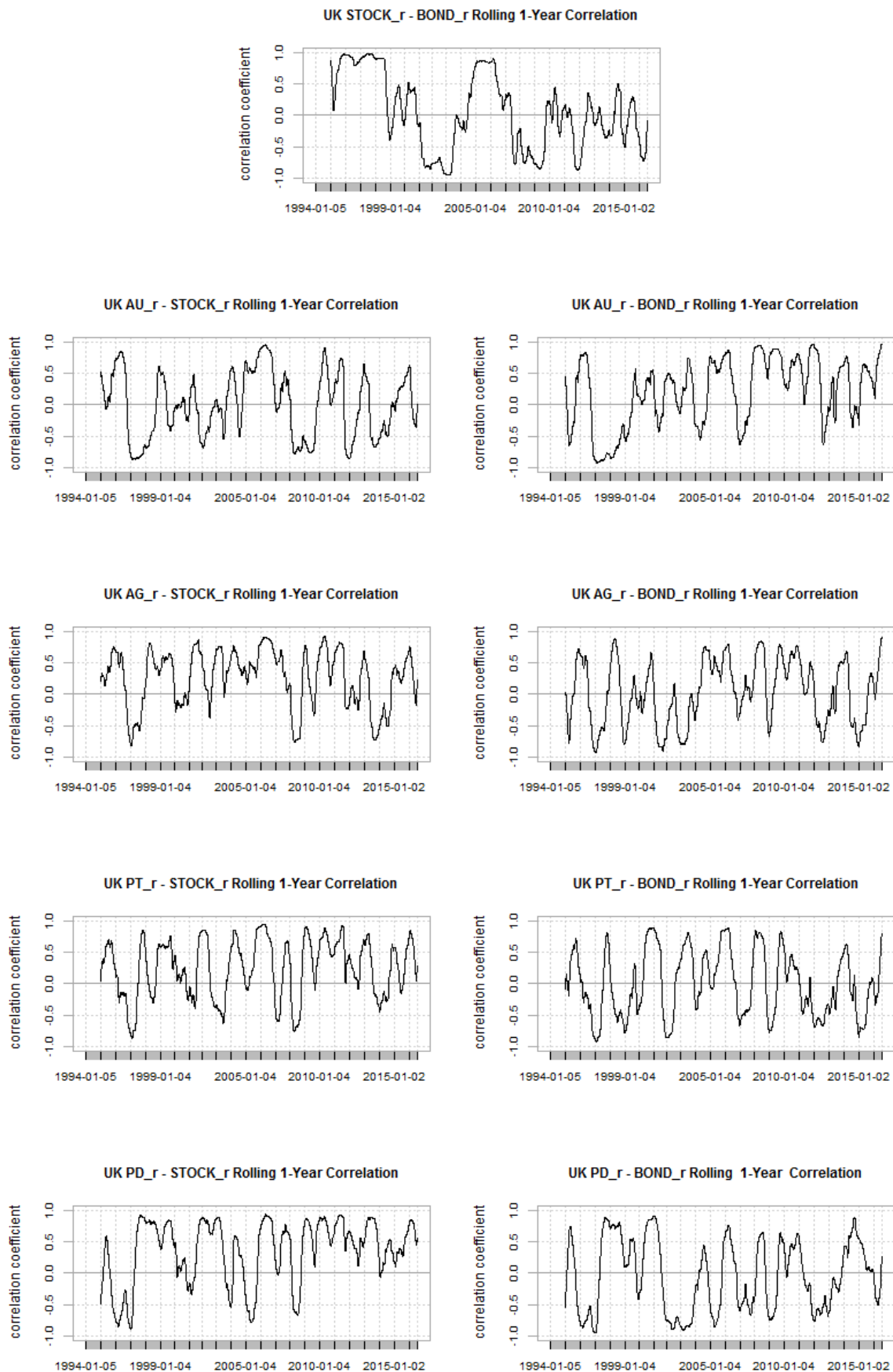


Figure E.14: 1-Year Rolling Correlation Coefficients — Germany

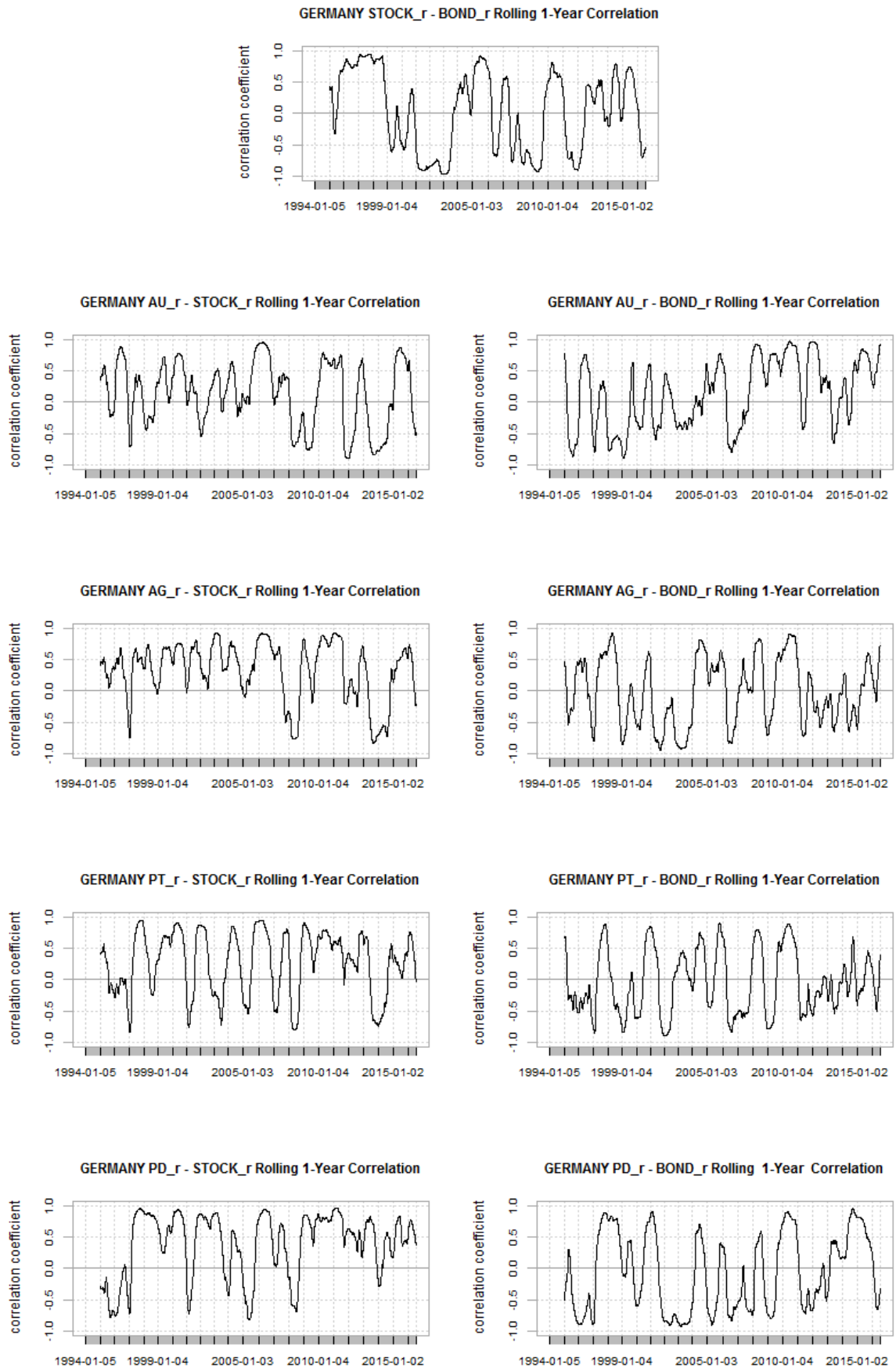


Figure E.15: 1-Year Rolling Correlation Coefficients — France

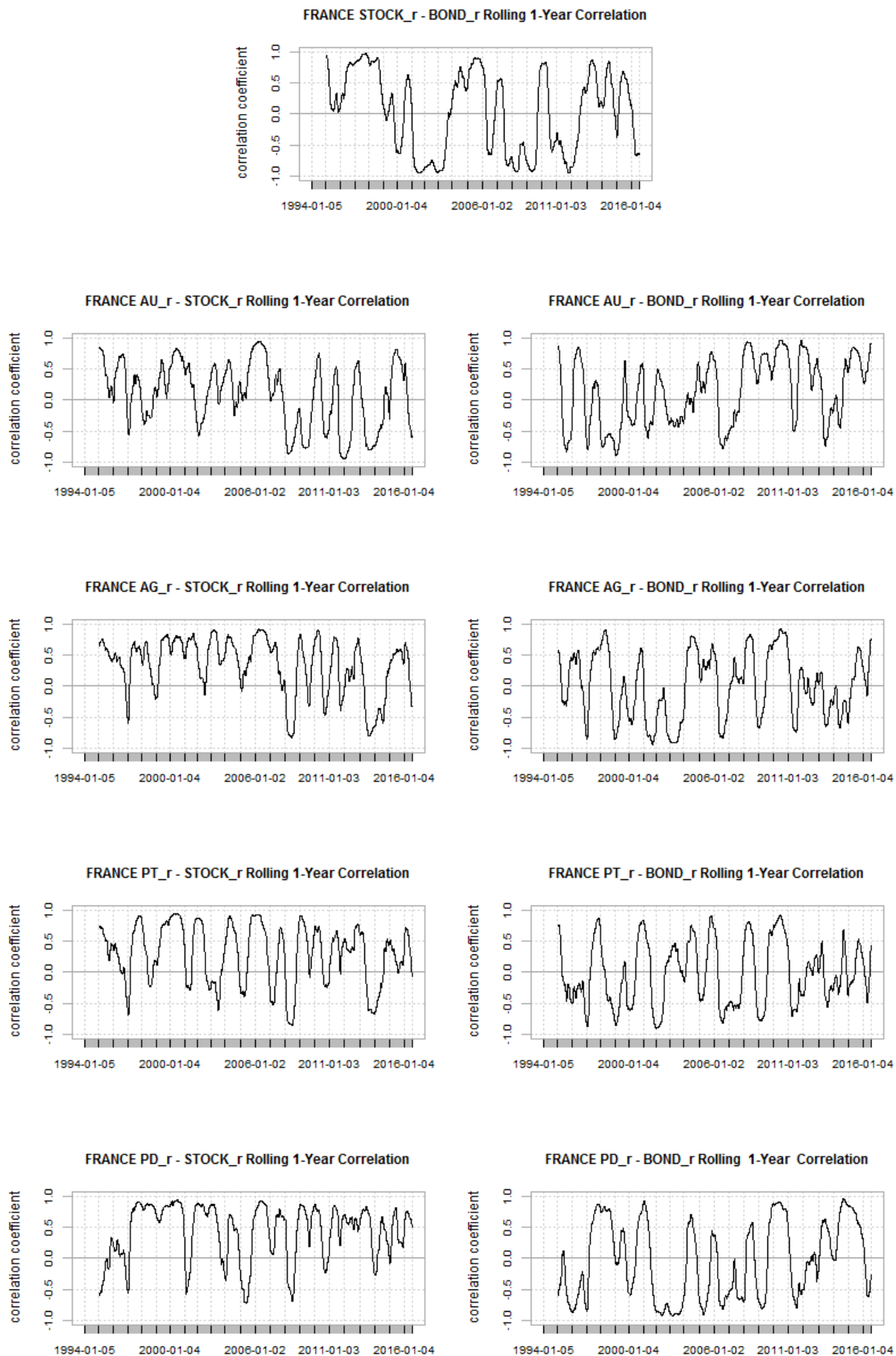


Figure E.16: 1-Year Rolling Correlation Coefficients — Italy

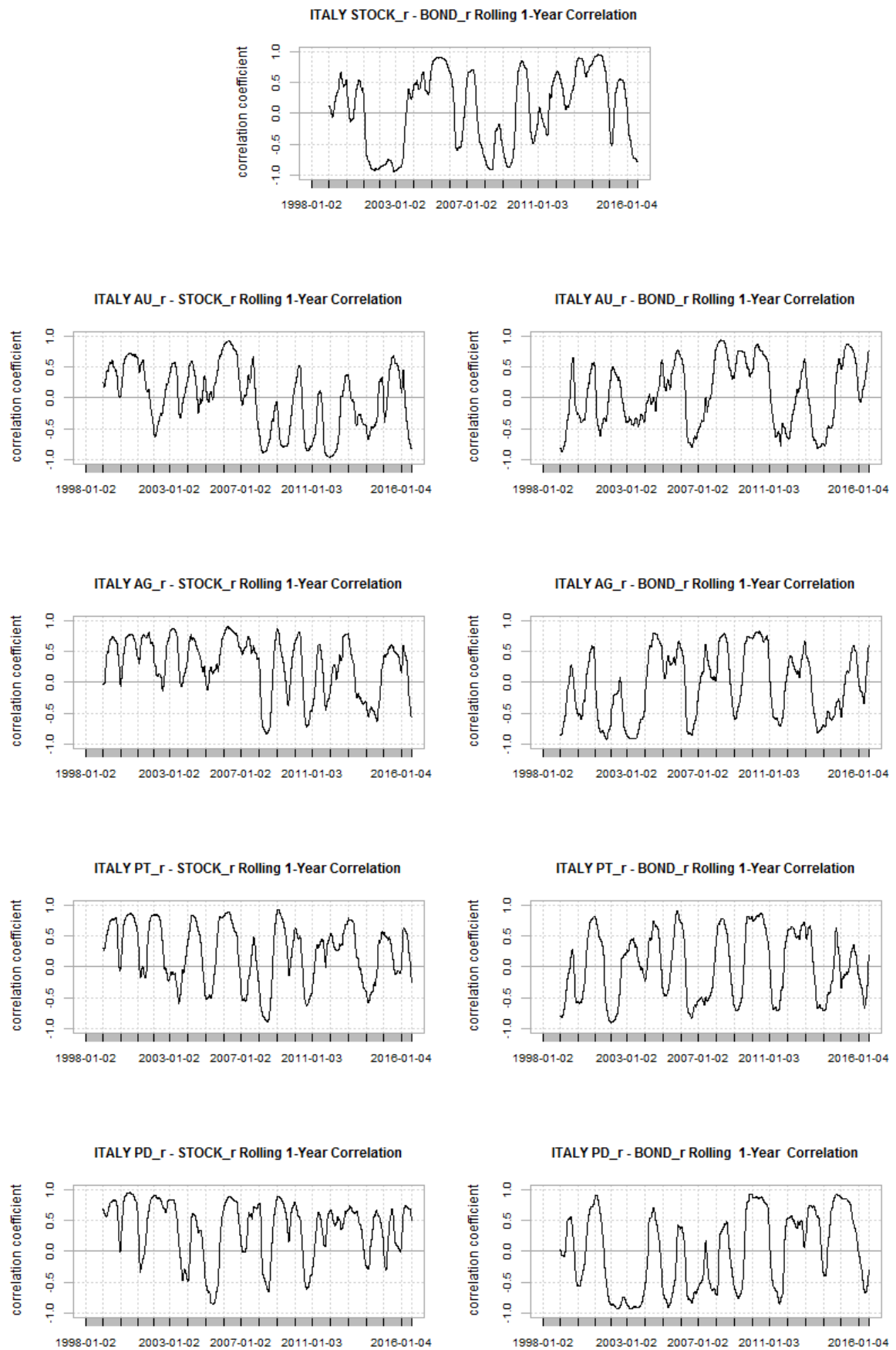


Figure E.17: 1-Year Rolling Correlation Coefficients — Switzerland

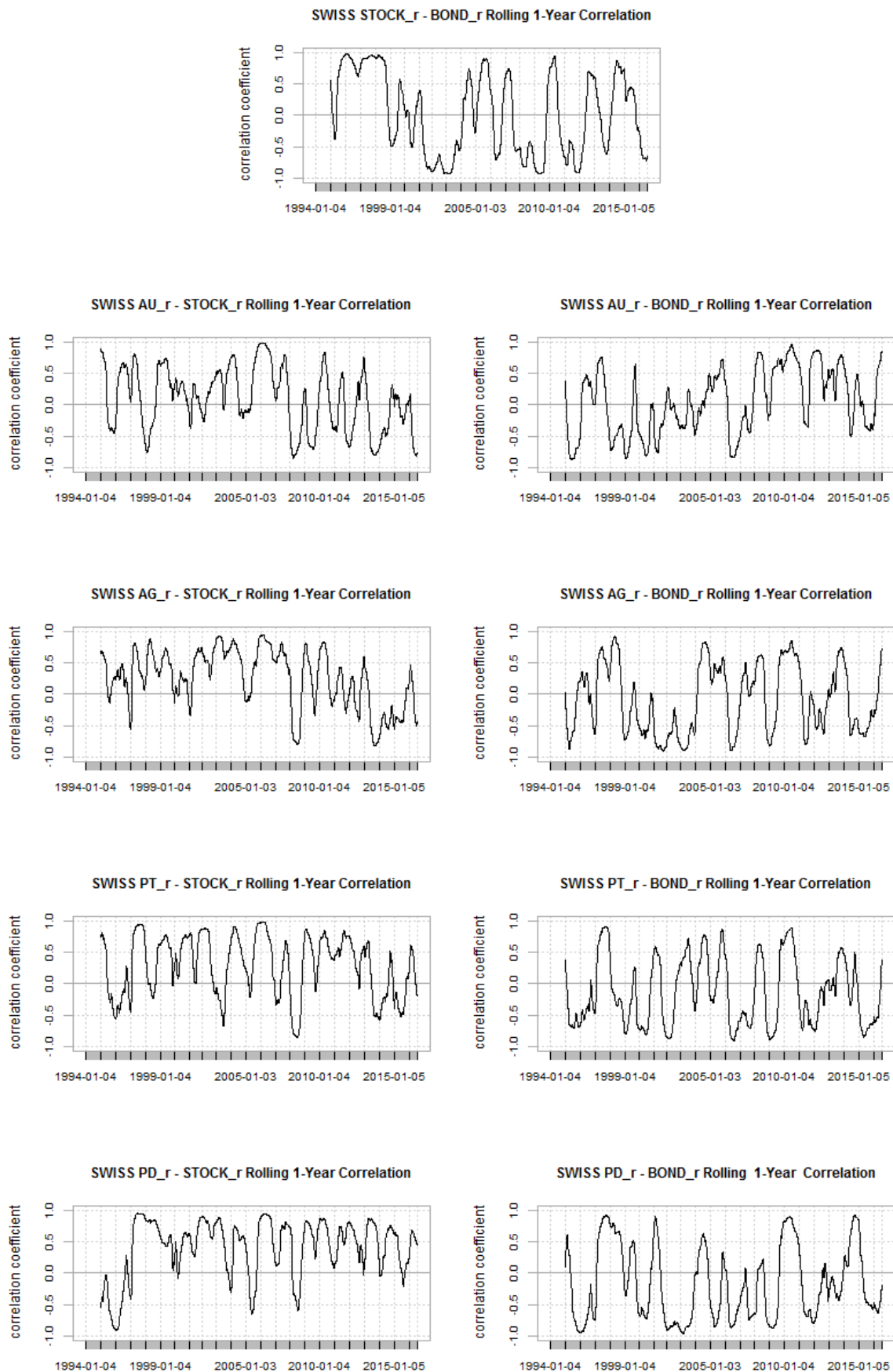


Figure E.18: 1-Year Rolling Correlation Coefficients — Canada

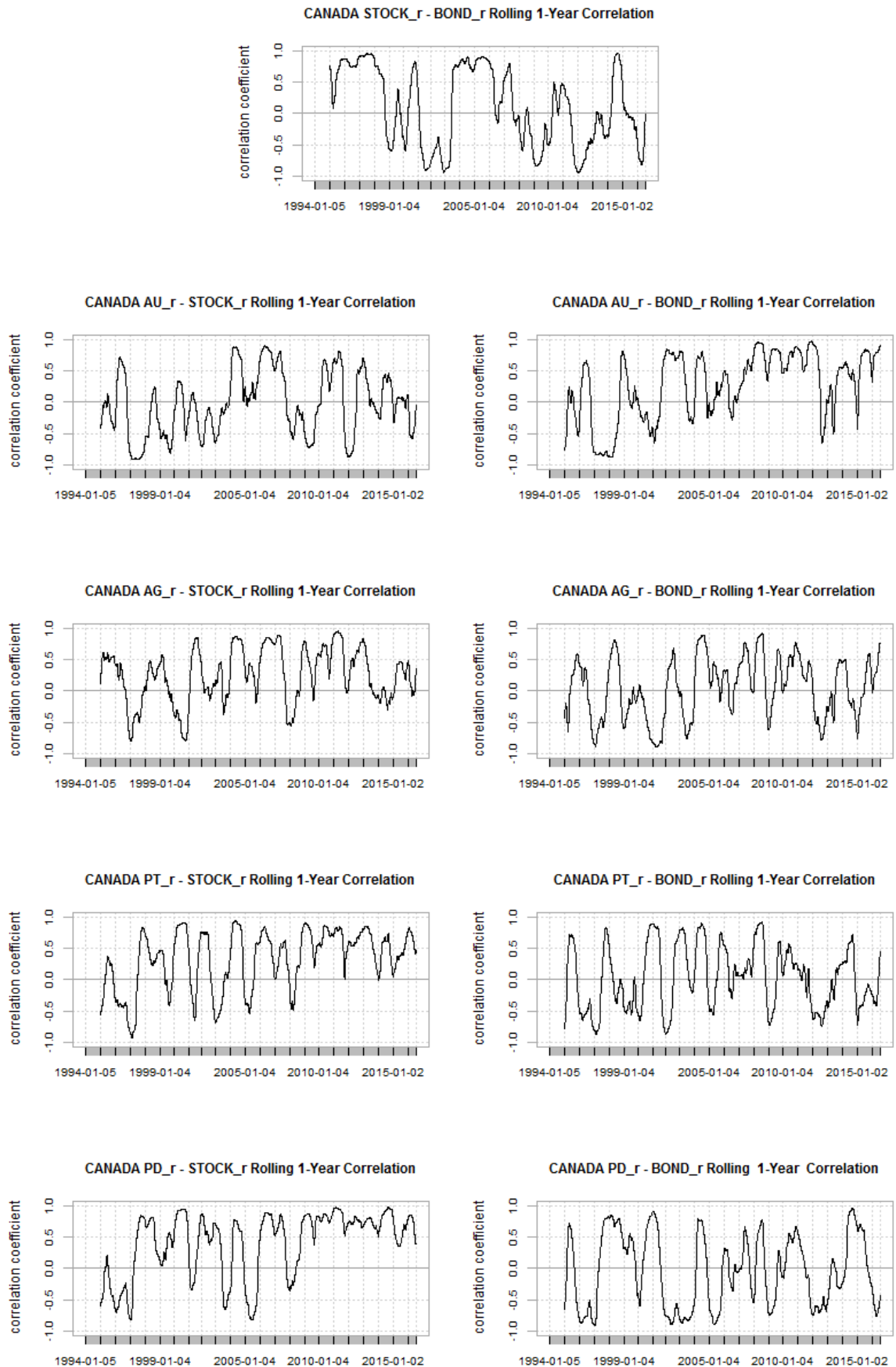


Figure E.19: 1-Year Rolling Correlation Coefficients — Japan

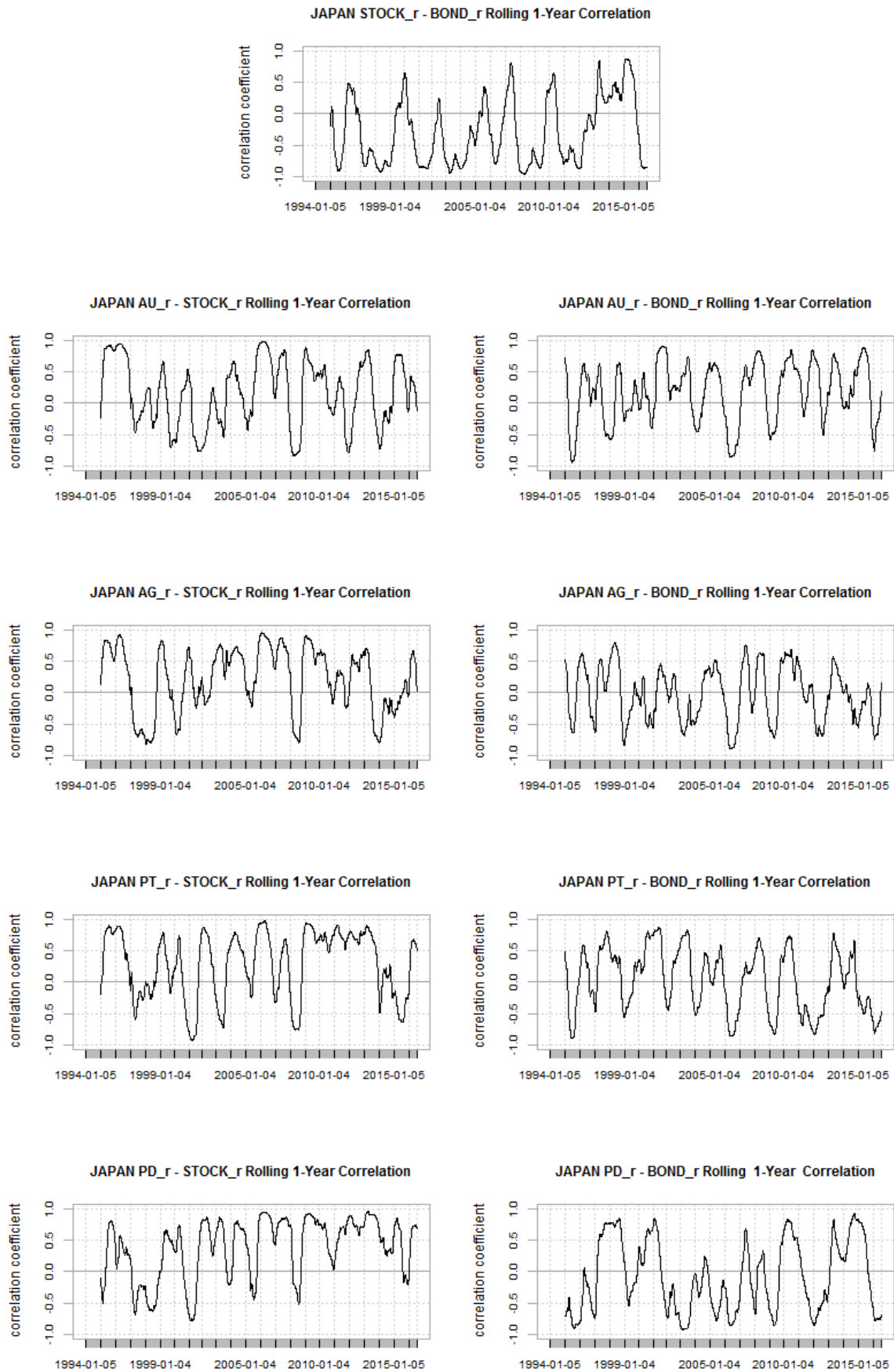


Figure E.20: 1-Year Rolling Correlation Coefficients — China

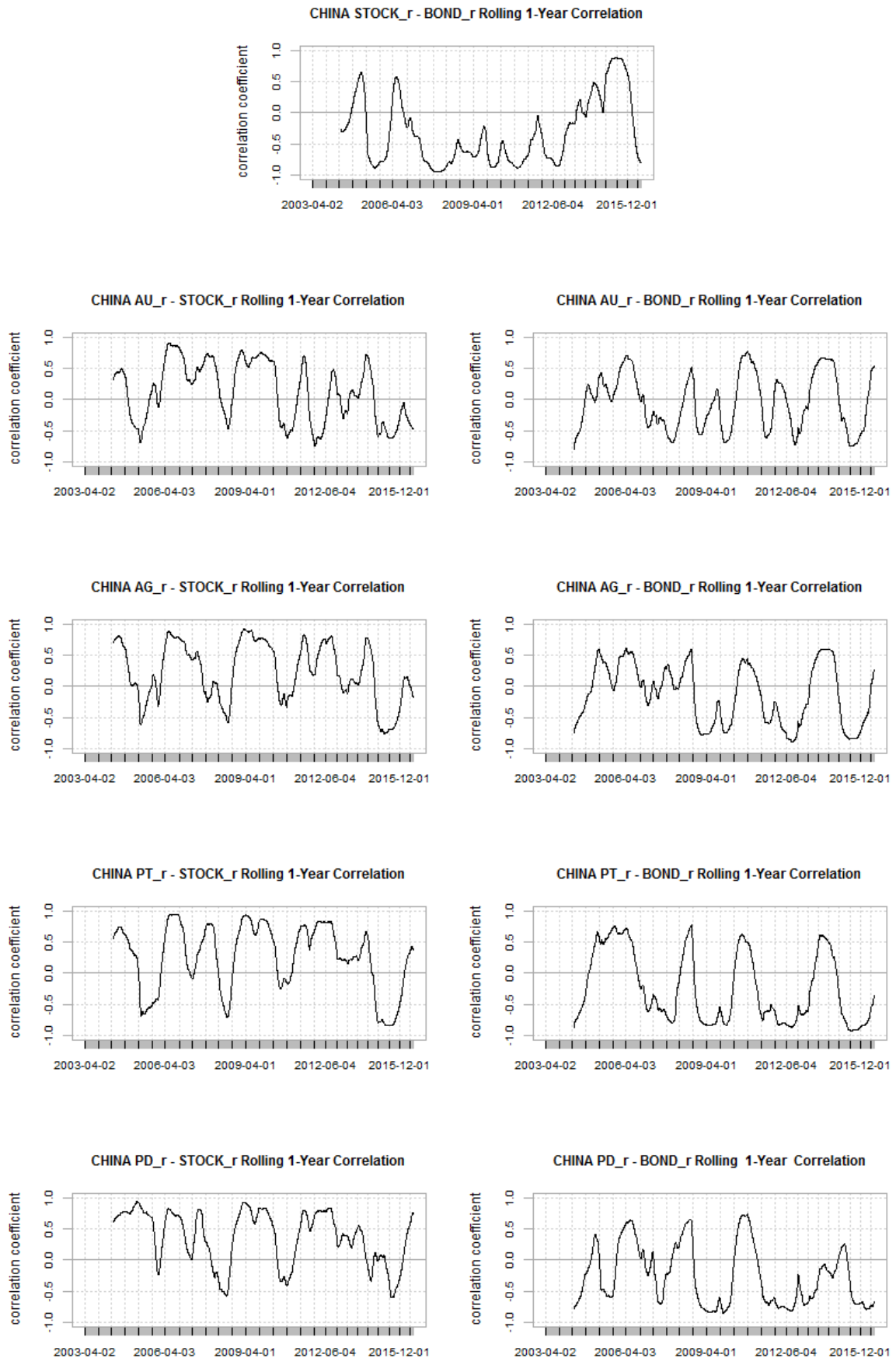


Figure E.21: 1-Year Rolling Correlation Coefficients — India

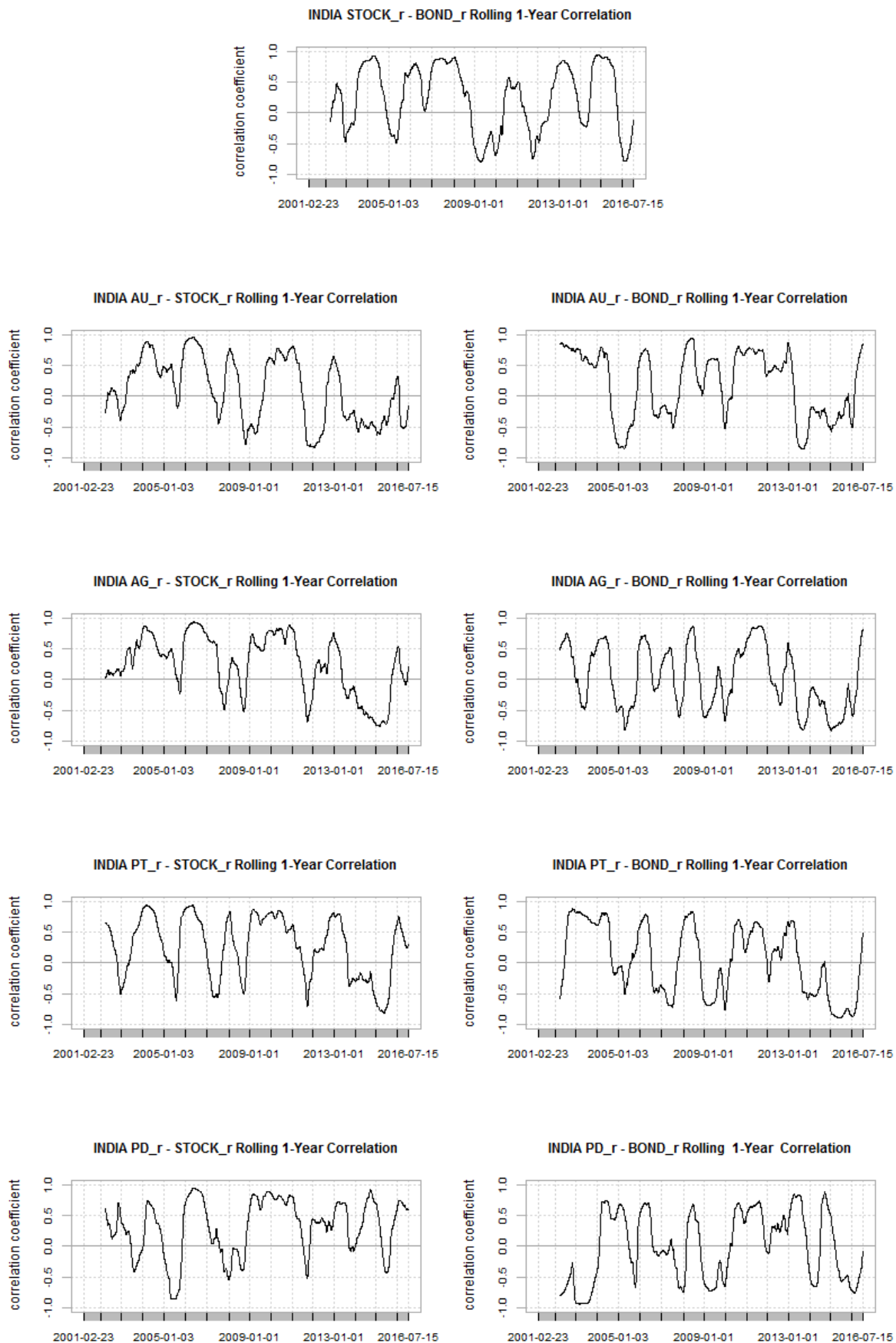
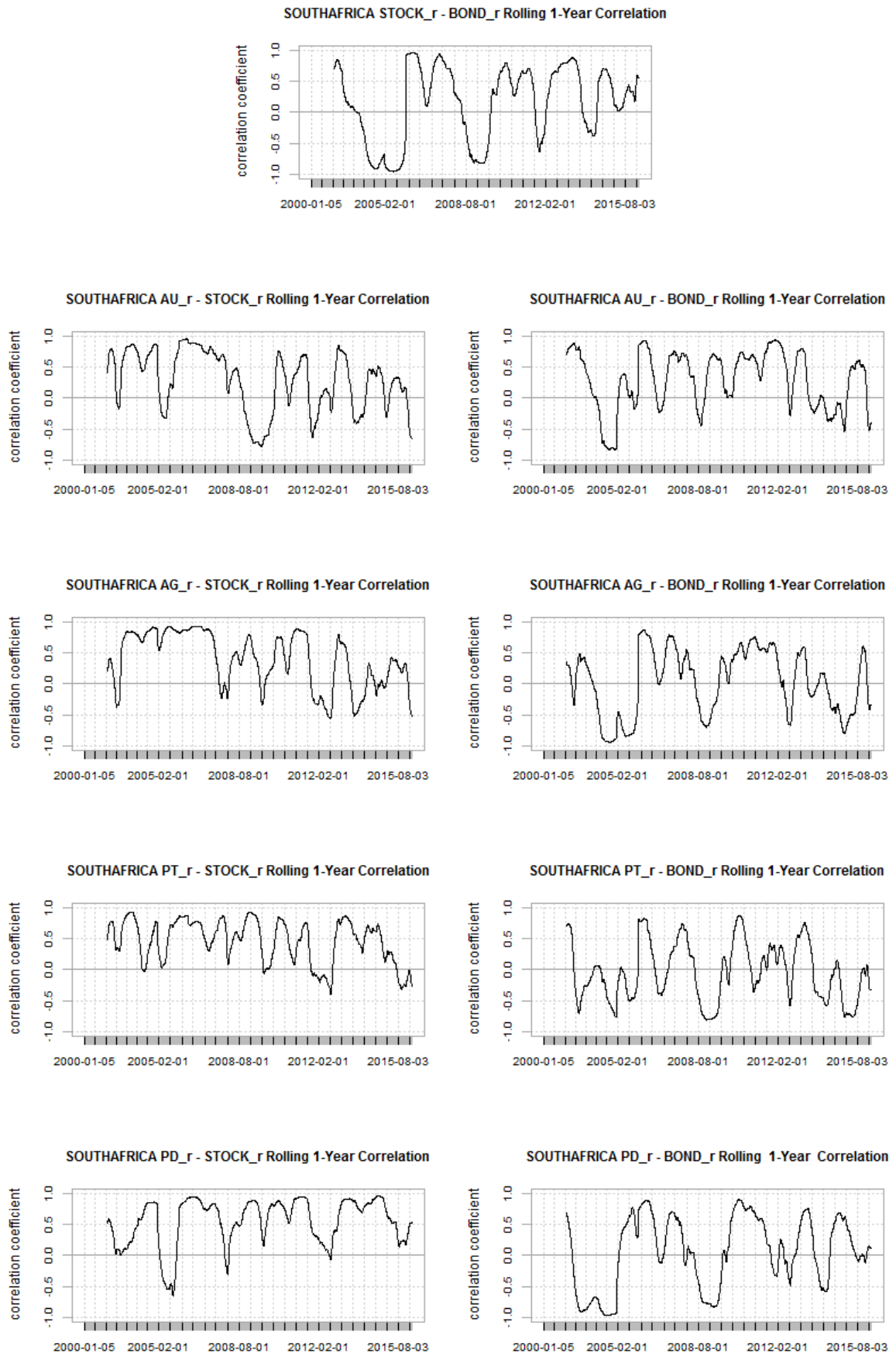


Figure E.22: 1-Year Rolling Correlation Coefficients — South Africa



Appendix F

Plots of Strong Safe Haven Results

The following eleven plots show the accumulated daily and final strong safe haven results of each country as obtained and discussed in Chapter 5 Precious Metals as Safe Haven - Evidence.

Figure F.1: Strong safe haven results accumulated vs. modified — US

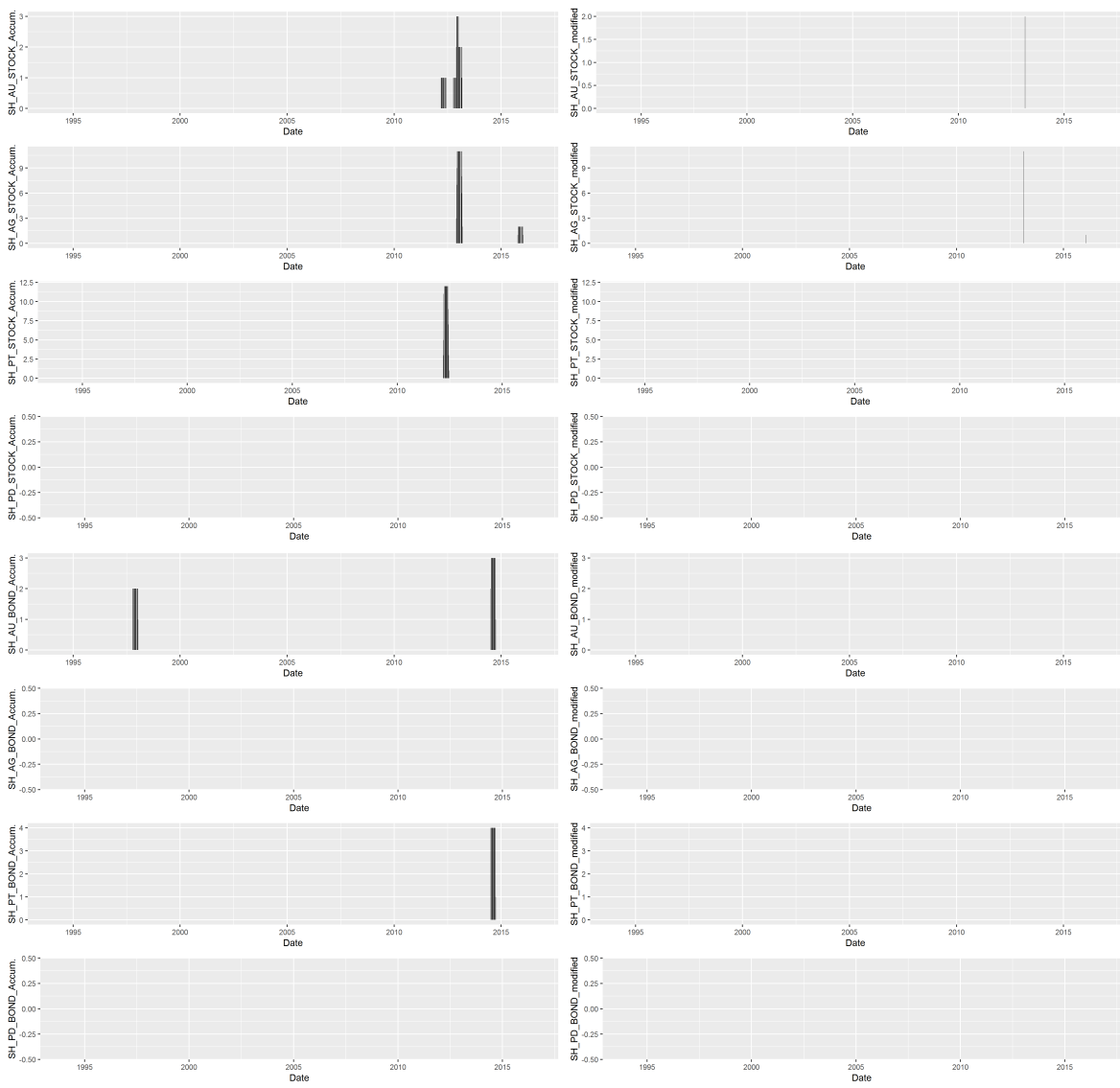


Figure F.2: Strong safe haven results accumulated vs. modified — UK

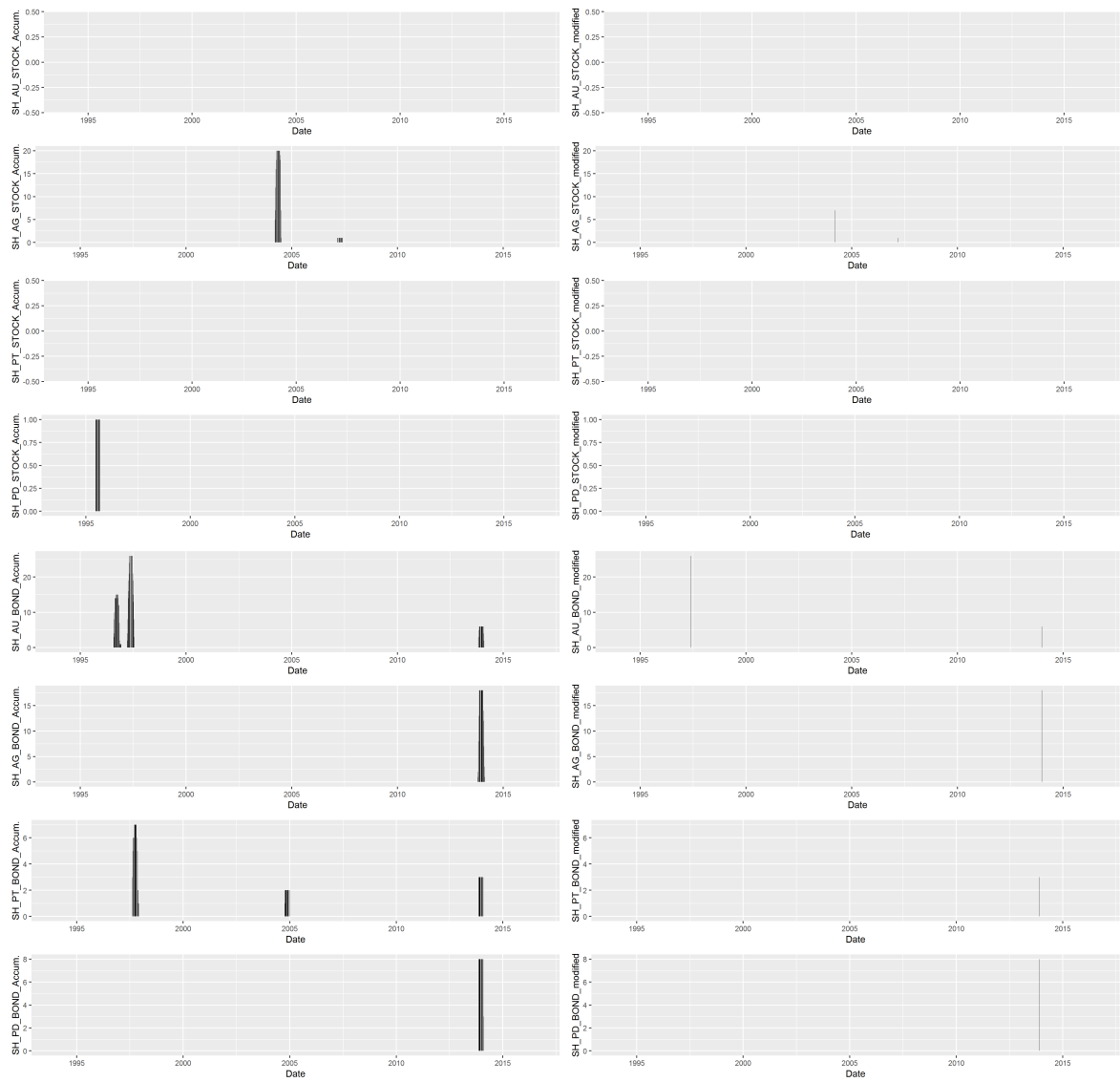


Figure F.3: Strong safe haven results accumulated vs. modified — Germany

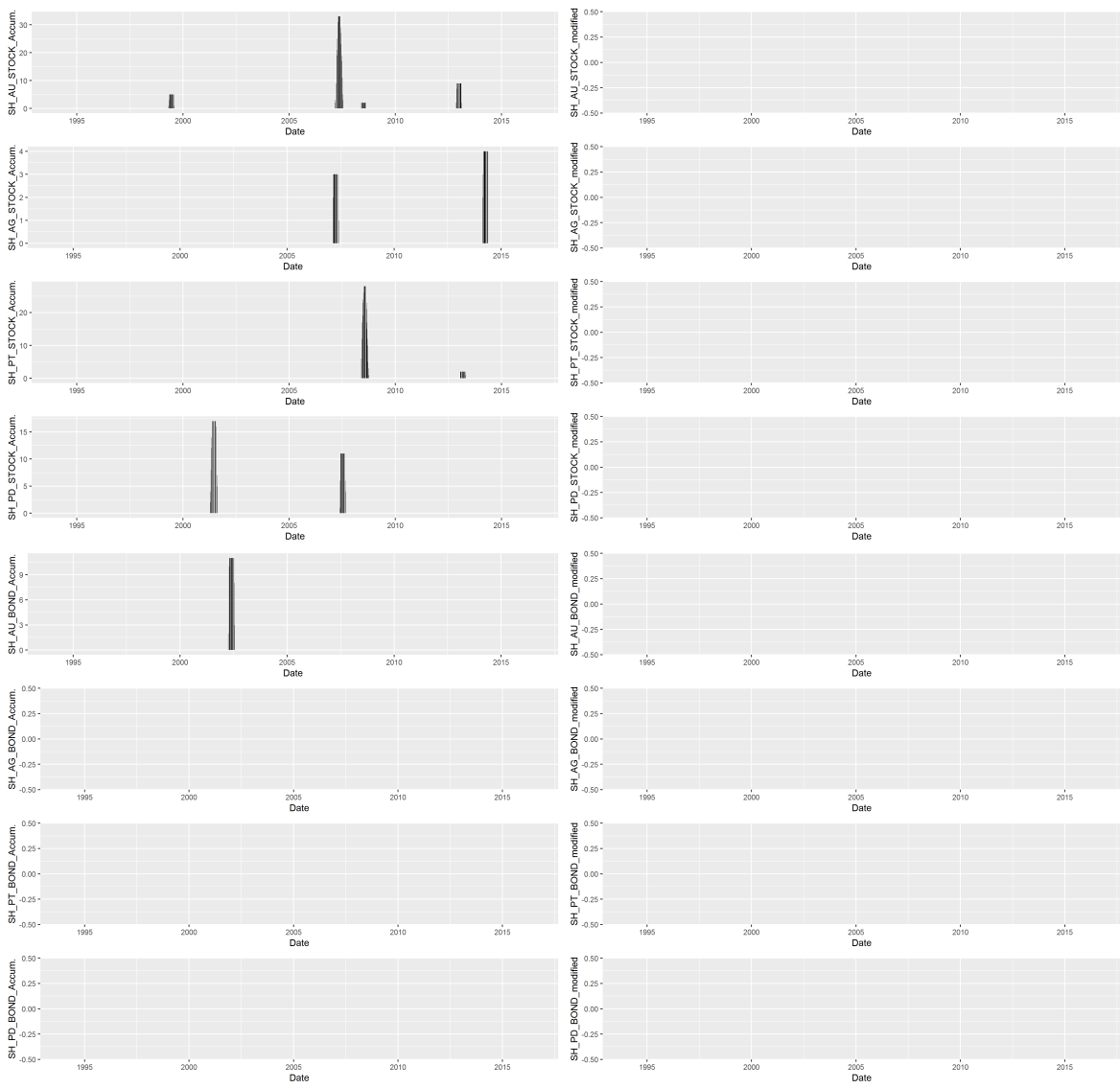


Figure F.4: Strong safe haven results accumulated vs. modified — France

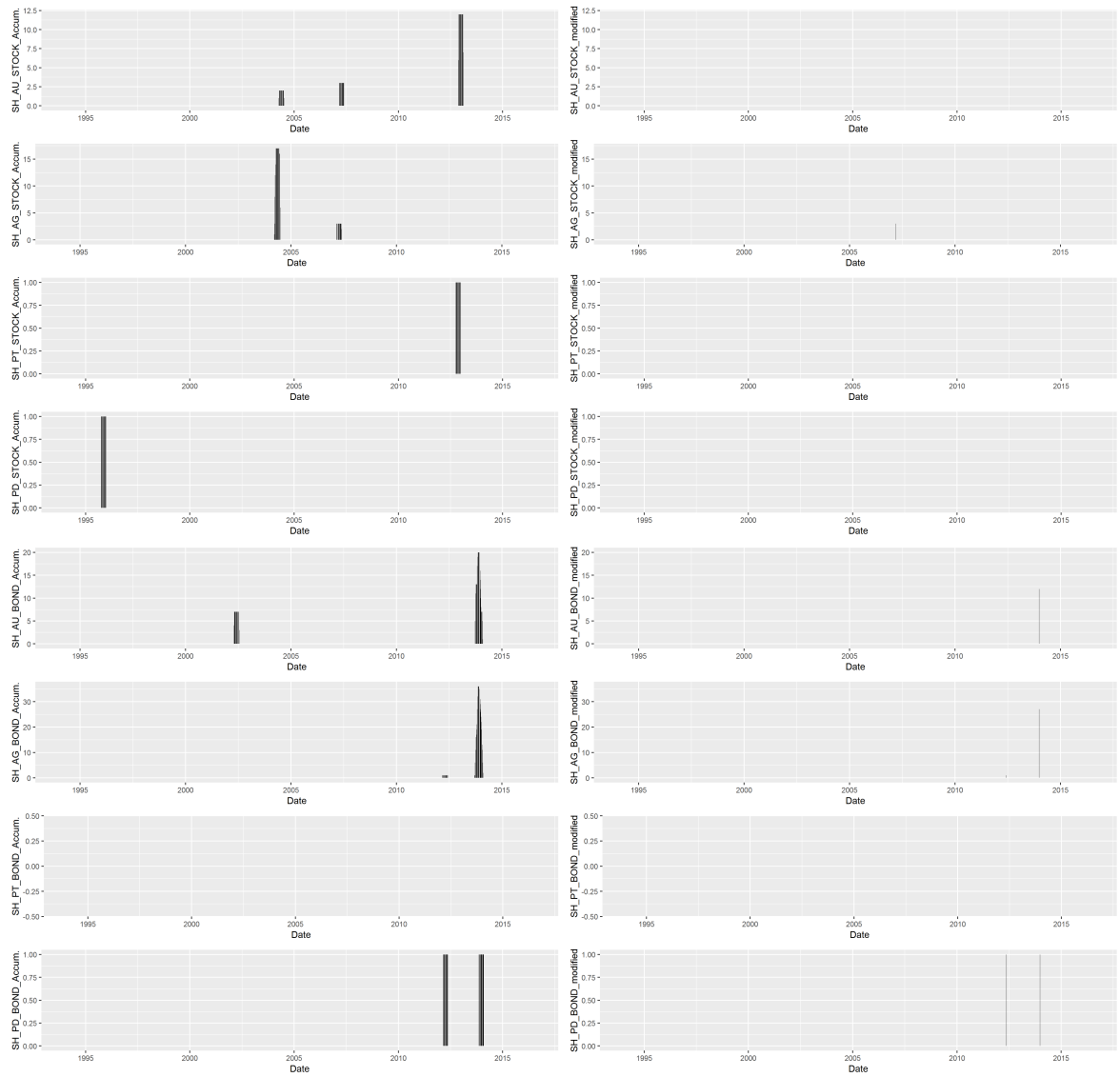


Figure F.5: Strong safe haven results accumulated vs. modified — Italy

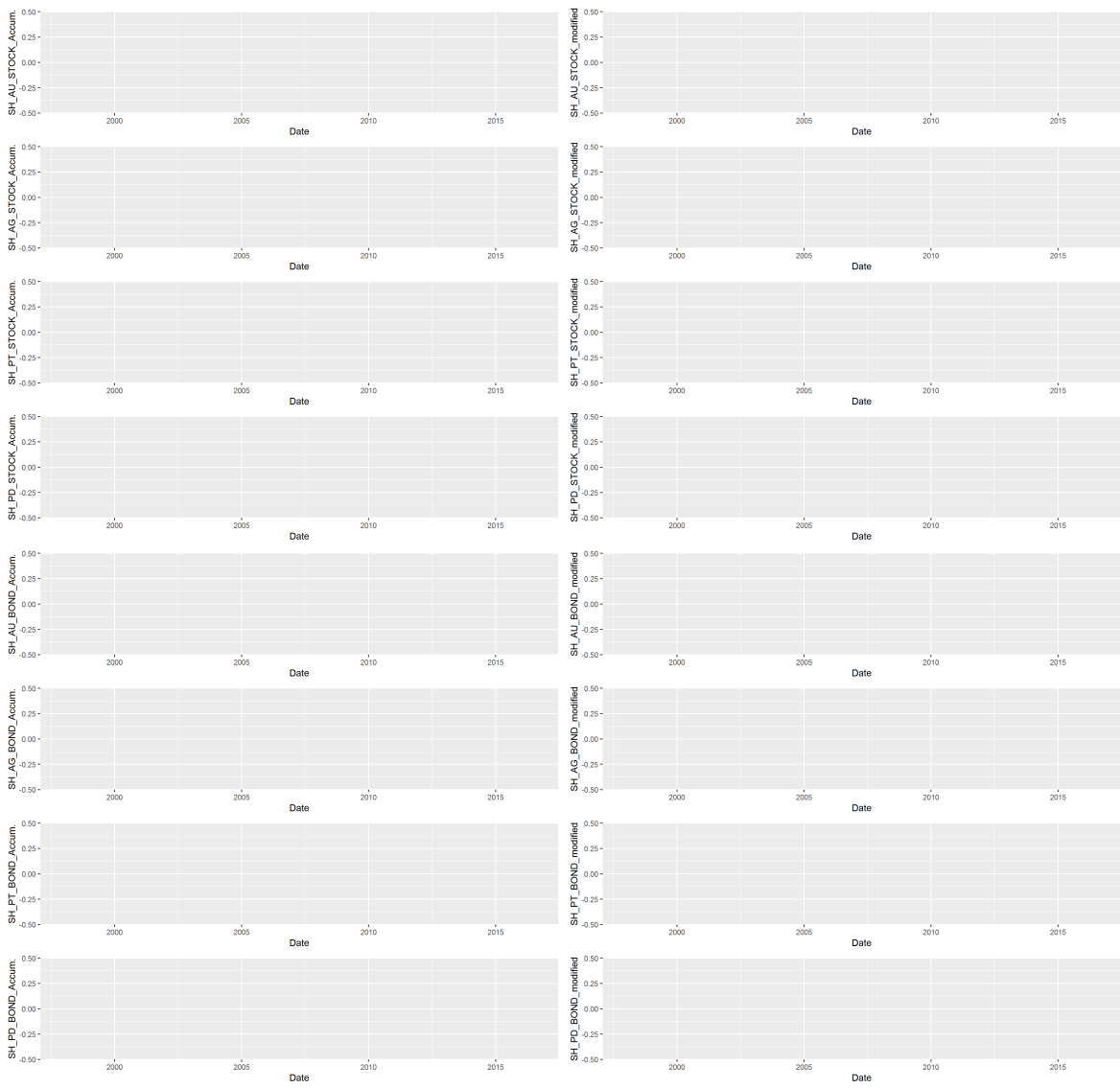


Figure F.6: Strong safe haven results accumulated vs. modified — Switzerland

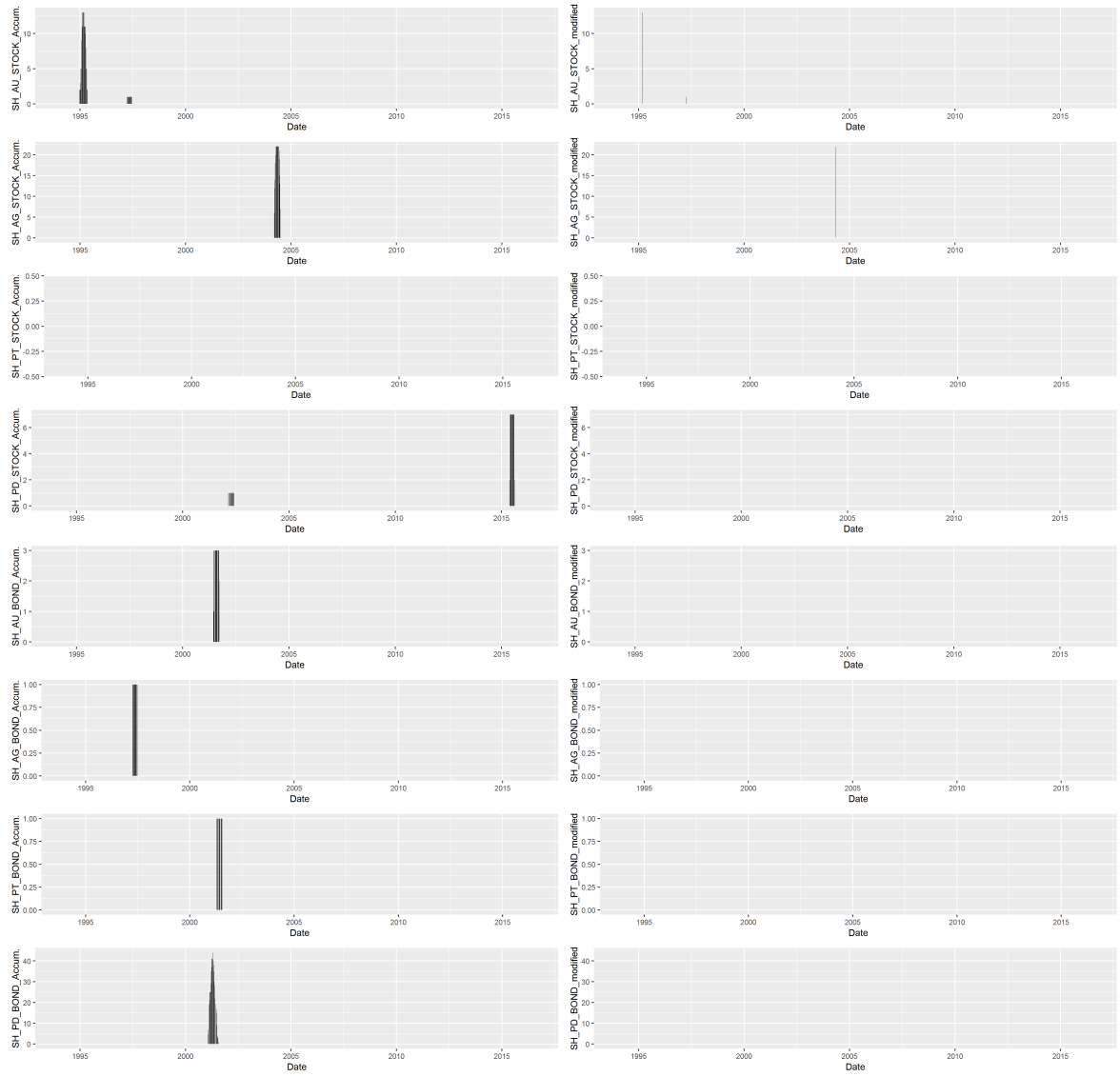


Figure F.7: Strong safe haven results accumulated vs. modified — Canada

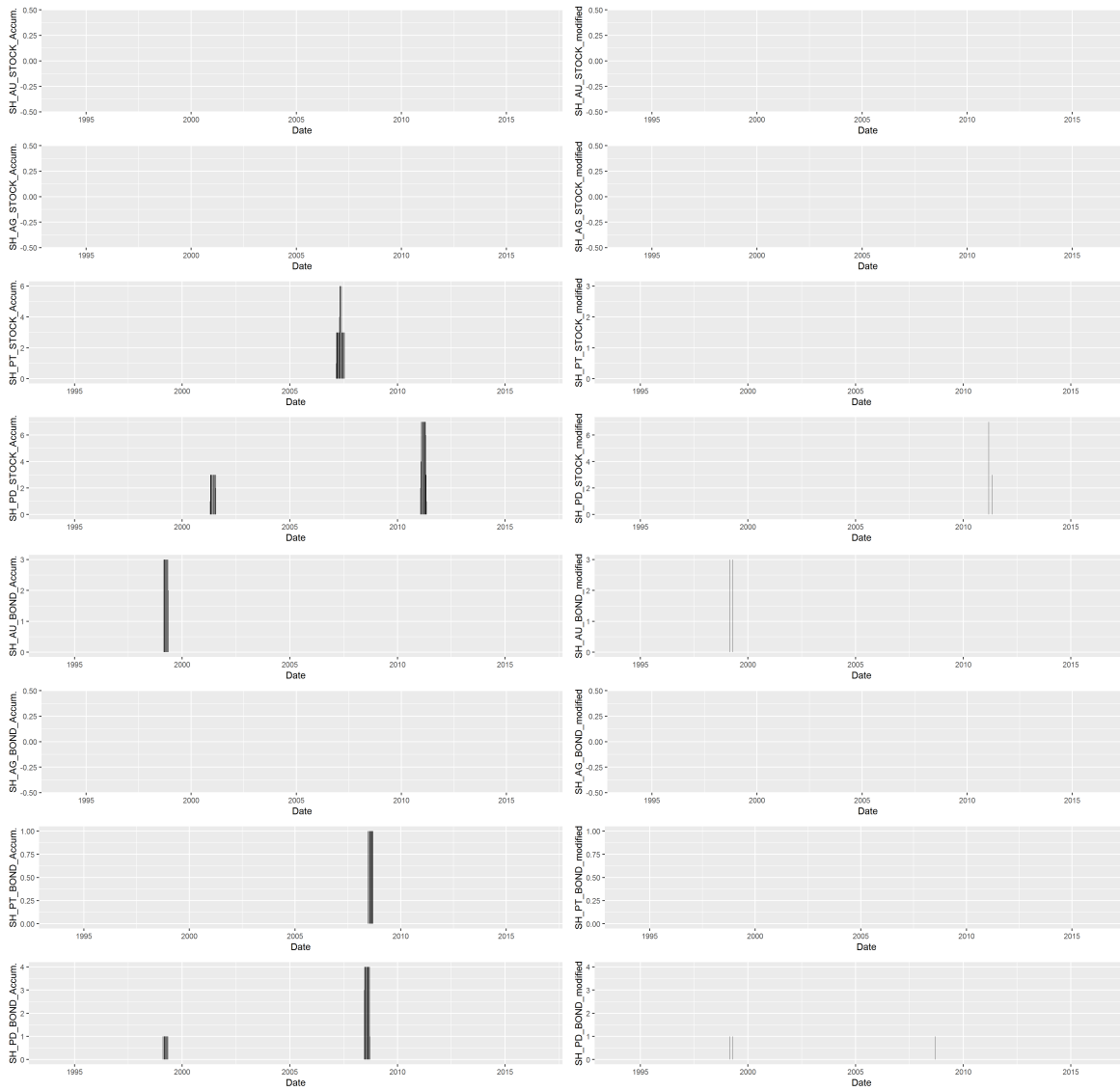


Figure F.8: Strong safe haven results accumulated vs. modified — Japan

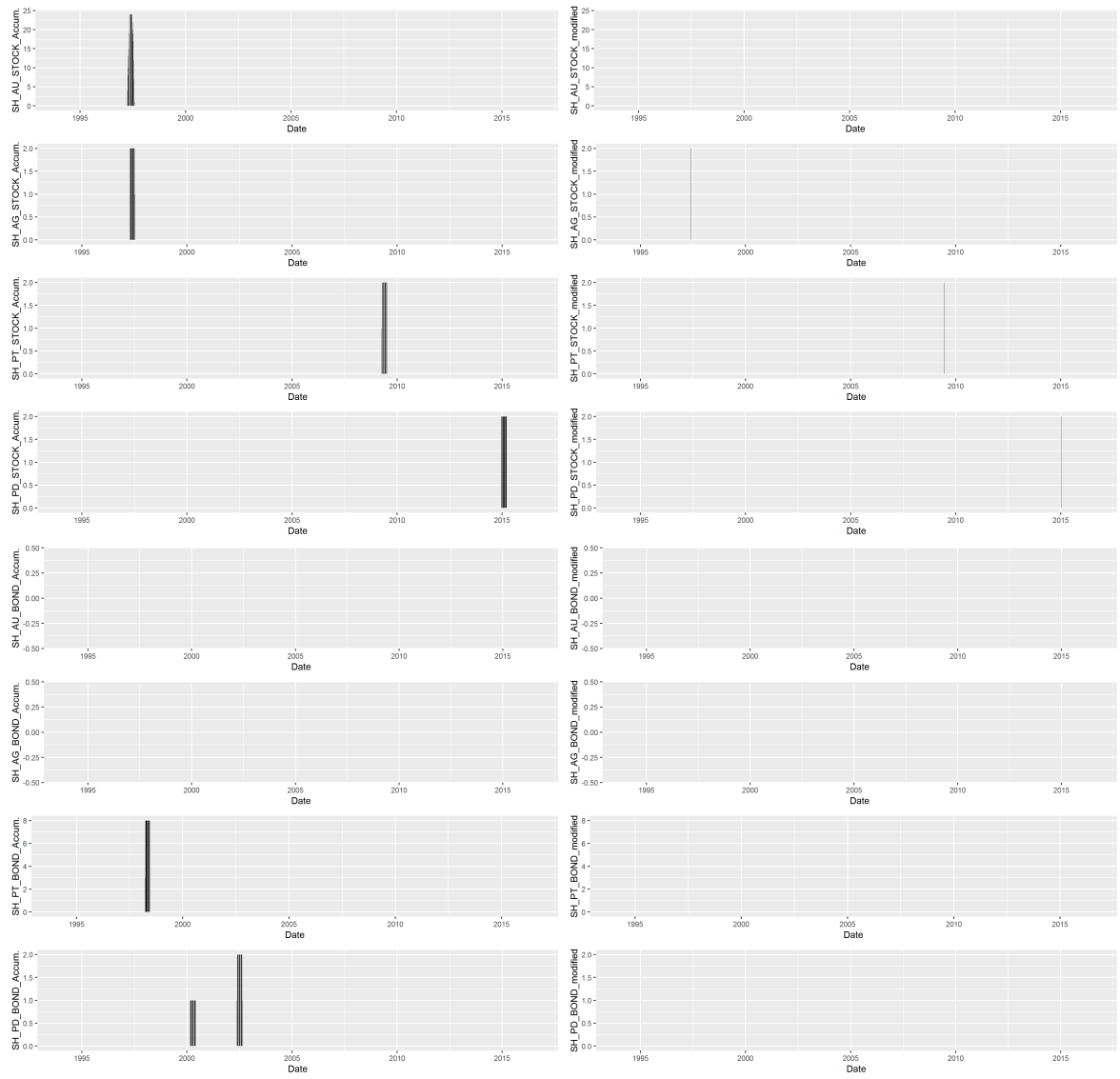


Figure F.9: Strong safe haven results accumulated vs. modified — China

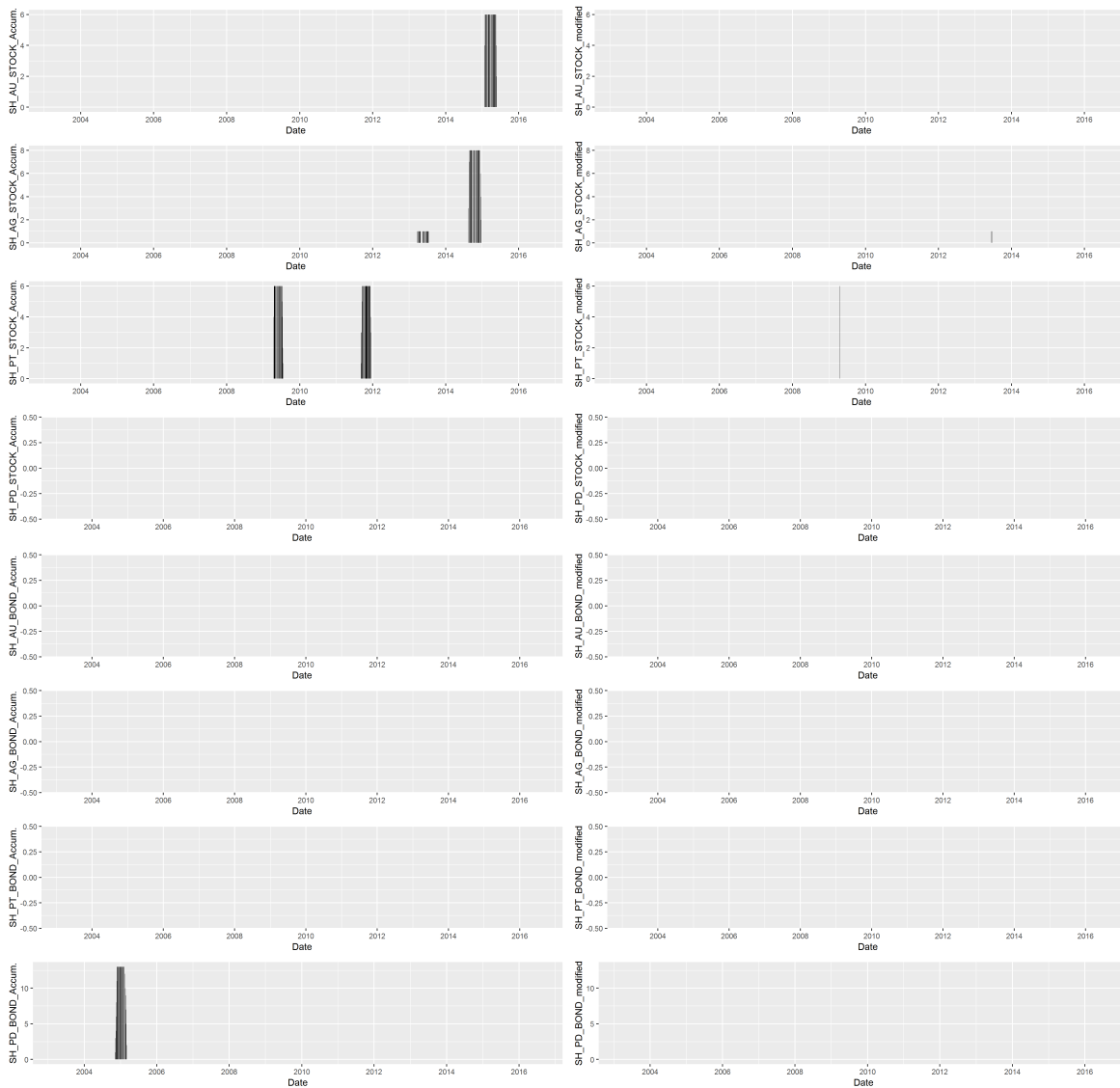


Figure F.10: Strong safe haven results accumulated vs. modified — India

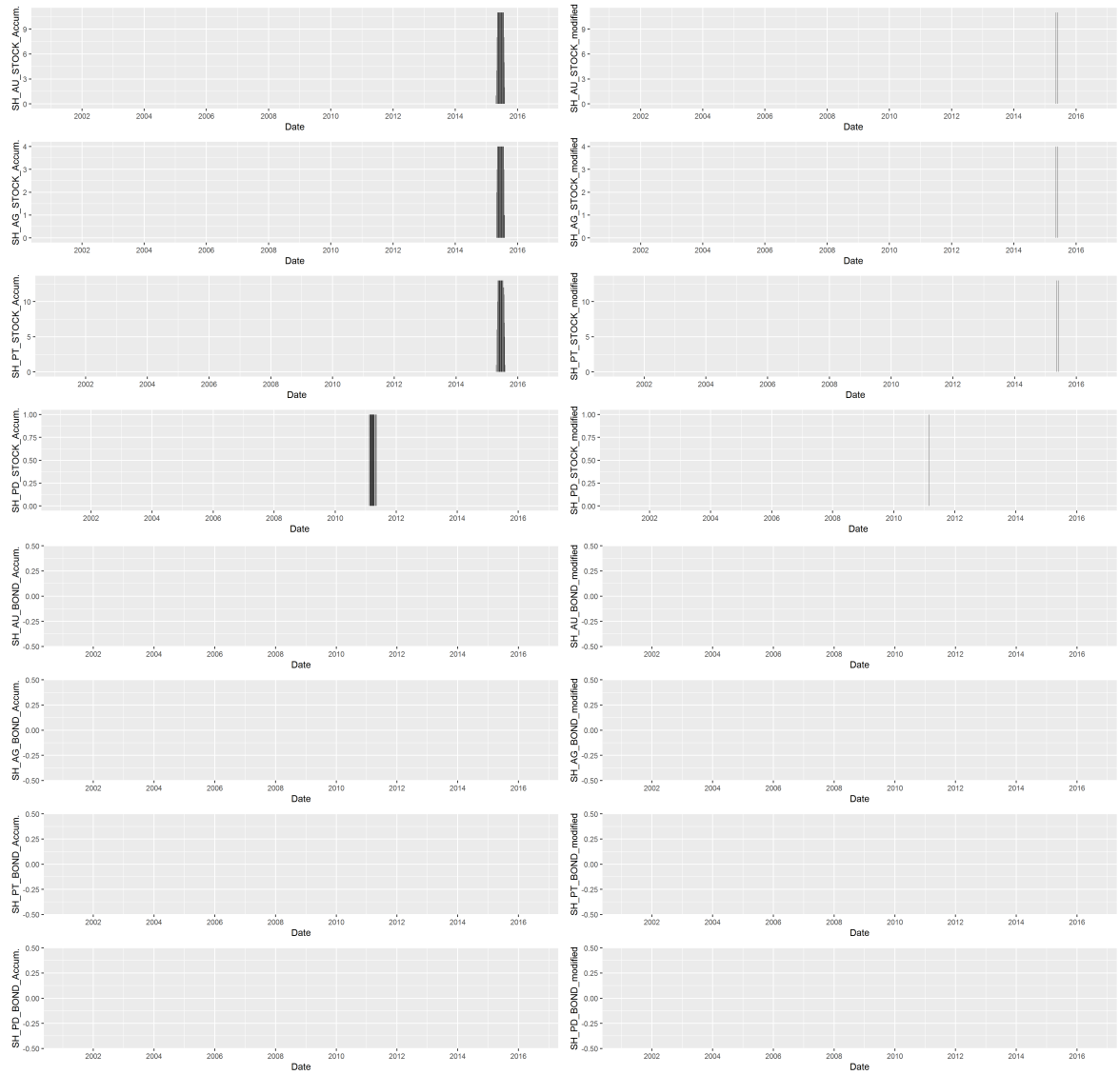
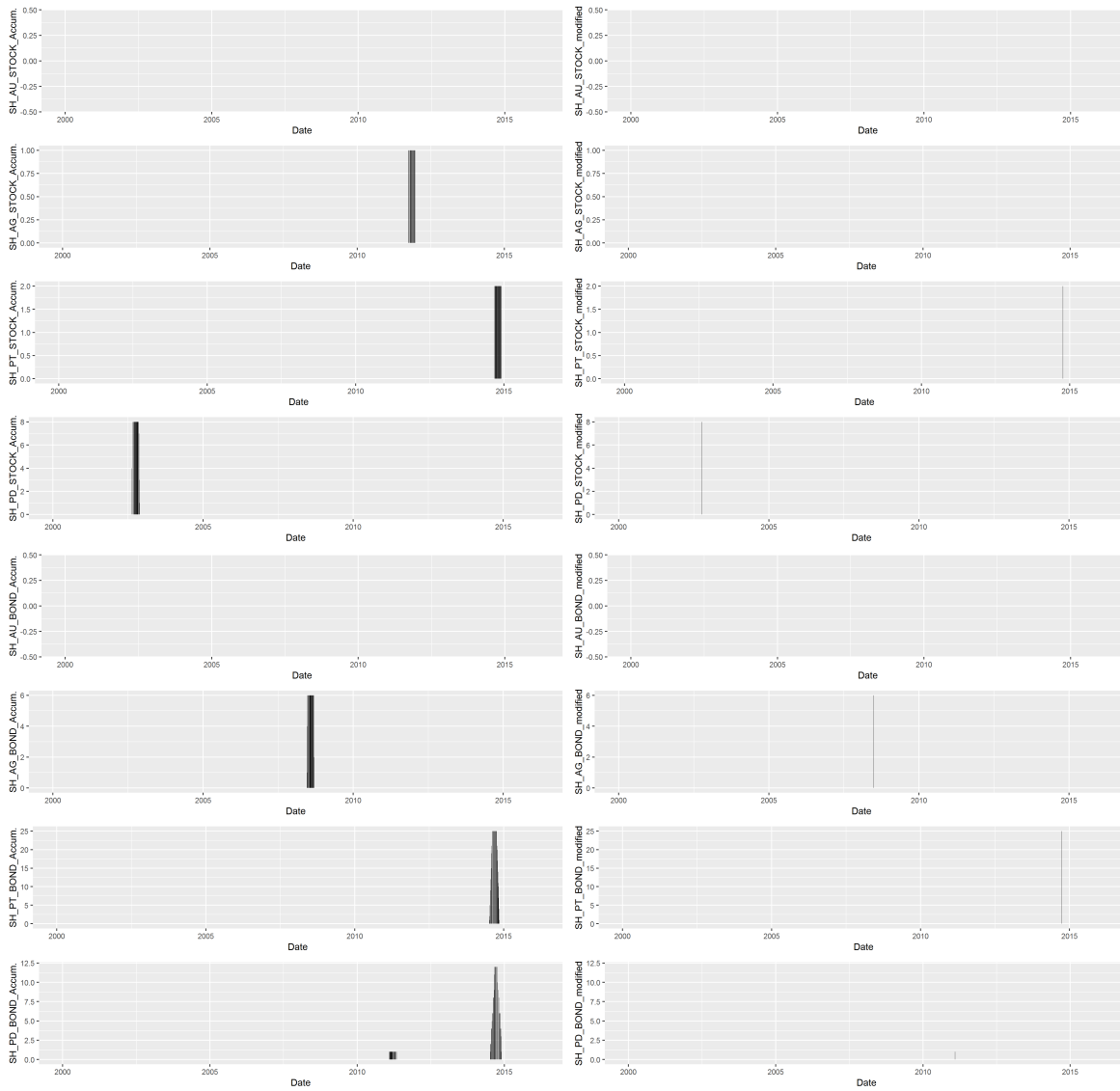


Figure F.11: Strong safe haven results accumulated vs. modified — South Africa



Appendix G

Zero-Inflated Poisson Regression Results

Below tables summarize results of Overdispersion Ratios, and the Zero-Inflated Poisson (ZIP) regressions applied in the Chapter 6 - Determinants of Precious Metals as Safe Haven.

Table G.1: Overdispersion ratio

Country	Metal	Safe Haven results for stocks		Safe Haven results for bonds	
		Overdispersion ratio	P-value	Overdispersion ratio	P-value
US	Gold	21.45	1	34.72	1
	Silver	23.67	1	20.70	1
	Platinum	24.75	1	28.56	1
	Palladium	10.98	1	15.15	1
UK	Gold	27.14	1	20.43	1
	Silver	26.23	1	24.96	1
	Platinum	16.90	1	20.02	1
	Palladium	10.72	1	98.61	1
Germany	Gold	29.62	1	20.58	1
	Silver	20.89	1	16.80	1
	Platinum	19.46	1	15.07	1
	Palladium	26.25	1	23.74	1
France	Gold	28.99	1	24.22	1
	Silver	17.97	1	32.32	1
	Platinum	12.78	1	27.13	1
	Palladium	26.82	1	30.88	1
Italy	Gold	14.00	1	6.77	1
	Silver	26.47	1	11.43	1
	Platinum	18.23	1	13.11	1
	Palladium	15.17	1	28.73	1
Switzerland	Gold	29.38	1	23.79	1
	Silver	24.49	1	24.03	1
	Platinum	33.21	1	13.13	1
	Palladium	26.73	1	9.56	1
Canada	Gold	13.25	1	16.12	1
	Silver	13.94	1	15.76	1
	Platinum	40.76	1	19.14	1
	Palladium	36.76	1	22.47	1
Japan	Gold	23.28	1	17.03	1
	Silver	26.53	1	22.82	1
	Platinum	20.77	1	26.16	1
	Palladium	22.29	1	16.56	1
China	Gold	21.48	1	14.45	1
	Silver	33.27	1	13.69	1
	Platinum	16.02	1	22.62	1
	Palladium	12.89	1	18.71	1
India	Gold	8.88	1	15757266572.60	1
	Silver	18.14	1	10.82	1
	Platinum	10.67	1	57.68	1
	Palladium	1768.93	1	2.43	1
South Africa	Gold	30.00	1	54.36	1
	Silver	38.43	1	14.99	1
	Platinum	16.34	1	17.16	1
	Palladium	10.41	1	16.93	1

Notes: a large estimated overdispersion ratio and high p-value suggesting that the probability is very small that the additional variation beyond what should be predicted under the Poisson model, hence there is overdispersion.

Table G.2: Summary of zero-inflated Poisson regression results — the US

	Stock Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)	Bond Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)
Count Model (Intercept)	2.88* (0)	2.79* (0)	3.03* (0)	2.24* (0)	2.52* (0)	2.56* (0)	2.67* (0)	2.11* (0)
Δvix	-0.17* (0)	-0.10* (0)	-0.11* (0)	-0.06 (0.04)	0.06 (0.025)	0.12* (0)	0.07* (0.002)	0.05 (0.227)
Δfsi	-0.85* (0)	-0.06 (0.596)	-0.40* (0.01)	-0.20 (0.209)	0.58* (0.001)	0.86* (0)	0.66* (0)	-0.37 (0.176)
$\Delta sentiment$	0.04* (0)	0.05* (0)	0.03* (0.001)	0.02 (0.123)	0.02* (0.01)	-0.01 (0.442)	0.00 (0.803)	-0.08* (0)
Δepu	0.00 (0.117)	0.00 (0.205)	0.00* (0)	0.00* (0)	0.00 (0.114)	0.00* (0)	0.00 (0.36)	0.01* (0)
Δr	0.35 (0.869)	0.78 (0.517)	-1.88* (0)	-2.24 (0.037)	32.27 (0.774)	6.29* (0.003)	-0.97 (0.079)	5.45* (0.008)
Δcpi	0.36 (0.021)	0.29* (0.005)	0.27 (0.06)	-0.25 (0.134)	-0.11 (0.462)	-0.22 (0.127)	-0.13 (0.255)	-1.72* (0)
ΔUSD	0.34* (0.001)	0.17 (0.029)	0.31* (0.001)	1.09* (0)	0.29* (0.004)	0.47* (0)	0.51* (0)	0.29 (0.035)
$\Delta ind\_production$	0.04 (0.524)	0.26* (0)	0.09 (0.051)	0.49* (0)	0.95* (0)	0.40* (0)	0.18 (0.021)	0.67* (0)
$\Delta creditspreads$	-0.71* (0)	0.02 (0.727)	-0.95* (0)	-1.57* (0)	-1.85* (0)	-1.64* (0)	0.17 (0.382)	-1.66* (0)
$\Delta gsci$	0.15* (0)	0.04* (0)	0.08* (0)	0.02* (0.141)	-0.02 (0.368)	-0.02 (0.462)	-0.05* (0.004)	0.06 (0.02)
Δoil	-0.65* (0)	-0.12 (0.013)	-0.34* (0)	-0.13 (0.103)	0.22* (0.004)	0.28* (0.004)	0.26* (0.003)	-0.13 (0.282)
Zero-inflated Model (Intercept)	5.49* (0)	5.04* (0)	5.35* (0)	5.34* (0)	5.88* (0)	5.84* (0)	5.62* (0)	5.97* (0)
$R.i, q_{5\%}$	170.84* (0)	178.64* (0)	140.81* (0)	173.82* (0)	450.62* (0)	457.88* (0)	409.87* (0)	434.57* (0)

Notes:

1. This table shows Poisson regression coefficients for each of the variables along with standard p-values. The second part corresponds to the inflation model, which includes logit coefficients for predicting excess zeros along with the standard p-values.
2. * denotes a significant level of 1%.
3. N/A denotes a variable dropped due to linear singularity problem.

Table G.3: Summary of zero-inflated Poisson regression results — the UK

	Stock Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)	Bond Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)
Count Model (Intercept)	2.93* (0)	2.28* (0)	2.51* (0)	2.15* (0)	3.35* (0)	2.97* (0)	2.99* (0)	3.41* (0)
$\Delta vfts$	0.09* (0)	0.10* (0.003)	-0.16* (0)	-0.16* (0)	-0.01 (0.605)	-0.14* (0)	0.00 (0.92)	-0.08 (0.01)
Δfsi	-1.04* (0)	-3.14* (0)	-0.86 (0.132)	-4.16* (0)	-7.00* (0)	-6.58* (0)	-6.74* (0)	-8.48* (0)
$\Delta sentiment$	-0.04* (0)	0.07* (0)	-0.06* (0.006)	0.19* (0)	0.07* (0.005)	0.05 (0.023)	-0.02 (0.434)	0.12* (0.001)
Δepu	0.00 (0.246)	0.00* (0)	0.00 (0.175)	0.01* (0)	0.00 (0.217)	0.00* (0)	0.00 (0.41)	0.00 (0.448)
Δr	14.20* (0)	28.77 (0.715)	24.90 (0.558)	20.38 (0.483)	4.37* (0)	5.05* (0)	N/A (N/A)	8.33* (0)
Δcpi	0.70* (0)	0.63* (0)	0.20 (0.138)	-0.58* (0)	0.96* (0)	1.02* (0)	1.34* (0)	0.81* (0.002)
ΔGBP	3.86 (0.173)	-16.55* (0.003)	-3.42 (0.539)	1.23 (0.848)	12.79* (0.001)	-14.53* (0)	24.95* (0)	19.31* (0)
$\Delta ind\_production$	-0.03 (0.387)	0.09 (0.066)	0.11 (0.07)	-0.06 (0.156)	-0.19* (0.008)	0.06 (0.373)	-0.42* (0)	-0.42* (0)
$\Delta creditspreads$	0.07 (0.797)	0.34 (0.324)	1.37* (0.003)	-1.37* (0.008)	-0.71 (0.059)	1.92* (0)	-1.08 (0.021)	-4.38* (0)
$\Delta gsci$	0.01 (0.373)	0.04 (0.07)	0.06* (0.002)	0.11* (0)	0.09* (0)	0.08* (0)	0.12* (0)	0.12* (0)
Δoil	0.05 (0.409)	-0.05 (0.643)	-0.24 (0.018)	-0.48* (0)	-0.12 (0.079)	-0.16 (0.011)	-0.19* (0.009)	-0.19* (0.007)
Zero-inflated Model (Intercept)	4.92* (0)	5.20* (0)	5.24* (0)	5.59* (0)	5.99* (0)	6.04* (0)	6.0* (0)	6.07* (0)
$R_{-i, q5\%}$	129.48* (0)	125.94* (0)	136.79* (0)	180.06* (0)	659.15* (0)	660.53* (0)	606.64* (0)	633.48* (0)

Notes:

1. This table shows Poisson regression coefficients for each of the variables along with standard p-values. The second part corresponds to the inflation model, which includes logit coefficients for predicting excess zeros along with the standard p-value
2. * denotes a significant level of 1%.
3. N/A denotes a variable dropped due to linear singularity problem.

Table G.4: Summary of zero-inflated Poisson regression results — Germany

	Stock Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)	Bond Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)
Count Model (Intercept)	2.88* (0)	1.97* (0)	-2.60* (0)	1.66* (0)	2.14* (0)	3.88* (0)	2.72* (0)	3.37* (0)
$\Delta v1x$	-0.02 (0.243)	-0.04 (0.145)	-0.19* (0)	-0.03 (0.36)	0.12* (0)	-0.03 (0.191)	-0.01 (0.833)	0.13* (0)
Δfsi	2.46* (0)	-2.53* (0.005)	5.33* (0)	-2.56* (0.002)	6.64* (0)	-0.05 (0.948)	0.44 (0.714)	-4.07* (0)
$\Delta sentiment$	0.03 (0.135)	0.07* (0.009)	0.09* (0)	-0.02 (0.182)	0.23* (0)	0.27* (0)	0.23* (0)	0.06* (0.007)
Δepu	0.00 (0.117)	0.00 (0.214)	-0.01* (0.001)	0.00* (0.002)	0.00 (0.239)	0.00* (0)	0.01* (0)	0.00 (0.265)
Δr	0.84* (0)	1.51* (0.007)	4.26* (0)	0.93* (0.002)	-2.35* (0)	-1.96* (0.001)	-0.59 (0.341)	-1.73* (0)
Δcpi	0.21 (0.033)	0.67* (0)	0.49 (0.015)	-0.14 (0.118)	0.14 (0.295)	-0.51* (0)	-1.10* (0)	0.37 (0.011)
ΔEUR	-20.20* (0)	-33.51* (0)	4.05* (0)	1.24* (0)	-27.42* (0)	7.47 (0.108)	1.72 (0.803)	-10.87* (0.007)
$\Delta ind\_production$	0.11* (0)	-0.02 (0.524)	0.16* (0)	-0.15* (0)	-0.07 (0.051)	-0.17* (0)	0.02 (0.574)	0.04 (0.087)
$\Delta creditspreads$	0.13* (0.001)	0.32* (0)	-0.03 (0.739)	-0.28* (0)	0.36* (0)	-0.80* (0)	-0.31* (0)	-0.50* (0)
$\Delta gsci$	0.01 (0.449)	0.03 (0.061)	0.07* (0.002)	0.00 (0.852)	0.04* (0.002)	-0.01 (0.527)	-0.08* (0)	0.05* (0.004)
Δoil	0.15* (0.023)	0.13 (0.102)	-0.23 (0.071)	-0.03 (0.693)	-0.02 (0.814)	-0.07 (0.303)	0.43* (0)	-0.12 (0.14)
Zero-inflated Model (Intercept)	5.37* (0)	5.19* (0)	6.12* (0)	5.07* (0)	5.60* (0)	5.56* (0)	5.70* (0)	5.49* (0)
$R.i, q_{5\%}$	127.39* (0)	121.76* (0)	158.98* (0)	108.13* (0)	563.44* (0)	578.99* (0)	566.10* (0)	554.66* (0)

Notes:

1. This table shows Poisson regression coefficients for each of the variables along with standard p-values. The second part corresponds to the inflation model, which includes logit coefficients for predicting excess zeros along with the standard p-value
2. * denotes a significant level of 1%.
3. N/A denotes a variable dropped due to linear singularity problem.

Table G.5: Summary of zero-inflated Poisson regression results — France

	Stock Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)	Bond Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)
Count Model (Intercept)	2.28*	2.47*	1.95*	2.45*	2.65*	3.07*	2.49*	2.85*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Δvac	0.18*	0.05*	0.15*	0.14*	0.01	-0.06*	0.04*	-0.01
	(0)	(0)	(0)	(0)	(0.557)	(0.003)	(0.004)	(0.695)
Δfsi	-0.13	-3.01*	2.77	-3.66*	-2.51*	-4.52*	-2.85*	-1.15
	(0.894)	(0)	(0.055)	(0.001)	(0)	(0)	(0)	(0.082)
$\Delta sentiment$	0.08*	0.08*	0.08*	0.15*	-0.04*	0.00	-0.06*	0.01
	(0)	(0)	(0.003)	(0)	(0)	(0.753)	(0)	(0.171)
Δepu	0.00*	0.00*	0.00	0.00	0.00*	0.00	0.00	0.00
	(0)	(0)	(0.574)	(0.6)	(0)	(0.221)	(0.022)	(0.27)
Δr	1.15*	1.15*	2.71*	1.49*	0.03	0.46	0.70*	1.27*
	(0)	(0)	(0)	(0)	(0.904)	(0.137)	(0)	(0)
Δcpi	0.86*	0.19	1.26*	0.52*	-0.85*	-1.18*	-0.64*	0.74*
	(0)	(0.047)	(0)	(0)	(0)	(0)	(0)	(0)
ΔEUR	9.37	2.63	-26.63*	7.18	1.63	-22.21*	-5.05	-9.21*
	(0.019)	(0.468)	(0)	(0.109)	(0.581)	(0)	(0.085)	(0)
$\Delta ind\_production$	0.23*	0.02	-0.10	0.03	-0.12*	0.02	-0.14*	-0.01
	(0)	(0.46)	(0.025)	(0.201)	(0)	(0.523)	(0)	(0.587)
$\Delta creditspreads$	-2.21*	-1.88*	-6.57*	2.42*	3.03*	1.21*	1.89*	-0.20
	(0)	(0)	(0)	(0)	(0)	(0.002)	(0)	(0.602)
$\Delta gsci$	0.08*	-0.04*	0.00	0.03	-0.01*	0.01	0.03*	0.03*
	(0)	(0.002)	(0.982)	(0.026)	(0.208)	(0.543)	(0.002)	(0.001)
Δoil	-0.33*	0.07	-0.10	-0.34*	0.07	-0.04	-0.20*	-0.11*
	(0)	(0.247)	(0.284)	(0)	(0.119)	(0.58)	(0)	(0.008)
Zero-inflated Model (Intercept)	5.37*	5.10*	5.19*	5.36*	5.22*	5.41*	5.24*	5.29*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
$R_{-i, q5\%}$	113.43*	117.91*	99.61*	100.36*	638.57*	541.20*	704.36*	618.74*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

Notes:

1. This table shows Poisson regression coefficients for each of the variables along with standard p-values. The second part corresponds to the inflation model, which includes logit coefficients for predicting excess zeros along with the standard p-value
2. * denotes a significant level of 1%.
3. N/A denotes a variable dropped due to linear singularity problem.

Table G.6: Summary of zero-inflated Poisson regression results — Italy

	Stock Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)	Bond Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)
Count Model (Intercept)	3.40* (0)	0.87* (0.006)	2.47* (0)	-0.65 (0.113)	0.09 (0.896)	2.93* (0)	2.29* (0)	2.68* (0)
$\Delta mibivi$	-0.41* (0)	-0.07* (0.002)	0.03 (0.266)	-0.10* (0.006)	0.02 (0.671)	-0.10* (0.006)	0.06 (0.086)	0.03 (0.349)
Δfsi	5.94* (0.005)	-7.66* (0)	-4.03* (0.003)	6.57* (0)	-10.99* (0.002)	5.02 (0.014)	4.17 (0.033)	-0.40 (0.856)
$\Delta sentiment$	0.04 (0.193)	-0.07* (0.006)	-0.07 (0.037)	-0.15* (0.004)	0.59* (0)	0.13* (0)	0.20* (0)	-0.11 (0.019)
Δepu	-0.01 (0.065)	0.02* (0)	0.00 (0.944)	0.03* (0)	0.01 (0.162)	-0.01 (0.014)	0.00 (0.818)	0.00 (0.285)
Δr	1.27 (0.04)	1.11 (0.027)	1.06 (0.108)	1.32 (0.227)	2.22* (0.001)	0.70 (0.115)	1.15* (0.007)	-2.75* (0)
Δcpi	-1.23* (0.003)	-0.50 (0.056)	-0.74* (0.006)	-0.73 (0.03)	0.26 (0.735)	-0.53 (0.111)	0.53 (0.125)	-0.40 (0.188)
ΔEUR	38.41* (0)	-15.63 (0.058)	17.72 (0.033)	-14.89 (0.073)	-27.54 (0.029)	-13.55 (0.096)	-22.31* (0.003)	14.54* (0.007)
$\Delta ind\_production$	0.24* (0.001)	-0.05 (0.304)	-0.37* (0)	0.08 (0.339)	-0.53 (0.01)	0.34* (0)	-0.03 (0.713)	0.06 (0.326)
$\Delta creditspreads$	1.32* (0)	-2.00* (0)	-2.50* (0)	-1.87* (0)	-13.56 (0.035)	-0.02 (0.941)	-5.11* (0)	-4.61* (0)
$\Delta gsci$	0.05 (0.124)	0.01 (0.479)	-0.03 (0.068)	-0.15* (0)	0.41 (0)	0.00 (0.977)	0.07 (0.003)	-0.03 (0.557)
Δoil	-0.10 (0.408)	-0.11 (0.122)	0.07 (0.358)	0.47* (0)	-1.48 (0)	0.03 (0.815)	-0.20 (0.036)	-0.02 (0.893)
Zero-inflated Model (Intercept)	5.64* (0)	5.09* (0)	4.99* (0)	5.20* (0)	4.73* (0)	4.33* (0)	4.29* (0)	4.32* (0)
$R.i, q_{5\%}$	157.30* (0)	116.06* (0)	114.54* (0)	104.50* (0)	164.30* (0)	254.63* (0)	217.06* (0)	205.87* (0)

Notes:

1. This table shows Poisson regression coefficients for each of the variables along with standard p-values. The second part corresponds to the inflation model, which includes logit coefficients for predicting excess zeros along with the standard p-value
2. * denotes a significant level of 1%.
3. N/A denotes a variable dropped due to linear singularity problem.

Table G.7: Summary of zero-inflated Poisson regression results — Switzerland

	Stock Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)	Bond Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)
Count Model (Intercept)	4.33* (0)	6.95* (0)	4.90* (0)	5.07* (0)	4.10* (0)	2.64* (0)	3.02* (0)	2.73* (0)
$\Delta vsmi$	-0.09* (0)	-0.23* (0)	-0.12* (0)	-0.12* (0)	-0.08* (0)	-0.01 (0.645)	-0.04* (0)	-0.04 (0.02)
$\Delta sentiment$	4.92 (0.933)	17.14 (0.999)	0.20 (0.09)	0.27 (0.029)	N/A N/A	-15.15 (0.999)	19.80 (1)	17.61 (0.999)
Δr	27.27 (0.8)	56.60 (0.997)	28.34 (0.838)	N/A (N/A)	18.37 (0.879)	4.56 (0.944)	10.04 (0.887)	N/A (N/A)
Δcpi	-0.17 (0.298)	-0.48 (0.021)	-0.59* (0)	-0.50* (0.001)	-0.27 (0.042)	-0.79* (0)	-0.22 (0.109)	1.69* (0)
Δchf	19.98* (0.005)	-7.40 (0.413)	25.29* (0)	28.45* (0)	3.12 (0.553)	-9.50 (0.192)	N/A (N/A)	N/A (N/A)
$\Delta ind\_production$	-0.12* (0)	-0.04 (0.16)	0.06* (0)	-0.02 (0.138)	-0.05* (0)	-0.11* (0)	0.05* (0)	0.06* (0.004)
$\Delta creditspreads$	-1.26* (0.002)	1.09 (0.089)	1.97* (0)	1.78* (0)	2.08* (0)	-6.15* (0)	3.17* (0)	7.81* (0)
$\Delta gsci$	0.06* (0.009)	0.13* (0)	0.12* (0)	0.00 (0.868)	-0.02 (0.108)	0.00 (0.806)	0.01 (0.466)	-0.08* (0.002)
Δoil	-0.20 (0.03)	-0.47* (0)	-0.47* (0)	0.04 (0.594)	-0.01 (0.859)	-0.06 (0.447)	-0.07 (0.369)	0.34 (0.016)
Zero-inflated Model (Intercept)	6.26 (0)	6.96 (0)	6.69 (0)	6.62 (0)	5.79 (0)	5.47 (0)	5.39 (0)	5.80 (0)
$R.i, q_{5\%}$	219.05	281.76	258.57	243.63	1108.92	819.44	923.33	810.37

Notes:

1. This table shows Poisson regression coefficients for each of the variables along with standard p-values. The second part corresponds to the inflation model, which includes logit coefficients for predicting excess zeros along with the standard p-value
2. * denotes a significant level of 1%.
3. N/A denotes a variable dropped due to linear singularity problem.

Table G.8: Summary of zero-inflated Poisson regression results — Canada

	Stock				Bond			
	Gold	Silver	Platinum	Palladium	Gold	Silver	Platinum	Palladium
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
	(p value)	(p value)	(p value)	(p value)	(p value)	(p value)	(p value)	(p value)
Count Model								
(Intercept)	-1.18 (0.268)	2.23* (0)	2.74* (0)	2.74* (0)	2.27* (0)	2.49* (0)	2.46* (0)	2.38* (0)
$\Delta vixc$	1.57 (0.1)	0.03 (0.605)	0.12* (0.006)	0.08 (0.084)	0.07 (0.262)	0.05 (0.139)	0.13* (0.005)	0.42* (0)
$\Delta sentiment$	-0.04 (0.618)	0.06* (0)	0.03 (0.013)	0.08* (0)	0.02 (0.103)	0.00 (0.767)	0.01 (0.421)	-0.03 (0.05)
Δepu	-0.01 (0.353)	0.00 (0.442)	0.00 (0.034)	0.02* (0.001)	-0.01* (0)	0.00 (0.038)	0.00 (0.323)	0.00 (0.275)
Δr	-13.42 (0.946)	N/A (N/A)	N/A (N/A)	N/A (N/A)	N/A (N/A)	N/A (N/A)	N/A (N/A)	N/A (N/A)
Δcpi	0.84 (0.405)	-0.16 (0.439)	1.28* (0)	1.61* (0)	-0.55* (0.003)	-0.77* (0)	-0.21 (0.1)	-1.75* (0)
ΔCAD	-163.63 (0.261)	-40.67* (0)	5.03 (0.518)	2.00 (0.785)	-64.89* (0)	-18.42 (0.08)	-38.68* (0)	-55.13* (0)
$\Delta ind\_production$	6.32 (0.033)	-0.37 (0.223)	-0.40 (0.096)	0.28 (0.343)	0.00 (0.982)	-0.60* (0.007)	0.88* (0)	0.80* (0.001)
$\Delta creditspreads$	5.05 (0.294)	-1.53 (0.127)	-0.48 (0.842)	7.96* (0)	0.39 (0.658)	-3.35* (0)	-0.58 (0.256)	-4.57* (0.001)
$\Delta gsci$	0.67 (0.039)	-0.05 (0.178)	0.02 (0.597)	-0.18* (0)	0.06 (0.016)	-0.04 (0.161)	0.03 (0.089)	-0.07 (0.051)
Δoil	-2.32* (0.009)	-0.27 (0.11)	-0.18 (0.204)	0.68* (0.001)	-0.35* (0.001)	0.32* (0.006)	-0.16 (0.023)	0.30 (0.044)
Zero-inflated Model								
(Intercept)	6.34* (0)	6.07* (0)	6.17* (0)	5.90* (0)	6.27* (0)	5.79* (0)	5.83* (0)	6.38* (0)
$R.i, q_{5\%}$	205.45* (0)	256.45* (0)	225.80* (0)	209.95* (0)	889.47* (0)	810.16* (0)	830.00* (0)	768.71* (0)

Notes:

1. This table shows Poisson regression coefficients for each of the variables along with standard p-values. The second part corresponds to the inflation model, which includes logit coefficients for predicting excess zeros along with the standard p-value
2. * denotes a significant level of 1%.
3. N/A denotes a variable dropped due to linear singularity problem.

Table G.9: Summary of zero-inflated Poisson regression results — Japan

	Stock Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)	Bond Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)
Count Model (Intercept)	2.27* (0)	2.25 (0)	2.17* (0)	2.78* (0)	2.62* (0)	2.63* (0)	2.41* (0)	2.50* (0)
Δvxj	0.00 (0.814)	-0.02 (0.067)	-0.02 (0.027)	-0.10* (0)	0.10* (0)	0.09* (0)	0.09* (0)	0.09* (0)
Δepu	0.01* (0)	0.01 (0)	0.01* (0)	0.00 (0.088)	0.00 (0.68)	0.00 (0.093)	0.00 (0.191)	0.00* (0.008)
$\Delta sentiment$	0.00 (0.977)	-0.03 (0)	-0.02* (0)	-0.05* (0)	0.00 (0.548)	0.01* (0.001)	0.00 (0.283)	0.01 (0.05)
Δr	2.29 (0.336)	3.72 (0.027)	1.71 (0.373)	-10.54 (0.032)	16.16* (0)	19.92* (0)	-17.65* (0)	-30.21* (0.008)
Δcpi	0.43* (0)	0.64 (0)	0.19 (0.197)	-0.07 (0.699)	0.14 (0.585)	-0.45* (0.001)	-1.35* (0)	-0.39 (0.076)
ΔYEN	0.12* (0.01)	0.08 (0.092)	0.03 (0.572)	0.09 (0.107)	-0.03 (0.645)	-0.10* (0.007)	-0.13 (0.083)	-0.02 (0.623)
$\Delta ind\_production$	0.14* (0)	0.03 (0.206)	0.19* (0)	0.14* (0)	0.12* (0)	0.01 (0.513)	0.12* (0)	0.02 (0.546)
$\Delta creditspreads$	-2.09* (0)	-4.55 (0)	-2.64* (0)	1.45* (0.009)	-0.33 (0.815)	-1.37 (0.091)	-2.58* (0.006)	-6.33* (0)
$\Delta gsci$	0.08* (0)	0.04 (0.002)	0.03 (0.043)	0.05* (0)	0.03 (0.031)	0.05* (0)	-0.07* (0)	0.00 (0.926)
Δoil	-0.29* (0)	-0.16 (0.01)	-0.16 (0.012)	-0.23* (0)	-0.28* (0.002)	-0.45* (0)	0.34* (0)	0.06 (0.509)
Zero-inflated Model (Intercept)	4.85* (0)	4.99* (0)	5.07* (0)	5.29* (0)	5.63* (0)	5.4* (0)	5.60* (0)	5.63* (0)
$R.i, q_{5\%}$	98.27* (0)	97.08* (0)	94.47* (0)	99.46* (0)	611.53* (0)	821.80* (0)	757.78* (0)	774.79* (0)

Notes:

1. This table shows Poisson regression coefficients for each of the variables along with standard p-values. The second part corresponds to the inflation model, which includes logit coefficients for predicting excess zeros along with the standard p-value
2. * denotes a significant level of 1%.
3. N/A denotes a variable dropped due to linear singularity problem.

Table G.10: Summary of zero-inflated Poisson regression results — China

	Stock				Bond			
	Gold	Silver	Platinum	Palladium	Gold	Silver	Platinum	Palladium
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
	(p value)	(p value)	(p value)	(p value)	(p value)	(p value)	(p value)	(p value)
Count Model								
(Intercept)	2.33*	3.02*	2.25*	2.50*	2.55*	2.36*	2.06*	2.52*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
$\Delta sentiment$	-0.28*	-0.16*	-0.21*	0.11	-0.08*	-0.09	-0.36*	-0.22*
	(0)	(0)	(0)	(0.216)	(0.004)	(0.015)	(0)	(0)
Δepu	0.00	0.00	0.00	-0.01*	-0.01*	-0.01*	0.00*	0.00
	(0.622)	(0.139)	(0.238)	(0.001)	(0)	(0)	(0.001)	(0.019)
Δr	-39.35	N/A	-37.96	-20.78	-21.27	17.29	3.65	N/A
	(0.838)	(N/A)	(0.852)	(0.882)	(0.884)	(0.903)	(0.986)	(N/A)
Δcpi	0.97*	0.81*	0.94*	0.20	0.90*	0.41	1.81*	0.31
	(0)	(0)	(0.004)	(0.53)	(0)	(0.121)	(0)	(0.225)
ΔCNY	13.15	50.89*	-24.43	14.89	-7.25	-27.48*	-1.46	-25.64
	(0.525)	(0)	(0.345)	(0.559)	(0.362)	(0.005)	(0.889)	(0.053)
$\Delta ind\_production$	0.03*	0.03*	0.04*	0.03*	-0.07*	-0.04*	0.00	0.01
	(0)	(0)	(0)	(0.003)	(0)	(0)	(0.726)	(0.083)
$\Delta creditspreads$	1.19	-0.52	-0.10	4.49*	0.98	-0.50	-4.54*	-4.09*
	(0.057)	(0.249)	(0.898)	(0.001)	(0.029)	(0.263)	(0)	(0)
$\Delta gsci$	-0.02	0.03	-0.06	-0.28	-0.05	0.07	-0.06*	0.02
	(0.756)	(0.392)	(0.31)	(0.067)	(0.145)	(0.021)	(0.004)	(0.321)
Δoil	0.12	0.00	0.31	0.70	0.08	-0.22	0.00	-0.23
	(0.62)	(0.975)	(0.196)	(0.161)	(0.541)	(0.068)	(0.97)	(0.011)
Zero-inflated Model								
(Intercept)	4.71*	4.70*	4.79*	5.16*	4.80*	4.58*	6.04*	6.13*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
$R.i, q_{5\%}$	71.85*	65.23*	58.44*	75.96*	497.21*	358.38*	1173.08*	1079.12*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

Notes:

1. This table shows Poisson regression coefficients for each of the variables along with standard p-values. The second part corresponds to the inflation model, which includes logit coefficients for predicting excess zeros along with the standard p-value
2. * denotes a significant level of 1%.
3. N/A denotes a variable dropped due to linear singularity problem.

Table G.11: Summary of zero-inflated Poisson regression results — India

	Stock Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)	Bond Gold Coef. (p value)	Silver Coef. (p value)	Platinum Coef. (p value)	Palladium Coef. (p value)
Count Model (Intercept)	4.17* (0)	2.99* (0.001)	0.41 (0.504)	2.10* (0)	-48.35 (0.399)	-61.68 (0.586)	-18.27 (0.01)	-4.21 (0.164)
$\Delta nselv$	0.00 (0.019)	0.01 (0.013)	0.00 (0.76)	0.00 (0.11)	N/A (0.399)	N/A (0.586)	-0.57* (0.003)	-0.35 (0.06)
$\Delta sentiment$	-0.59 (0.477)	1.77 (0.018)	3.59* (0)	0.95* (0)	4.18 (0.46)	76.16 (0.559)	10.48* (0.002)	-3.98 (0.387)
Δepu	0.00 (0.976)	-0.02 (0.028)	-0.03* (0)	0.00 (0.811)	0.11 (0.5)	0.38 (0.581)	0.07* (0.002)	-0.09 (0.18)
Δr	-8.86 (0.035)	0.21 (0.952)	9.68* (0)	N/A (0.811)	N/A (0.5)	N/A (0.581)	N/A (0.002)	N/A (0.18)
Δcpi	-1.35 (0.164)	0.89 (0.289)	3.13* (0)	0.02 (0.945)	-17.26 (0.366)	58.00 (0.58)	13.19* (0.006)	0.34 (0.9)
ΔINR	0.18 (0.326)	0.38 (0.115)	0.29 (0.235)	N/A (0.235)	47.16 (0.377)	-31.43 (0.602)	-46.49* (0.003)	N/A (0.003)
$\Delta ind\_production$	-0.10 (0)	-0.05 (0.05)	N/A (0.05)	-0.02 (0.363)	0.58 (0.503)	2.53* (0.551)	-0.79 (0.008)	N/A (0.008)
$\Delta creditspreads$	0.82 (0.639)	-2.59 (0.099)	-7.77* (0)	-2.46 (0.054)	77.63 (0.392)	N/A (0.392)	N/A (0.392)	N/A (0.392)
$\Delta gsci$	0.18 (0.145)	0.22 (0.166)	-0.23 (0.01)	-0.24 (0.25)	-13.42 (0.378)	-18.45 (0.562)	-4.81 (0.002)	0.67 (0.39)
Δoil	-0.72 (0.159)	-0.65 (0.277)	1.02* (0.003)	0.88 (0.321)	13.10 (0.41)	54.50 (0.567)	N/A (0.567)	-4.13 (0.134)
Zero-inflated Model (Intercept)	7.82* (0)	8.48* (0)	6.91* (0)	6.29* (0)	3.82* (0)	4.77* (0)	4.26* (0)	4.74* (0)
$R.i, q_{5\%}$	313.26* (0)	382.29* (0)	268.72* (0)	210.28* (0)	237.34* (0.029)	184.28* (0.008)	180.30* (0.001)	159.54* (0.001)

Notes:

1. This table shows output containing Poisson regression coefficients for each of the variables along with standard p-values. The second part corresponds to the inflation model, which includes logit coefficients for predicting excess zeros along with the standard p-values.
2. * denotes a significant level of 1%.
3. N/A denotes a variable dropped due to linear singularity problem.

Table G.12: Summary of zero-inflated Poisson regression results — South Africa

	Stock				Bond			
	Gold	Silver	Platinum	Palladium	Gold	Silver	Platinum	Palladium
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
	(p value)	(p value)	(p value)	(p value)	(p value)	(p value)	(p value)	(p value)
Count Model								
(Intercept)	2.85*	3.35*	2.62*	1.66*	4.81*	2.00*	2.42*	3.09*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
$\Delta savit40$	-0.17*	-0.32*	0.00	-0.23*	1.82*	-0.68*	-0.04	-1.00*
	(0)	(0)	(0.989)	(0.001)	(0.001)	(0)	(0.762)	(0)
$\Delta sentiment$	0.00	0.06*	-0.01	0.01	-0.38*	-0.08*	0.07*	0.08*
	(0.307)	(0)	(0.197)	(0.613)	(0)	(0)	(0)	(0)
Δr	N/A	N/A	N/A	N/A	24.39	23.82	12.88	1.41*
	N/A	N/A	N/A	N/A	(0.685)	(0.979)	(0.856)	(0.004)
Δcpi	0.18	-0.27	0.03	0.54	-8.71*	0.46	0.20	-0.62*
	(0.134)	(0.016)	(0.785)	(0.028)	(0)	(0.348)	(0.503)	(0.005)
ΔZAR	0.00	1.67*	0.24	0.11	30.75*	-4.65*	2.21	0.81
	(0.999)	(0)	(0.046)	(0.656)	(0.002)	(0)	(0.026)	(0.273)
$\Delta creditspreads$	-0.05	0.09*	0.06	-0.08	-2.17*	0.23	0.45*	0.82*
	(0.045)	(0)	(0.085)	(0.483)	(0)	(0.272)	(0)	(0)
$\Delta gsci$	0.03*	0.04*	-0.01	0.01	0.69*	0.35*	0.12*	0.03
	(0)	(0)	(0.256)	(0.391)	(0)	(0)	(0)	(0.345)
Δoil	-0.21*	-0.25*	0.04	-0.15	-2.32*	-1.15*	-0.46*	-0.15
	(0)	(0)	(0.236)	(0.03)	(0.001)	(0)	(0.001)	(0.278)
$\Delta ind\_production$	-0.05	-0.23*	0.00	-0.03	0.47*	0.09*	0.00	0.12*
	(0.032)	(0)	(0.975)	(0.335)	(0)	(0.002)	(0.974)	(0)
Zero-inflated Model								
(Intercept)	5.53*	5.09*	5.92*	6.02*	5.16*	5.38*	4.97*	5.07*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
$R.i, q_{5\%}$	158.19*	109.48*	196.60*	185.60*	216.57*	331.61*	304.96*	364.90*
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

Notes:

1. This table shows output containing Poisson regression coefficients for each of the variables along with standard p-values. The second part corresponds to the inflation model, which includes logit coefficients for predicting excess zeros along with the standard p-values.
2. * denotes a significant level of 1%.
3. N/A denotes a variable dropped due to linear singularity problem.

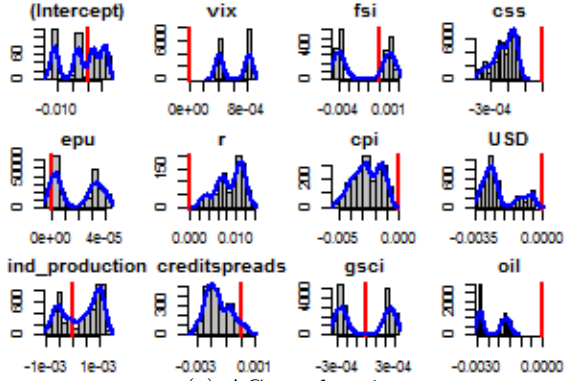
Appendix H

Histograms of Extreme Bond Analysis Results

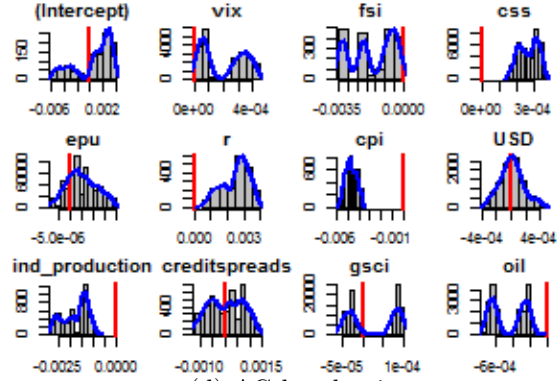
A set of histograms that present the results of extreme bounds analysis graphically is presented here. Each histogram illustrates the distribution of regression coefficients across the models estimated in the course of EBA. The red lines indicate the value of the regression coefficient assumed under the null hypothesis (0). Blue curves indicate the distribution's kernel density.

Figure H.1: EBA Naive — the US

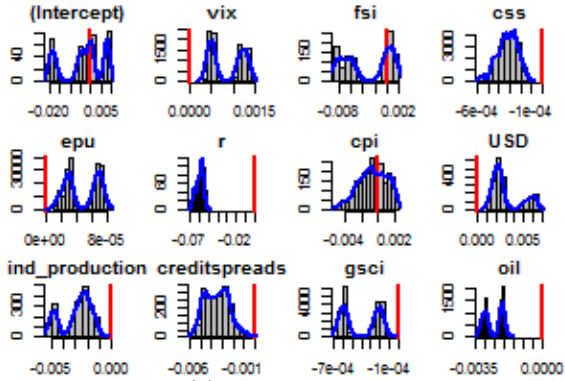
(a) AU stock naive



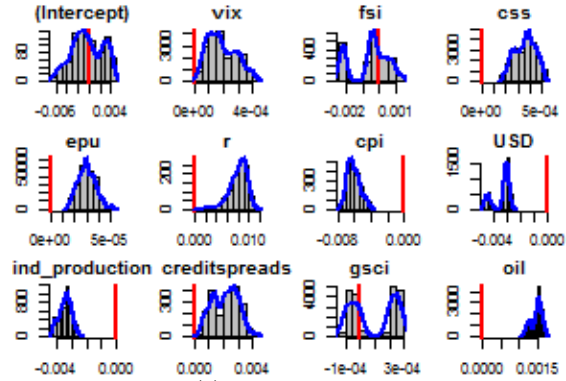
(b) AU bond naive



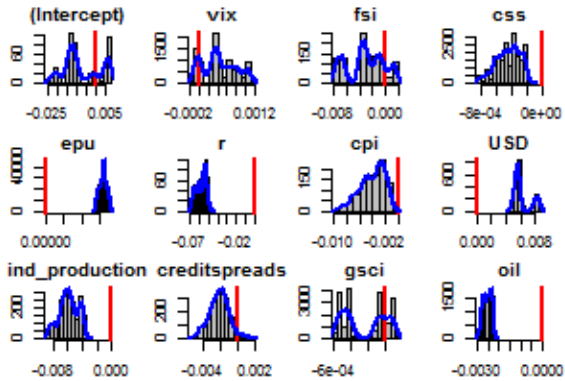
(c) AG stock naive



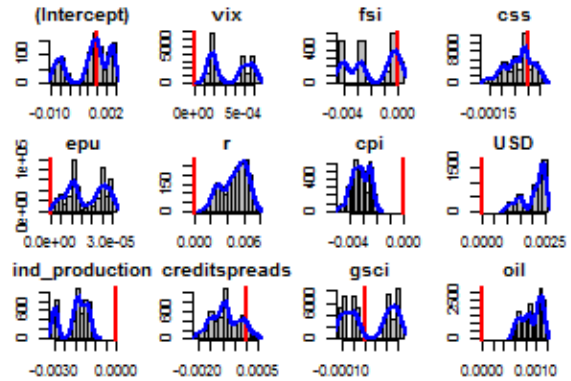
(d) AG bond naive



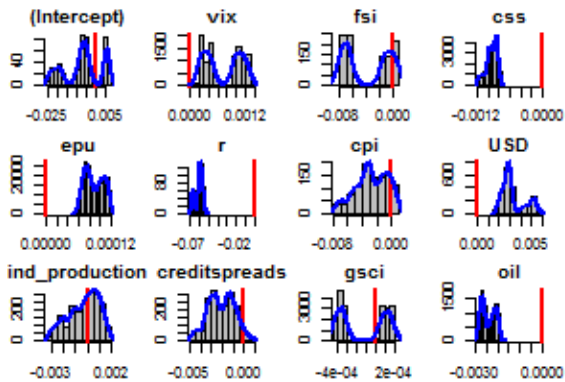
(e) PT stock naive



(f) PT bond naive



(g) PD stock naive



(h) PD bond naive

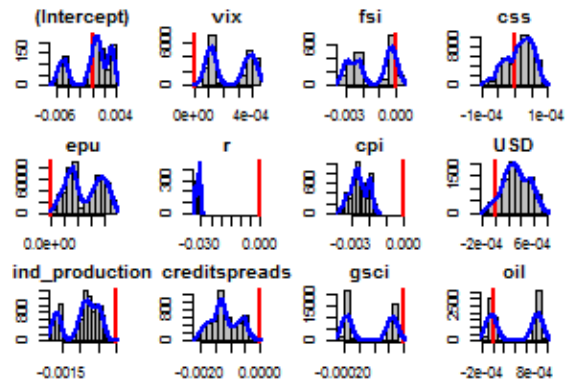
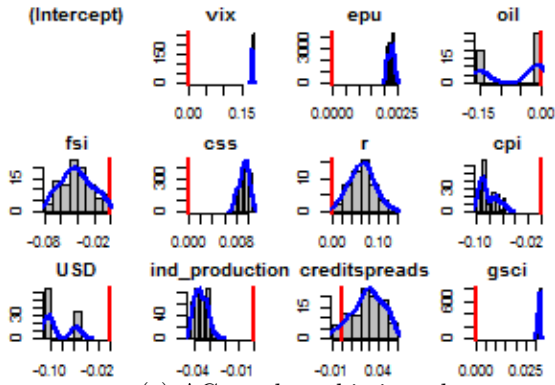
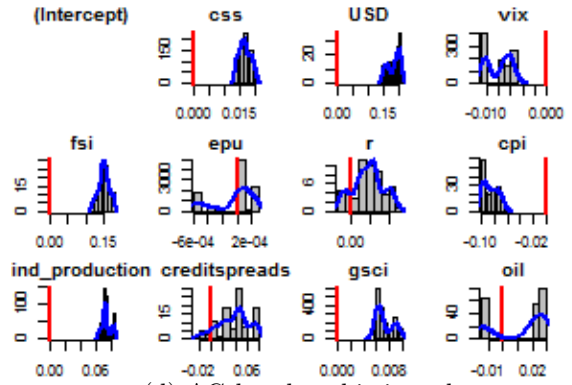


Figure H.2: EBA Sophisticated — the US

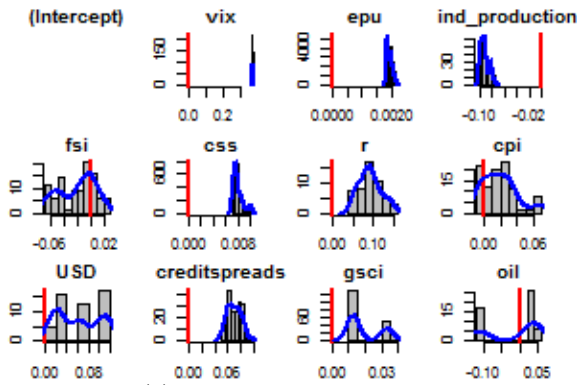
(a) AU stock sophisticated



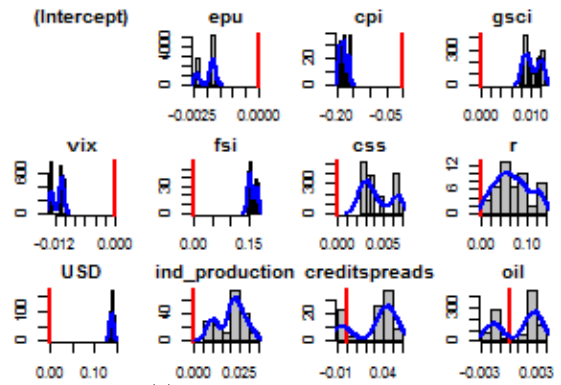
(b) AU bond sophisticated



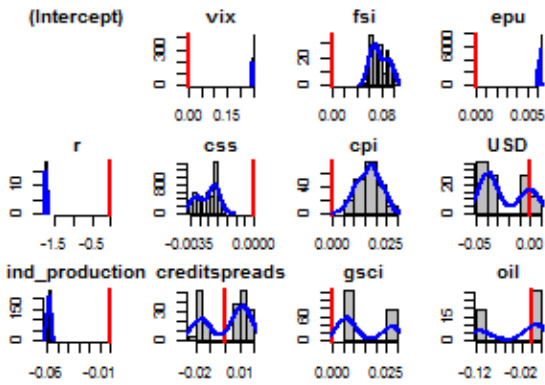
(c) AG stock sophisticated



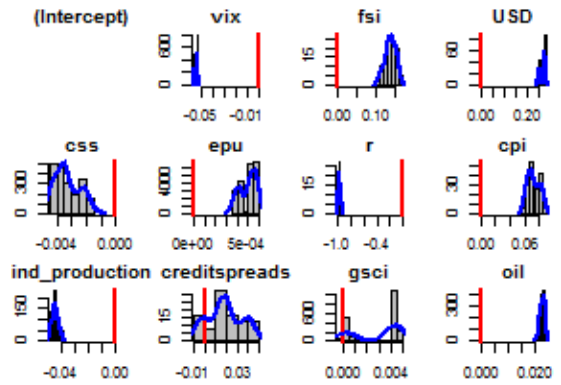
(d) AG bond sophisticated



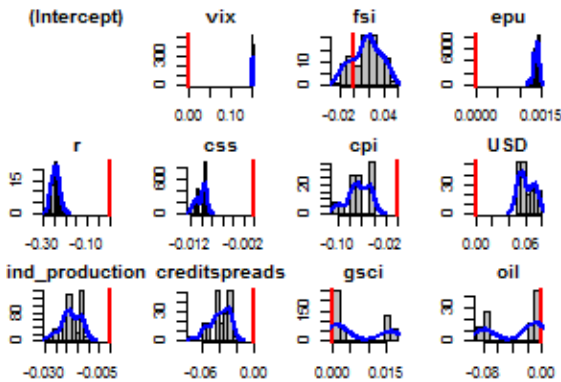
(e) PT stock sophisticated



(f) PT bond sophisticated



(g) PD stock sophisticated



(h) PD bond sophisticated

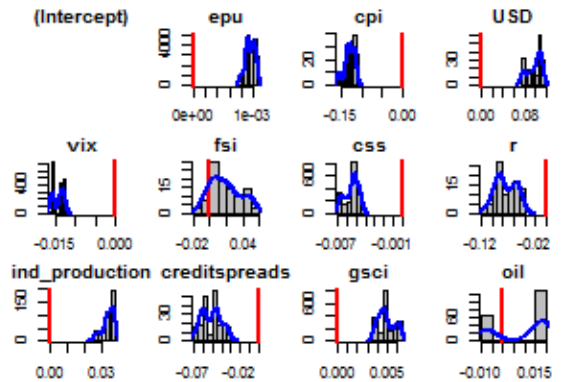


Figure H.3: EBA Naive — the UK

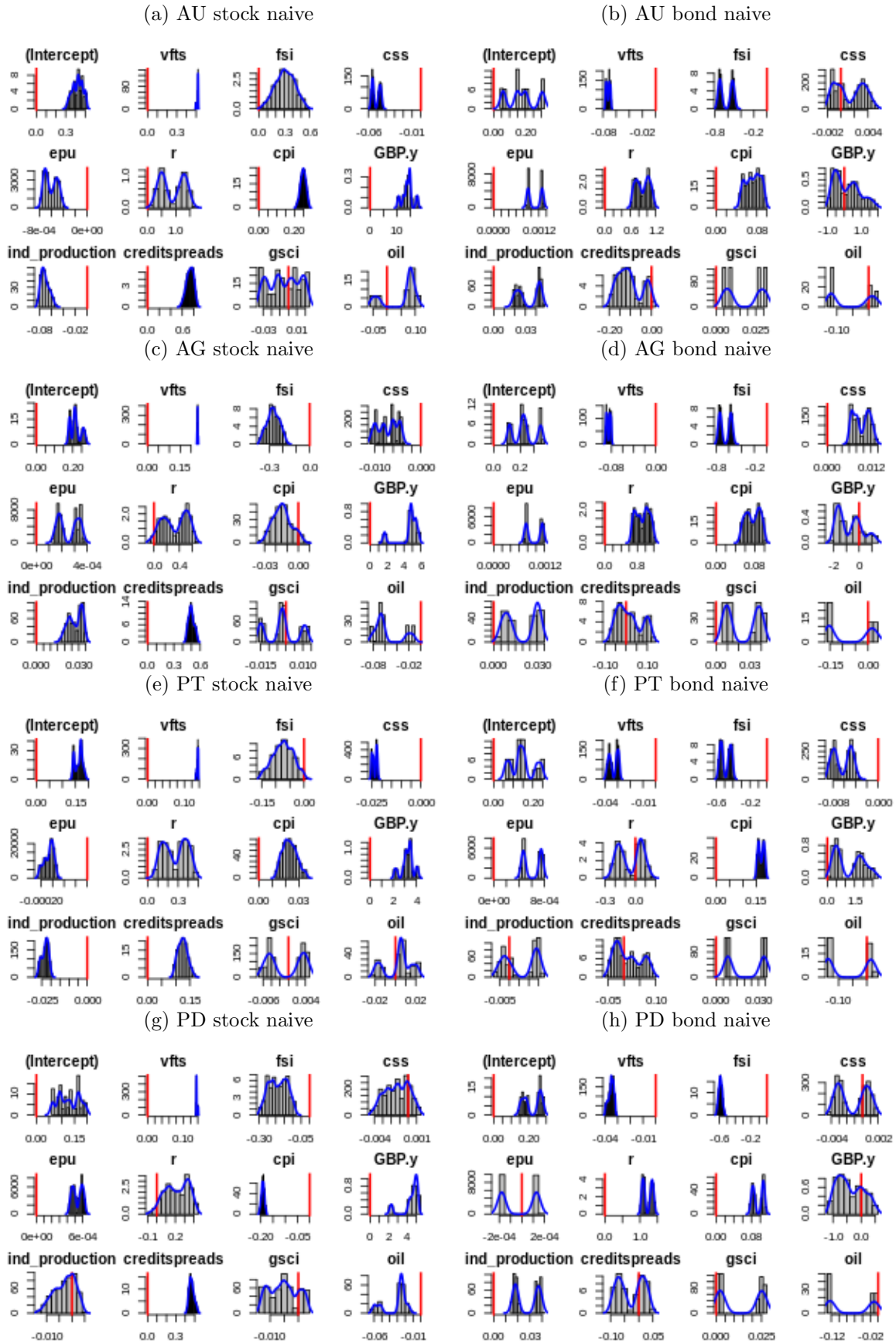
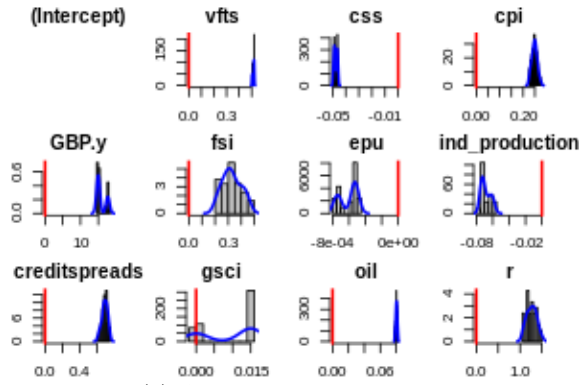
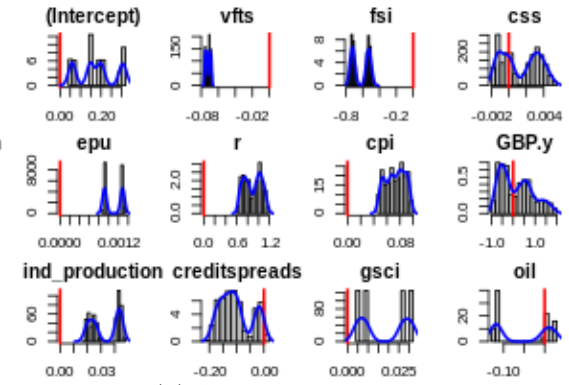


Figure H.4: EBA Sophisticated — the UK

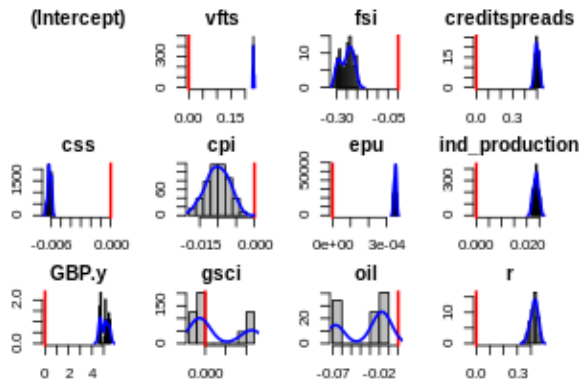
(a) AU stock sophisticated



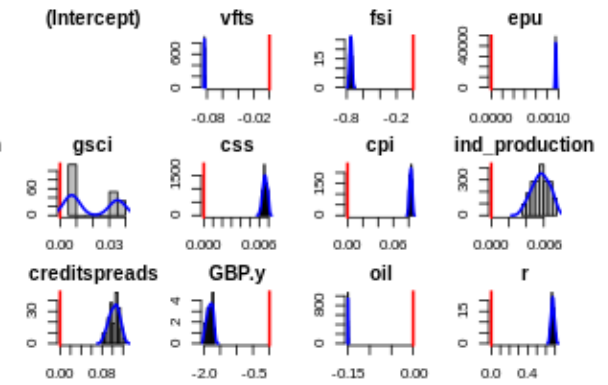
(b) AU bond sophisticated



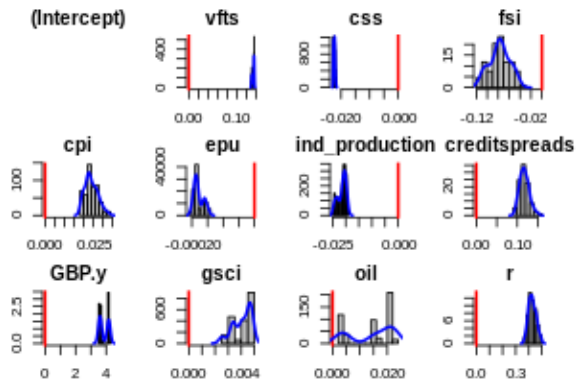
(c) AG stock sophisticated



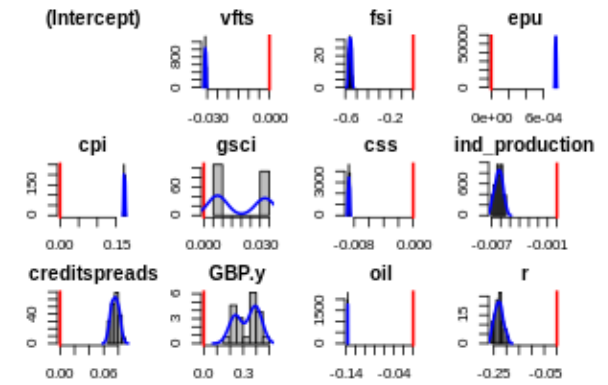
(d) AG bond sophisticated



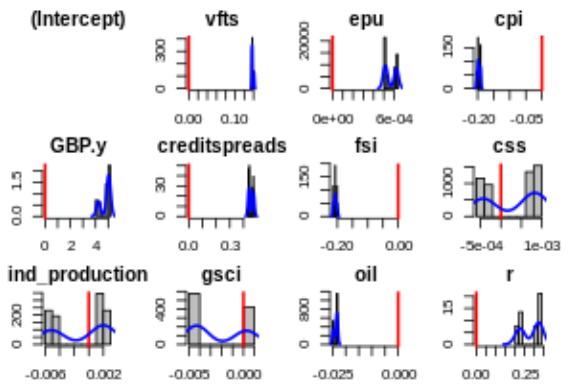
(e) PT stock sophisticated



(f) PT bond sophisticated



(g) PD stock sophisticated



(h) PD bond sophisticated

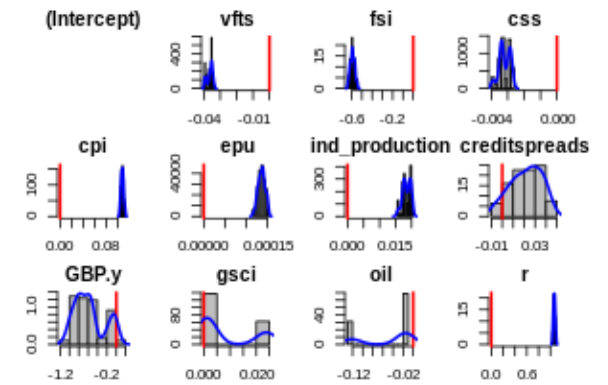
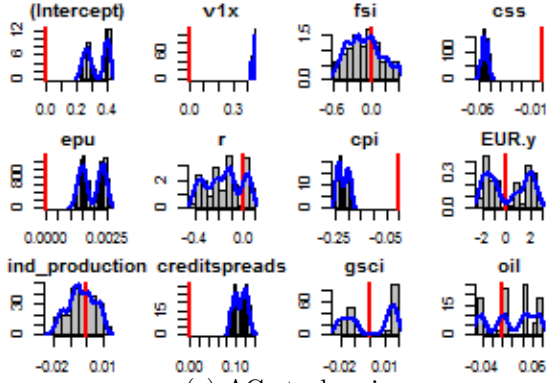
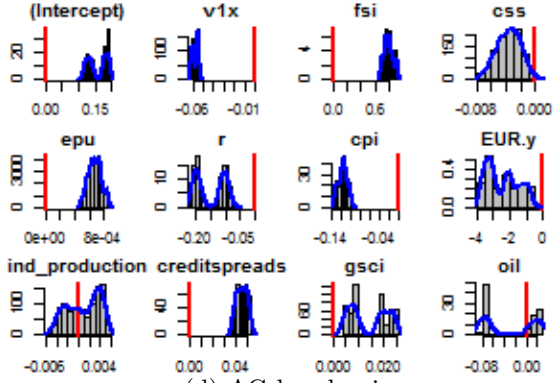


Figure H.5: EBA Naive — Germany

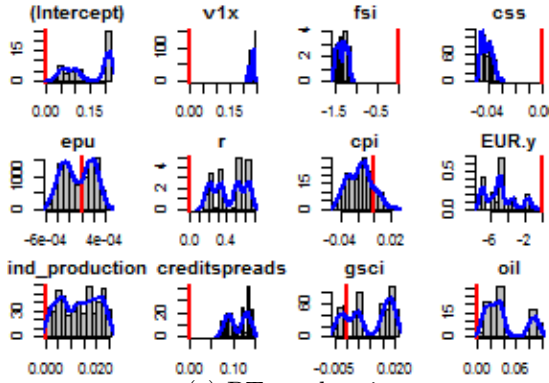
(a) AU stock naive



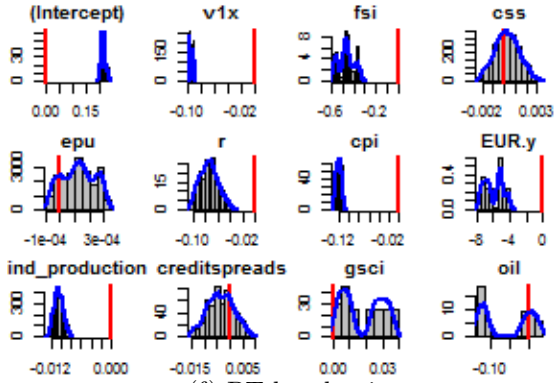
(b) AU bond naive



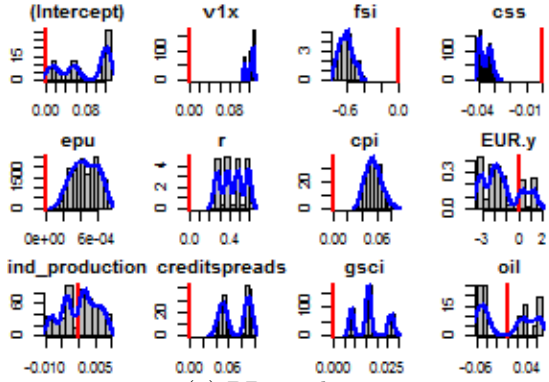
(c) AG stock naive



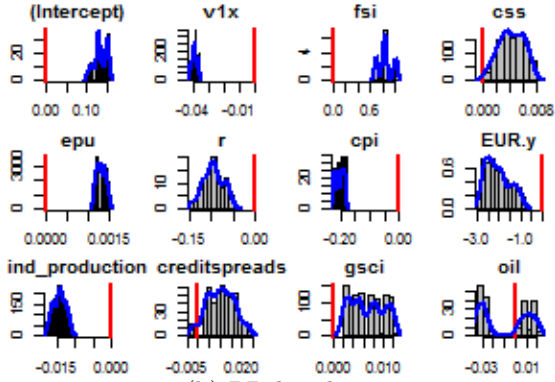
(d) AG bond naive



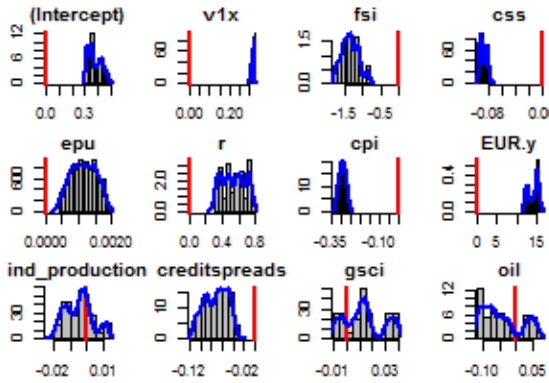
(e) PT stock naive



(f) PT bond naive



(g) PD stock naive



(h) PD bond naive

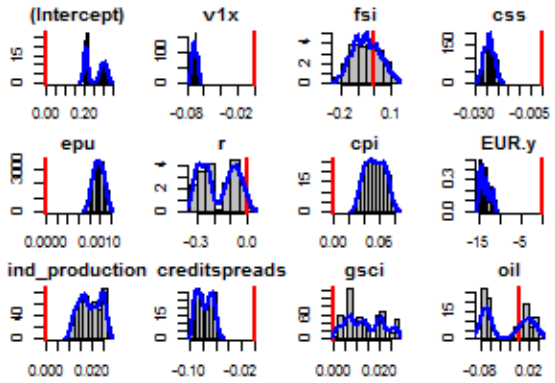
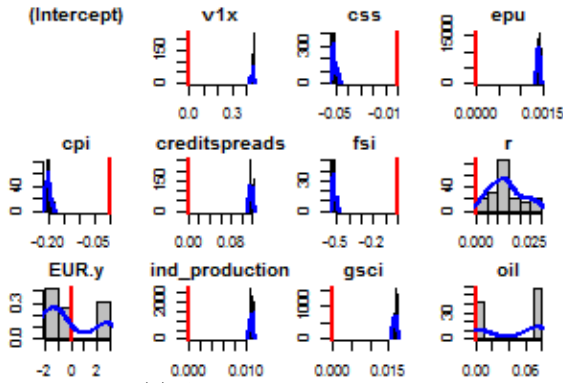
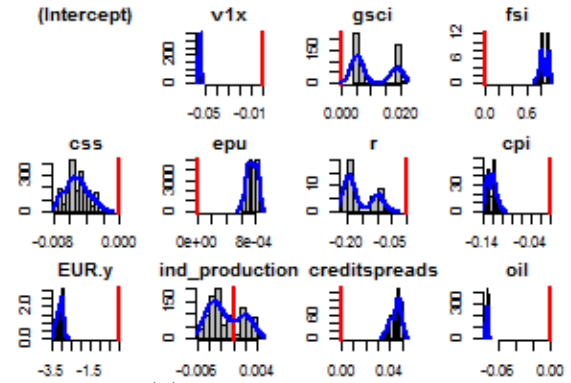


Figure H.6: EBA Sophisticated — Germany

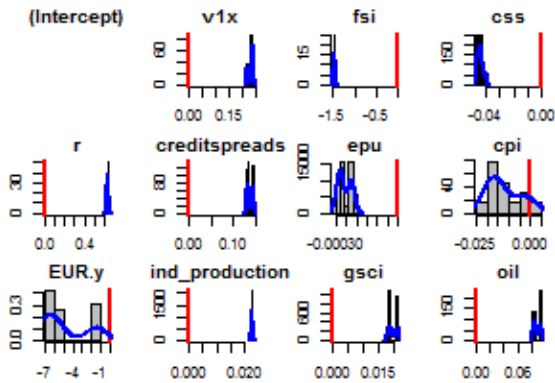
(a) AU stock sophisticated



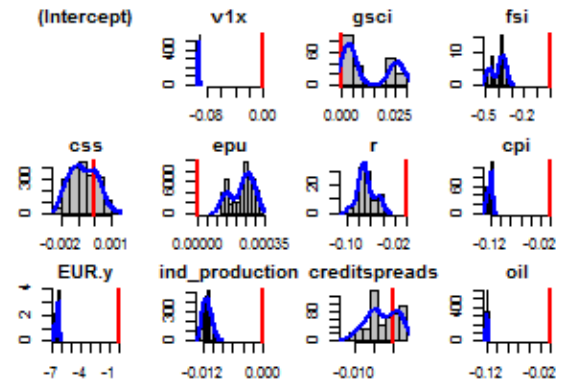
(b) AU bond sophisticated



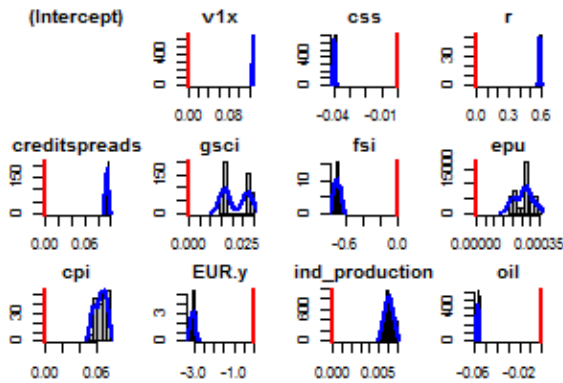
(c) AG stock sophisticated



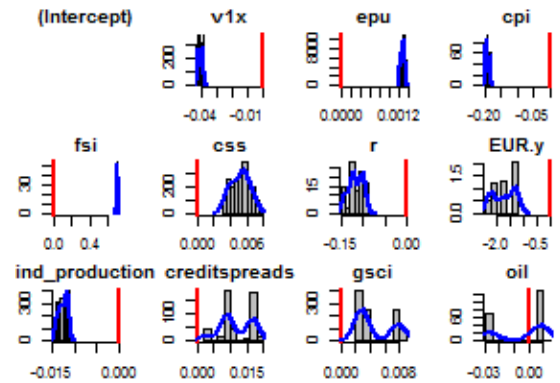
(d) AG bond sophisticated



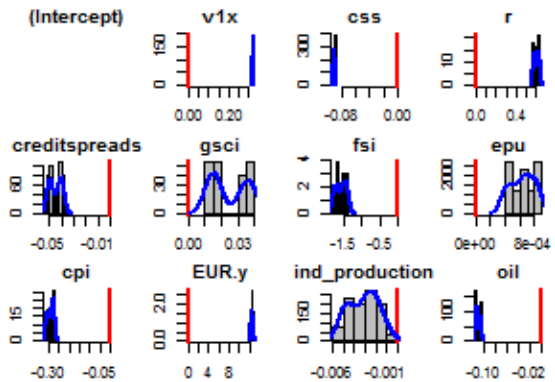
(e) PT stock sophisticated



(f) PT bond sophisticated



(g) PD stock sophisticated



(h) PD bond sophisticated

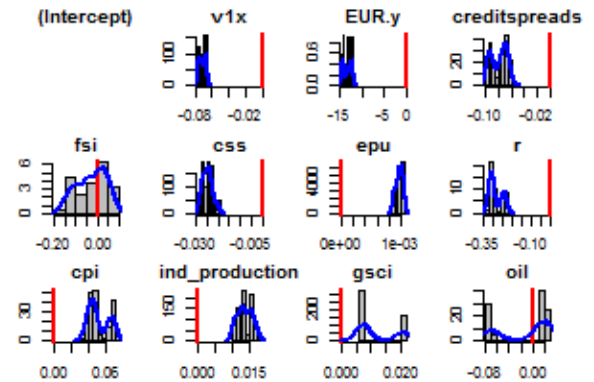


Figure H.7: EBA Naive — France

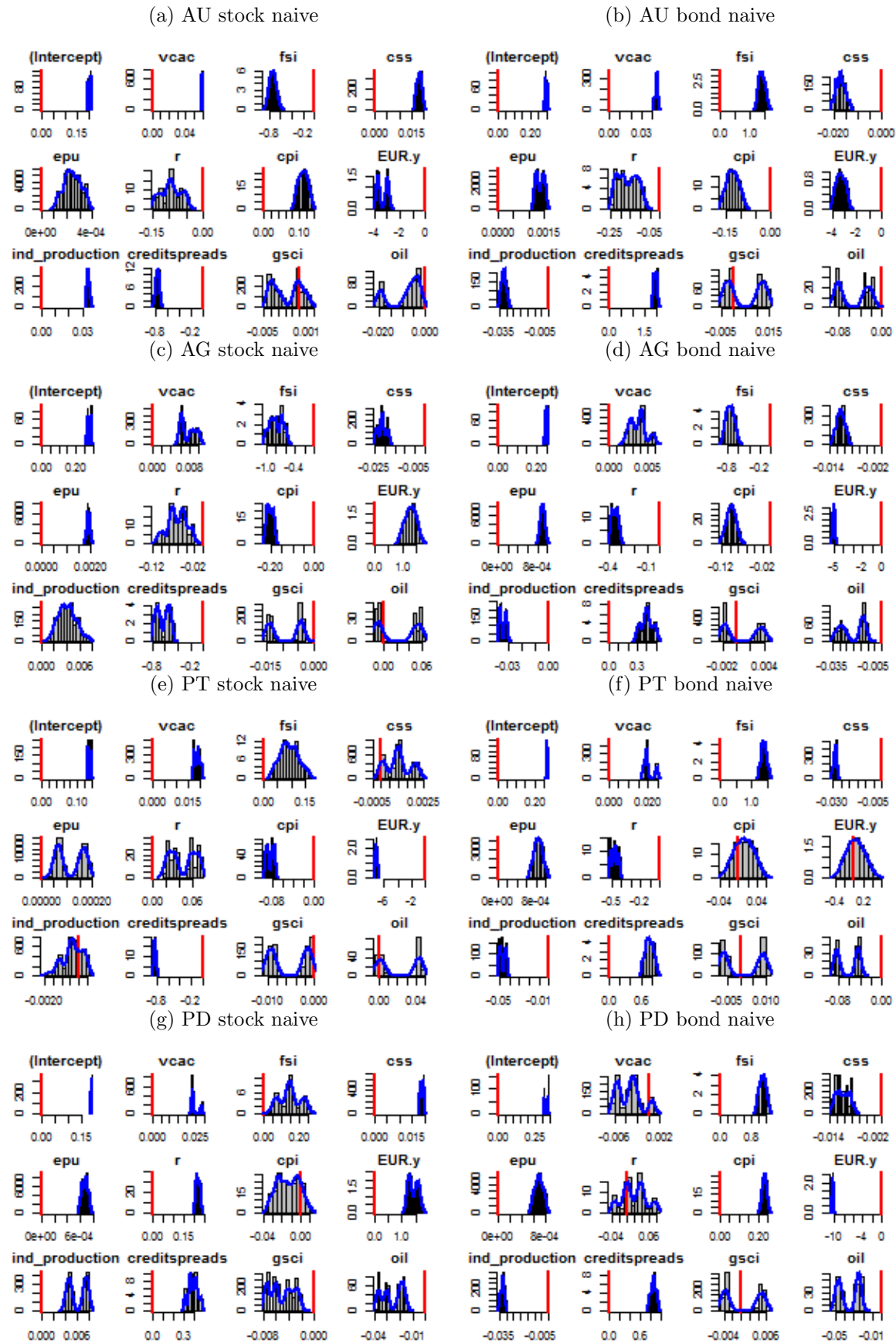
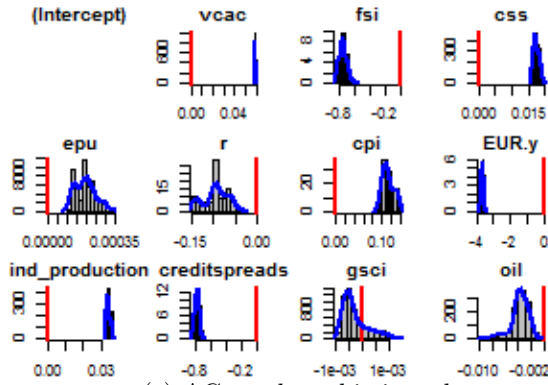
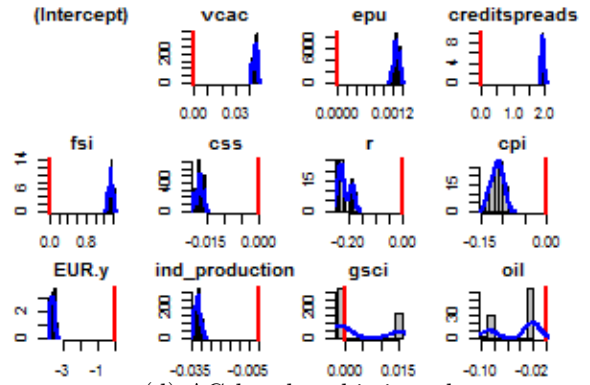


Figure H.8: EBA Sophisticated — France

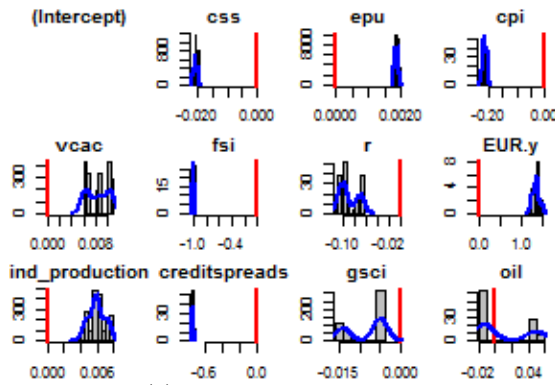
(a) AU stock sophisticated



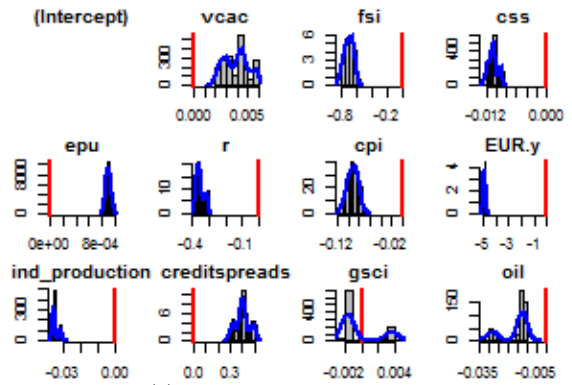
(b) AU bond sophisticated



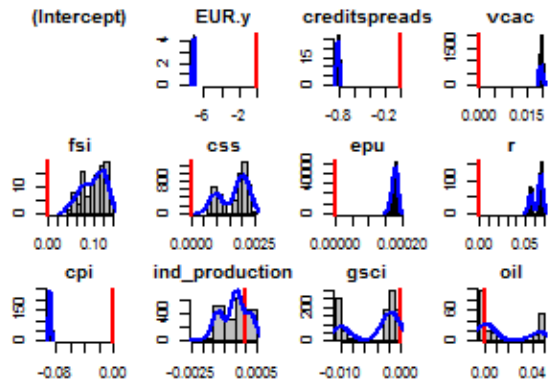
(c) AG stock sophisticated



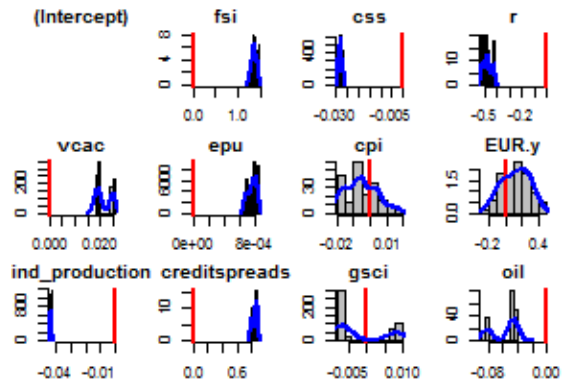
(d) AG bond sophisticated



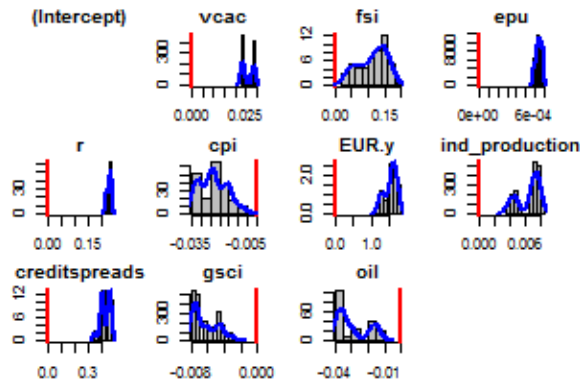
(e) PT stock sophisticated



(f) PT bond sophisticated



(g) PD stock sophisticated



(h) PD bond sophisticated

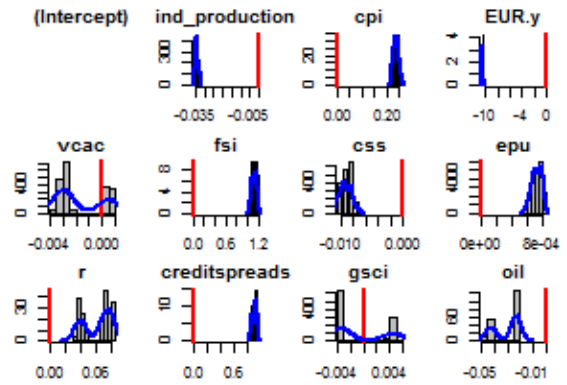


Figure H.9: EBA Naive — Italy

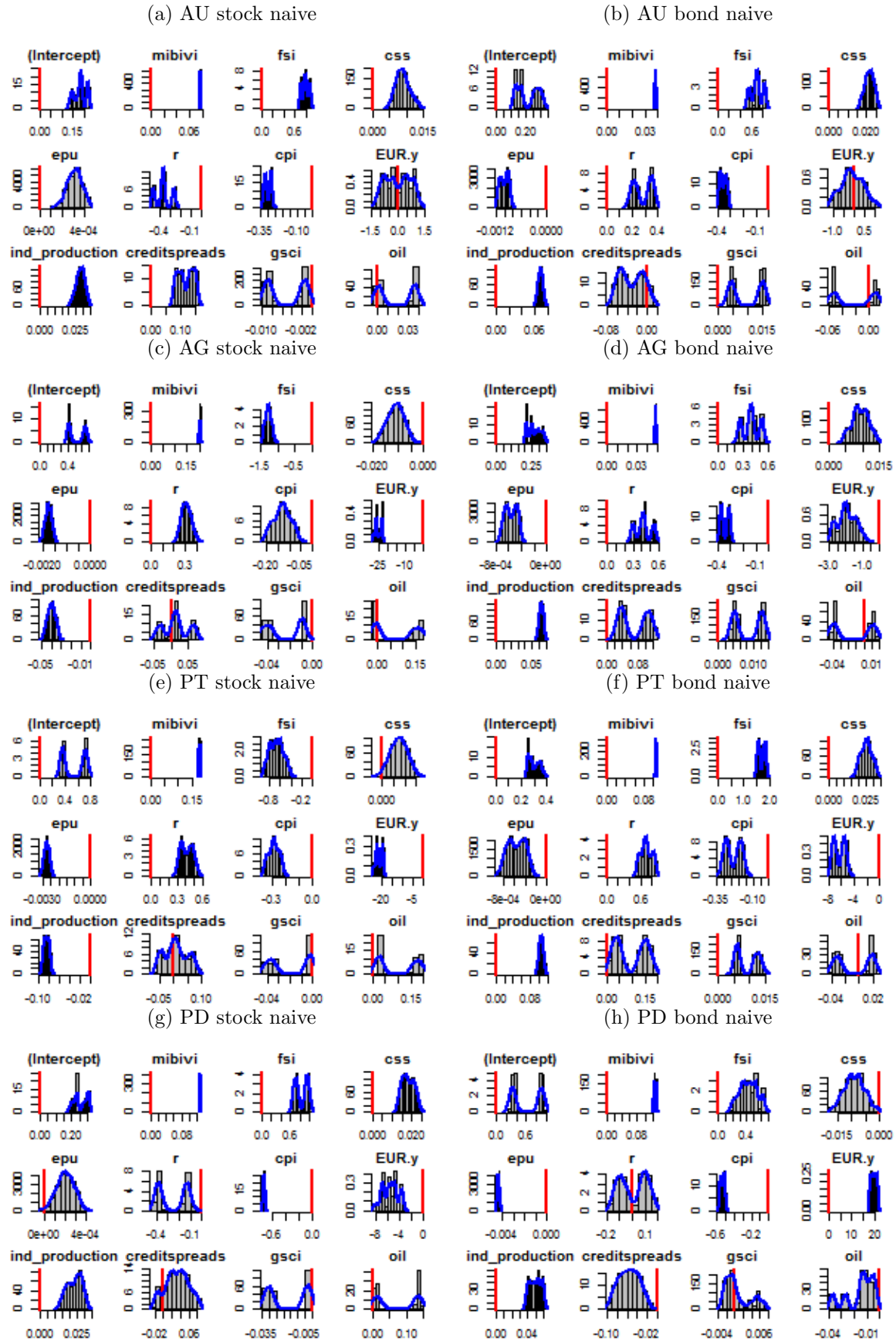
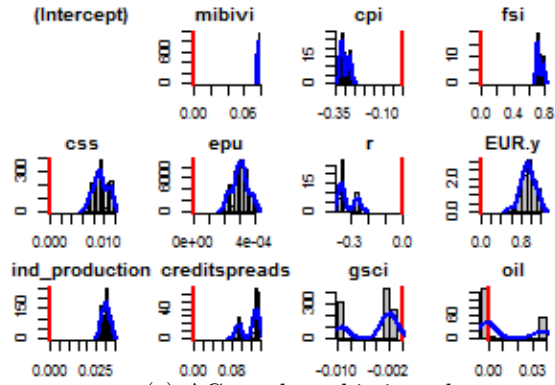
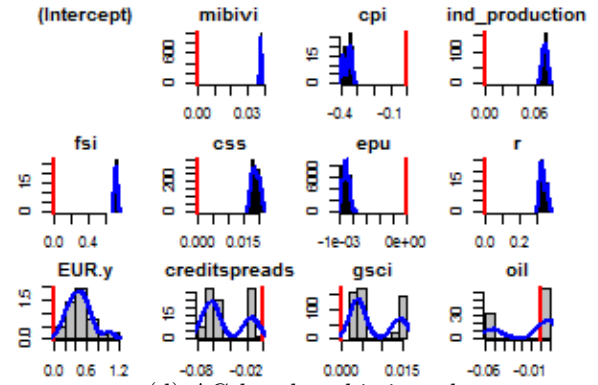


Figure H.10: EBA Sophisticated — Italy

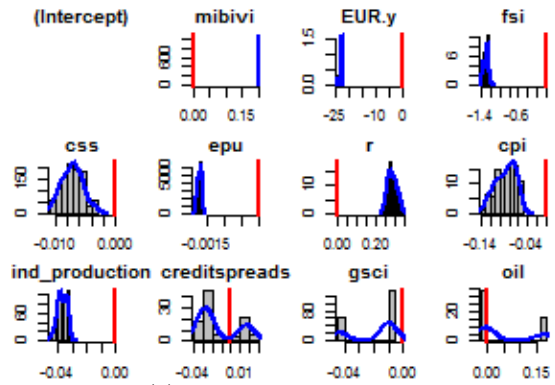
(a) AU stock sophisticated



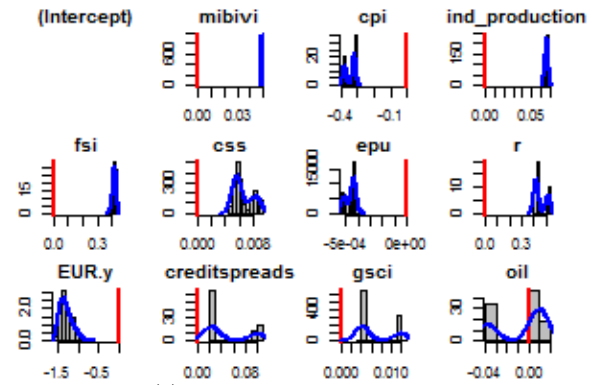
(b) AU bond sophisticated



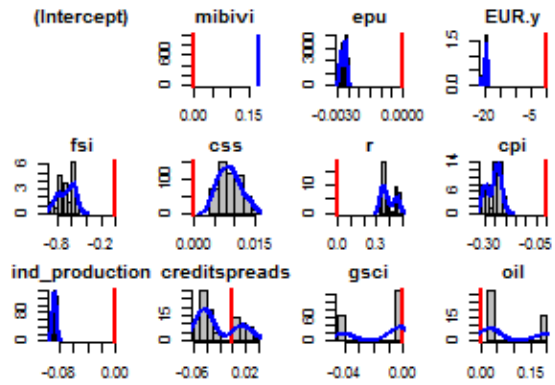
(c) AG stock sophisticated



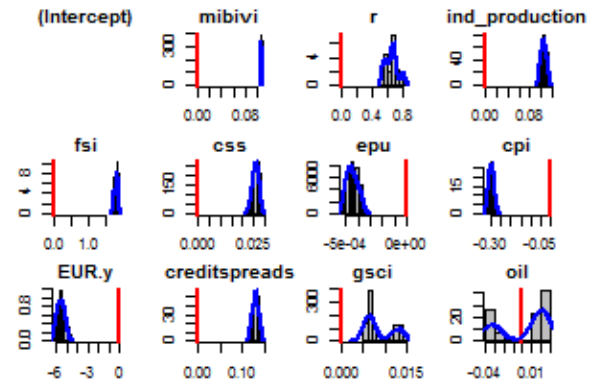
(d) AG bond sophisticated



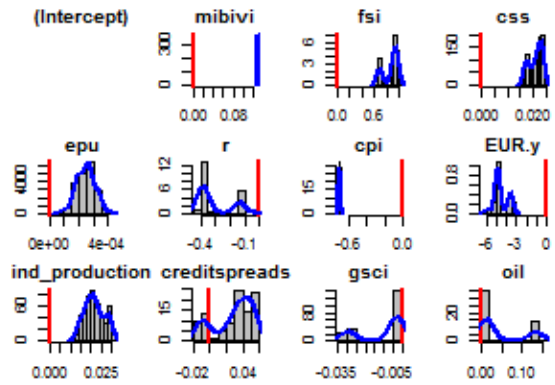
(e) PT stock sophisticated



(f) PT bond sophisticated



(g) PD stock sophisticated



(h) PD bond sophisticated

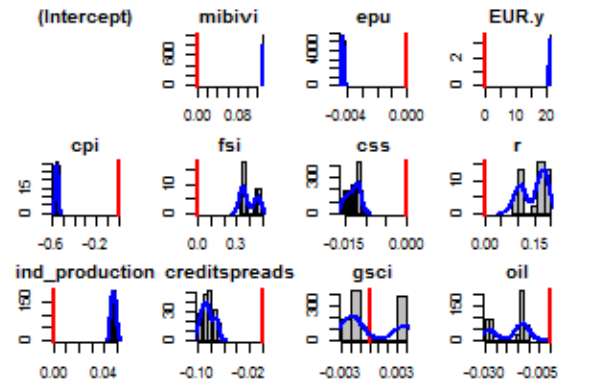
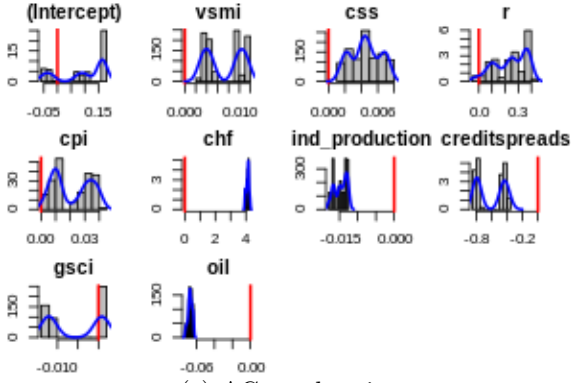
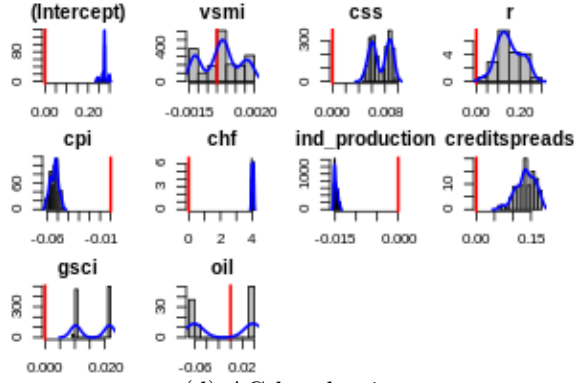


Figure H.11: EBA Naive — Switzerland

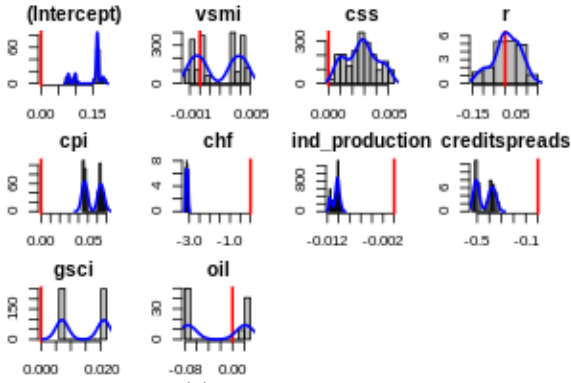
(a) AU stock naive



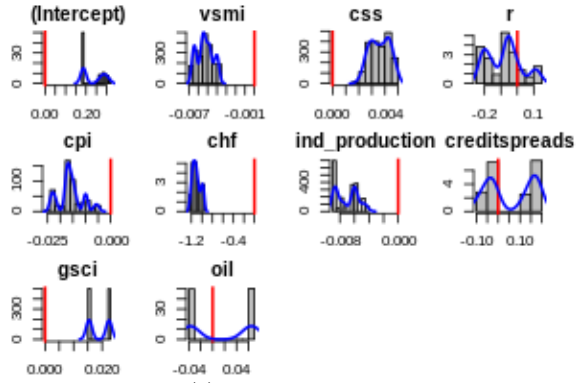
(b) AU bond naive



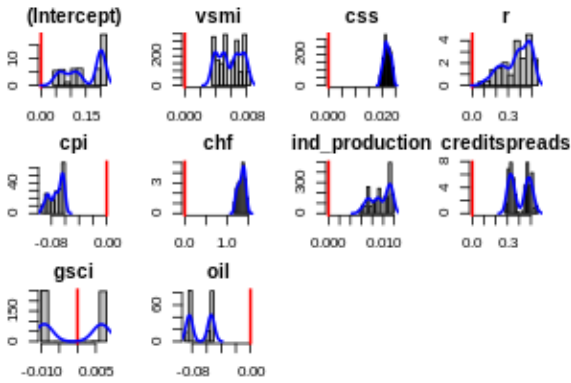
(c) AG stock naive



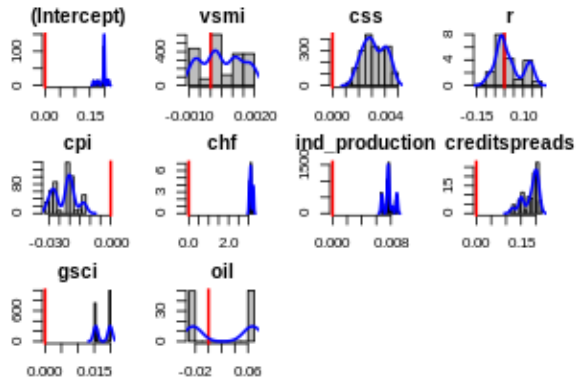
(d) AG bond naive



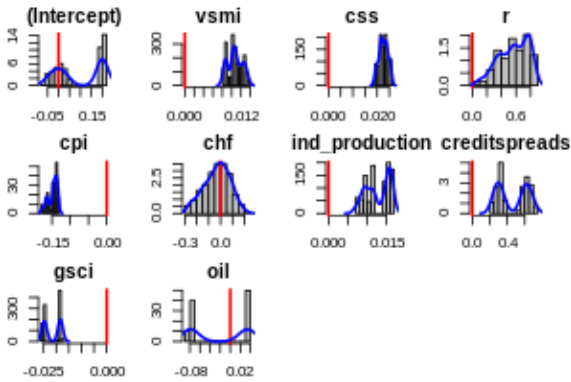
(e) PT stock naive



(f) PT bond naive



(g) PD stock naive



(h) PD bond naive

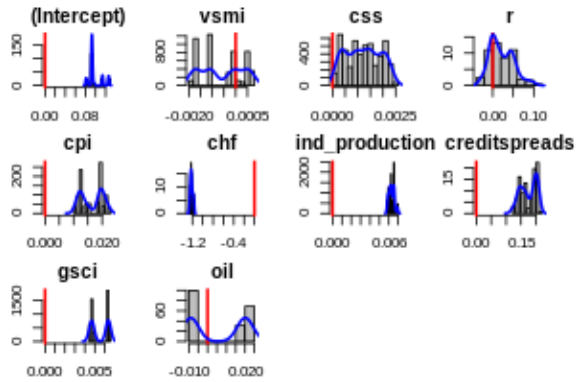
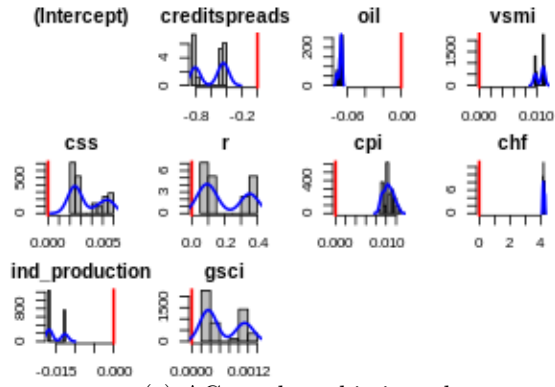
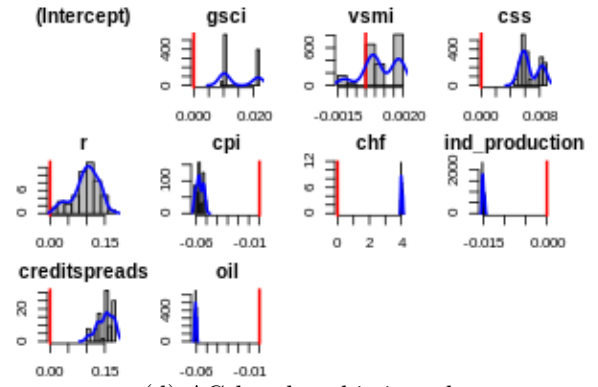


Figure H.12: EBA Sophisticated — Switzerland

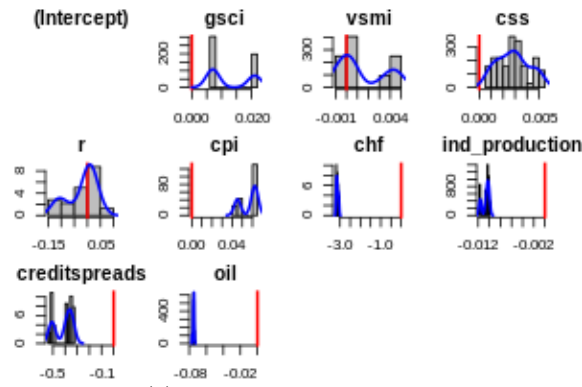
(a) AU stock sophisticated



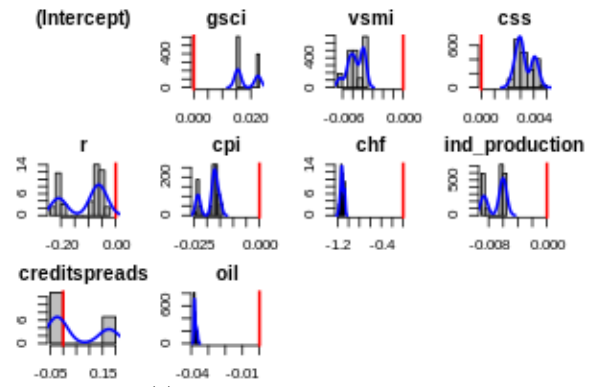
(b) AU bond sophisticated



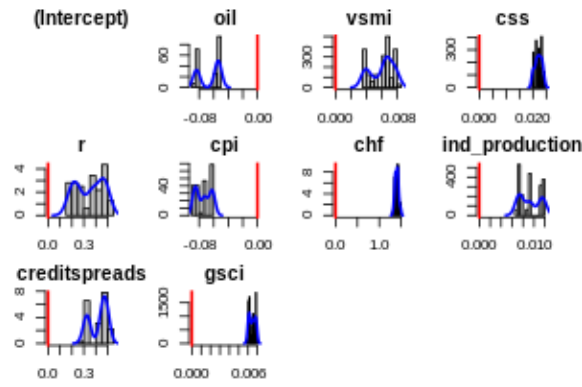
(c) AG stock sophisticated



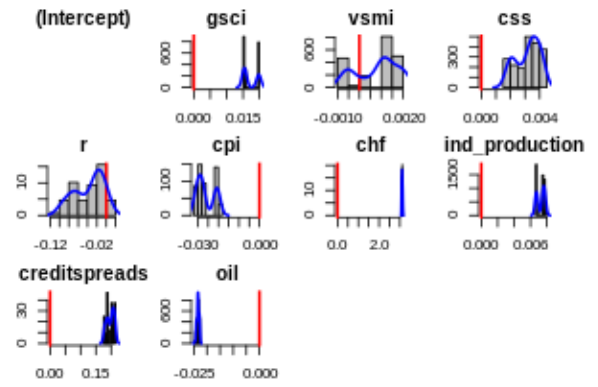
(d) AG bond sophisticated



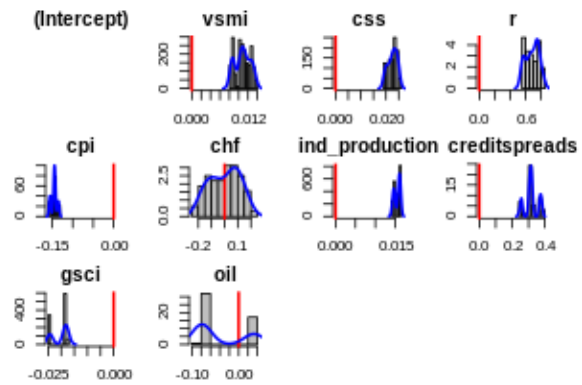
(e) PT stock sophisticated



(f) PT bond sophisticated



(g) PD stock sophisticated



(h) PD bond sophisticated

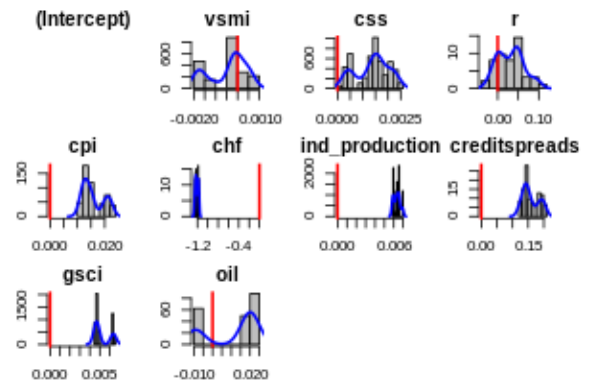
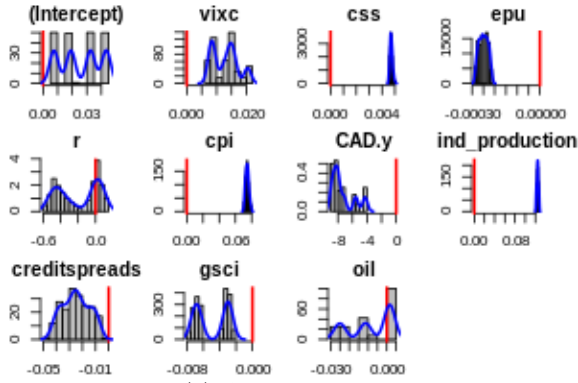
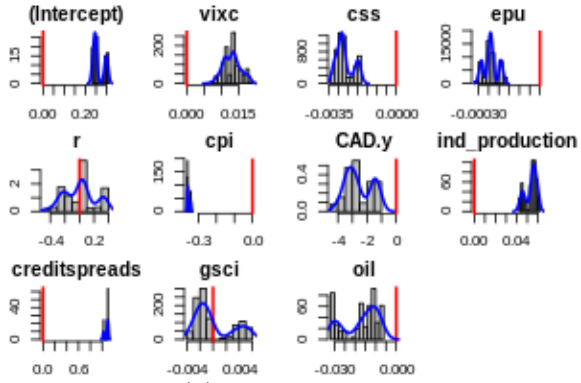


Figure H.13: EBA Naive — Canada

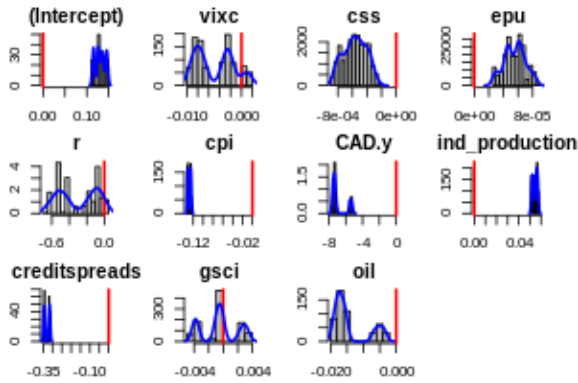
(a) AU stock naive



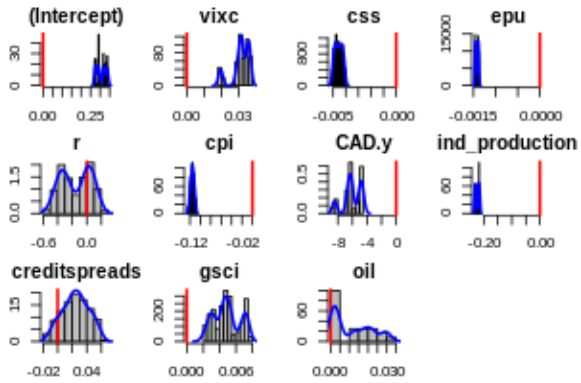
(b) AU bond naive



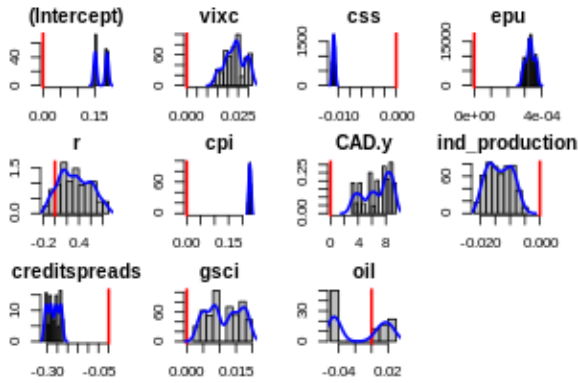
(c) AG stock naive



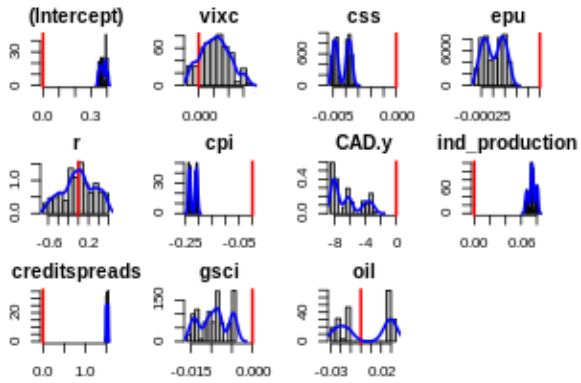
(d) AG bond naive



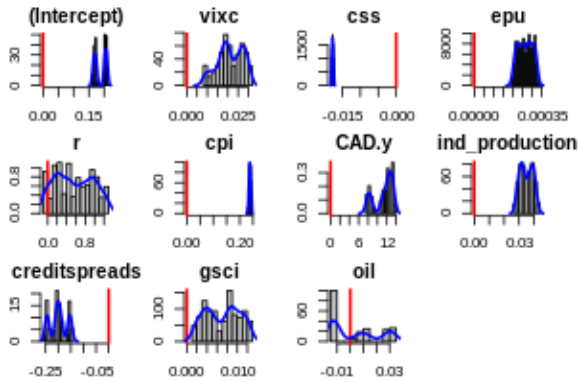
(e) PT stock naive



(f) PT bond naive



(g) PD stock naive



(h) PD bond naive

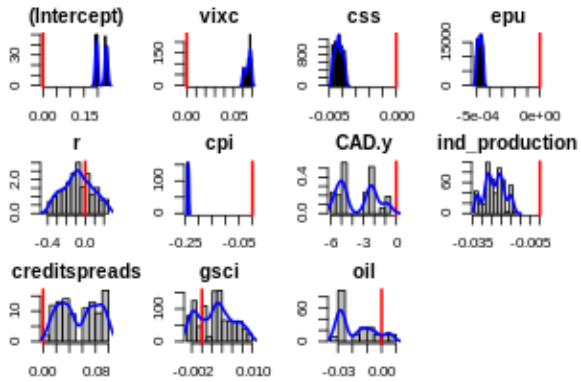
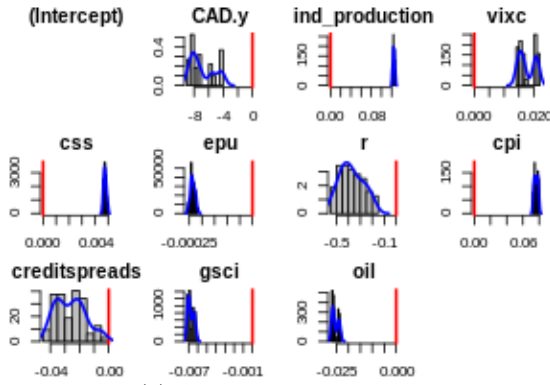
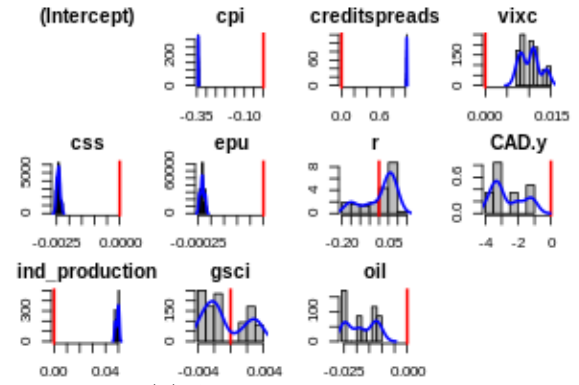


Figure H.14: EBA Sophisticated — Canada

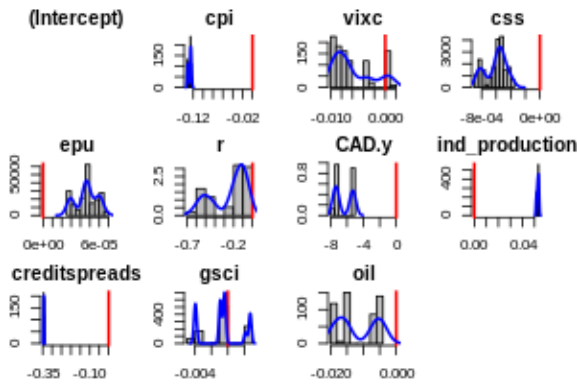
(a) AU stock sophisticated



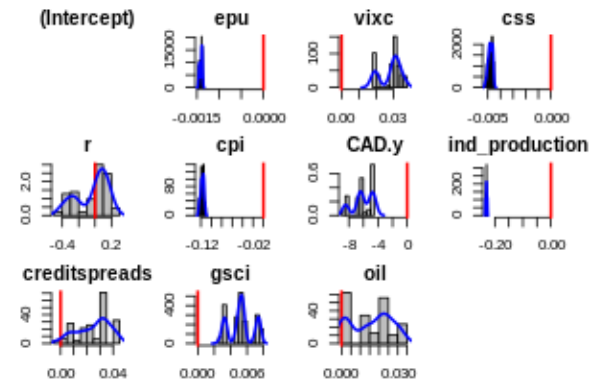
(b) AU bond sophisticated



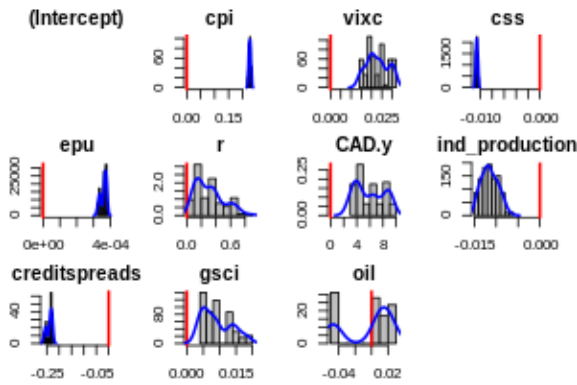
(c) AG stock sophisticated



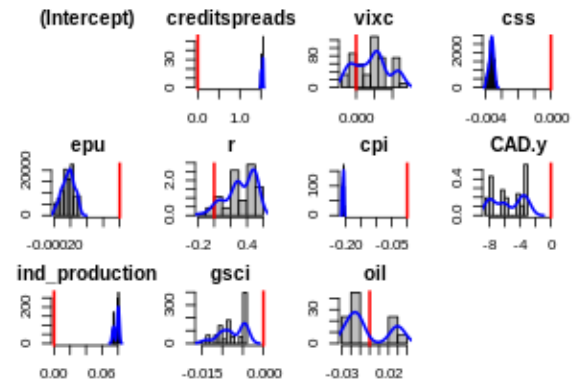
(d) AG bond sophisticated



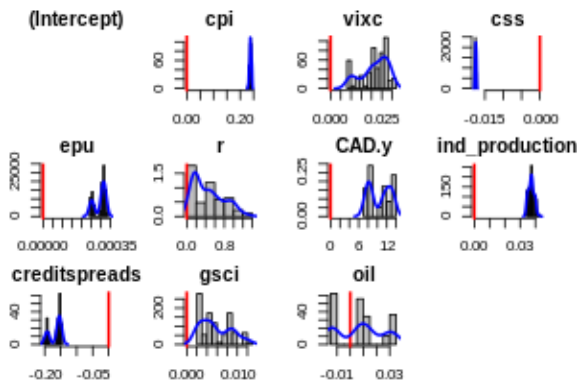
(e) PT stock sophisticated



(f) PT bond sophisticated



(g) PD stock sophisticated



(h) PD bond sophisticated

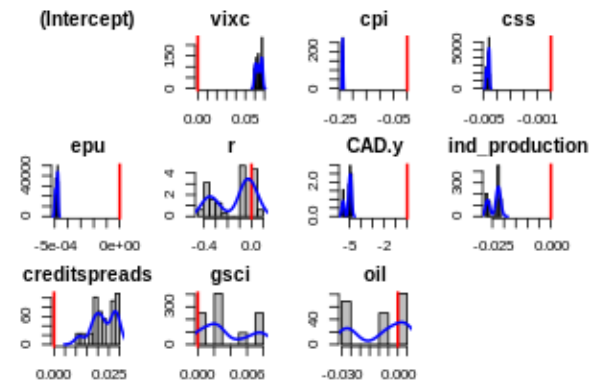


Figure H.15: EBA Naive — Japan

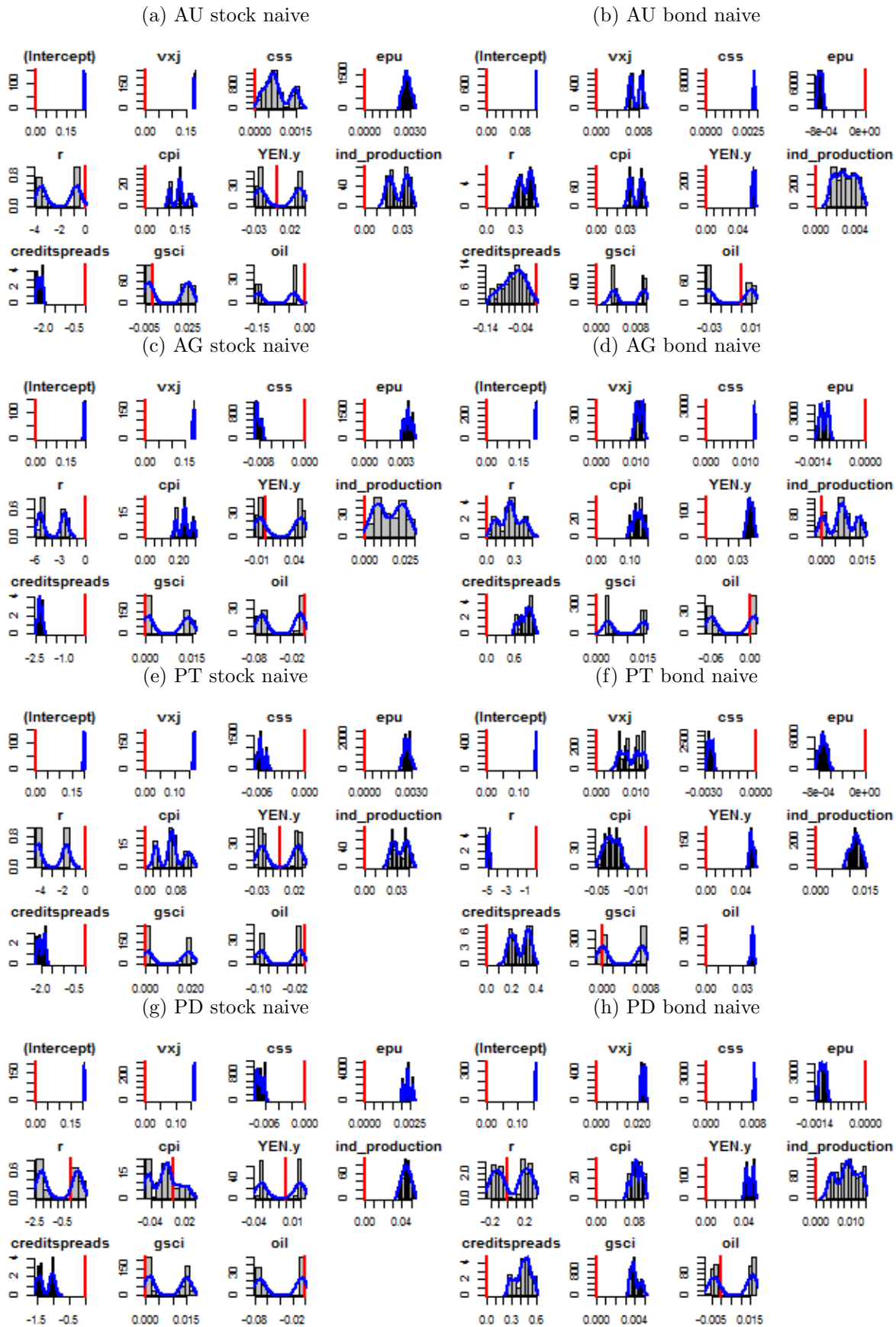
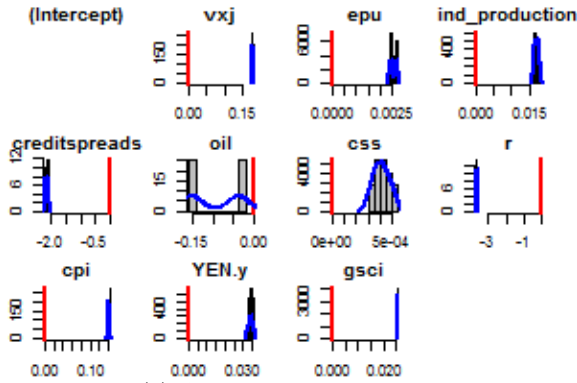
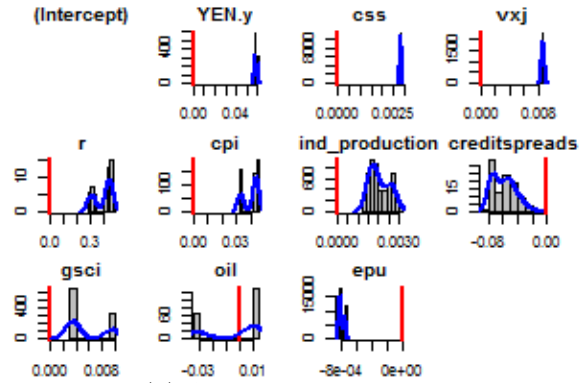


Figure H.16: EBA Sophisticated — Japan

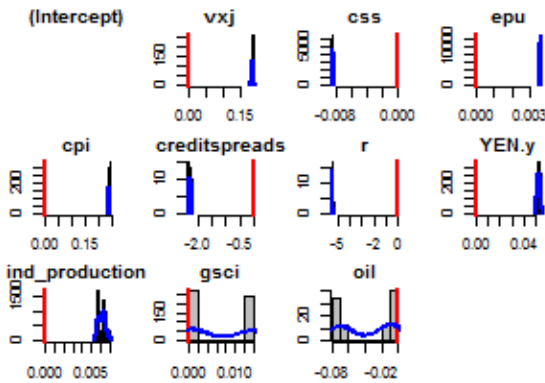
(a) AU stock sophisticated



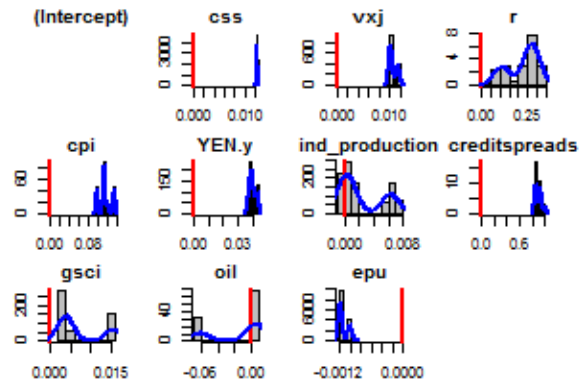
(b) AU bond sophisticated



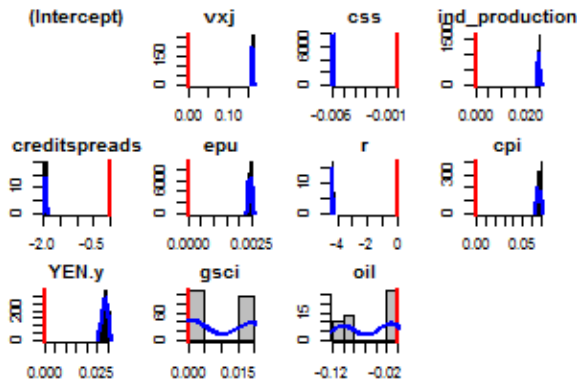
(c) AG stock sophisticated



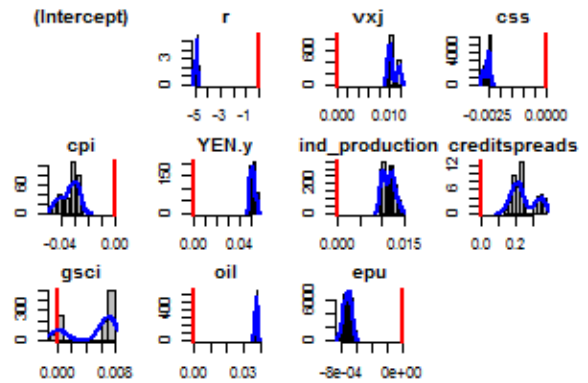
(d) AG bond sophisticated



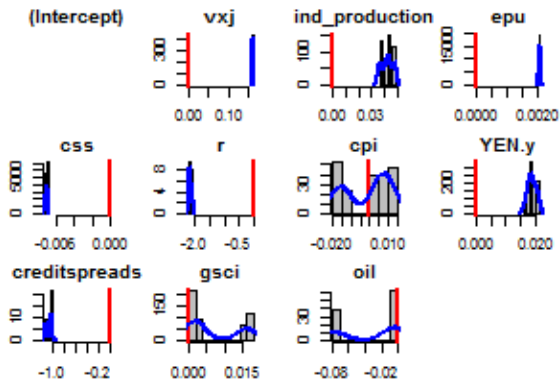
(e) PT stock sophisticated



(f) PT bond sophisticated



(g) PD stock sophisticated



(h) PD bond sophisticated

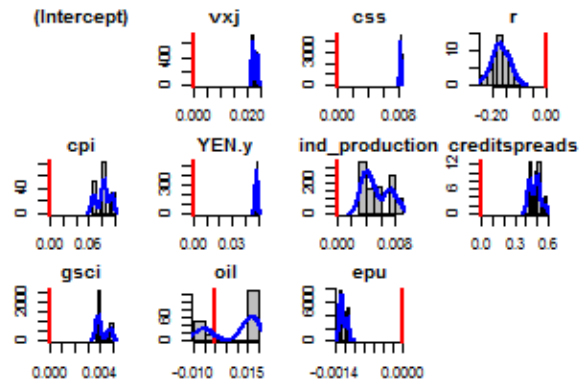


Figure H.17: EBA Naive — China

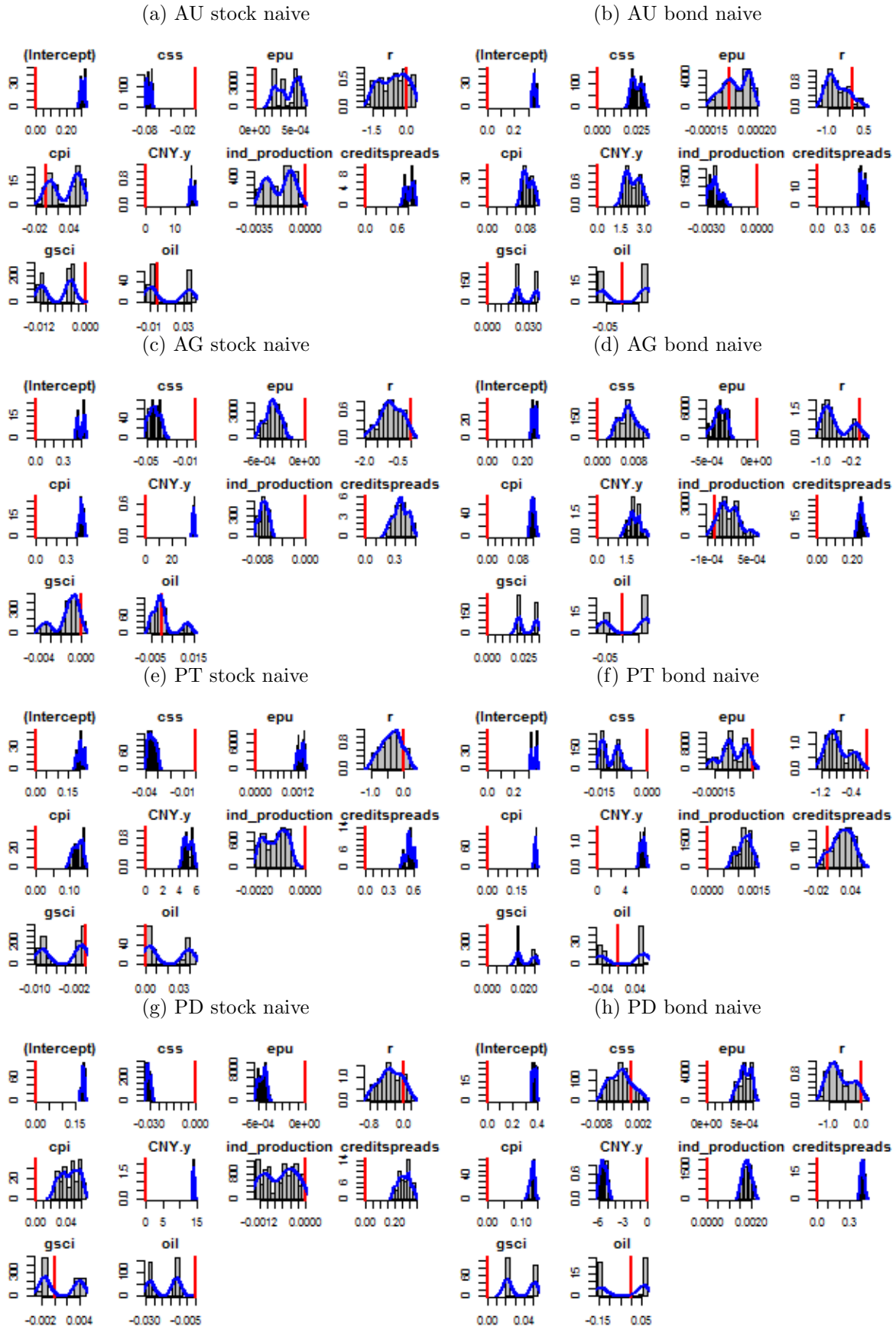
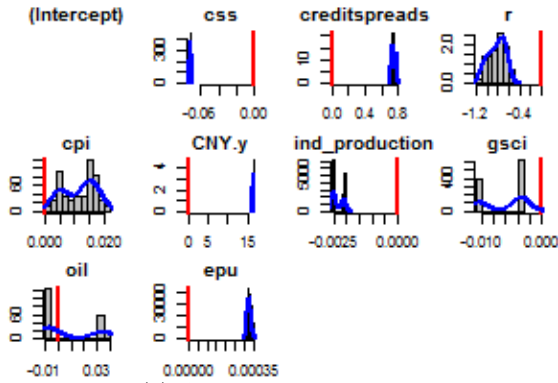
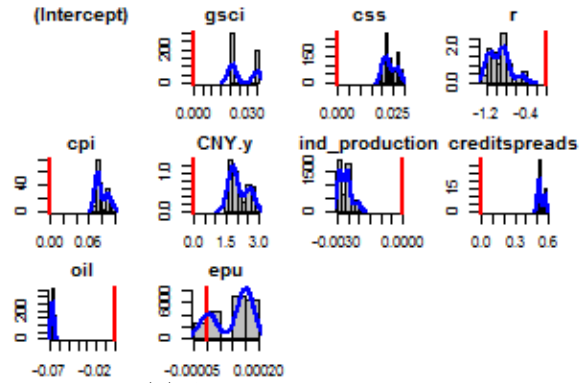


Figure H.18: EBA Sophisticated — China

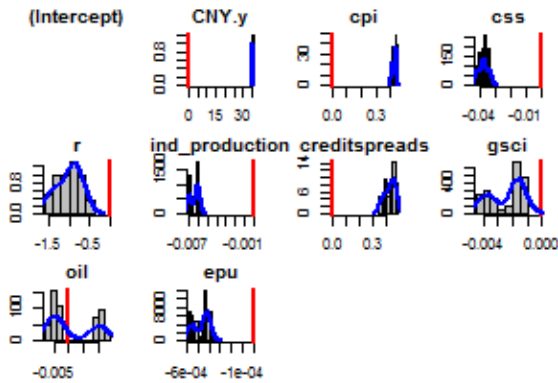
(a) AU stock sophisticated



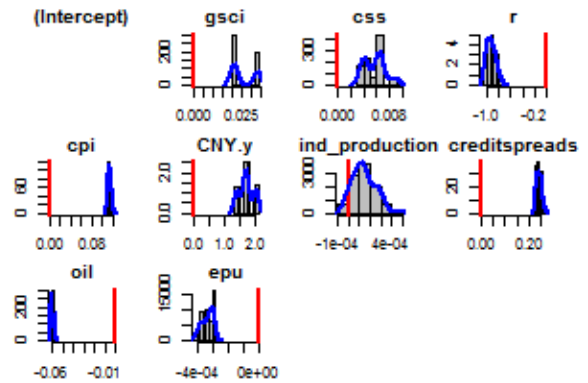
(b) AU bond sophisticated



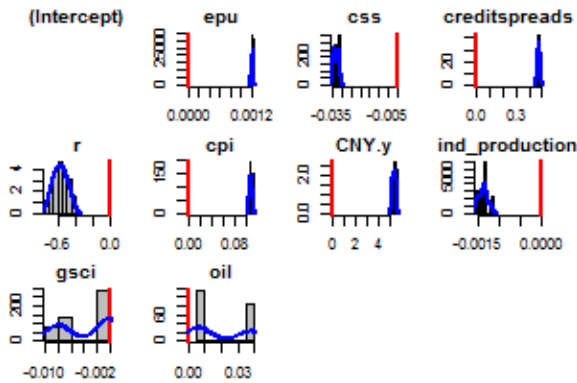
(c) AG stock sophisticated



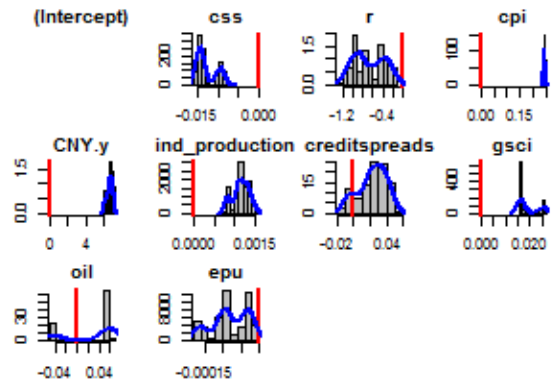
(d) AG bond sophisticated



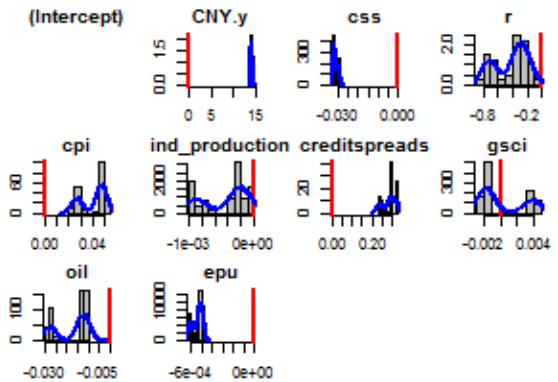
(e) PT stock sophisticated



(f) PT bond sophisticated



(g) PD stock sophisticated



(h) PD bond sophisticated

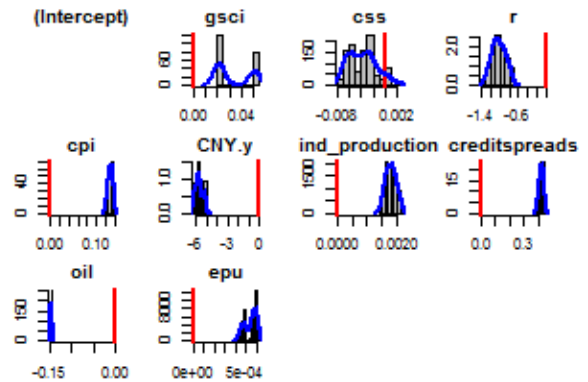
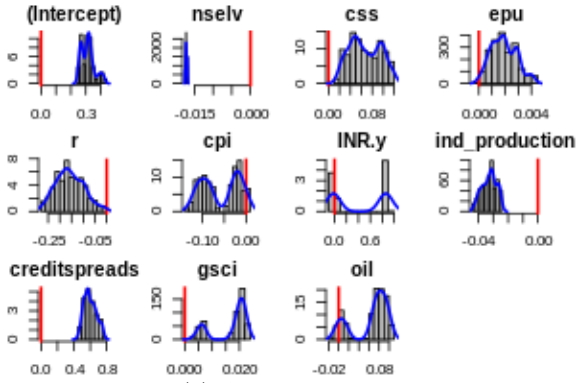
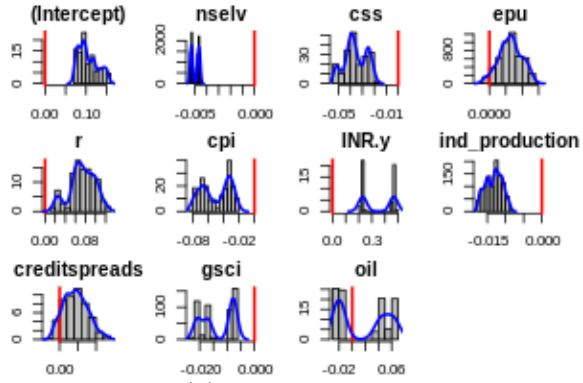


Figure H.19: EBA Naive — India

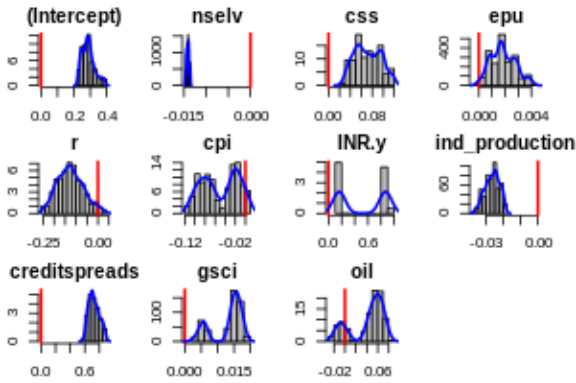
(a) AU stock naive



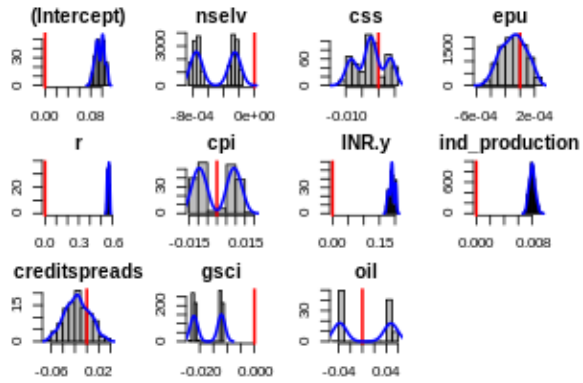
(b) AU bond naive



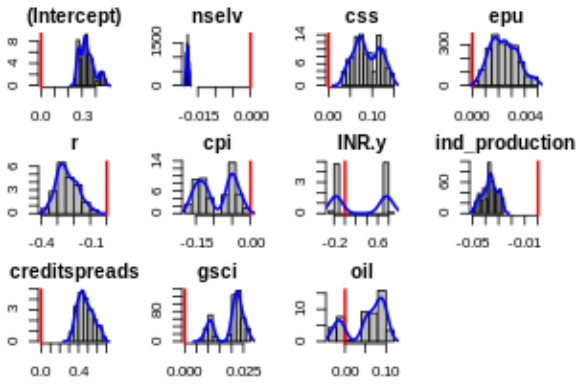
(c) AG stock naive



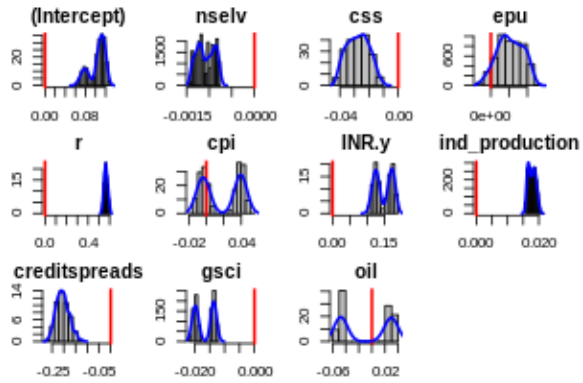
(d) AG bond naive



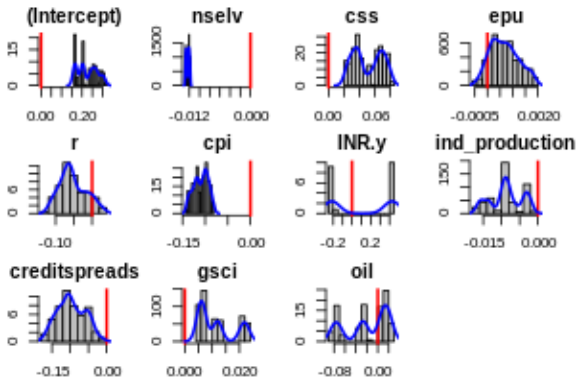
(e) PT stock naive



(f) PT bond naive



(g) PD stock naive



(h) PD bond naive

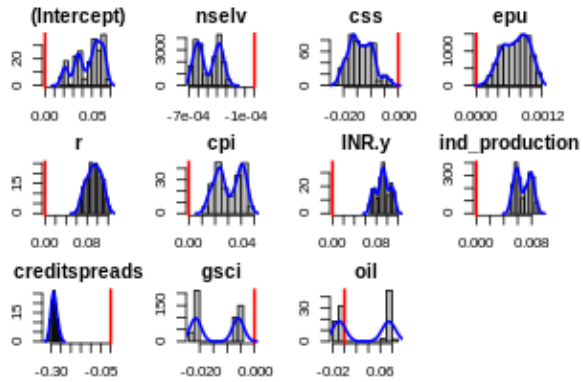
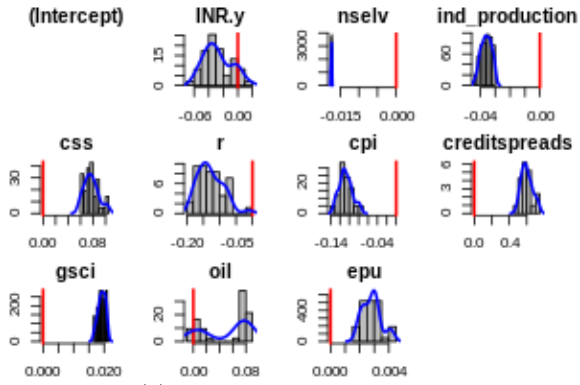
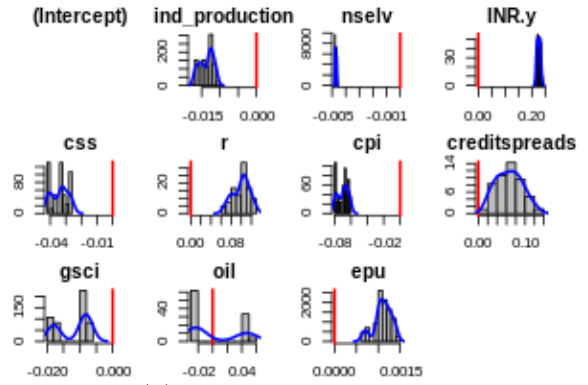


Figure H.20: EBA Sophisticated — India

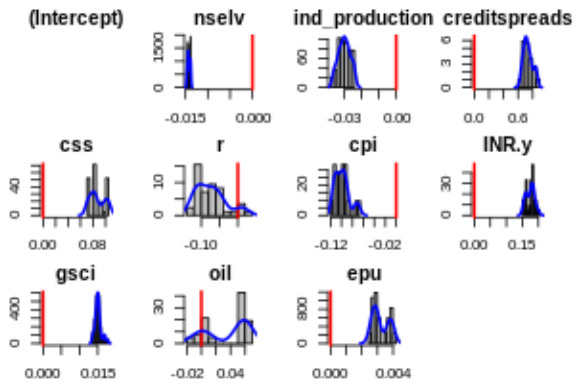
(a) AU stock sophisticated



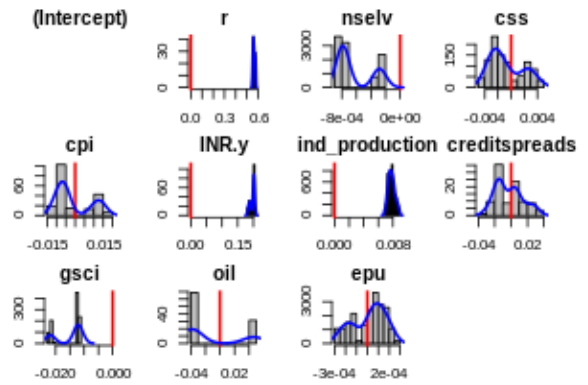
(b) AU bond sophisticated



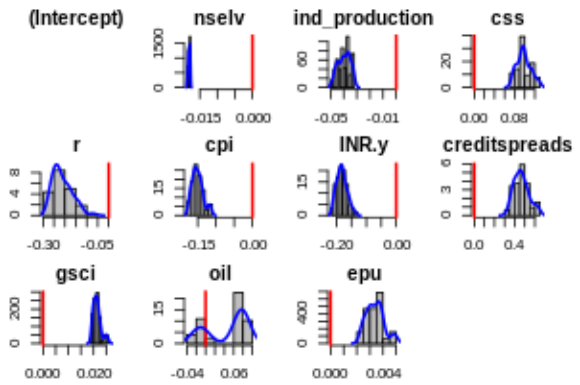
(c) AG stock sophisticated



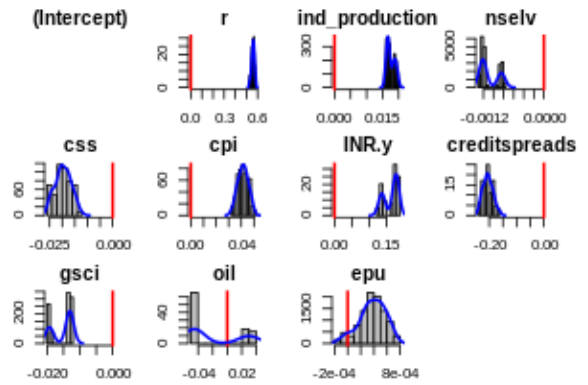
(d) AG bond sophisticated



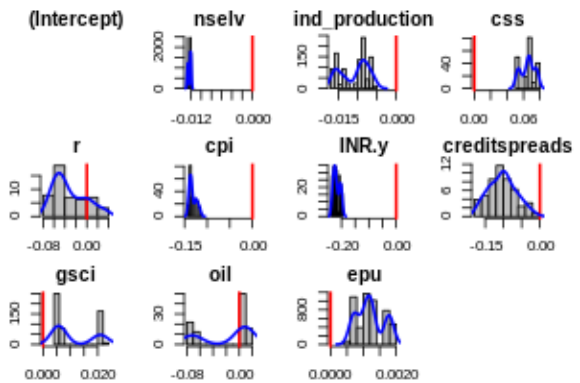
(e) PT stock sophisticated



(f) PT bond sophisticated



(g) PD stock sophisticated



(h) PD bond sophisticated

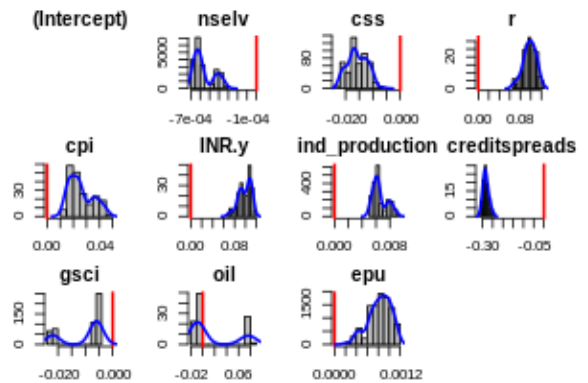
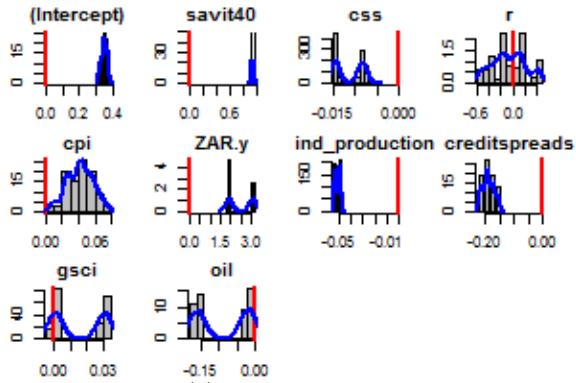
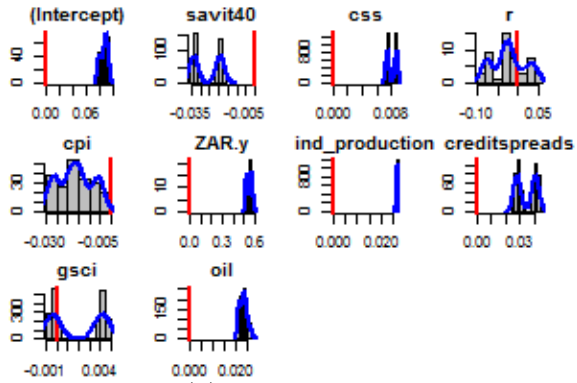


Figure H.21: EBA Naive — South Africa

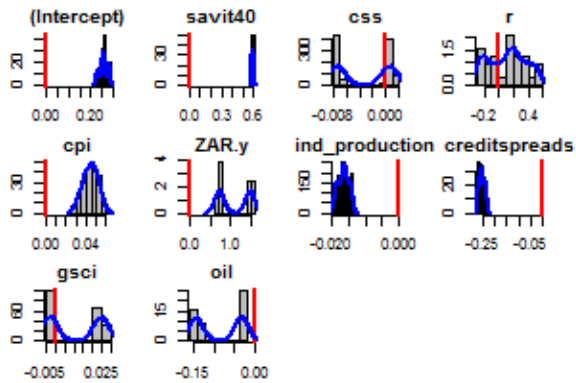
(a) AU stock naive



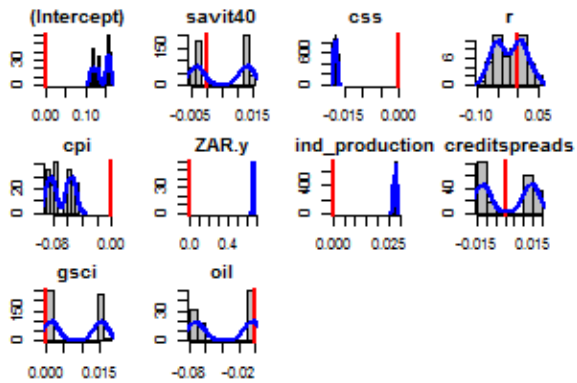
(b) AU bond naive



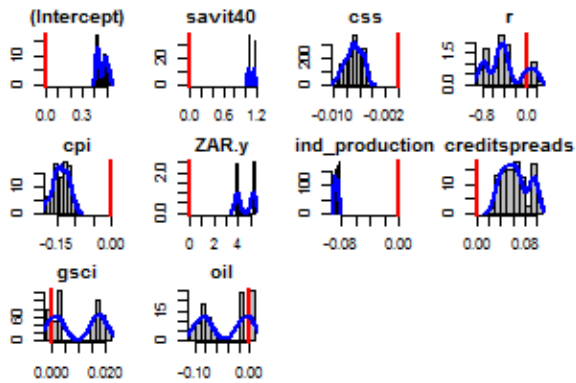
(c) AG stock naive



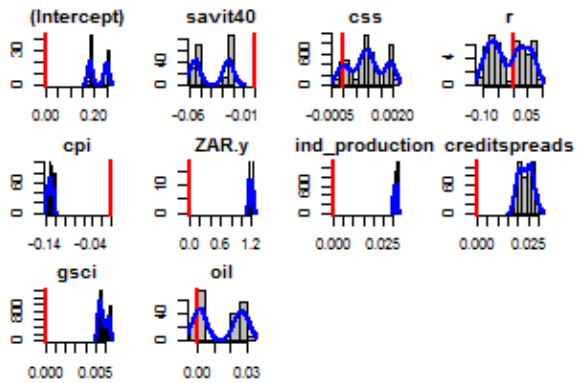
(d) AG bond naive



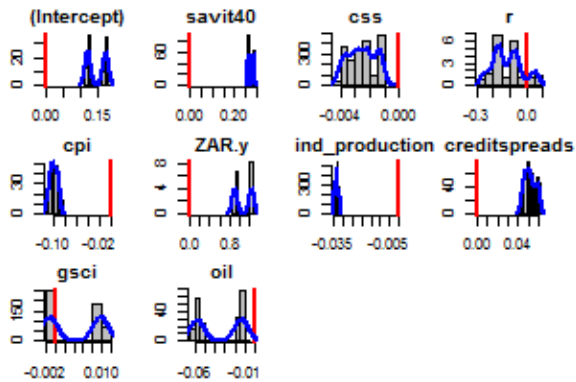
(e) PT stock naive



(f) PT bond naive



(g) PD stock naive



(h) PD bond naive

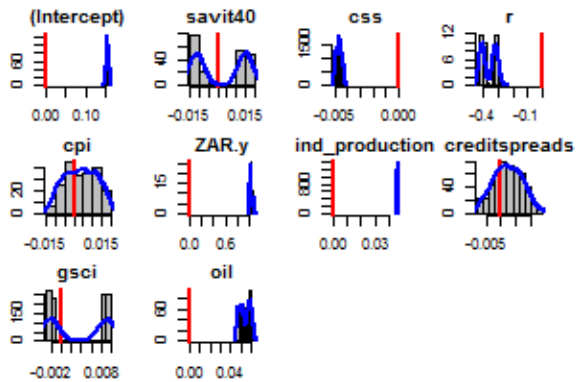
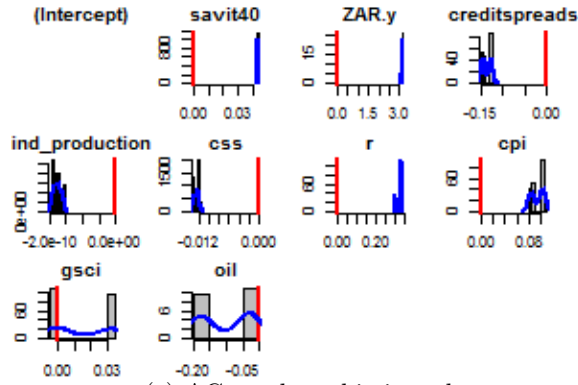
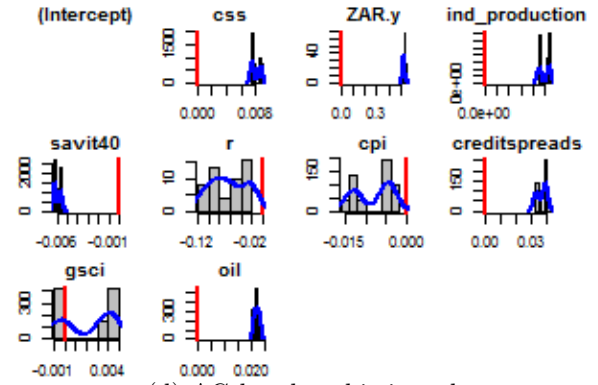


Figure H.22: EBA Sophisticated — South Africa

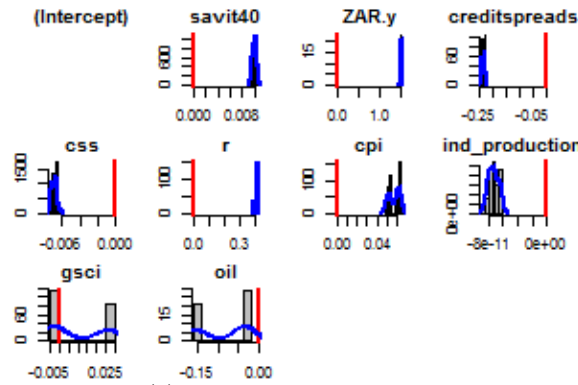
(a) AU stock sophisticated



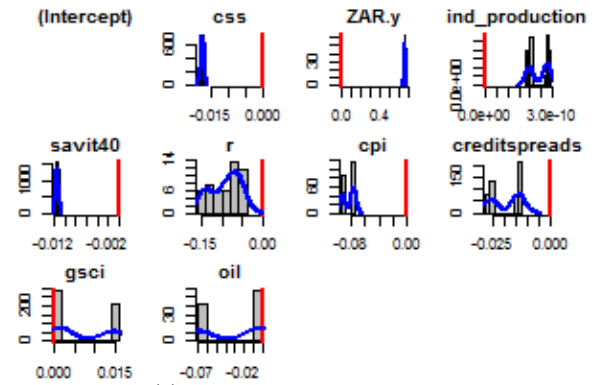
(b) AU bond sophisticated



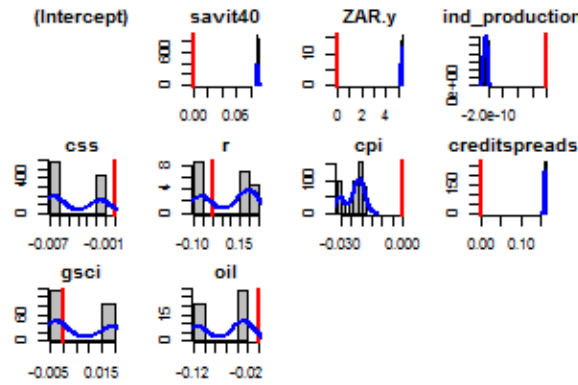
(c) AG stock sophisticated



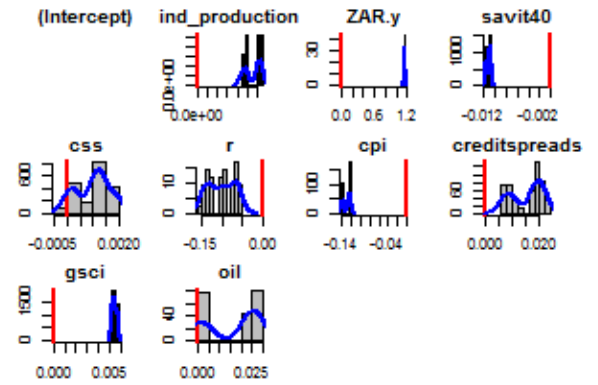
(d) AG bond sophisticated



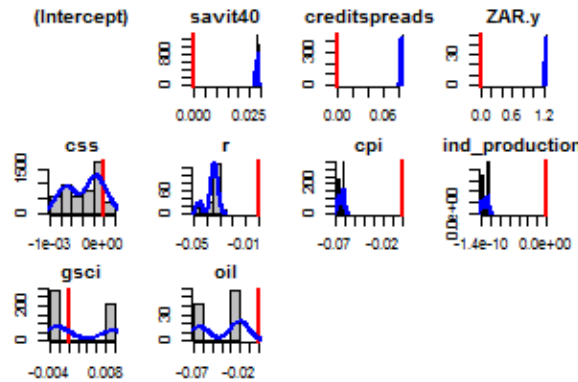
(e) PT stock sophisticated



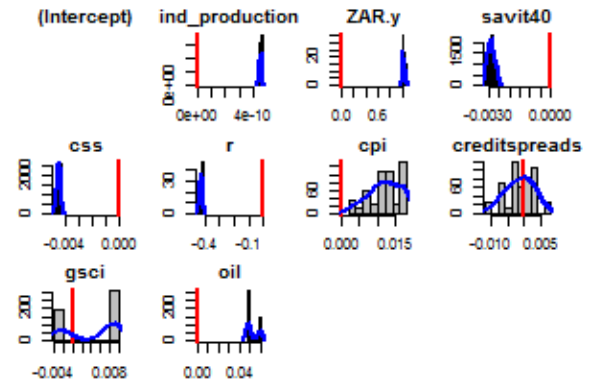
(f) PT bond sophisticated



(g) PD stock sophisticated



(h) PD bond sophisticated

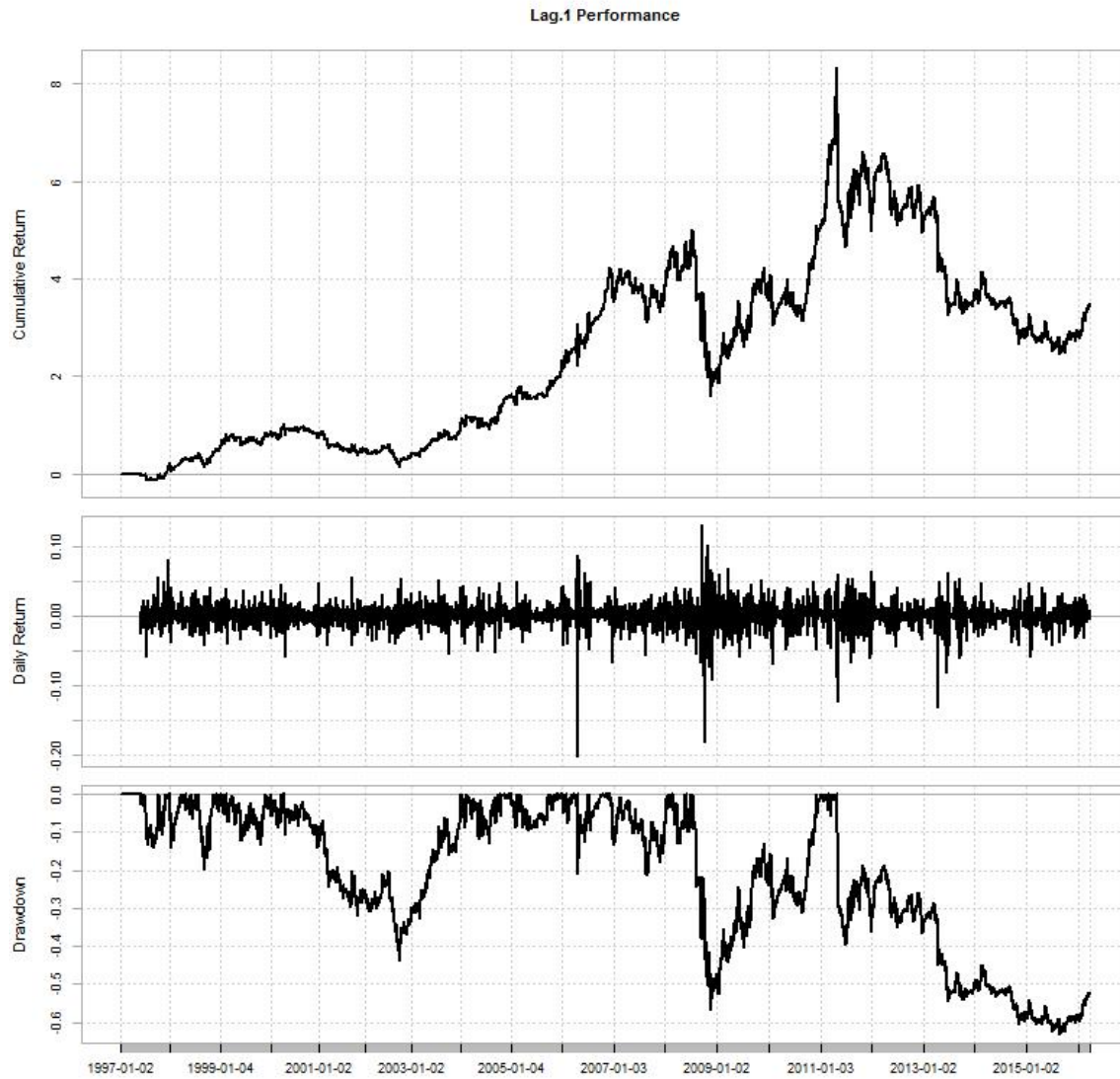


Appendix I

Portfolio Performance Plots

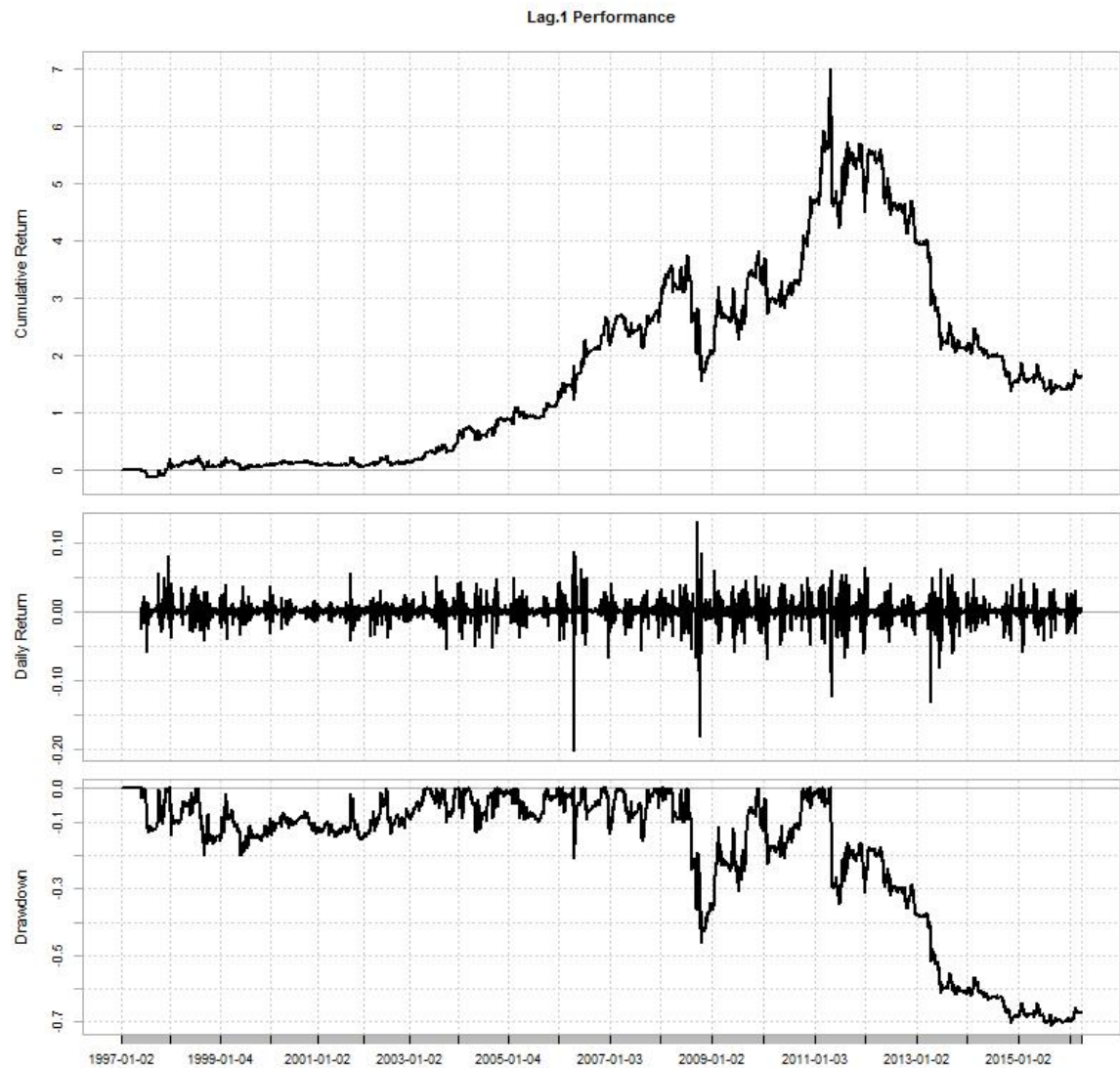
A set of portfolio performance plots obtained in the Chapter 6 Determinants of Precious Metals as Safe Haven Section 4 Portfolio Analysis is included here.

Figure I.1: US Stock and Silver Portfolio Performance Summary - EPU Long Only MACD Strategy



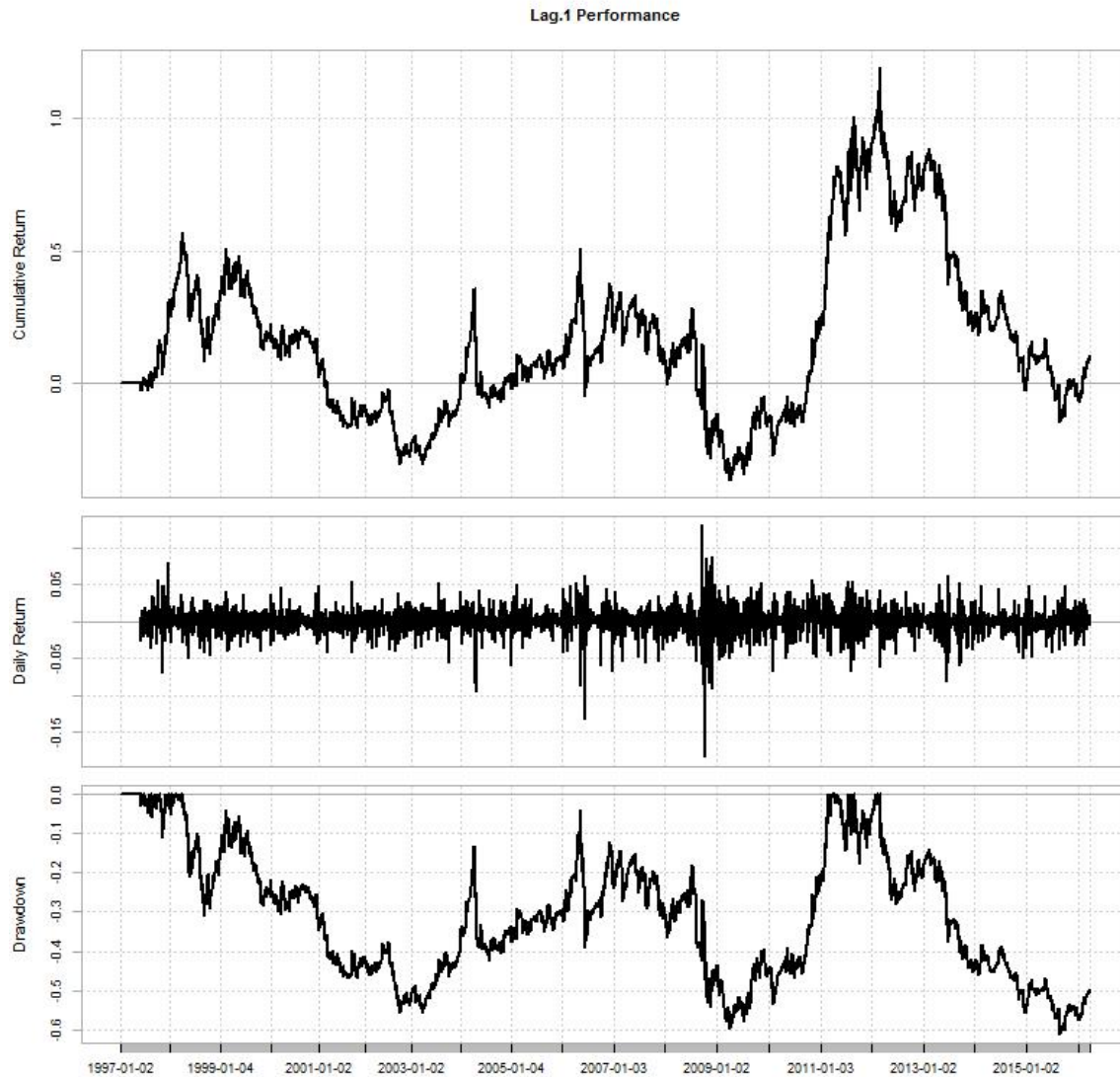
- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure I.2: US Stock and Silver Portfolio Performance Summary - Stock Volatility Long Only MACD Strategy



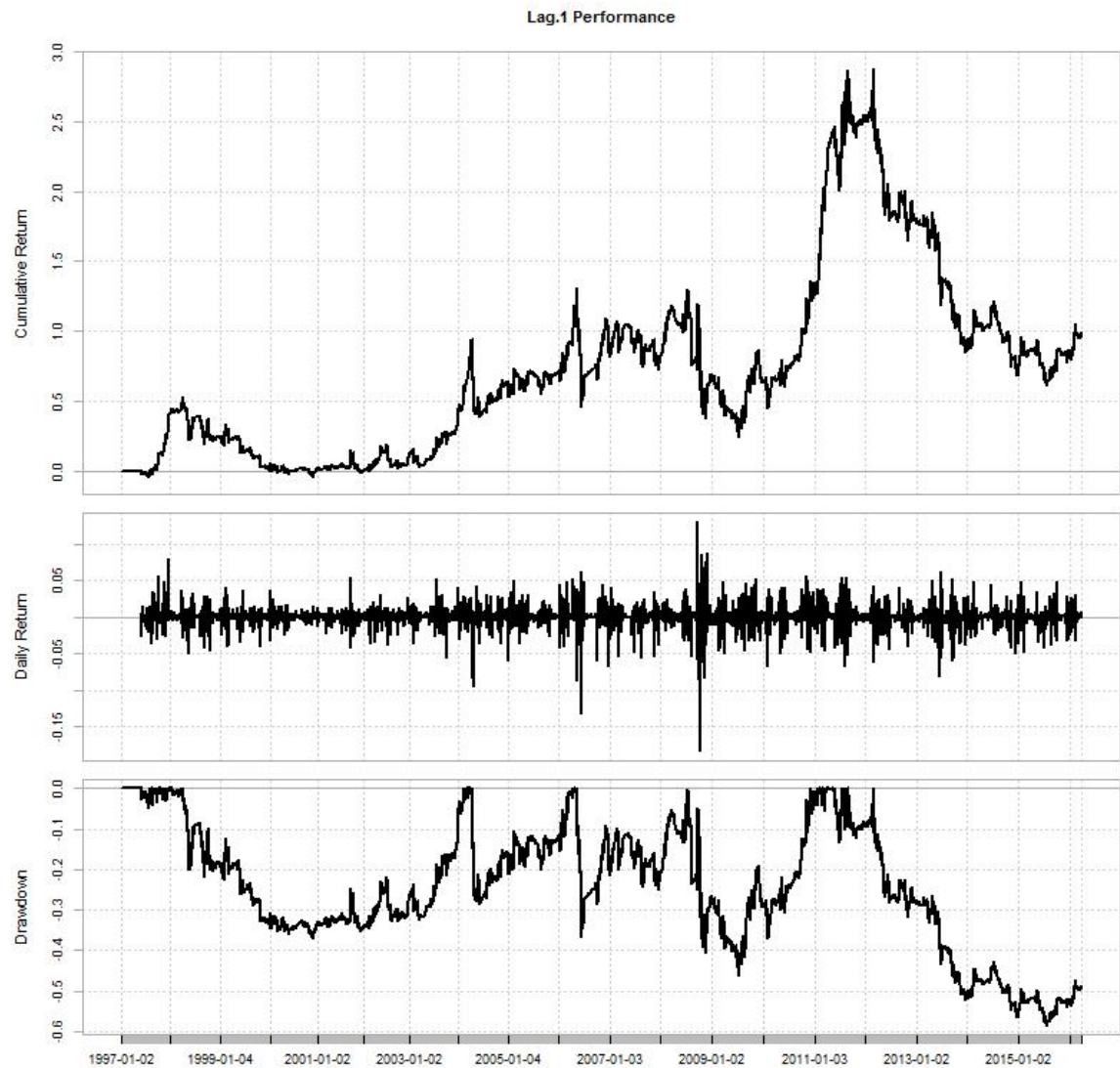
- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure I.3: US Bond and Silver Portfolio Performance Summary - EPU Long Only MACD Strategy



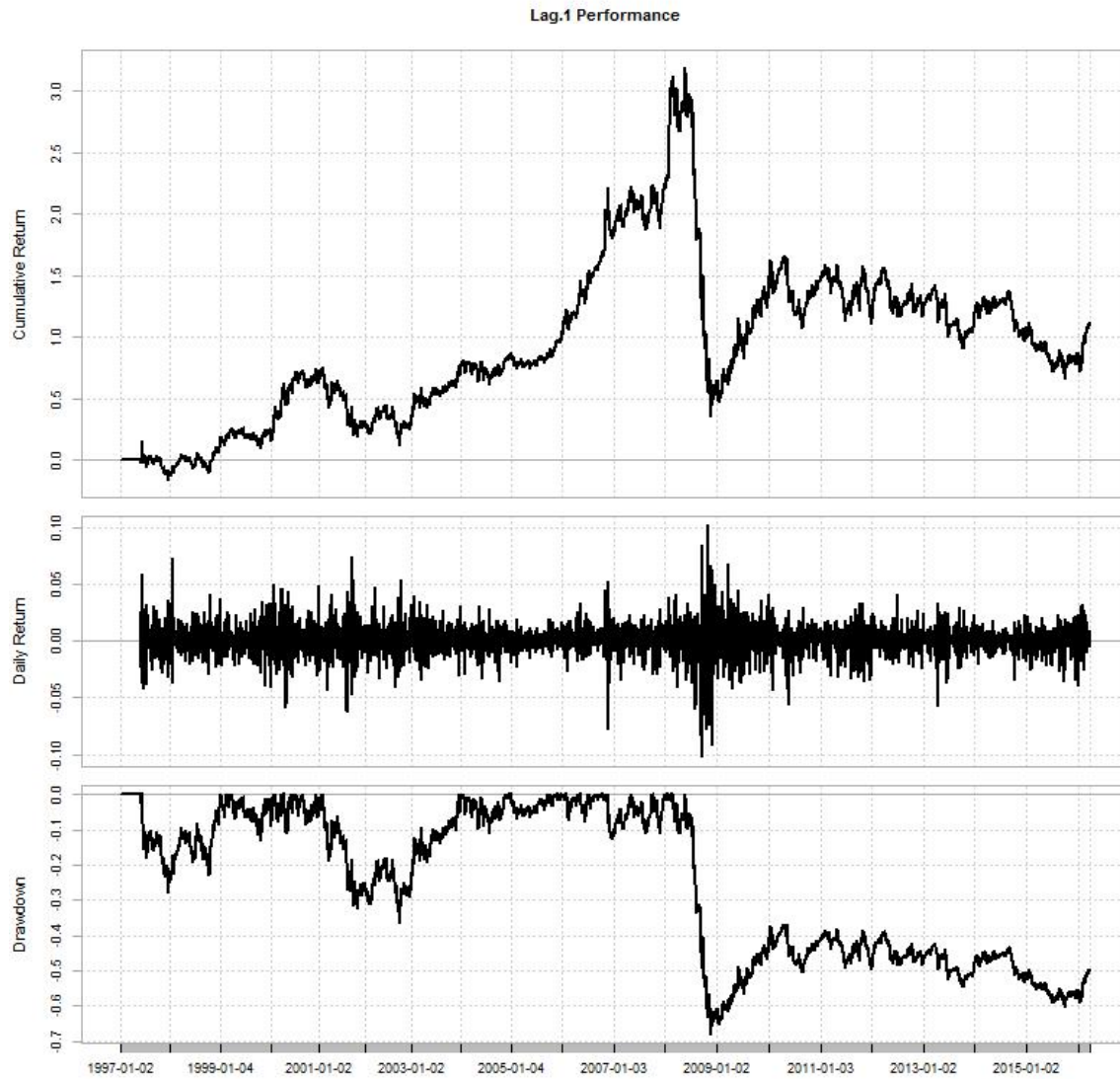
- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure I.4: US Bond and Silver Portfolio Performance Summary - Stock Volatility Long Only MACD Strategy



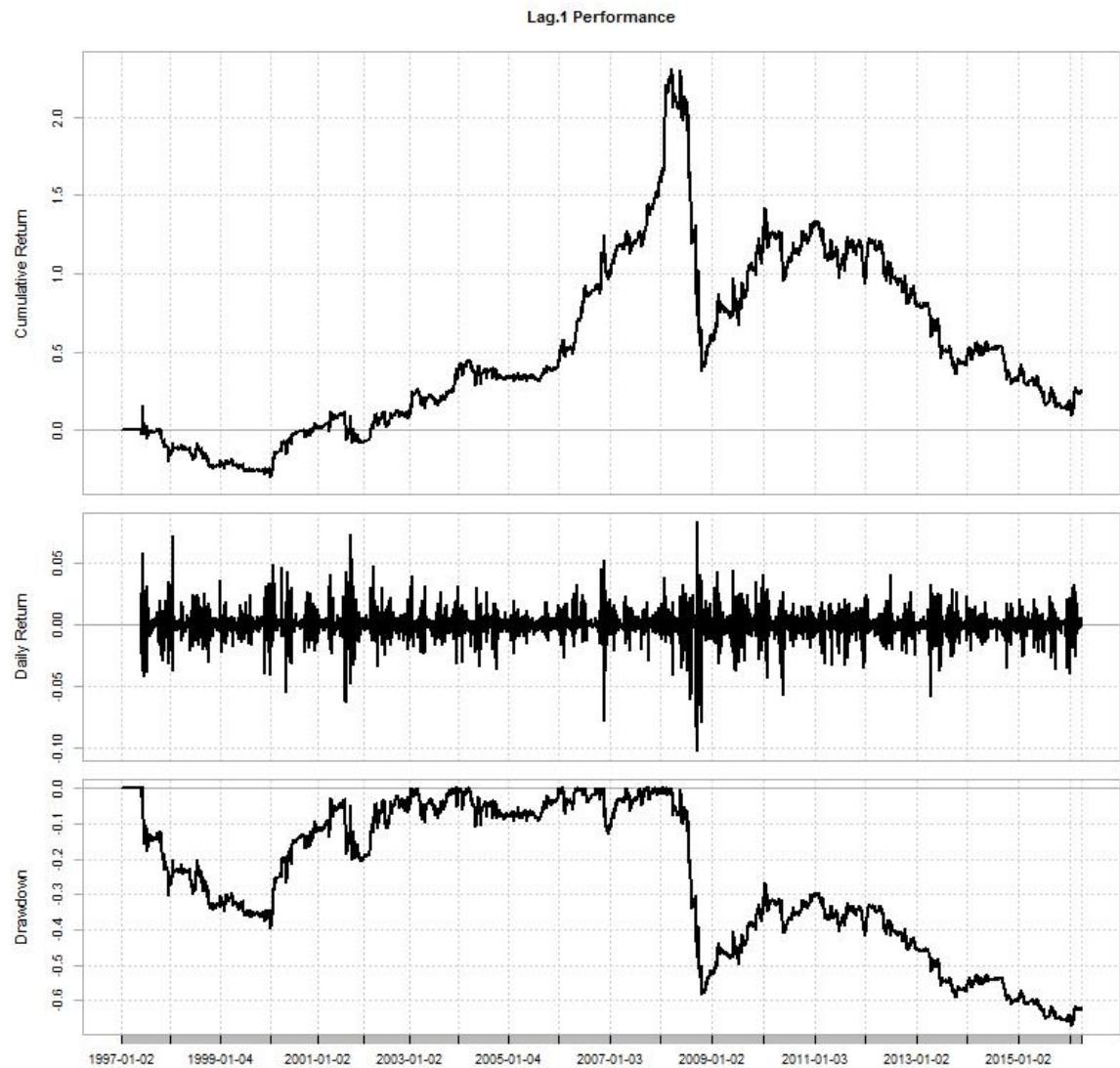
- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at T-1.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure I.5: US Stock and Platinum Portfolio Performance Summary - EPU Long Only MACD Strategy



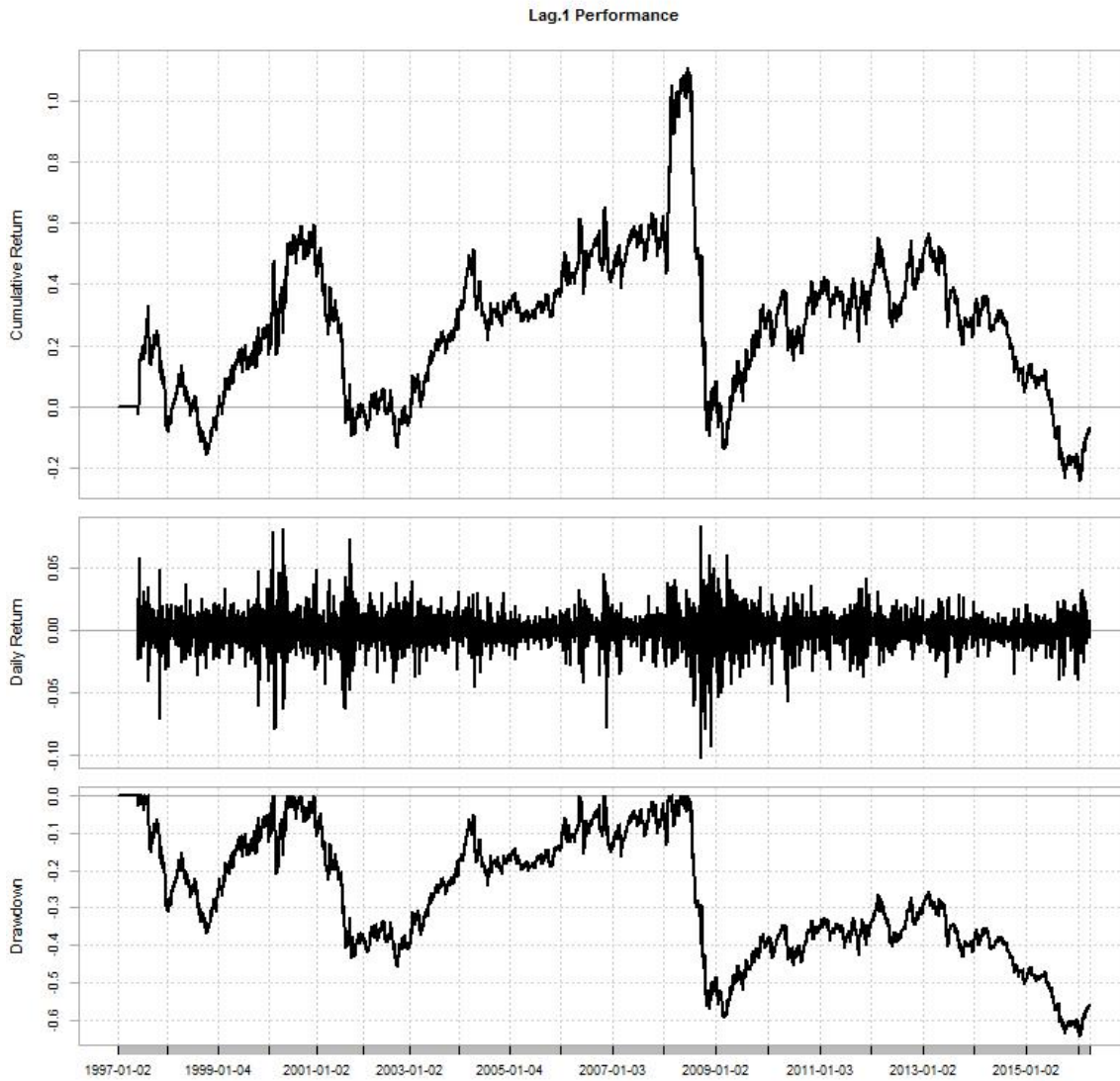
- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure I.6: US Stock and Platinum Portfolio Performance Summary - Stock Volatility Long Only MACD Strategy



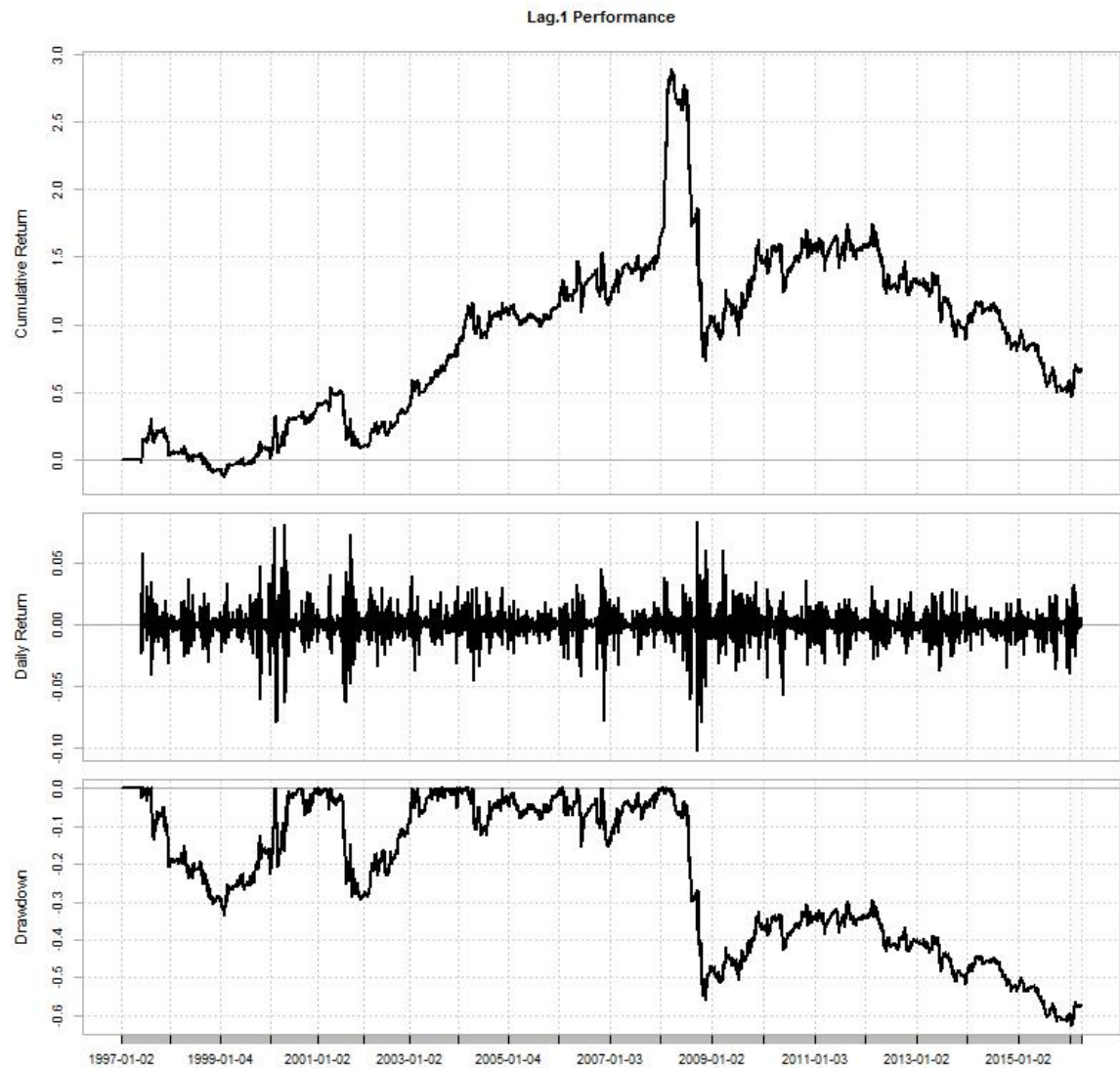
- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure I.7: US Bond and Platinum Portfolio Performance Summary - EPU Long Only MACD Strategy



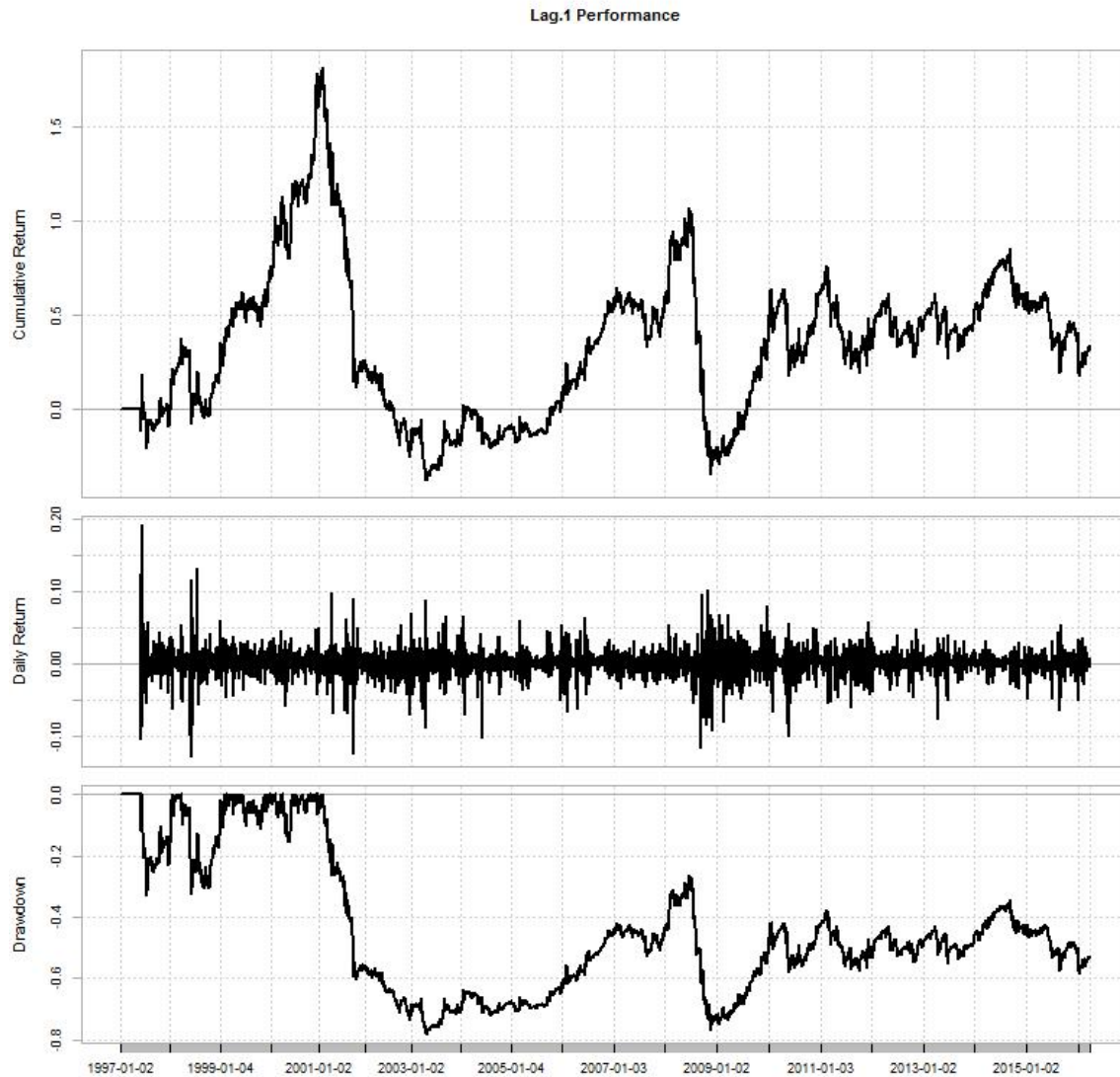
- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure I.8: US Bond and Platinum Portfolio Performance Summary - Stock Volatility Long Only MACD Strategy



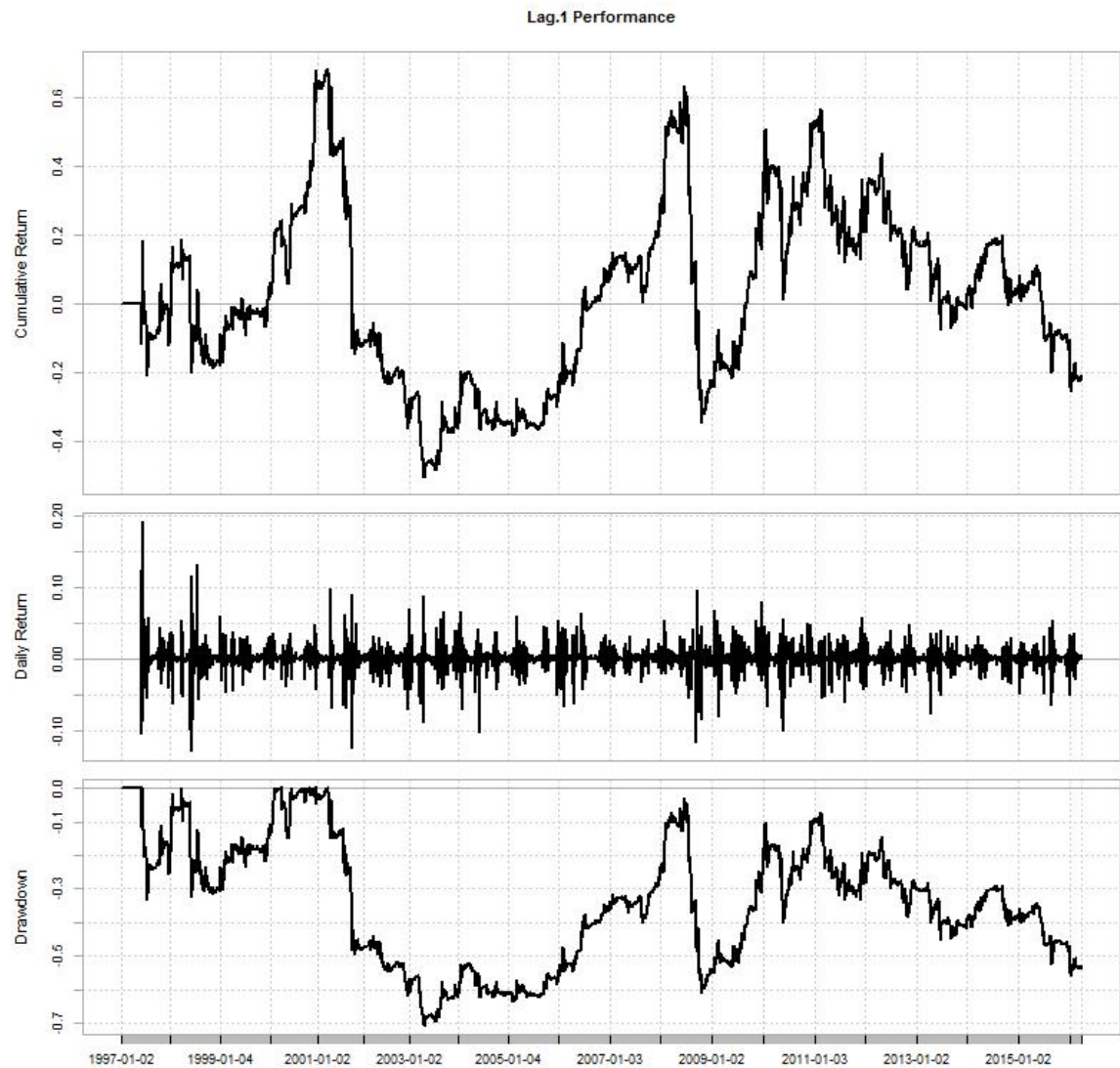
- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure I.9: US Stock and Palladium Portfolio Performance Summary - EPU Long Only MACD Strategy



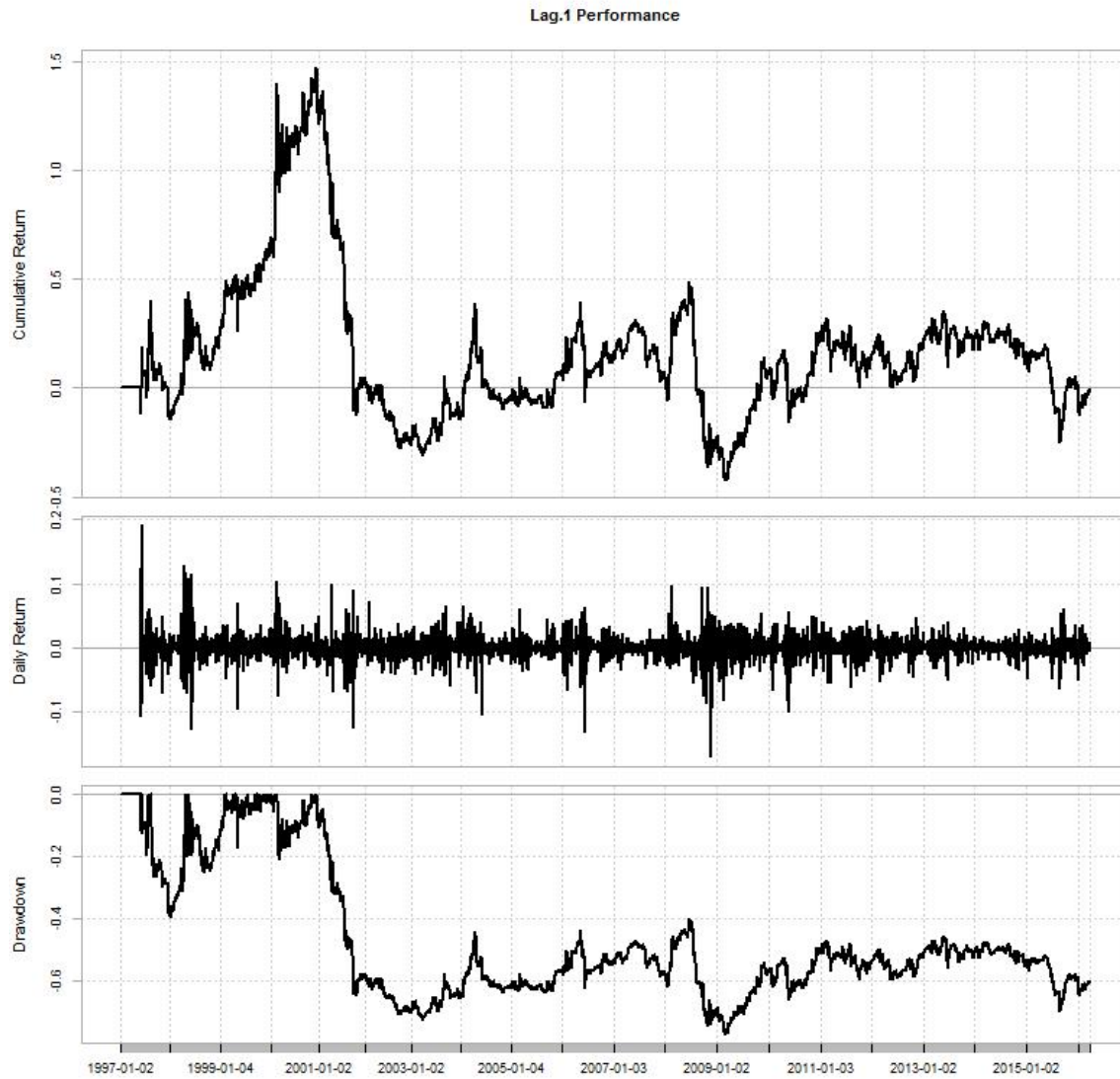
- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure I.10: US Stock and Palladium Portfolio Performance Summary - Stock Volatility Long Only MACD Strategy



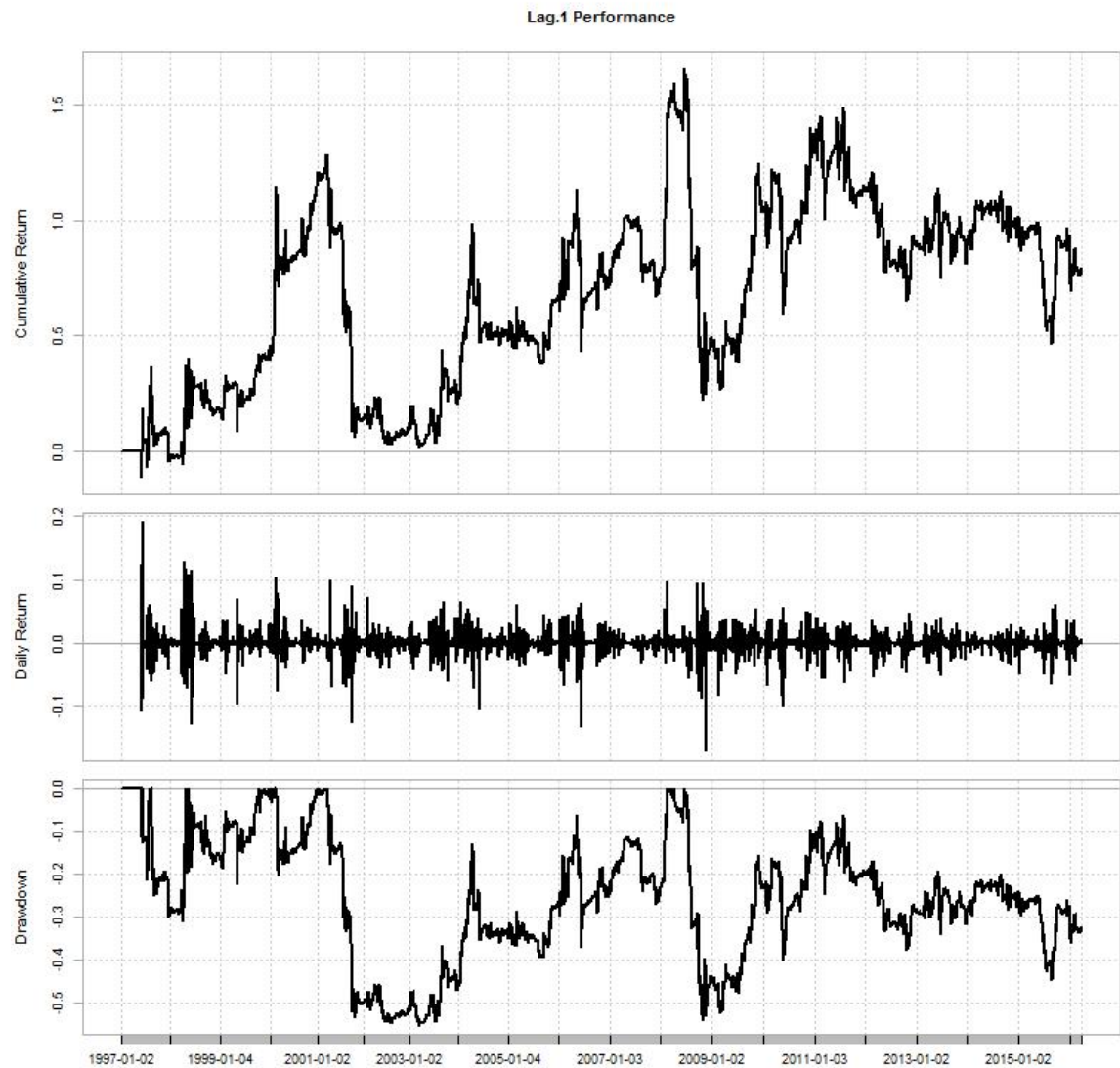
- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure I.11: US Bond and Palladium Portfolio Performance Summary - EPU Long Only MACD Strategy



- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Figure I.12: US Bond and Palladium Portfolio Performance Summary - Stock Volatility Long Only MACD Strategy



- Lag.1 performance refers to that signal at T is calculated based on information of the indicator at $T-1$.
- Drawdown refers to the peak-to-trough decline during a specific period of the investment. It is measured as a percentage of that maximum cumulative return.

Appendix J

Spillover Results by Country

The following five figures, each compiles return spillover indices for gold, Swiss Franc, US dollar and Japanese Yen (asset X). It contains nine plots, the heading of which indicates where the spillover is from and towards where. “GT” refers to search volume of *the* asset; “SH” refers to search volume of “safe haven”; and finally “X” refers to gold, US dollar, Swiss Franc and Japanese Yen. For instance, the top left plot within Figure J.1 “GT-GT” shows spillover from $\Delta SearchVolume_{gold}$ in the worldwide to itself (red), from $\Delta SearchVolume_{CHF}$ in the worldwide to itself (green), and so on. The right plot in the second row “SH-X” shows spillover from $\Delta SearchVolume_{safehaven}$ to gold return (red), to Swiss Franc return (green), to US dollar (blue) and Japanese Yen (purple). As a result, “GT-X” and “SH-X” show how search activities contribute to variances of safe haven asset returns; “X-GT” and “X-SH” show how safe haven asset returns impact on public search interests of the asset itself as well as safe haven assets. Plots “SH-GT” and “GT-SH” show spillovers between searches specific on the asset and generally on potential safe haven asset. And finally plots “GT-GT”, “SH-SH” and “X-X” show spillover effect to the variable themselves.

Figure J.1: Spillover index between online search interests and safe haven assets - Worldwide



Figure J.2: Spillover index between online search interests and safe haven assets — the US



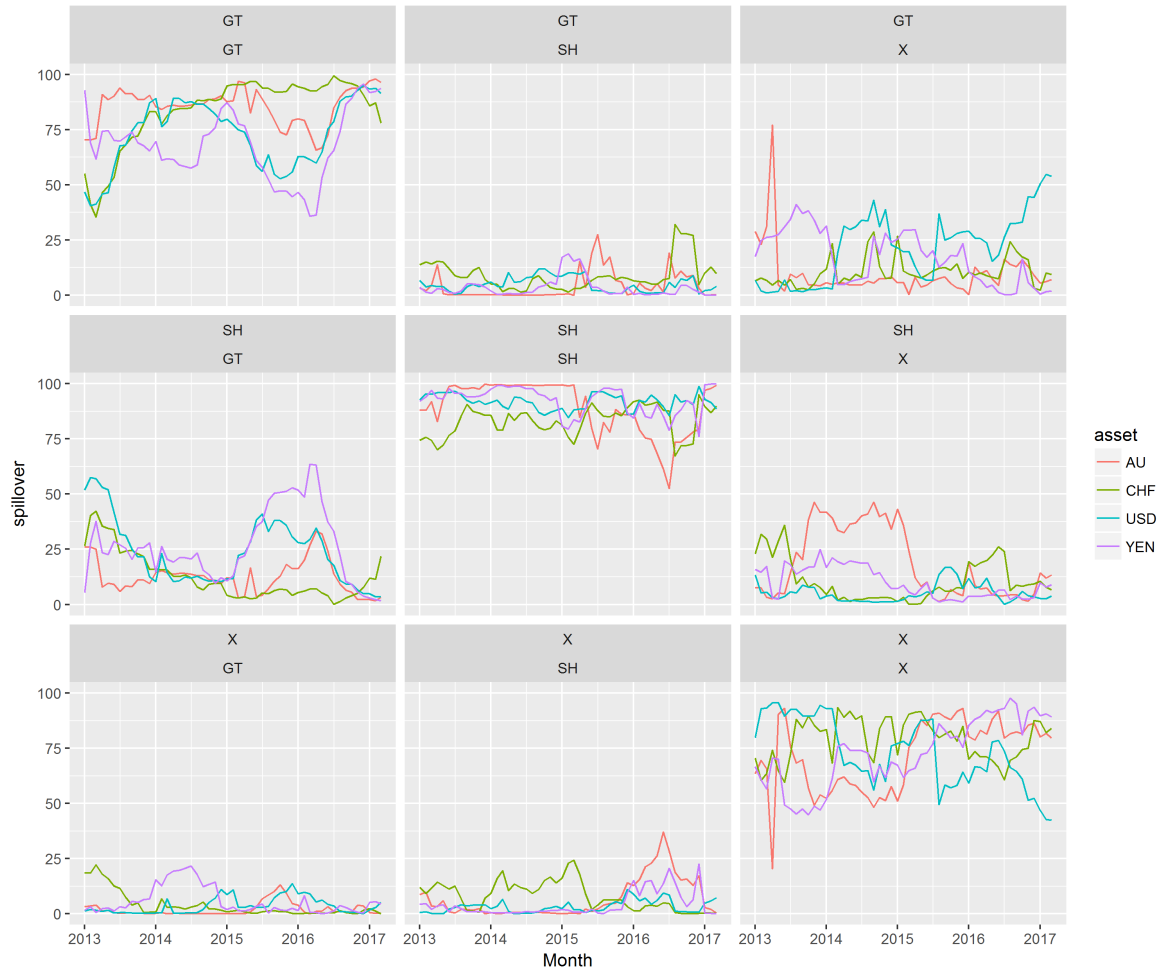
Figure J.3: Spillover index between online search interests and safe haven assets — the UK



Figure J.4: Spillover index between online search interests and safe haven assets — Germany



Figure J.5: Spillover index between online search interests and safe haven assets — China



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