An alternative perspective on investing in mining stocks, credit bonds and statistical arbitrage strategies

A dissertation submitted in fulfilment of the requirements for the Degree of Doctor of Philosophy in Business Studies.

2018

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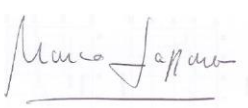

ID number: 07130279

Date: 08th November 2018**S**

Summary

This thesis is a collection of three distinct essays providing advice to investors in three areas of Finance. The first investigates the sensitivity of mining stocks to metals using multifactor models. The second researches value investing opportunities in credit markets using an analysis of corporates' fundamentals. The third discusses statistical arbitrage, a common financial term for which there is still no generally accepted definition in the literature.

In the first study, I investigate the sensitivity of world mining stocks to both precious and industrial metals by adding a metal factor to the CAPM and Fama-French models. I analyse all investible mining firms (421 in total) domiciled in both developed and emerging markets during the period 1990 to 2015. I enhance existing research to include all metals and provide an original comparison of mining stocks' sensitivities across both precious and industrial metals. I use both panel data and time series regressions on equal and value weighted portfolios. I find that metals are fundamental in explaining mining stocks' returns and more influential than Fama-French factors. I also find that metals are more significant for stocks of precious than industrial metals and the effect is stronger for firms domiciled in developed markets. The market factor is more relevant for industrial metal stocks. My results suggest that investors should treat mining stocks differently to other stocks and should also distinguish between precious and industrial mining firms when investing.

In the second study, I investigate value opportunities in credit markets across two geographical areas (U.S.A. and Euro Zone) and using two alternative ratings (Investment Grade and High Yield). By combining spreads with fundamental measures, I create two ratios: the spread over

leverage (SL) and the spread over leverage and the reciprocal of interest coverage (SLC). The higher these ratios, the higher is the spread investors receive per unit of leverage and interest coverage. In this sense, SL and SLC normalize spreads by credit quality. I use spreads, SL and SLC ratios as indicators of value opportunities for credit markets in the same way price-earnings and price-to-book ratios are used in equity markets. In particular, I analyse the returns from investing in bonds categorized into quintiles based on various value indicators. I find that average returns are higher when spreads are in the higher quintiles and the effect is stronger over longer time horizons (three to five years). These value strategies perform better if based on SL and SLC ratios than on spreads but the outperformance is not statistically significant. My results indicate that SL and SLC ratios work as well as spreads in identifying value opportunities but can enhance spreads by detecting value opportunities also within investment grade bonds of different ratings. This suggests that researchers should further investigate the use of SL and SLC ratios in building value factors for credit markets.

In the final study I investigate Statistical Arbitrage (SA). This is a common financial term for which, however, there is no common definition in the literature while investors use the expression SA for a variety of different strategies. I investigate SA strategies across equity, fixed income and, for the first time, commodity. In total, I review 165 articles on the subject, published between 1995 and 2016. The analysis of strategies' key features indicates that no existing definition fully describes them. To bridge this gap, I identify a general definition and propose a classification system that encompasses the current forms of SA strategies while facilitating the inclusion of new types as they emerge.

Acknowledgments

I am grateful to my supervisors Dr. Jenny Berrill and Dr. Aleksandar Šević for all their help and encouragement.

I would also like to thank faculty members and staff at the School of Business, Trinity College Dublin for their help, support and encouragement and, in particular, Joseph McDonagh, for his assistance.

I would like to thank my wife and family.

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1 Introduction

1.1 Introduction

In this thesis, I provide an alternative perspective on investing in mining stocks, credit bonds and statistical arbitrage strategies. As I show, these three distinct topics are connected and topical in financial literature. The popularity of factor investing has increased in financial markets with factor-based strategies becoming progressively more accessible to investors (Ang, Goetzmann and Schaefer, 2009; Citi, 2016). The literature on factor investing is broad and has existed for several decades (Fama and French, 1993; Carhart, 1997) with a large number of studies dedicated to the subject (Fama and French, 2015; Clarke, De Silva and Thorley, 2016). Researchers focus mostly on the broader equity market while analyses on industry specific factors are less common. This is surprising, considering that the progressive capital market integration underpins focusing on industries as well as countries (Beckers, Connor and Curds, 1996). Investigating factor models by sectors is particularly relevant for those groups of stocks which show distinct risk-return features such as mining firms (Ball and Brown, 1980). For mining stocks, existing studies investigate gold and the market factor with limited focus on industrial metals and Fama-French factors (Tufano, 1998; Gilmore et al., 2009). To bridge this gap in literature, my first study discusses the sensitivity of mining stocks to metals with the use of factor models.

Factor investing finds its origins in well studied market phenomena such as value and momentum (Basu, 1977; Jegadeesh and Titman, 1993). However, the literature is primarily focused on equity, with limited emphasis on other asset classes (Asness, Moskowitz and Pedersen, 2013). Research on value investing is sparse and has only recently focussed on corporate bonds (Correia, Richardson and Tuna, 2012; Bektic et al., 2016). Credit markets have no commonly accepted value measures as in equity (such as price-to-book or price-earnings) and are characterized by more fragmented data (Campbell and Taksler, 2003). My second study expands existing research for credit markets with an original investigation of value indicators for credit bonds.

Factor and value strategies are finding significant interest in alternative investments where they are often used to uncover statistical arbitrage opportunities (Maeso and Martellini, 2017). Statistical arbitrage is a common financial term which has been extensively investigated in literature. However researchers either focus on theoretical definitions or on developing and testing investment strategies, while I am not aware of any attempt to reconcile these two areas of research. My final study bridges this gap in literature with a comprehensive review of statistical arbitrage across asset classes.

1.2 Research Questions

My work addresses three main research questions:

Q1: How sensitive are mining stocks to metal prices?

Q2: Does value investing work in credit markets?

Q3: What is statistical arbitrage?

For each question I provide below a summary, reporting the motivation for the analysis and the methodology used. I also detail main findings while a separate section describes the research contributions.

1.2.1 Q1: How sensitive are mining stocks to metal prices?

Metals exercise a significant influence on equity markets (Jacobsen, Marshall and Visaltanachoti, 2010) and, particularly, on mining stocks. However, I am unaware of studies investigating the relationship between returns on mining securities and metals prices. Existing research focuses on gold and gold mining stocks (Blose and Shieh, 1995; Tufano, 1998; Davidson, Faff and Hillier, 2003; Baur and Lucey, 2010) with limited attention to industrial metals, which represent a larger part of the world mining industry than precious metals (MSCI, 2015). Additionally, existing studies do not have a global focus but analyse only selected countries or regions (McDonald and Solnick, 1977; Blose and Shieh, 1995; Gilmore et al., 2009). I bridge the gap in the existing literature by providing a comprehensive analysis of world mining stocks sensitivity to metal returns. I classify mining stocks into three groups for precious metals (gold, silver and platinum) and four groups for industrial metals (steel, iron ore, copper and aluminium), using three alternative classifications: Bloomberg, Global Industry Classification Standard (GICS) and a modified version of GICS. I examine the sensitivity of mining stocks in each group adding a metal factor to four models: the CAPM, the Fama-French 3-factor model, the Fama-French 4-factor global model and the more recent Fama-French 5-factor model (Fama and French, 1993; Fama and French, 2012; Fama and French, 2015). I use both panel data and time series regressions on equal and value weighted portfolios (Blake et al., 2014). A breakpoint analysis to test for robustness completes the study. I find that metals are fundamental in explaining mining stocks' returns. In particular, the metal factor is more significant for stocks of precious metals while the market factor is more significant for stocks of industrial metals. In most cases, the metal factor has a greater significance for firms domiciled in developed markets. The addition of Fama-French factors improve the performance of the models, however their combined contribution is less influential than the metal factor. My results suggest that investors should treat mining stocks differently to stocks in other industries given their particular sensitivity to metals and Fama-French factors.

1.2.2 Q2: Does value investing work in credit markets?

The existence of a value effect has been broadly debated in the context of market efficiency (Chan and Lakonishok, 2004; Daniel and Titman, 1997; Fama and French, 2004). However, existing research focuses mostly on equities (Stattman, 1980; Fama and French, 1992) while the literature on value investing for credit is quite limited (L'Hoir and Boulhabel, 2010; Correia, Richardson and Tuna, 2012). In credit markets, bonds are deemed to be cheap or expensive primarily through the analysis of credit spreads (L'Hoir and Boulhabel, 2010; Correia, Richardson and Tuna, 2012; Low et al., 2017). I am not aware of studies combining spreads with credit fundamentals, such as leverage and interest coverage, to identify indicators of value opportunities in corporate bonds. Additionally, I could not find studies exploring how the value effect changes over different time horizons. To bridge this gap in literature, I investigate value opportunities in credit markets using spreads and fundamentals. I define two ratios: the spread over leverage (SL) and the spread over leverage and the reciprocal of interest coverage (SLC). I use spreads, SL and SLC ratios as indicators of value opportunities for corporate bonds. The higher the SL and SLC ratios, the more spread investors receive per unit of leverage and interest coverage. I analyse the average returns from buying corporate bonds when value indicators are in the higher quintiles and compare them with the returns earned when value indicators are in the lower quintiles. I find that returns are higher when value indicators are in the higher quintiles and these value strategies perform positively over longer time horizons. The results are consistent across geographical areas (U.S.A. and Euro Zone) and ratings (Investment Grade and High Yield). Value strategies perform better if based on SL and SLC ratios than on spreads but the outperformance is not statistically significant. My results show that SL and SLC ratios work similarly to spreads in identifying value opportunities. However, the analysis suggests that they can enhance spreads by detecting value opportunities within investment grade bonds of different ratings.

1.2.3 Q3: What is statistical arbitrage?

In the final study I investigate Statistical Arbitrage (SA), a common financial term for which there is no common definition in the literature while investors use the expression SA for a variety of different strategies. SA has been broadly investigated in literature, however existing studies either focus on definitions (Ledoit, 1995; Chochrane and Saa-Requejo, 1998; Bernardo and Ledoit, 2000; Bertsimas, Kogam and Lo, 2001; Carr, Geman and Madan, 2001; Bondarenko, 2003; Hogan et al., 2004) or on developing and testing investment strategies (Vidyamurthy, 2004; Stefanini, 2006; Pole, 2007), while I am not aware of any attempt to reconcile these two areas of research. I bridge this gap by investigating SA strategies across equity, fixed income and commodity. The analysis of strategies' key features indicates that no existing definition fully describes them. I identify a general definition and propose a classification system that encompasses the current forms of SA strategies while facilitating the inclusion of new types as they emerge.

1.3 Research contributions

This thesis makes several contributions to the academic literature across three fields of Finance. My findings are also of practical benefit to analysts and portfolio managers.

In answering my first research question, I make several contributions to the literature on factor models for mining stocks. First, I consider all world miners domiciled in both developed and emerging markets while previous research studied only stocks in selected countries. Second, my study extends the existing literature on gold miners to miners of all available metals, both precious and industrial. Third, for the first time I compare the sensitivities of precious and industrial metals miners. Fourth, I modify the Global Industry Classification Standard (GICS) classification using stricter criteria to ensure the robustness of the results. Fifth, I compare results across geographical areas (North America, developed markets and emerging markets), size (large caps and small caps), industry classifications (Bloomberg, GICS and modified GICS), metal prices (spot and future prices) and data frequency (weekly and monthly). My results have practical implications as they suggest investors should treat mining stocks differently than the broader equity market and distinguish between stocks of precious and industrial metals.

In addressing my second research question, I make several contributions to the literature on value investing in credit markets. First, I originally combine market spreads with fundamentals (leverage and interest coverage) to identify value indicators and their effectiveness. This bridges the gap in literature between credit and equity where these types of indicators (often called multiples) have been extensively used. Second, I study the strength and the significance of the value effect over different time horizons (three months, six months, nine months, one year, two years, three years, four years and five years). Third, I rank and discuss value measures using quintiles calculated over different periods (three years, four years and five years). Fourth, I compare results across geographical areas (U.S.A. and Europe) and ratings (investment grade, high yield, A and BBB). Fifth, I provide an original review of key value indicators used by the credit analysts of the largest investment banks. My results also have practical contributions as they suggest that the analysis of fundamentals can be used to identify value opportunities among investment grade bonds.

In answering my third question, I make several contributions to the literature on statistical arbitrage (SA). First, I provide a comprehensive review and comparison of the theoretical definitions of arbitrage. Second, I survey statistically determined arbitrage strategies with an innovative investigation both in academic and financial industry research. In particular, for the first time, I analyse SA across all asset classes (equity, fixed income and commodity) identifying common features and defining elements of SA strategies. Third, I originally compare existing theoretical definitions of SA with strategies. This bridges an important gap in literature where researches either focused on definitions or on testing strategies. Fourth, I identify a general definition, which encompasses all SA strategies and introduce a classification system that facilitates their study. My analysis has practical contributions as it brings clarity in SA investing and allows investors to have a flexible framework to assess different investment opportunities across asset classes.

1.4 Structure of the thesis

Given the three distinct topics, the thesis is organized into three independent chapters. Chapter 2 investigates the sensitivity of mining stocks to metal prices. Chapter 3 studies value investing opportunities in credit markets. Chapter 4 investigates how SA is defined and implemented. Each chapter contains its own literature review, data analysis, discussion of results and conclusions. To facilitate the reading, each chapter has also an introduction, which elaborates and extends the overview provided in this chapter.

1.4 Conference presentations and journal submissions

A paper based on my findings in Chapter 2 has been submitted for publication. I am currently working on Chapter 3 to be submitted for publication. A paper entitled "What is statistical arbitrage?" based on Chapter 4 of this dissertation was presented at Bachelier Finance Society 7th World Conference, Sydney 2012.

1.5 Conclusions

In this chapter, I introduce the research questions and summarise my main findings. I also report the contributions made to the literature and the practical implications of my results with advice to investors. I conclude the chapter by outlining the structure of the thesis. In the following chapters, I address my three research questions.

2 Mining Stocks Sensitivity to Metals

2.1 Introduction

Commodities play a major role in the global economy (IMF, 2013) and have been traded throughout the history of humankind (Geman, 2005). Metals are among the oldest traded commodities and in 2015 represented a third of the world commodity market (Bloomberg Indexes, 2016). Metals exercise a strong influence on equity markets (Jacobsen, Marshall and Visaltanachoti, 2010) and, particularly, on mining stocks. A priori, it is reasonable to expect that the returns on mining securities are related to changes in metals prices. However, I am unaware of previous studies investigating this relationship. Existing research focuses mainly on gold and gold mining stocks (Blose and Shieh, 1995; Faff and Chan, 1998a; Tufano, 1998; Davidson, Faff and Hillier, 2003; Baur and Lucey, 2010; Ntantamis and Zhou, 2015) with limited attention to silver (Morgan, 2006) and no emphasis on industrial metals despite the fact that their prices are now more readily observable in listed markets (futures for steel began trading in 2009 and for iron ore in 2013).

Focusing on industrial metals is particularly relevant, considering that gold represents just 25% of world metal production (S&P Dow Jones Indices, 2015) and gold mining stocks just 14% of the world mining industry (MSCI, 2015). I make this distinction between precious and industrial metals in my analysis. While existing studies focus on selected countries or regions such as North America (Blose and Shieh, 1995; Tufano, 1998; Gilmore, McManus, Sharma and Tezel, 2009), South Africa (McDonald and Solnick, 1977) and Australia (Chan and Faff, 1998a; Twite, 2002), I take a global perspective which I believe is more relevant as markets become more integrated (Beckers, Connor and Curds, 1996; Lee and Chou, 2012; Asgharian and Nossman, 2013). I also use alternative methodologies and extend existing research on multifactor models (Faff and Chan, 1998; Chau, 2012) by adding a metal factor to existing Fama-French models (Fama and French, 1993; Fama and French, 2012; Fama and French, 2015).

I aim to bridge the gap in the existing literature by providing a comprehensive analysis of mining stocks sensitivity to metal returns. I investigate all investible mining firms (421 in total) domiciled in both developed and emerging markets during the period 1990 to 2015. I extend existing research to include all metals, providing an original comparison of mining stocks' sensitivities across both precious and industrial metals. Mining stocks exposed primarily to a specific metal are divided into three groups for precious metals (gold, silver and platinum) and four groups for industrial metals (steel, iron ore, copper and aluminium). Stocks are categorized by metals using two leading classifications: Bloomberg and Global Industry Classification Standard (GICS). A third classification is also introduced by modifying the GICS methodology to provide an additional robustness check. I examine the sensitivity of mining stocks in each group to their respective metal, a market factor and Fama-French factors. A metal factor is added to four models: the CAPM (Sharpe, 1964; Lintner, 1965), the Fama-French 3-factor model (Fama and French, 1993), the Fama-French 4-factor global model (Fama and French, 2012) and the more recent Fama-French 5-factor model (Fama and French, 2015). I use both panel data and time series regressions with OLS methods on equal and value weighted portfolios (Blake, Caulfield, Ioannidis and Tonksd, 2014). I also create various subsets based on location (North America, developed markets and emerging markets) and size. My analysis uses both spot prices of metals (Blose and Shieh, 1995; Blose, 1996; Tufano, 1998; Smith, 2001; Gilmore, McManus, Sharma and Tezel, 2009) and futures, which have become progressively more accessible and actively traded (Gorton and Rouwenhorst, 2006). I also perform a sub-period analysis to investigate the stability of my parameters.

I find that metals are fundamental in explaining the returns on mining stocks. In particular, the metal factor is more significant for stocks of precious metals while the market factor is more significant for stocks of industrial metals. The more a precious metal is used for industrial purposes (for example in electronics and catalytic industry), the less significant is the metal factor and the more relevant is the market factor. The addition of Fama-French factors improve the performance of the models, however their combined contribution is less influential than the metal factor on returns. This suggests that investors should treat mining stocks differently to other stocks when creating portfolios. In most cases, the metal factor has a greater significance for firms from developed markets than emerging markets. These findings remain valid in each of the four sub-periods analysed. My results suggest that it is fundamental for investors to differentiate between mining stocks of precious and industrial metals.

The higher significance of precious metals to the metal factor is possibly due to their role as safe havens and countercyclical nature (Baur and Lucey, 2010). The greater influence of the metal factor on precious metals can also be explained by the higher financialization (Cheng and Xiong, 2014) of precious metals, and particularly gold, with more frequent and sizeable exchange based trading (J.P. Morgan, 2017). The market factor is more relevant for miners of industrial metals as they are arguably more sensitive to economic growth and, consequently, to the stock market (Creti, Joëts and Mignon, 2013). The lower significance of metals for firms domiciled in emerging markets is possibly due to the lower efficiency of these markets (De Santis and

Imrohoroglu, 1997; Bekaert and Campbell, 2002; Morck, Yeung and Yu, 2000; Griffin, Kelly and Nardari, 2010).

The remainder of this chapter is organized as follows. In Section 2.2, I provide a review of the existing literature. In Section 2.3, I describe my data and methodology. In Section 2.4, I present the results of my analysis. Finally, in Section 2.5, I summarize my findings and draw together my conclusions.

2.2 Literature review

The influence of commodities on broad equity markets is widely investigated within the literature and focuses particularly on oil and gold (Jones and Kaul, 1996; Faff and Chan, 1998; Davidson, Faff and Hillier, 2003; Kilian and Park, 2009; Baur and Lucey, 2010; Ciner, Gurdgiev and Lucey, 2013), while some studies encompass a broader set of commodities (Creti, Joëts and Mignon, 2013; Silvennoinen and Thorp, 2013; Ntantamis and Zhou, 2015; Bekiros, Nguyen, Uddin and Sjö, 2016). Most research focuses on modelling the correlation between commodities and stocks. Creti, Joëts and Mignon (2013) find that the correlations between 25 different commodities and the S&P 500 change through time. Ntantamis and Zhou (2015) find little evidence that bull and bear markets for Canadian stocks are related to those of oil and metals. Baruník, Kočenda and Vácha (2016) note the existence of dynamic and changing correlations between gold, oil and stocks. Gokmenoglu and Fazlollahi (2015) provide evidence of a long run equilibrium in the interactions between gold, oil and stocks. For precious metals, Hillier, Draper and Faff (2006) find that gold, silver and platinum have low correlations with stock index returns suggesting that these metals provide diversification benefits. In the case of gold, a significant part of the research investigates the role of gold as a hedge or safe haven and finds contrasting results (Ciner, Gurdgiev and Lucey, 2013; Choudhry, Hassan and Shabi, 2015; Gokmenoglu and Fazlollahi, 2015; Caliskan and Najand, 2016). The literature on industrial metal prices is more limited. Labys, Achouch and Terraza (1999) identify a statistical relationship between the fluctuations of industrial metal prices and macroeconomic variables including a global equity index. Jacobsen, Marshall and Visaltanachoti (2010) and Valcarel, Vivian and Wohar (2017) find that metal prices can be used to predict equity returns.

Several studies examine the sensitivity of mining stocks to metals focusing on the relations between gold prices and gold mining company returns (McDonald and Solnick, 1977; Blose and Shieh, 1995; Sjaastad, 2008; Tufano, 1998; Christie, Chaudhry and Koch, 2000; Twite, 2002; Faff and Hillier, 2004; Fang, Lin and Poon, 2007; Ap Gwilym, Clare, Seaton and Thomas, 2011; Shen, Chokethaworn and Chaiboonsri, 2013). These studies mostly use multi-factor models and generally conclude that the price of gold is an important factor in explaining the valuation of gold stocks. Blose and Shieh (1995) and Blose (1996) observe that the prices of gold mining stocks are influenced by several factors including gold prices. Chan and Faff (1998) conclude that the gold factor is more important than the market factor in explaining gold mining stocks' returns. Tufano (1998) uses a two-factor model with a market factor and a gold factor. His analysis finds that on average American gold mining stocks' prices move 2% for each 1% change in gold prices and are significantly affected by a firm's hedging levels. This result is supported by Chau (2012) who finds that gold mining stocks are a leveraged commodity play. Twite (2002) uses discounted cash flow models including factors such as managerial flexibility and real options to explain the relations between gold and Australian gold mining stocks. Davidson, Faff and Hillier (2003) find that global industry indices are sensitive to gold prices and provide evidence in favour of the two-factor international asset pricing model. Gorton and Rouwenhorst (2006) note that mining firms are not a pure commodity play as they are also influenced by management and business diversification. Areal, Oliveira and Sampaio (2015) find that gold is always a safe haven while gold proxies (mining firms) cannot be considered substitutes for gold due to their lack of negative correlations with the market in times of turmoil. On silver miners, McGuire (2013) qualitatively discusses the relationship between silver and silver miners. On industrial metals, Chen (2017) finds that the returns of a small set of mining stocks can improve forecasting industrial metals prices. I am not aware of any research discussing the sensitivity of industrial metal stocks to metal and Fama-French factors.

2.3 Data and methodology

2.3.1 Data

My initial sample contains constituent firms of the MSCI All Country World Select Metals & Mining Producers as of December 2015. To avoid survivorship bias (Grinblatt and Titman, 1989; Brown, Goetzman, Ibbotson and Ross, 1992; Rohleder, Scholz and Wilkens, 2010), I include delisted or acquired securities using the Bloomberg World Index database. The final sample contains 421 companies (see Table 2.1).

Table 2.1: **Mining stocks**

The table reports the breakdown by countries and metals of the mining companies included in my sample. It reports the number of stocks and the aggregate market capitalization weight for the countries with the largest number of stocks: Canada, Australia, United States and Japan. The category 'Diversified' contains companies which do not have the majority of their revenues generated by a single metal.

	Number of Stocks						Market Capitalization Weights (%)					
Miners	Canada	Australia	U.S.	Japan	Others	Total	Canada	Australia	U.S.	Japan	Others	Total
1. Precious Metals	**36**	**13**	**8**	**-**	**25**	**82**	**5.3**	**1.3**	**1.4**	**0.0**	**3.9**	**11.9**
Gold	24	12	5		15	56	4.4	1.3	1.2	0.0	2.2	9.0
Silver	11	1	2		4	18	0.9	0.0	0.1	0.0	1.0	2.0
Platinum	1		1		6	8	0.0	0.0	0.1	0.0	0.7	0.9
2. Industrial Metals	**9**	**15**	**19**	**14**	**102**	**159**	**1.1**	**1.2**	**6.3**	**5.7**	**24.9**	**39.2**
Steel	1	2	13	12	76	104	0.1	0.2	3.6	5.5	13.8	23.3
Iron Ore	1	8	1		14	24	0.1	0.5	0.0	0.0	4.6	5.2
Copper	7	4	1		8	20	1.0	0.2	0.9	0.0	4.2	6.3
Aluminum		1	4	2	4	11	0.0	0.3	1.8	0.1	2.2	4.4
3. Diversified	**25**	**25**	**20**	**11**	**99**	**180**	**1.2**	**16.8**	**1.0**	**2.2**	**27.7**	**48.9**
Precious + Industrial	45	28	27	14	127	241	6.4	2.5	7.7	5.7	28.8	51.1
Total	**70**	**53**	**47**	**25**	**226**	**421**	**7.6**	**19.3**	**8.7**	**7.8**	**56.5**	**100.0**

Most firms are from Canada (70), followed by Australia (53) and the United States (47). Australia has the highest market capitalization weight (19.3%) but I note that BHP Billiton which has the largest market weight in the sample (7.8%) is based in Australia. Miners are classified by metals using the Bloomberg classification[1]. The precious miners group contains 82 securities and represents 11.9% of the market weight of the data set. Among precious metals, gold is the largest group (56 firms) followed by silver (18 firms) and platinum (8 firms). The industrial metals group contains 159 securities and accounts for 39.2% of the market capitalization of the data set. Steel miners are the most numerous (104), followed by iron ore (24), copper (20) and aluminium (11). The firms classified as diversified do not focus on a specific metal but engage in a diversified business involving several metals, transformation and

[1] Bloomberg classifies companies by tracking their primary business activities as measured by their primary source of revenue based on various qualitative and quantitative measures (Bloomberg, 2014).

distribution. Some of the largest stocks in the data set are classified as diversified (for example, BHP Billiton, Rio Tinto and Glencore). However, the majority of firms (241) are classified either as precious or industrial metals and represent 51.1% of the data set.

The sensitivity to metals is investigated using the time series of spot metal prices following existing studies on gold (Blose and Shieh, 1995; Blose, 1996; Tufano, 1998; Smith, 2001; Gilmore, McManus, Sharma and Tezel, 2009). The sample period is from 1990 to 2015. Monthly metal prices are sourced from 1990 as this is the first year global Fama-French factors are available. Some metals are available from later dates: aluminium (from 2003), steel (from 2003) and iron ore (from 2011). Prices are quoted in US dollars with the exception of aluminium and steel which are quoted in Chinese Renminbi and converted to US dollars. I also use futures metal prices as a robustness check (Xu and Fung, 2005; Elder and Jin, 2009). Most futures are listed in the United States: gold, silver and copper on COMEX while platinum and iron ore on the New York Mercantile Exchange. Aluminium is traded on the London Metals Exchange and steel on the Shanghai Futures Exchange. Metal futures are available since 1990 with the exception of steel (2009) and iron ore (2013). All futures are quoted in U.S. dollars with the exception of steel futures which are traded in Chinese renminbi. All data is sourced from Bloomberg.

In Table 2.2, I report summary statistics on the data used in my regression analysis: spot and future prices of metals and equally and value weighted returns of miners for each group. Average returns are higher for precious than industrial metals. The equally-weighted portfolio of silver miners has the highest average return (+3.9%) while the lowest average return is for iron ore futures (-3.5%, as prices are available only from 2013). Spot and future prices have similar returns with the exception of steel and iron ore, whose futures are available for a shorter time horizon than spot prices. Equally weighted portfolios have a higher allocation into small capitalization firms and have mostly higher average returns and volatility than value weighted portfolios (Banz, 1981; Amihud and Mendelson, 1989; Vassalou and Xing, 2004). Mining firms are more volatile than metals in each group with the highest volatility for silver miners (66.5%) and the lowest volatilities for the spot prices of gold (15.5%) and aluminium (15.2%). The highest ratios of average returns to volatilities are for the equally weighted portfolios of silver (0.2) and copper (0.21). Stocks also show higher maximum returns and lower minimum returns than metals.

Table 2.2: **Summary statistics**

This table reports summary statistics for monthly percent returns of spot and futures prices of metals and for equally and value weighted returns of miners. Standard deviations are annualized.

		Precious metals				Industrial metals				
Statistic	**Type**	**Gold**	**Silver**	**Platinum**	**Average**	**Steel**	**Iron Ore**	**Copper**	**Aluminum**	**Average**
Mean return (%)	Metal: Spot	0.4	0.7	0.4	0.5	-0.0	-2.0	0.4	0.1	-0.4
	Metal: Futures	0.4	0.7	0.4	0.5	-0.5	-3.5	0.5	0.1	-0.9
	Stocks: Equal-weighted	1.7	3.9	0.6	2.0	0.9	1.5	2.8	0.7	1.5
	Stocks: Value-weighted	0.4	0.9	0.3	0.5	0.3	1.3	1.0	0.4	0.7
Standard deviation (%)	Metal: Spot	15.5	28.5	20.2	21.4	21.2	29.6	25.3	15.2	22.8
	Metal: Futures	15.7	28.9	20.5	21.7	21.9	26.7	25.9	18.7	23.3
	Stocks: Equal-weighted	38.5	66.5	37.9	47.6	26.8	41.2	45.8	29.7	35.9
	Stocks: Value-weighted	35.8	48.1	39.9	41.3	26.8	38.4	41.0	30.8	34.2
Mean return /Standard deviation	Metal: Spot	0.10	0.08	0.07	0.08	-0.00	-0.24	0.06	0.01	-0.06
	Metal: Futures	0.10	0.08	0.06	0.08	-0.09	-0.46	0.06	0.02	-0.13
	Stocks: Equal-weighted	0.15	0.20	0.05	0.15	0.12	0.12	0.21	0.08	0.14
	Stocks: Value-weighted	0.04	0.06	0.03	0.04	0.04	0.12	0.08	0.05	0.08
Min return (%)	Metal: Spot	-16.9	-28.0	-32.0	-25.6	-28.0	-24.7	-35.8	-12.8	-25.3
	Metal: Futures	-17.8	-27.9	-31.9	-25.9	-16.7	-17.0	-36.5	-16.1	-21.6
	Stocks: Equal-weighted	-41.0	-51.0	-50.7	-47.6	-37.0	-51.9	-43.7	-35.4	-42.0
	Stocks: Value-weighted	-36.8	-55.7	-52.0	-48.2	-37.1	-32.8	-59.1	-42.3	-42.8
Max return (%)	Metal: Spot	16.8	27.2	24.1	22.7	15.0	20.7	31.1	15.7	20.6
	Metal: Futures	16.0	28.2	25.5	23.3	17.3	17.7	35.4	16.0	21.6
	Stocks: Equal-weighted	40.4	124.2	35.2	66.6	27.1	35.1	91.2	36.6	47.5
	Stocks: Value-weighted	58.9	46.7	59.7	55.1	25.1	43.1	77.8	35.8	45.4

In Figure 2.1, I show the historical performance of mining stocks and metals. I also add a portfolio of global stocks as calculated by Fama and French (2012) to compare mining stocks to the broader equity market. All charts show similar dynamics. Metals rose from the 1990's until the Global Financial Crisis (GFC) during the commodity super-cycle (Erten and Ocampo, 2013). Then metals declined during the GFC, to recover in 2009. After 2010, metals started declining showing a clear divergence with equity markets, which instead kept advancing (Brenes, Camacho, Ciravegna and Pichardo, 2016). In all cases, mining stocks are influenced by the equity market factor and, mostly, by the metal they mine. Gold miners closely follow gold prices in my sample, while they diverge from equity markets in the periods 1996-2000 and 2013-2015. A similar behaviour can be observed for stocks of silver while platinum miners deviate from the equity market mainly in the period 2013-2015. Stocks of platinum are less sensitive to the price movements of metals, similarly to other industrial metals. Miners of steel and iron ore also show less sensitivity to the metal for the available period. Miners of copper show a significant degree of volatility and follow quite closely metal prices. Stocks of aluminium follow closely metal prices but are less sensitive to them in the period 2011-2015. This graphical analysis supports further investigation into the sensitivity of mining stocks to both the metal and market factor.

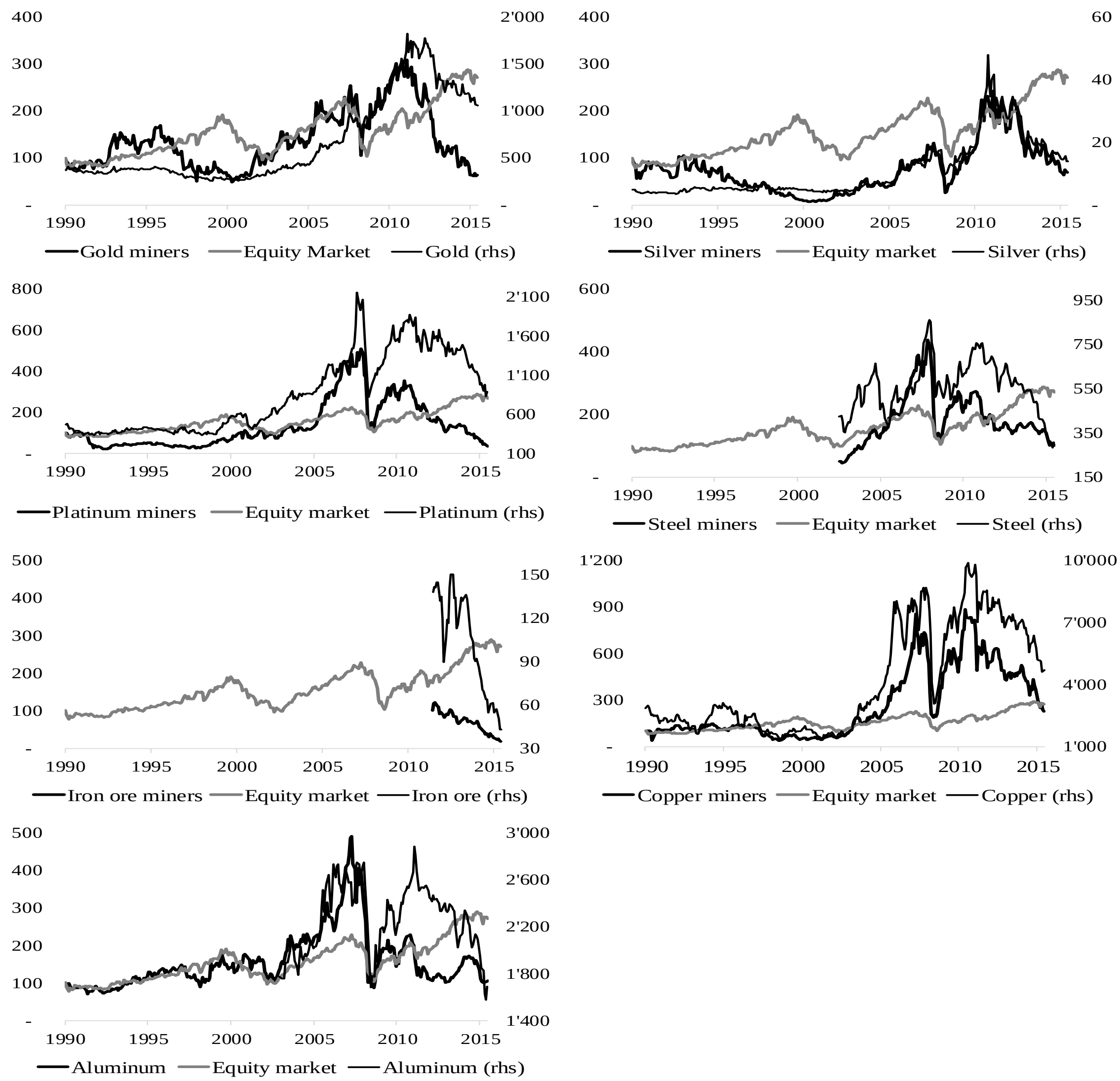

Figure 2.1: **Performance of mining stocks, metals and equity markets**

Mining stocks are reported as a value weighted portfolio, metals with spot prices and equity markets with a portfolio of global stocks as calculated by Fama and French (2012).

2.3.2 Methodology

I study mining stocks sensitivity using factor models based on the Capital Asset Pricing Model (CAPM) and Fama-French models (Sharpe, 1964; Lintner, 1965; Sharpe, 1992; Fama and French, 1993; Fama and French, 2012; Fama and French, 2015). Since its introduction, the CAPM has played a prominent role in research, marking the birth of asset pricing theory and being used in a variety of applications, such as the estimation of firms' cost of capital and performance evaluation (Sharpe, 1964; Lintner, 1965; Fama and French, 2004). However, the academic literature has widely debated the limits of the CAPM in explaining the pricing of risky assets (Faff and Chan, 1998; Faff, 2001; Fama and French, 2004). In this context, multifactor models have been introduced to take into account additional sources of risk (Lessard, 1973; Shanken, 1985; Schneeweiss and Mathes, 1995; Chan and Karceski, 1999; Faff, 2003). Multifactor models include a market factor (MacKinlay, 1995; Fama and French, 1996; Alexander and Dimitriu, 2004; Moss and Price, 2010) and additional factors to describe specific features of traded stocks such as: size and style (Fama and French, 1993; Van Dijk, 2011), momentum (Carhart, 1997; Fama and French, 2012), profitability and investment patterns (Fama and French, 2015). Increasing capital market integration supports focusing on industries as well as countries (Beckers, Connor and Curds, 1996), particularly for mining stocks which show quite distinct risk-return features (Ball and Brown, 1980).

I investigate the sensitivity of mining stocks to metals by adding a metal factor to four models: the Capital Asset Pricing Model (CAPM), the Fama-French 3-factor model (FF3), the Fama-French 4-factor model (FF4) and the Fama-French 5-factor model (FF5) (Fama and French, 1993; Fama and French, 2012 and Fama and French, 2015).

I refer to the metals-enhanced models as MCAPM, MFF3, MFF4 and MFF5. The MCAPM equation is as follows:

$$R_{j,t} - R_{F,t} = \alpha_j + \beta_{MET,j} R_{MET,t} + \beta_{MKT,j}\left(R_{MKT,t} - R_{F,t}\right) + \varepsilon_{j,t} \tag{2.1}$$

where $R_{j,t}$ is the return of miner *j* at time *t*, $R_{F,t}$ is the risk free rate measured using the one-month U.S. Treasury Bill yield, $R_{MKT,t}$ is the return of a global market portfolio calculated by Fama and French (2012), $R_{MET,t}$ is the return of the underlying metal and $\varepsilon_{j,t}$ is the error term.

In the MFF3 model, size and style factors are added. The size factor (SMB) is calculated as the difference between the return on a portfolio of small and large stocks. The style factor (HML) is calculated as the difference of the return on a portfolio of high and low book-to-market stocks. The MFF3 formula is as follows:

$$\begin{aligned} R_{j,t} - R_{F,t} = {} & \alpha_j + \beta_{MET,j} R_{MET,t} + \beta_{MKT,j}\left(R_{MKT,t} - R_{F,t}\right) + \beta_{SMB,j} R_{SMB,t} \\ & + \beta_{HML,j} R_{HML,t} + \varepsilon_{j,t} \end{aligned} \tag{2.2}$$

where $R_{j,t}$ is the return of miner *j* at time *t*, $R_{F,t}$ is the risk free rate measured using the one-month U.S. Treasury Bill yield, $R_{MKT,t}$ is the return of a global market portfolio calculated by Fama and French (2012), $R_{MET,t}$ is the return of the underlying metal, $R_{SMB,t}$ is the return of the SMB factor, $R_{HML,t}$ is the returns of the HML factor and and $\varepsilon_{j,t}$ is the error term.

The MFF4 model adds a momentum factor (WML) to the MFF3 model. The WML factor was introduced by Carhart (1997) to take into account of the momentum shown by U.S. stocks

(Jegadeesh and Titman, 1993) and is calculated as the difference between the returns on diversified portfolios of the winners and losers of the previous year. The MFF4 formula is as follows:

$$R_{j,t} - R_{F,t} = \alpha_j + \beta_{MET,j} R_{MET,t} + \beta_{MKT,j}(R_{MKT,t} - R_{F,t}) + \beta_{SMB,j} R_{SMB,t} + \beta_{HML,j} R_{HML,t} + \beta_{WML,j} R_{WML,t} + \varepsilon_{j,t} \tag{2.3}$$

where $R_{j,t}$ is the return of miner *j* at time *t*, $R_{F,t}$ is the risk free rate measured using the one-month U.S. Treasury Bill yield, $R_{MKT,t}$ is the return of a global market portfolio calculated by Fama and French (2012), $R_{MET,t}$ is the return of the underlying metal, $R_{SMB,t}$ is the return of the SMB factor, $R_{HML,t}$ is the returns of the HML factor, $R_{WML,t}$ is the return of the WML factor and and $\varepsilon_{j,t}$ is the error term..

The MFF5 model adds profitability and investment pattern factors to the MFF3 model. The profitability factor (RMW) is calculated as the difference between the returns on portfolios of stocks with robust and weak profitability. The investment pattern factor (CMA) is the difference between the returns on diversified portfolios of the stocks of low and high investment firms, called conservative and aggressive. The MFF5 formula is as follows:

$$R_{j,t} - R_{F,t} = \alpha_j + \beta_{MET,j} R_{MET,t} + \beta_{MKT,j}(R_{MKT,t} - R_{F,t}) + \beta_{SMB,j} R_{SMB,t} + \beta_{HML,j} R_{HML,t} + \beta_{RMW,j} R_{RMW,t} + \beta_{CMA,j} R_{CMA,t} + \varepsilon_{j,t} \tag{2.4}$$

where $R_{j,t}$ is the return of miner *j* at time *t*, $R_{F,t}$ is the risk free rate measured using the one-month U.S. Treasury Bill yield, $R_{MKT,t}$ is the return of a global market portfolio calculated by

Fama and French (2012), $R_{MET,t}$ is the return of the underlying metal, $R_{SMB,t}$ is the return of the SMB factor, $R_{HML,t}$ is the returns of the HML factor, where $R_{RMW,t}$ is the return of the RMW factor, $R_{CMA,t}$ is the returns of the CMA factor and and $\varepsilon_{j,t}$ is the error term.

The literature on Fama-French factors is extensive and more detailed discussions are provided in Griffin (2002) and Simpson and Ramchander (2008). All factors returns are available from K. French's website (French, 2005). I use monthly observations as this is the most granular frequency available for global factors (Fama and French, 2012) and to minimize the noise of closing prices in different time zones. As part of the robustness analysis, I also use weekly data.

I analyse mining stocks grouped by metals and aggregated into equally weighted portfolios (Blose and Shieh, 1995; Faff and Chan, 1998; Tufano, 1998; Blake, Caulfield, Ioannidis and Tonksd, 2014) and market value weighted portfolios (Twite, 2002; Gilmore, McManus, Sharma and Tezel, 2009; Blake, Caulfield, Ioannidis and Tonksd, 2014). The use of both equal and value weights allows me to identify potential size biases in the groups[2]. For each metal group, I use both time series regressions and panel data analysis (Blake, Caulfield and Tonksd, 2014; Vidal-Garcia and Vidal, 2014; Zhang, 2015). I perform standard time series regressions using OLS methods but also panel data analysis to take into account the panel structure of data and provide a more robust investigation for samples with shorter time series (particularly iron ore).

Panel data models can be estimated using both fixed and random effects (Asteriou and Hall, 2007). With the fixed effect method, the model $Y_{it} = a_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + \beta_k X_{kit} + u_{it}$

[2] Charts with equally and value weighted portfolios, metal prices and Fama-French factors are reported in Appendix A.1 in Figures A.1.1 to A.1.3

allows for different constants a_i for each group $i = 1,2,...,N$. An alternative method is the random effect model. According to this method, the constants are not fixed but given by a random parameter $a_i + v_i$ where v_i is a zero-mean standard random variable. The Hausman test (Hausman, 1978) is used to choose between fixed and random effects and uses the following test statistic

$$H = \left(\hat{\beta}^{FE} - \hat{\beta}^{RE}\right)' \left[Var\left(\hat{\beta}^{FE}\right) - Var\left(\hat{\beta}^{RE}\right)\right]^{-1} \left(\hat{\beta}^{FE} - \hat{\beta}^{RE}\right) \tag{2.5}$$

where $\hat{\beta}^{FE}$ and $\hat{\beta}^{RE}$ are the estimated coefficients using the fixed effect (FE) and random effect (RE).

If the value of the statistic is large, then the difference between the estimates is significant so the null hypothesis of random effect is rejected in favor of the alternative fixed effect. I perform panel data analysis with fixed or random effects based on the Hausman test as per standard procedure (Davidson and MacKinnon, 1993; Asteriou and Hall, 2007).

2.4 Results

2.4.1 Mining stocks sensitivities

I begin by investigating the sensitivity of mining stocks to various factors using the MCAPM, MFF3, MFF4 and MFF5 models. I investigate the significance of each of the factors across various metals and models. Results are presented in Table 2.3. I find that metals are fundamental in explaining mining stocks' returns. The analysis shows that the metal factor is significant across all mining stocks. This is an important finding as for the first time it shows that mining firms' prices are significantly influenced by the metal they mine, irrespective of the type of metal.

The market factor is also significant across all types of mining stocks. Results show that the sensitivity of the metal factor is higher for stocks of precious metals than stocks of industrial metals. The opposite behaviour is observed for the market factor whose beta is larger for stocks of industrial metals than precious metals. This dynamic is possibly related to the role of precious metals as safe havens and their countercyclical behaviour (Baur and Lucey, 2010).

Table 2.3

Sensitivity analysis

The table reports the regression betas of precious (Panel A) and industrials (Panel B) mining companies. Firms are categorized in 7 metal groups (gold, silver, platinum, steel, iron ore, copper and aluminum). The regression analysis is performed on equal and value weighted portfolios. OLS models are estimated. Panel data analysis is also performed.

		Metal				Market				SMB			HML			WML	RMW	CMA
Group	Type	MCAPM	MFF3	MFF4	MFF5	MCAPM	MFF3	MFF4	MFF5	MFF3	MFF4	MFF5	MFF3	MFF4	MFF5	MFF4	MFF5	MFF5
Panel A: Precious metals																		
Gold	Equal-weighted	1.81 **	1.65 **	1.66 **	1.66 **	0.59 **	0.67 **	0.66 **	0.66 **	1.48 **	1.47 **	1.48 **	0.36 *	0.38 *	0.45	0.05	0.07	-0.18
	Value-weighted	1.71 **	1.67 **	1.68 **	1.67 **	0.45 **	0.49 **	0.48 **	0.52 **	0.48 **	0.45 *	0.54 **	0.37 *	0.41 *	0.43	0.10	0.32	-0.14
	Panel data	1.73 **	1.61 **	1.61 **	1.60 **	0.61 **	0.65 **	0.64 **	0.60 **	1.47 **	1.47 **	1.47 **	0.37 **	0.38 **	0.61 **	0.02	0.17	-0.47 **
Silver	Equal-weighted	1.11 **	1.00 **	1.00 **	1.00 **	0.78 **	0.93 **	0.93 **	0.90 **	2.60 **	2.61 **	2.58 **	0.44	0.41	0.55	-0.04	-0.02	-0.20
	Value-weighted	1.10 **	1.05 **	1.04 **	1.05 **	0.57 **	0.68 **	0.69 **	0.68 **	1.23 **	1.16 **	1.26 **	0.75 **	0.67 **	0.81 *	-0.08	0.13	-0.12
	Panel data	1.13 **	1.02 **	1.03 **	1.02 **	0.85 **	0.92 **	0.88 **	0.84 **	2.64 **	2.68 **	2.63 **	0.36	0.27	0.76 **	-0.18	0.19	-0.75
Platinum	Equal-weighted	0.96 **	0.89 **	0.89 **	0.89 **	0.98 **	1.09 **	1.07 **	1.10 **	1.06 **	1.07 **	1.10 **	0.67 **	0.62 **	0.76 **	-0.11	0.20	-0.18
	Value-weighted	0.77 **	0.72 **	0.71 **	0.72 **	1.01 **	1.11 **	1.09 **	1.19 **	0.71 **	0.71 **	0.80 **	0.76 **	0.70 **	0.63	-0.11	0.31	0.21
	Panel data	0.94 **	0.87 **	0.86 **	0.86 **	1.04 **	1.13 **	1.11 **	1.12 **	1.06 **	1.07 **	1.09 **	0.72 **	0.66 **	0.88 **	-0.09	0.19	-0.33
Panel B: Industrial metals																		
Steel	Equal-weighted	0.30 **	0.26 **	0.27 **	0.24 **	1.51 **	1.46 **	1.42 **	1.28 **	1.03 **	1.04 **	0.98 **	0.31	0.22	1.19 **	-0.15	0.59	-1.69 **
	Value-weighted	0.35 **	0.32 **	0.32 **	0.31 **	1.55 **	1.52 **	1.52 **	1.28 **	0.85 **	0.85 **	0.74 **	0.12	0.14	0.99 **	0.03	0.28	-1.89 **
	Panel data	0.29 **	0.25 **	0.26 **	0.24 **	1.51 **	1.45 **	1.41 **	1.27 **	1.05 **	1.05 **	0.98 **	0.30 **	0.20 **	1.17 **	-0.16 **	0.59 **	-1.69 **
Iron Ore	Equal-weighted	0.60 **	0.44 **	0.44 **	0.55 **	1.45 **	1.42 **	1.18 **	1.52 **	1.24 *	1.11	1.90 **	1.52 *	0.96	3.54 **	-0.89 *	3.98 **	-4.40 **
	Value-weighted	0.64 **	0.52 **	0.53 **	0.62 **	1.54 **	1.47 **	1.05 **	1.58 **	0.51	0.30	1.18	1.33	0.37	3.07 **	-1.54 **	3.60 *	-3.62 *
	Panel data	0.59 **	0.43 **	0.43 **	0.55 **	1.44 **	1.41 **	1.17 **	1.51 **	1.24 **	1.11 **	1.90 **	1.51 **	0.97 **	3.53 **	-0.88 **	3.96 **	-4.38 **
Copper	Equal-weighted	0.59 **	0.52 **	0.50 **	0.50 **	1.09 **	1.19 **	1.30 **	1.15 **	1.32 **	1.26 **	1.35 **	0.37	0.39	0.76	0.07	0.29	-0.72
	Value-weighted	0.61 **	0.55 **	0.56 **	0.53 **	1.12 **	1.22 **	1.23 **	1.16 **	0.98 **	0.96 **	1.02 **	0.69 **	0.72 **	1.20 **	0.08	0.33	-0.93 *
	Panel data	0.61 **	0.54 **	0.54 **	0.53 **	1.15 **	1.22 **	1.27 **	1.25 **	1.31 **	1.28 **	1.44 **	0.31	1.28 **	0.60 **	0.33	0.68 *	-0.59
Aluminum	Equal-weighted	0.33 **	0.30 **	0.30 **	0.28 **	1.66 **	1.60 **	1.59 **	1.48 **	1.19 **	1.20 **	1.14 **	0.28	0.26	0.68	-0.04	0.07	-0.89
	Value-weighted	0.25 *	0.23	0.24	0.20	1.75 **	1.73 **	1.72 **	1.53 **	0.81 *	0.82 *	0.72 *	-0.01	-0.03	0.68	-0.04	0.18	-1.50 **
	Panel data	0.33 **	0.30 **	0.30 **	0.28 **	1.63 **	1.58 **	1.56 **	1.45 **	1.19 **	1.19 **	1.13 **	0.26	0.21	0.70 **	-0.07	0.12	-0.94 *

** and * indicate statistical significance at the 0.05 and 0.10 level, respectively

The sensitivity to the metal factor, as measured by beta, is highest for mining stocks of gold, followed by silver and platinum. In relation to these metals, in 2011 Deutsche Bank reports that only a marginal part of gold production is destined to industrial use (11%) which is instead predominant for silver (54%) and platinum (56%) particularly in the automotive and catalytic industry. This suggests that the more a precious metal is used for industrial purposes, the less sensitive it will be to the metal factor and the more sensitive it will be to the market factor. In particular, platinum stocks share features of both precious and industrial metals – they are more sensitive to metals than industrial metals stocks and more sensitive to the market than other precious metals stocks. Mining firms of industrial metals show a lower sensitivity to metals (with the lowest beta for steel and aluminium) and a higher sensitivity to the market factor. The market factor is more significant for miners of industrial metals as, possibly, they are more sensitive to economic growth and, as a consequence, to the stock market (Creti, Joëts and Mignon, 2013). Industrial metals are also less financialized (Cheng and Xiong, 2014) with less frequent and sizeable trading on exchange than precious metals (J.P. Morgan, 2017). This may make them less reactive to changes in financial markets than the market factor and explain their lower significance in my regressions.

Results are consistent using equally weighted portfolios, value weighted portfolios and panel data analysis. The significance of the SMB factor is higher using equally weighted portfolios and panel data analysis, confirming results found in Fama and French (1993). Overall, equally weighted portfolios and panel data analysis produce similar results. Across models, the differences in results for the market and metal factor are small but higher for Fama-French factors with the greatest discrepancies for SMB and RMA factors.

Not all Fama-French factors are significant. In particular, the WML and RMW factors are the least relevant as they are significant only in a few instances for industrial metals (in four out of 21 cases for WML and five cases out of 21 cases for RMW). The CMA is more likely to be significant for industrial metals. The HML factor is significant in 36 out of 63 cases while the SMB factor is almost always significant (there are only four out of 63 cases in which it is not significant). The beta of the SMB factor is reduced when value weighted portfolios are analysed across all metals.

Traditionally, precious metals are seen as a defensive play during economic instability (Maloney, 2015). In particular, literature has broadly investigated the role of gold as a hedge and safe haven (Jaffe, 1989; Hillier, Draper, and Faff, 2006; Baur and Lucey, 2010; Hood and Malik, 2013) with researchers extending the analysis to other precious metals more recently (Hammoudeh et al., 2010; Lucey and Li, 2015). These studies focus on the benefits of holding precious metals in periods of markets turmoil. I take an alternative approach and investigate the benefits of investing in mining stocks. Investors who want exposure to precious metals can buy them directly in a physical form (bars, coins or exchange-traded funds) or invest in mining firms. However, buying shares in a mining firm not only gives access to metals but also exposes the investor to other factors such as management skills (Baur, 2014) and market dynamics (Tufano, 1998). To account for additional determinants, my research investigates the sensitivities of mining stocks to precious metals as well as market factor and Fama-French factors. My results add to the existing literature by showing that investments in mining stocks have a higher sensitivity to metals than to the market factor. If precious metals provide a hedge during market downturns, then precious metals stocks will provide a defensive investment. Additionally, my analysis enhances existing literature on precious metals by quantifying the sensitivity of mining stocks across different metals and periods.

The performance of the models is assessed using the adjusted coefficient of determination (R^2) (Fama and French, 2015). The FF3 model performs significantly better than the CAPM while FF4 and FF5 add only marginal improvements to FF3, suggesting little explanatory power in the additional factors (see Table 2.4). The addition of a metal factor significantly improves the performance of all models across all metals. Notably, the MCAPM has an adjusted R^2 higher than all Fama-French models (FF3, FF4 and FF5), suggesting that the metal factor is more important than the Fama-French factors for mining stocks. The metal factor brings the largest improvement for gold mining stocks. Iron ore miners show the second largest increase in adjusted R^2 while copper has the smallest increase. The addition of Fama-French factors to MCAPM brings only minor R^2 improvements (MFF3, MFF4 and MFF5). My analysis confirms that the addition of Fama-French factors improves the performance of the model (Fama and French, 2015), however their contribution is less relevant than adding a metal factor.

Table 2.4: **Regressions significance**

The table reports the adjusted coefficient of determination and their changes when a metal factor is added to CAPM, FF3, FF4 and FF5. OLS models are estimated. Regressions results are presented for equally weighted portfolios, value weighted portfolios and panel data.

		R^2 without metal				R^2 after adding a metal factor				
Group	Type	CAPM	FF3	FF4	FF5	MCAPM	MFF3	MFF4	MFF5	Average R^2 increase adding a metal factor
Panel A: Precious metals										
Gold	Equal-weighted	0.09	0.26	0.26	0.26	0.61	0.68	0.68	0.68	0.37
	Value-weighted	0.06	0.12	0.12	0.12	0.61	0.62	0.62	0.62	
	Panel data	0.03	0.08	0.08	0.08	0.19	0.21	0.21	0.22	
Silver	Equal-weighted	0.08	0.20	0.19	0.20	0.29	0.37	0.36	0.36	0.20
	Value-weighted	0.11	0.20	0.19	0.19	0.51	0.55	0.54	0.55	
	Panel data	0.03	0.06	0.06	0.05	0.09	0.10	0.10	0.10	
Platinum	Equal-weighted	0.29	0.38	0.38	0.38	0.53	0.58	0.58	0.58	0.15
	Value-weighted	0.25	0.30	0.29	0.30	0.38	0.41	0.41	0.41	
	Panel data	0.18	0.23	0.23	0.23	0.31	0.33	0.34	0.34	
Panel B: Industrial metals										
Steel	Equal-weighted	0.57	0.65	0.66	0.67	0.73	0.76	0.76	0.81	0.12
	Value-weighted	0.56	0.64	0.64	0.65	0.72	0.74	0.74	0.79	
	Panel data	0.14	0.16	0.16	0.17	0.24	0.25	0.25	0.27	
Iron Ore	Equal-weighted	0.33	0.38	0.38	0.40	0.60	0.65	0.68	0.75	0.23
	Value-weighted	0.25	0.27	0.26	0.32	0.58	0.59	0.69	0.65	
	Panel data	0.14	0.17	0.17	0.18	0.18	0.20	0.21	0.23	
Copper	Equal-weighted	0.23	0.29	0.30	0.30	0.32	0.36	0.36	0.36	0.06
	Value-weighted	0.30	0.36	0.36	0.38	0.42	0.45	0.45	0.46	
	Panel data	0.06	0.07	0.07	0.07	0.08	0.09	0.09	0.09	
Aluminum	Equal-weighted	0.55	0.64	0.65	0.64	0.66	0.70	0.69	0.70	0.08
	Value-weighted	0.48	0.52	0.55	0.54	0.62	0.63	0.63	0.65	
	Panel data	0.23	0.26	0.27	0.26	0.29	0.31	0.31	0.31	
Average	All	0.24	0.30	0.30	0.30	0.43	0.46	0.46	0.47	0.17

2.4.2 Analysis by area and size

I next segregate my sample into stocks from different geographical regions (North America, developed markets and emerging markets) and large versus small stocks. I examine North American companies independently due to better data quality and availability while it also allows me to compare my results with existing studies (Blose and Shieh, 1995; Tufano, 1998;

Gilmore, McManus, Sharma and Tezel, 2009). Developed markets and emerging markets are investigated separately as the literature suggests that they are likely to show different features (De Santis and Imrohoroglu, 1997; Bekaert and Campbell, 2002; Morck, Yeung and Yu, 2000; Griffin, Kelly and Nardari, 2010). The MSCI Country Classification Standard (MSCI, 2014) is used to categorize countries as developed and emerging. Small and large firms are also analysed as the size factor is the most relevant Fama-French factor in my regression analysis. Following Fama and French (1993), large and small firms are categorized with reference to the median market capitalisation of the sample.

Table 2.5 shows the number and percentage of firms in each category. North American companies (72) make up almost a third of the data set and predominantly mine gold (29), steel (14) and silver (13). Companies based in developed markets comprise approximately two thirds of the dataset (145). They are primarily miners of industrial metals (81) although the largest metal group is gold (47). Among the 96 miners based in emerging markets, the majority (59) focus on steel, a metal which is mostly used in emerging economies and particularly China (Deutsche Bank, 2011). Finally, 114 firms are categorized as large and 127 as small.

Table 2.5: **Breakdown by area and size**

The table reports the breakdown of the data set by area and size for each metal. World is the overall sample considered in my analysis comprehensive of developed and emerging markets. The categories North America, developed markets and emerging markets are based on the MSCI country classification. The developed markets group includes North America. Large and small firms are categorized using the median market cap of the sample.

Group	World	North America	Developed markets	Emerging markets	Large caps	Small caps
1. Precious Metals	**82**	**44**	**64**	**18**	**38**	**44**
Gold	56	29	47	9	28	28
Silver	18	13	15	3	6	12
Platinum	8	2	2	6	4	4
2. Industrial Metals	**159**	**28**	**81**	**78**	**76**	**83**
Steel	104	14	45	59	54	50
Iron Ore	24	2	13	11	5	19
Copper	20	8	14	6	10	10
Aluminum	11	4	9	2	7	4
Total	**241**	**72**	**145**	**96**	**114**	**127**

The results of my subset analysis are presented in Table 2.6 and confirm the findings from the broader sample. Unsurprisingly, the differences between North American and World securities are small both in sensitivities and R^2. The largest differences are for platinum and iron ore which include only two North American securities each. With the exception of platinum and steel, the sensitivity to the metal factor is lower for mining stocks in emerging than in developed markets. This may be due to the fact that emerging markets show a higher probability than developed markets of large price movements (De Santis and Imrohoroglu, 1997) which are unrelated to fundamentals (Morck, Yeung and Yu, 2000) and suggest market inefficiencies (Griffin, Kelly and Nardari, 2010). With the exception of aluminium the sensitivity to the SMB factor is higher for stocks in developed markets than in emerging markets. Small cap firms are more sensitive to the size factor than large cap firms, confirming results from Fama and French (1993).

Table 2.6: **Sensitivity by area and size**

The table reports the averages of the regression betas using the MFF5 model (for metal, market, SMB, HML, RMW and CMA factors) and the MFF4 model (for WML factor). OLS models are estimated. The table reports also the average R^2 increase when a metal factor is added to CAPM, FF3, FF4 and FF5.

Group	**Type**	**MET**	**MKT**	**SMB**	**HML**	**RMW**	**CMA**	**WML**	**Average R^2 increase adding a metal factor**
Panel A: Precious metals									
Gold	World	1.66 **	0.59 **	1.01 **	0.44	0.20	-0.16	0.07	0.48
	North America	1.70 **	0.58 **	1.09 *	0.39	0.17	-0.02	0.08	0.45
	Developed markets	1.67 **	0.62 **	1.00 *	0.42	0.26	-0.13	0.03	0.47
	Emerging markets	1.62 **	0.40	0.96 **	0.64	0.06	-0.27	0.19	0.38
	Large caps	1.71 **	0.57 **	0.57 *	0.41	0.37	-0.12	0.08	0.51
	Small caps	1.72 **	0.71 *	1.44 *	0.20	-0.82	0.02	0.08	0.17
Silver	World	1.02 **	0.79 **	1.92 **	0.68	0.05	-0.16	-0.06	0.27
	North America	1.04 **	0.79 **	2.01 **	0.73	0.01	-0.18	-0.02	0.27
	Developed markets	1.03 **	0.81 **	1.97 **	0.69	0.05	-0.09	-0.01	0.27
	Emerging markets	0.92 **	0.13	0.40	0.48	-1.05	-3.78 **	-0.99 **	0.27
	Large caps	0.80 **	0.55 **	1.21 **	0.60	0.25	-0.38	-0.02	0.28
	Small caps	0.94 **	0.75	2.31 **	0.13	0.67	-0.68	-0.05	0.09
Platinum	World	0.80 **	1.15 **	0.95 **	0.69 *	0.25	0.02	-0.11	0.16
	North America	0.78 **	1.28 **	1.88 **	0.98	-0.10	-1.73	-0.17	0.11
	Developed markets	0.78 **	1.28 **	1.88 **	0.98	-0.10	-1.73	-0.17	0.11
	Emerging markets	0.80 **	1.05 **	0.85 **	0.81 *	0.18	-0.03	-0.11	0.16
	Large caps	0.63 **	0.81 **	0.66 **	1.00 **	0.29	-0.70 *	-0.06	0.16
	Small caps	0.89 **	0.97 **	0.93 **	0.92 *	0.36	-0.80	-0.07	0.17
Panel B: Industrial metals									
Steel	World	0.27 **	1.28 **	0.86 **	1.09 **	0.44	-1.79 **	-0.06	0.13
	North America	0.25 **	1.32 **	0.51	0.98 *	-0.53	-1.77 **	0.10	0.09
	Developed markets	0.24 **	1.25 **	0.85 **	1.16 **	0.14	-1.52 **	0.02	0.08
	Emerging markets	0.32 **	1.31 **	0.84 **	1.07 **	0.73	-2.07 **	-0.14	0.24
	Large caps	0.28 **	1.28 **	0.78 **	1.00 **	0.20	-1.96 **	-0.06	0.11
	Small caps	0.23 **	1.25 **	1.01 **	1.41 **	1.13 **	-1.33 **	-0.07	0.20
Iron ore	World	0.59 **	1.55 **	1.54	3.30 **	3.79 **	-4.01 *	-1.22 *	0.33
	North America	0.66 **	1.46 **	1.79	5.26 **	4.25	-4.43	-1.06	0.12
	Developed markets	0.75 **	1.76 **	1.77	3.73 **	4.33 *	-4.83 *	-0.88	0.29
	Emerging markets	0.45 **	1.35 **	1.26	2.77 **	2.83	-3.51 *	-1.41 **	0.21
	Large caps	0.65 **	1.38 **	1.25	3.04 **	3.17 *	-4.55 *	-1.56 **	0.34
	Small caps	0.42 **	1.61 **	1.96 *	3.47 **	4.35 **	-3.45 *	-0.28	0.30
Copper	World	0.51 **	1.16 **	1.18 **	0.98 *	0.31	-0.83	0.07	0.08
	North America	0.64 **	1.10 **	1.32 **	0.75	0.58	-0.62	0.07	0.09
	Developed markets	0.55 **	1.18 **	1.22 **	1.10	0.63	-1.14	0.06	0.08
	Emerging markets	0.53 **	1.13 **	1.02 **	0.58	-0.02	-0.13	0.06	0.11
	Large caps	0.62 **	1.05 **	1.07 **	0.93 **	0.17	-0.54	0.07	0.16
	Small caps	0.42 **	1.30 **	1.28 **	0.79	0.55	-0.90	0.15	0.04
Aluminum	World	0.24 *	1.51 **	0.93 *	0.68	0.12	-1.19 *	-0.04	0.09
	North America	0.40 **	1.57 **	0.67	1.04	-0.19	-0.91	-0.07	0.11
	Developed markets	0.30 **	1.48 **	0.87 *	0.79 *	0.15	-1.05 *	0.05	0.12
	Emerging markets	0.24	1.59 **	1.03	0.31	-0.40	-1.22	-0.10	0.02
	Large caps	0.18	1.56 **	0.73 *	0.77	-0.02	-1.64 **	-0.09	0.14
	Small caps	0.44 **	1.36 **	1.37 **	0.53	0.45	0.27	0.19	0.15

** and * indicate statistical significance at the 0.05 and 0.10 level, respectively.

2.4.3 Robustness analysis

I assess the robustness of my results using four criteria: alternative industry classifications, exclusion of outliers, weekly observations and metal futures. I first compare my results using the Bloomberg classification with those obtained using two alternative industry classifications: the Global Industry Classification Standard (GICS) and a new classification system which I name Modified GICS. The Bloomberg classification does not openly disclose their classification criteria which are both quantitative and qualitative (Bloomberg, 2014). GICS is an industry taxonomy developed in 1999 by MSCI and Standard & Poor's which classifies by sub-industry depending on which mining operation provides more than 60% of the revenues in the current year or, when this cannot be appropriately assessed, qualitative and undisclosed criteria (MSCI, 2015). I introduce a Modified GICS classification system, whereby companies are categorized according to the mining operation that generates more than 60% of revenues in every year of the sample period. This new classification system provides a more homogeneous and transparent sample as there is no qualitative assessment. It allows me to categorize companies which have alternative classifications in Bloomberg and GICS. For example the multinational miner Vale is categorised under iron ore in Bloomberg and steel in GICS. However, since 2012 Vale does not openly disclose the revenues generated by a single metal, while in the past it reported only the contribution of iron ore which changed significantly over the years. For these reasons, Vale is classified as Diversified according to the Modified GICS. Additionally, my new classification identifies companies in nickel, tin, zinc, manganese and titanium which are not included in the existing classifications. This is the case for the zinc producing company Horsehead Holding Corp. Although I do not discuss these metals (given the small number of securities in each of them) the Modified GICS classification method allows me to exclude the presence of large metal groups which are not classified by Bloomberg and GICS. A comparison of the three classifications is provided in Table 2.7.

Table 2.7: **Classification of mining stocks using Bloomberg, GICS and Modified GICS**

The table reports the breakdown of the data set by metals using three different classifications: Bloomberg, GICS and Modified GICS. Both number of stocks and market capitalization weights are reported for each metal group.

	Number of Stocks			Market Capitalization Weights (%)		
Miners Groups	Bloomberg	GICS	Modified GICS	Bloomberg	GICS	Modified GICS
1. Precious Metals	82	78	43	11.9	10.5	8.1
Gold	56	59	35	9.0	9.4	7.3
Silver	18	19	4	2.0	1.1	0.7
Platinum	8		4	0.9	-	0.1
2. Industrial Metals	159	173	82	39.2	32.9	17.8
Steel	104	159	47	23.3	28.1	10.2
Irone Ore	24		11	5.2	-	0.6
Copper	20		10	6.3	-	4.8
Aluminum	11	14	5	4.4	4.7	2.0
Nickel			5	-	-	0.1
Tin			1	-	-	0.0
Zinc			1	-	-	0.0
Manganese			1	-	-	0.0
Titanium			1	-	-	0.1
3. Diversified	180	170	296	48.9	56.6	74.1
Total	421	421	421	100.0	100.0	100.0

The Modified GICS is the most granular as it provides the breakdown of mining stocks into 12 metals. However, it leaves the largest number of securities unclassified by metal in the diversified category (296). The GICS classification is the least granular as it distinguishes only four metals but it leaves fewer securities unclassified (170). The Bloomberg classification has intermediate features between GICS and Modified GICS.

Additional robustness checks are performed using weekly observations and excluding outliers. The analysis with weekly observations is not performed for the WML factor for which only monthly returns are available. The analysis excluding outliers is performed by trimming the data set to exclude 1% and 99% outliers observations (Barnett and Lewis, 1974; Ruppert, 2011). A final robustness check is performed using metals futures rather than spot price data (Gorton and Rouwenhorst, 2006).

The analysis shows that my results are robust (see Table 2.8). Across criteria, the most significant factors are the metal factor (in 36 out of 39 cases), the market factor (in 38 out of 39 cases) and the SMB factor (in 32 cases out of 39 cases). The least significant factors are the RMW (in just 5 out of 39 cases) and the WML (in 4 out of 32 cases). The robustness analysis confirms that the metal factor is more relevant for precious metals while the market factor is more significant for industrial metals. Adding a metal factor improves the R^2, particularly for precious metals. Differences between classifications are generally small, suggesting that there is little benefit from using alternative classifications. The largest difference between Bloomberg and other classifications is with the SMB factor for silver with Modified GICS (1.92 versus 3.23). The exclusion of outliers produces similar results to those obtained by Bloomberg with the largest difference in the SMB factor for silver (1.92 versus 1.08). The regression coefficients calculated using weekly observations are close to those obtained with monthly observations for both the metal and the market factors. Additionally, the R^2 improves with the addition of the metal factor and increases more than with monthly observations with the exception of platinum and iron ore. Sensitivities calculated with futures are very similar to those with spot prices for precious metals. Differences are small but larger for industrial metals, particularly when futures have been more recently introduced.

Table 2.8: **Robustness tests**

The table reports the averages of the regression betas using the MFF5 model (for the metal, market, SMB, HML, RMW and CMA factors) and the MFF4 model (for WML factor) across robustness criteria. OLS models are estimated. The table also reports the average R^2 increase when a metal factor is added to CAPM, FF3, FF4 and FF5.

Group	Type	MET	MKT	SMB	HML	RMW	CMA	WML	Average R^2 increase adding a metal factor
Panel A: Precious metals									
Gold	Bloomberg	1.66 **	0.59 **	1.01 **	0.44	0.20	-0.16	0.07	0.48
	GICS	1.64 **	0.61 **	1.02 **	0.46	0.20	-0.17	0.09	0.46
	Modified GICS	1.66 **	0.54 **	0.94 **	0.40	0.22	-0.12	0.07	0.47
	Excluding Outliers	1.55 **	0.53 **	0.80 **	0.56 *	0.25	-0.26	0.05	0.50
	Weekly Observations	1.58 **	0.60 **	0.52 **	0.55 **	0.23	-0.12		0.50
	Metal Futures	1.65 **	0.55 **	0.99 **	0.51 *	0.18	-0.25	0.06	0.48
Silver	Bloomberg	1.02 **	0.79 **	1.92 **	0.68	0.05	-0.16	-0.06	0.27
	GICS	0.99 **	0.75 **	1.87 **	0.51	-0.17	0.11	0.04	0.28
	Modified GICS	1.24 **	1.02	3.23 **	0.47	0.67	-0.12	-0.13	0.15
	Excluding Outliers	0.91 **	0.52 **	1.08 **	0.44	0.10	0.07	-0.06	0.36
	Weekly Observations	1.02 **	0.60 **	0.75 **	0.64 **	0.08	-0.38		0.32
	Metal Futures	1.02 **	0.81 **	1.96 **	0.60	0.08	-0.06	-0.09	0.28
Platinum	Bloomberg	0.80 **	1.15 **	0.95 **	0.69 *	0.25	0.02	-0.11	0.16
	Modified GICS	0.81 **	1.12 **	0.96 **	1.53 **	0.14	-1.07	0.02	0.16
	Excluding Outliers	0.75 **	1.02 **	0.89 **	0.78 *	0.12	-0.09	-0.09	0.17
	Weekly Observations	0.57 **	1.09 **	0.69 **	0.86 **	-0.18	-0.61 **		0.09
	Metal Futures	0.79 **	1.11 **	0.96 **	0.71 *	0.25	-0.01	-0.13	0.17
Panel B: Industrial metals									
Steel	Bloomberg	0.27 **	1.28 **	0.86 **	1.09 **	0.44	-1.79 **	-0.06	0.13
	GICS	0.30 **	1.31 **	0.93 **	1.08 **	0.61	-1.86 **	-0.04	0.10
	Modified GICS	0.32 **	1.23 **	0.97 **	1.28 **	0.58	-1.80 **	0.01	0.12
	Excluding Outliers	0.20 **	1.18 **	0.77 **	1.06 **	0.39	-1.36 **	-0.01	0.09
	Weekly Observations	0.22 **	1.37 **	0.85 **	0.52 **	0.28	-1.15 **		0.13
	Metal Futures	0.15 *	1.36 **	0.75 *	1.05 **	0.04	-1.88 **	-0.36 **	0.19
Iron ore	Bloomberg	0.59 **	1.55 **	1.54	3.30 **	3.79 **	-4.01 *	-1.22 *	0.33
	Modified GICS	0.75 **	1.72 **	1.77	4.10 **	4.24 *	-5.52 **	-1.02	0.32
	Excluding Outliers	0.62 **	1.46 **	1.15	2.96 **	3.55 **	-4.02 *	-1.22 **	0.35
	Weekly Observations	0.59 **	1.43 **	-0.21	1.67 **	1.84 *	-2.43 **		0.18
	Metal Futures	0.35	1.80 **	2.07	3.31 *	3.66	-0.32	-1.63 *	0.21
Copper	Bloomberg	0.51 **	1.16 **	1.18 **	0.98 *	0.31	-0.83	0.07	0.08
	Modified GICS	0.60 **	1.02 *	1.07 *	0.83	-0.18	-0.53	0.10	0.08
	Excluding Outliers	0.46 **	1.05 **	1.14 **	0.68 **	0.33	-0.29	0.03	0.11
	Weekly Observations	0.47 **	1.18 **	0.82 **	1.13 **	0.63 **	-0.96 **		0.09
	Metal Futures	0.54 **	1.11 **	1.21 **	0.93 *	0.30	-0.76	0.08	0.09
Aluminum	Bloomberg	0.24 *	1.51 **	0.93 *	0.68	0.12	-1.19 *	-0.04	0.09
	GICS	0.22	1.58 **	0.88 *	0.56	0.25	-0.95	0.04	0.21
	Modified GICS	0.30 *	1.42 **	0.65	0.49	-0.05	-0.66	-0.04	0.15
	Excluding Outliers	0.20	1.41 **	0.88 *	0.52	0.16	-0.86	0.05	0.08
	Weekly Observations	0.25 **	1.53 **	0.67 **	0.72 **	0.27	-1.70 **		0.17
	Metal Futures	0.38 **	1.33 **	0.79 **	0.74 **	0.34	-0.43	-0.07	0.05

** and * indicate statistical significance at the 0.05 and 0.10 level, respectively.

2.4.4 Discussion of spot and futures prices

To clarify the difference between spot and futures prices, I review the two main theories explaining their relationship: the theory of normal backwardation and the theory of storage

(Fama and French, 1987; Lautier, 2005; Gorton, Hayashi, and Rouwenhorst, 2012). The theory of normal backwardation (Keynes, 1930; Hicks, 1939; Gorton, Hayashi, and Rouwenhorst, 2012) assumes that commodity producers hedge their commodity holdings against adverse price movements with short futures positions. This selling pressure causes futures prices to trade at a discount to spot prices, i.e. in backwardation. This theory has several limitations. It relies on the assumption that commodity producers are generally short futures and is not supported by historical data, which shows that commodities term structures are also upward sloping (Carter, 1999; Lautier, 2005). The theory of storage (Kaldor, 1940; Working, 1949) assumes that market participants benefit from inventories as they allow firms to meet unexpected demand, putting commodities on the market when prices are high and holding them when prices are low. In literature, this implicit benefit is called convenience yield and has been investigated in several studies (Gibson and Schwartz, 1990; Routledge, Seppi, and Spatt, 2000; Helyette Geman, 2005). Some researchers see the convenience yield as an exogenous variable (Gibson and Schwartz, 1990) while others propose a convenience yield which is inventory dependent (Routledge, Seppi, and Spatt, 2000). Notably, the convenience yield benefits holders of physical commodities but not those of futures. Under certain assumptions, Geman (2005) formulates the relationship between spot and futures prices as

$$f^T(t) = S(t)e^{(r-y)(T-t)} \tag{2.6}$$

where f^T is the forward price for maturity T, $S(t)$ is the spot price at time *t*, *r* is the interest rate prevailing at date *t* and y is the convenience yield. Additionally, the convenience yield can be further decomposed into $y = benefit - storage\ cost$ as the benefit of holding a commodity is reduced by the costs to store it. In the case where $r - y$ is negative, the futures curve is in backwardation. This happens when interest rates and storage costs are low compared to the benefit of holding the physical commodity. When the opposite happens, the futures curve is said to be in contango.

I use metal spot prices in the regression analysis, following the most established approach in literature (Blose and Shieh, 1995; Blose, 1996; Tufano, 1998; Smith, 2001; Gilmore et al., 2009). As shown in equation 2.6, spot prices do not encompass the costs of storage, which negatively affect miners' returns. Highly variable costs of storage might influence my analysis. However, it is difficult to estimate their impact as historical time series of storage costs are not available (Geman and Smith, 2013). As such, I strengthen my study by running the analysis also against futures prices, which encompass storage costs.

The analysis with futures prices (Xu and Fung, 2005; Elder and Jin, 2009) enhances my study by taking into account storage costs and convenience yield (LBMA, 2017). Storage costs reduce miners' returns while the convenience yield enhances them. Their relative importance changes over time (Gibson and Schwartz, 1990; Routledge, Seppi, and Spatt, 2000; Helyette Geman, 2005) and impact the above-ground metals but not the metals that firms own through concessions and still need to be mined. However, the results based on futures prices are affected by 1) the need of rolling futures at maturity and 2) the shape of the term structure. If the futures curve is in backwardation, rolling expiring futures into nearby active contracts generates positive returns as the expiring future is sold at a higher price than the futures purchased. The opposite is true when the curve is in contango. To eliminate this effect, I use the returns of a futures contract versus its value on the previous day, also at expiry. This avoids the jumps in returns resulting from comparing the price of the expired futures contract with new futures contract. Futures returns are also a function of the shape of the term structure resulting from the combined effect of storage costs and convenience yield. Holding futures in backwardation (contango) generates a positive (negative) carry as futures prices increase (decrease) in time. I further investigate this effect by calculating the difference between the second and first futures contract of each metal for the entire sample. When the difference is positive (negative) the curve is in contango (backwardation), see Table 2.9. The analysis of average differences (Panel A) shows that four metals are on average in contango (gold, silver, aluminium and steel) while three metals (platinum, copper and iron ore) are on average in backwardation. The average differences vary significantly with the lowest value for iron ore (-3.11%) and the highest for steel (+0.96%). All metals spend time both in backwardation and in contango. Gold and silver trade mostly in contango (94% of the observations) confirming earlier findings in literature (LBMA, 2017). The other metals alternate between contango and backwardation more often, with significant volatility for steel and iron ore. Panel B shows that all metals are in contango in 2008, 2009 and 2012. There are no years with all metals in backwardation. In most years, metals are both in contango and in backwardation. Therefore, it is not practical to break the sample in periods where all metals are in backwardation (contango) and discuss how the approach might perform under these conditions. As gold and silver trade mostly in contango, futures returns are likely to be lower than spot returns. However, the robustness analysis in Table 2.8 shows that this does not affect the analysis as the sensitivities to metal factor are similar using spot (Bloomberg) and futures prices: gold (1.66 vs. 1.65) and silver (1.02 vs. 1.02). Sensitivities are very close also for the other metals: platinum (0.80 vs. 0.79), steel (0.27 vs. 0.15), iron ore (0.59 vs. 0.35), copper (0.51 vs. 0.54) and aluminium (0.24 vs. 0.38). The larger difference for steel and iron ore might result also from the higher volatility in the differences of futures prices.

Table 2.9: **Analysis of futures curve**

This table reports the statistics of the difference between the first and second futures contract for each metal.

	Gold	Silver	Platinum	Copper	Aluminum	Iron Ore	Steel
Panel A: Difference between second and first futures (%)							
Average	0.47	0.63	-0.07	-0.14	0.40	-3.11	0.96
Stdev	0.34	0.46	1.00	0.63	0.49	5.66	2.86
Min	-0.05	-0.09	-5.33	-3.74	-1.80	-11.32	-7.76
Max	1.23	1.80	1.81	0.71	2.60	7.05	8.79
Num Obs	301	301	301	222	222	24	82
Contango	94%	94%	62%	53%	80%	33%	66%
Backwardation	6%	6%	38%	47%	20%	67%	34%
Panel B: Contango vs. backwardation							
	1997	1998	1999	2000	2001	2002	2003
Metals in contantgo	4	4	4	2	1	4	3
Metals in bakwardation	1	1	1	3	4	1	2
	2004	2005	2006	2007	2008	2009	2010
Metals in contantgo	3	4	4	4	5	6	4
Metals in bakwardation	2	1	1	1	0	0	2
	2011	2012	2013	2014	2015		
Metals in contantgo	5	6	5	5	5		
Metals in bakwardation	1	0	2	2	2		

In conclusion, both spot and futures prices have advantages and disadvantages. By running the analysis with both spot and futures of prices, I use a comprehensive approach that takes into account the different aspects of the complex business of mining stocks. More importantly, both the analysis with spot and futures prices provide similar results confirming the robustness of my findings.

2.4.5 Sub-period analysis

I finally perform a sub-period analysis on a market weighted portfolio of metals as represented by S&P GSCI All Metals index (S&P Dow Jones Indices, 2015). In literature, there are several tests for parameter instability and structural changes in regression models. The Chow test (Chow, 1960) and the Andrews-Quandt test (Quandt, 1960; Andrews, 1993; Andrews and Ploberger, 1994) are commonly used but both require prior knowledge regarding the timing of potential breaks and the former allows for the determination of a single break-point only. Bai and Perron (1998) enhanced the Quandt-Andrews test by allowing for multiple unknown breakpoints. In their framework, a regression model is formulated as $y_t = X_t\beta + Z_t\delta_j + \varepsilon_t$ where the variables X are those whose parameters do not vary across regimes, while the variables Z have coefficients that are regime-specific. The Bai-Perron test identifies the m multiple breaks $\{T\}_m = (T_1,...T_m)$ which minimize the sums-of-squared residuals given by

$$BP(\beta,\delta|\{T\}) = \sum_{j=0}^{m}\left\{\sum_{t=T_j}^{T_{j+1}-1} y_t - X_t\beta - Z_t\delta_j\right\} \tag{2.7}$$

using standargd least squares regression to obtain estimates $(\hat{\beta},\hat{\delta},)$.

I use the Bai-Perron test (Creti, Joëts and Mignon, 2013) to identify four sub-periods which represent different phases of the metals cycle (see Figure 2.2) - November 1990 to April 2007, May 2007 to June 2009, July 2009 to July 2011 and August 2011 to December 2015. Metals rose from the 1990's until 2007 in what is often termed the commodity super-cycle (Erten and Ocampo, 2013). A major sell-off occurred during the Global Financial Crisis (GFC) after which commodities recovered making new highs. Since 2011, metals have followed a downward trend, marking the end of the commodity expansion (Brenes, Camacho, Ciravegna and Pichardo, 2016).

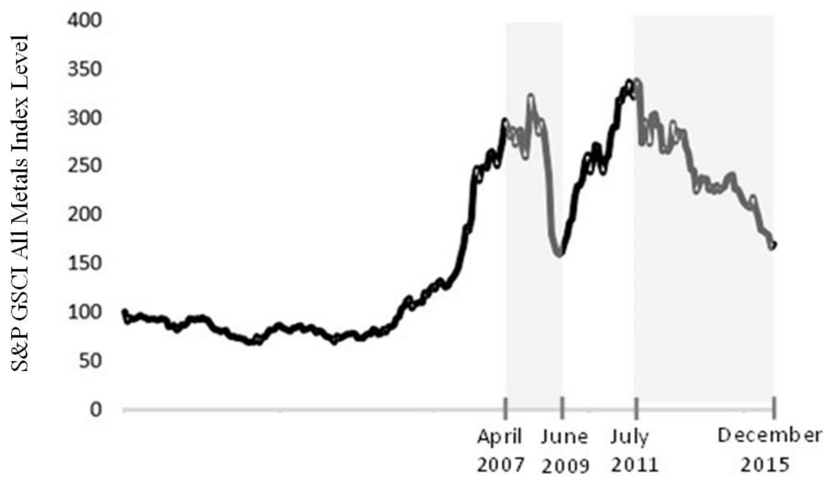

Figure 2.2: ***Metals markets sub-periods***

Charts with the sub-period analysis identified using the Bai-Perron test on a market weighted portfolio of metals.

Results presented in Table 2.9 confirm my previous findings. The metal and market factors are the most influential factors across most sub-periods. They are both significant in the sub-periods ending in April 2007 and June 2009 for all metals with the exception of aluminium. In the period post-GFC ending in July 2011, the market factor is not significant for gold and silver while the metal factor is not significant for silver, platinum, steel and aluminium.

Table 2.10: **Sub-period analysis**

The table reports the regression betas in four sub-periods using the MFF5 model (for the metal, market, SMB, HML, RMW and CMA factors) and the MFF4 model (for WML factor). OLS models are estimated. The table also reports the average R^2 increase when a metal factor is added to CAPM, FF3, FF4 and FF5.

Group	Period	Breakpoint	MET	MKT	SMB	HML	RMW	CMA	WML	Average R^2 increase adding a metal factor
Panel A: Precious metals										
Gold	1	Apr 2007	1.78 **	0.74 **	1.06 **	0.17	0.31	0.27	0.08	0.41
	2	Jun 2009	1.56 **	0.92 *	0.68	-1.24	0.40	0.17	-0.14	0.53
	3	Jul 2011	1.20 **	0.55	0.88	0.37	-2.08	-3.49 *	0.45	0.54
	4	Dec 2015	1.75 **	-0.21	0.28	2.63 **	1.16	-3.88 **	-0.32	0.60
Silver	1	Apr 2007	1.01 **	0.79 *	1.85 **	0.57	-0.44	0.54	0.16	0.22
	2	Jun 2009	1.15 **	1.87 *	2.37	-2.27	-0.89	1.11	-0.58	0.26
	3	Jul 2011	0.45	1.15	2.81	-1.45	-3.38	-5.03	0.94	0.23
	4	Dec 2015	1.12 **	-0.15	0.32	2.60 **	0.13	-3.77 *	-0.47	0.46
Platinum	1	Apr 2007	0.85 **	1.10 **	0.95 **	0.19	0.23	0.59	0.01	0.15
	2	Jun 2009	0.81 **	1.61 **	0.20	0.67	-0.14	0.01	-0.15	0.18
	3	Jul 2011	0.61	1.30 *	0.27	-0.24	-0.13	-0.19	0.45	0.03
	4	Dec 2015	0.56 **	1.26 **	1.70	2.86 **	2.31	-2.21	-0.88	0.08
Panel B: Industrial metals										
Steel	1	Apr 2007	0.23 *	1.85 **	0.65	3.05 **	0.41	-3.23 **	0.31	0.05
	2	Jun 2009	0.46 **	1.03 **	0.57	1.48 *	2.85 *	-2.15 **	-0.07	0.02
	3	Jul 2011	0.26	1.18 **	0.55	0.62	-0.07	-1.10	0.56	0.02
	4	Dec 2015	0.20	1.41 **	0.63	1.69 **	0.68	-2.63 **	-0.57 **	0.01
Iron ore	1	Apr 2007								
	2	Jun 2009								
	3	Jul 2011								
	4	Dec 2015	0.59 **	1.55 **	1.51	3.20 **	3.75 **	-3.95 *	-1.22 **	0.14
Copper	1	Apr 2007	0.38 **	1.03 **	1.12 **	1.57 *	-0.58	-1.08	0.11	0.05
	2	Jun 2009	0.39 *	1.28 **	0.25	-1.19	2.18	-1.87	-0.02	0.09
	3	Jul 2011	0.58 *	1.58 **	0.55	-1.19	0.98	0.52	-0.11	0.07
	4	Dec 2015	1.06 **	0.99 **	0.53	2.19 **	2.51	-2.41	-0.76 *	0.19
Aluminum	1	Apr 2007	0.18	2.13 **	0.23	2.93 *	-0.98	-3.28 *	0.52	0.07
	2	Jun 2009	0.17	1.98 **	1.33	0.53	2.89	-0.07	0.04	-0.01
	3	Jul 2011	0.62	1.40 **	0.75	0.06	-0.23	-0.29	0.81 *	0.04
	4	Dec 2015	0.63 *	1.10 **	0.28	1.09	-0.43	-1.93	-0.75 *	0.07

** and * indicate statistical significance at the 0.05 and 0.10 level, respectively.

In the final sub-period ending in December 2015 the metal factor is always significant with the exception of steel while gold and silver miners have a negative but not significant sensitivity to the market factor. Fama-French factors are significant only in 29 out of 125 cases. The R^2 increases with the addition of a metal factor in all periods, with the exception of aluminium during the GFC.

2.4.6 Testing regression assumptions

In this section, I ensure that linear regression assumptions are met: no high correlation among factors, no autocorrelation of residuals, no heteroscedasticity of the residuals and no unit roots in the regression time series (Asteriou and Hall, 2007). I check pairs' collinearity through correlations among factors and metals and I find that correlations are generally low (see Table 2.10).

Table 2.11: **Correlations**

The table reports the correlations of Fama-French factors with spot and futures metal prices. Correlations by models (FF3, FF4 and FF5) are reported in Appendix A.1 in Tables A.1.1 and A.1.2.

Metal/Factors	R_M-R_F	SMB	HML	WML	RMW	CMA
Panel A: Correlations with spot metal prices						
Gold	0.23	0.28	-0.01	-0.31 *	-0.18	-0.26
Silver	0.30 *	0.24	-0.08	-0.37 *	-0.21	-0.38 **
Platinum	0.46 **	0.09	0.25	-0.52 **	-0.34 *	-0.09
Steel	0.20	0.14	0.32 *	-0.31 *	-0.31 *	0.26
Iron	0.10	0.26	0.42 **	-0.20	-0.33 *	0.36 *
Copper	0.50 **	0.16	0.27	-0.55 **	-0.54 **	-0.24
Aluminum	0.01	0.01	0.01	0.04	-0.07	-0.06
Panel B: Correlations with futures metals						
Gold	0.08	0.19	0.07	-0.08	0.07	-0.12
Silver	0.13	0.18	-0.05	-0.05	0.14	-0.26
Platinum	0.25	-0.01	0.30	-0.31	0.02	0.09
Steel	0.21	-0.08	0.04	-0.15	0.00	0.26
Iron	-0.08	0.21	0.16	0.07	-0.10	0.19
Copper	0.35 *	0.06	0.37 *	-0.37 *	-0.36 *	-0.07
Aluminum	0.19	-0.04	0.23	-0.27	0.08	0.02

** and * indicate statistical significance at the 0.05 and 0.10 level, respectively.

The highest values are for platinum and copper spot prices when analysed with the market factor. Correlations of metals with the market factor are lower for futures prices with the exception of steel and aluminium.

I use the Durbin-Watson test to investigate the presence of autocorrelation. There is autocorrelation if it is not true that $Cov(\varepsilon_t, \varepsilon_s) = 0$ if $t \neq s$ where ε_t is the error term. This test has a null hypothesis that the residuals from a linear regression are uncorrelated. Results show no evidence of autocorrelation across metals. The null hypothesis is rejected only in a few instances and particularly for value weighted portfolios of gold and for Fama-French models for steel and iron ore (see Table 2.11).

Table 2.12: **Durbin-Watson test**

Group	Security	CAPM	MCAPM	FF3	MFF3	FF4	MFF4	FF5	MFF5
Gold	Equal-weighted	1.80	1.73 **	1.87	1.84	1.84	1.83 *	1.87	1.83 *
	Value-weighted	2.21	2.27 *	2.25 *	2.33 **	2.22	2.33 **	2.26 *	2.33 **
	Panel data	2.00	2.04	2.03	2.06	2.03	2.06	2.04	2.00
Silver	Equal-weighted	1.78 *	1.77 *	1.88	1.84	1.87	1.83 *	1.87	1.83 *
	Value-weighted	1.94	1.95	2.03	2.00	2.00	1.98	2.03	2.00
	Panel data	1.68	1.69	1.70	1.69	1.69	1.69	1.69	1.69
Platinum	Equal-weighted	1.88	1.96	1.86	1.93	1.87	1.95	1.87	1.92
	Value-weighted	2.13	2.24 *	2.13	2.24	2.12	2.24	2.12	2.24
	Panel data	1.99	2.05	1.99	2.05	2.00	2.05	2.00	2.05
Steel	Equal-weighted	1.51 **	1.87 **	1.65 **	1.87	1.65 **	1.93	1.66 **	1.90
	Value-weighted	1.60 **	1.92	1.65 **	1.93	1.66 **	1.92	1.63 **	1.96
	Panel data	1.94	1.96	1.96	1.96	1.96	1.96	1.97	1.96
Iron ore	Equal-weighted	1.61 **	1.69	1.66 **	1.74	1.61 **	1.65	1.67 **	1.71
	Value-weighted	1.77 *	2.46	1.81	2.42	1.75 **	2.25	1.77 *	2.36
	Panel data	1.83	1.86	1.85	1.88	1.84	1.87	1.86	1.88
Copper	Equal-weighted	1.83	1.85	1.93	1.94	1.93	1.93	1.91	1.92
	Value-weighted	2.05	2.16	2.15	2.23	2.15	2.22	2.10	2.19
	Panel data	1.93	1.94	1.95	1.95	1.95	1.95	1.95	1.94
Aluminum	Equal-weighted	1.74 *	1.98	1.87	2.06	1.93	2.07	1.87	2.02
	Value-weighted	1.93	2.16	1.98	2.14	1.98	2.15	1.95	2.13
	Panel data	1.94	1.91	1.96	1.95	1.97	1.95	1.96	1.91

** and * indicate rejection of the null hypothesis at the 0.05 and 0.10 level, respectively.

Heteroscedasticity exists if the variance of the residuals is not constant. Several tests exist in literature to identify heteroscedasticity in the residuals of a regression. The Breusch-Pagan test (Breusch and Pagan, 1979), the Harvey test (Harvey, 1976), the Glejser test (Glejser, 1969), White's test (White, 1980) and the ARCH test (Engle, 1982) are the most popular and involve performing an auxiliary regression using the residuals from the original equation. They test the null hypothesis of no heteroscedasticity against the alternative hypothesis of heteroscedasticity which is formulated differently in the various tests. I use the ARCH test with the alternative hypothesis of autoregressive conditional heteroscedasticity (ARCH) in the residuals. This heteroscedasticity specification is widely used and motivated by the observation that in many financial time series, the magnitude of residuals appears to be related to the magnitude of recent residuals. The test performs the regression for ARCH effects up to order q in the residuals ε_t

$$\varepsilon_t^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s \varepsilon_{t-s}^2 \right) + v_t \tag{2.8}$$

I use the ARCH test which shows that the null hypothesis is generally not rejected (see Table 2.12)

Table 2.13: **Arch test**

Group	Security	CAPM	MCAPM	FF3	MFF3	FF4	MFF4	FF5	MFF5
Gold miners	Equal-weighted	0.01	0.04	0.10	0.00	0.12	0.01	0.14	0.00
	Value-weighted	1.59	0.00	0.53	0.00	0.33	0.00	0.50	0.00
Silver miners	Equal-weighted	0.03	0.00	0.06	0.01	0.04	0.01	0.11	0.01
	Value-weighted	0.32	4.80 *	0.12	1.13	0.29	1.58	0.14	1.30
Platinum miners	Equal-weighted	0.01	0.11	0.38	0.05	0.26	0.16	0.48	0.04
	Value-weighted	24.57 **	32.26 **	31.69 **	37.36 **	31.58 **	37.06 **	31.65 **	37.44 **
Steel miners	Equal-weighted	2.24	0.27	0.16	0.42	0.00	0.22	0.57	0.57
	Value-weighted	1.77	0.14	0.87	0.33	1.97	0.35	0.06	1.31
Aluminum miners	Equal-weighted	0.30	0.00	0.48	0.00	0.28	0.00	0.42	0.01
	Value-weighted	6.74 **	0.66	8.74 **	0.59	3.01	0.65	6.01 *	0.26
Copper miners	Equal-weighted	0.03	0.03	0.05	0.01	0.04	0.01	0.04	0.01
	Value-weighted	60.53 **	65.61 **	54.08 **	58.11 **	53.97 **	57.88 **	59.27 **	62.35 **
Iron ore miners	Equal-weighted	1.92	1.86	7.93 **	2.37	5.38 *	2.68	3.95 *	0.61
	Value-weighted	30.48 **	1.91	32.16 **	1.53	32.70 **	0.78	26.87 **	0.07

** and * indicate rejection of the null hypothesis at the 0.05 and 0.10 level, respectively.

Finally, I ensure that regression time series are stationary using three different tests: the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test. The ADF and PP test have a null hypothesis that there are unit roots (which would imply series are not stationary). The KPSS uses a different approach and has a null hypothesis that a univariate time series is trend stationary. Results in Table 2.13 show that the time series used do not have unit roots.

Table 2.14: **Unit root tests**

		ADF	PP	KPSS
Panel A: Factors				
FF3	Market	-15.82 **	-15.82 **	0.05
	SMB	-17.64 **	-17.64 **	0.08
	HML	-12.52 **	-12.52 **	0.29 **
FF4	Market	-15.82 **	-15.82 **	0.05
	SMB	-17.64 **	-17.64 **	0.08
	HML	-12.52 **	-12.52 **	0.29 **
	WML	-14.29 **	-14.29 **	0.06
FF5	Market	-15.82 **	-15.82 **	0.05
	SMB	-17.64 **	-17.64 **	0.08
	HML	-12.52 **	-12.52 **	0.29 **
	RMW	-14.62 **	-14.62 **	0.06
	CMA	-12.46 **	-12.46 **	0.16 *
Panel B: Metals				
Spot	Gold	-19.36 **	-19.36 **	0.22 **
	Silver	-18.80 **	-18.80 **	0.11
	Platinum	-15.99 **	-15.99 **	0.19 *
	Steel	-14.95 **	-14.95 **	0.18 *
	Iron	-9.00 **	-9.00 **	0.06
	Copper	-5.93 **	-5.93 **	0.05
	Aluminum	-9.97 **	-9.97 **	0.04
Futures	Gold	-19.60 **	-19.60 **	0.21 *
	Silver	-18.88 **	-18.88 **	0.11
	Platinum	-16.33 **	-16.33 **	0.19 *
	Steel	-8.90 **	-8.90 **	0.02
	Iron Ore	-4.32 **	-4.32 **	0.06
	Copper	-16.02 **	-16.02 **	0.17 *
	Aluminum	-15.99 **	-15.99 **	0.08
Panel C: Miners				
Equal-weighted	Gold miners	-15.18 **	-15.18 **	0.17 *
	Silver miners	-14.31 **	-14.31 **	0.11
	Platinum miners	-15.90 **	-15.90 **	0.26 **
	Steel miners	-13.57 **	-13.57 **	0.25 **
	Iron ore miners	-13.76 **	-13.76 **	0.37 **
	Copper miners	-14.92 **	-14.92 **	0.12
	Aluminum miners	-14.98 **	-14.98 **	0.11
Value-weighted	Gold miners	-19.58 **	-19.58 **	0.09
	Silver miners	-16.84 **	-16.84 **	0.12
	Platinum miners	-17.78 **	-17.78 **	0.24 **
	Steel miners	-14.02 **	-14.02 **	0.19 *
	Iron ore miners	-15.09 **	-15.09 **	0.24 **
	Copper miners	-16.53 **	-16.53 **	0.14
	Aluminum miners	-16.41 **	-16.41 **	0.05

** and * indicate rejection of the null hypothesis at the 0.05 and 0.10 level, respectively.

2.5 Conclusions

In this chapter, I investigate the sensitivity of world mining stocks to precious and industrial metals. My data set consists of all investible mining firms (421) domiciled both in developed and emerging markets. The sample period is from 1990 to 2015. I classify companies into three groups for precious metals (gold, silver and platinum) and four groups for industrial metals (steel, iron ore, copper and aluminium). I investigate the sensitivity of mining stocks in each group to their relevant metal, a market factor and five factors: size (SMB), style (HMB), momentum (WML), profitability (RMW) and investment pattern (CMA). More specifically, I add a metal factor to four models: the CAPM, the Fama-French 3-factor model (FF3), the Fama-French 4-factor model (FF4) and the more recent Fama-French 5-factor model (FF5). I use both panel data and time series regressions on equal and value weighted portfolios. I also segregate the sample into subsets by location (North America, developed markets and emerging markets) and size (large and small cap). The robustness of my results in ensured by using spot and futures prices, monthly and weekly data, trimming the dataset and performing a sub-period analysis.

I find that metals are fundamental in explaining the returns of mining stocks and more influential than Fama-French factors. The metal factor is significant for all types of mining firms and notably increases the performance of my models. This effect is stronger for companies domiciled in developed markets than in emerging markets. I also find differences across groups, as the metal factor is more significant for firms of precious metals while the market factor is more significant for firms of industrial metals. The higher significance of gold in particular is possibly due to its role as a safe haven and countercyclical nature. The market factor is more relevant for miners of industrial metals that are arguably more sensitive to economic growth.

Silver and platinum, which are also used for industrial purposes, show sensitivities between gold and industrial metals. Fama-French factors bring limited improvements to the models and are not always significant. In particular, the SMB and HML factors are more significant while the WML, CMA and RMW are rarely relevant.

My finding suggests that mining stocks behave differently than other stocks and industry specific factors may be more relevant than broader factors (such as Fama-French factors) for specific group of securities (Heston and Rouwenhorst, 1995). This approach is supported by the increasing capital market integration which suggests focusing on industries as well as countries (Beckers, Connor, and Curds, 1996). Following my study on miners, future research could take an industry specific approach in factor modelling, particularly for highly specialized industry groups such as oil producers (Phan, Sharma and Narayan, 2015). Additionally, my results suggest that it is fundamental for investors to differentiate between mining stocks of precious and industrial metals while constructing portfolios as the factors driving their performance vary significantly.

3 Value investing in credit

3.1 Introduction

Value investing is one of the most established market strategies and involves buying securities, which are under-priced using various fundamental measures (Asness, Moskowitz and Pedersen, 2013). Value strategies play a central role in the debate of market efficiency (Lakonishok, Shleifer and Vishny, 1994; Shleifer and Vishny, 1997; Daniel and Titman, 1997; Fama and French, 2004) and focus primarily on equities (Stattman, 1980; Rosenberg, Reid and Lanstein, 1985; Fama and French, 1992), seldom on commodities and currencies (Asness, Moskowitz and Pedersen, 2013) while the literature on value investing for credit is just evolving (L'Hoir and Boulhabel, 2010; Correia, Richardson and Tuna, 2012).

To identify value opportunities in equities, analysts use a variety of ratios such as price-to-book (P/B), price-earnings (P/E), price-to-cash flow and dividend-to-price (Fama and French, 1992; Chan and Lakonishok, 2004; Arshanapalli, Fabozzi and Nelson, 2006; Qian, Sorensen and Hua, 2009). In particular, P/B and P/E ratios are the most common measures and are often termed multiples (Kane, Marcus and Noh, 1996). Defining value opportunities is more difficult in other asset classes that do not have comparable accounting metrics. Past returns are used for government bonds and commodities (Asness, Moskowitz and Pedersen, 2013). In credit markets, bonds are valued primarily through the comparison of credit spreads versus model-implied values (L'Hoir and Boulhabel, 2010; Correia, Richardson and Tuna, 2012). I am not aware of studies exploring the use of alternative indicators to identify value opportunities in credit. In particular, I did not find studies combining spreads with financial ratios to define multiples for credit markets.

To bridge this gap in academic literature, I use two financial ratios: leverage and interest coverage. Their relevance has been broadly documented in academic research (Merton, 1974; Collin-Dufresne and Goldstein, 2001; Campbell and Taksler, 2003; Flannery and Öztekin, 2012; Kim, Kraft and Ryan, 2013; Berg, Saunders and Steffen, 2016). I also find that their use is widespread in the financial industry. I conduct a survey of the investment outlooks of the 10 largest investment banks per revenues generated (Dealogic, 2016). Their credit analysts assess the quality of investment grade credit using a variety of measures but focus primarily on leverage and interest coverage (Citi, 2016b; Goldman Sachs, 2016; J.P. Morgan, 2016; Morgan Stanley, 2016). Leverage is typically measured as the percentage of a company's debt to earnings generated. The higher the leverage, the riskier the investment. Interest coverage is measured as the fraction of earnings over interest and indicates how easily a company can pay their interest on outstanding debt. These measures cover the two defining elements of fixed income securities (notional of debt and interest). Using these two fundamental measures, I create two unique indicators to more accurately assess investment opportunities in credit markets: 1) the fraction of spread over leverage (SL) and 2) the fraction of spread over leverage and the reciprocal of interest coverage (SLC). These ratios represent the spread that investors are willing to pay for a credit investment with a given leverage and interest coverage. High SL and SLC ratios indicate that investors are attractively compensated for the risk taken. In analogy to equity, I refer to SL and SLC as credit multiples.

I use these multiples to investigate value opportunities in credit. In particular, I compare the average returns from corporate bonds when multiples are in different quintiles calculated over a five-year period. The average performance is calculated over eight time horizons (3-month, 6-month, 9-month, 1-year, 2-year, 3-year, 4-year and 5-year) using both spread changes (L'Hoir and Boulhabel, 2010; Houweling and Van Zundert, 2016) and excess returns (L'Hoir and Boulhabel, 2010; Correia, Richardson and Tuna, 2012). I discuss the riskiness of the strategy using the maximum drawdown (Chekhlov, Uryasev and Zabarankin, 2005; Madhavan, 2012). I perform the analysis in four credit areas (U.S. Investment Grade, U.S. High Yield, European Investment Grade and European High Yield) and the two ratings of U.S. Investment Grade (A and BBB) for which Merrill Lynch provides fundamental measures. I also compare credit multiples across corporate bonds of different ratings and industries (Industrials and Utilities) grouped in three subsets by maturity (2-7 years, 7-15 years and longer than 15 years). The data period ranges from December 1996 to September 2016. Spreads are sourced from Bank of America Merrill Lynch.

I find that average returns are higher when spreads are in the higher quintiles and the effect is stronger over longer time horizons (three to five years). Value strategies perform better if based on SL and SLC ratios than on spreads but this outperformance is not statistically significant. SL and SLC ratios provide similar results, suggesting that the contribution made by interest coverage is limited. Value strategies in HY deliver higher returns than in IG, particularly in Europe. My analysis suggests that value investors should be prepared for drawdowns, particularly during the first year of implementation. My findings also imply that credit multiples normalize spreads by leverage and interest coverage for investment grade bonds but not high yield which provide a higher spread for the risk taken. The analysis of value indicators also identifies discrepancies among sectors with Industrials offering a better income than Utilities. My findings suggest that researchers should further investigate the use of credit multiples to detect value opportunities within investment grade bonds and build value factors in credit markets.

My study makes several contributions to the existing literature. I find that it is possible to identify alternative and more complete value indicators than simple spreads by combining market spreads and fundamental measures. I also find that value investing delivers positive returns over longer time horizons with results consistent across geographical areas (U.S. Investment Grade, U.S. High Yield, European Investment Grade and European High Yield) and ratings for U.S. Investment Grade (A and BBB). This study extends a recent report by Morgan Stanley's analysts (Low et al., 2017) who began an initial exploration of the effectiveness of different valuation metrics, such as spreads and spread over leverage, in predicting future returns. My analysis provides and original investigation of value indicators across ratings and industries.

The chapter is organized as follows. In section 3.2, I review the existing literature. In section 3.3, I describe the data used. In section 3.4, I introduce the credit multiples. In section 3.5, I analyse the performance of value strategies for credit. In section 3.6, I discuss SL and SLC ratios. Section 3.7 concludes the chapter.

3.2 Literature review

The literature on value investing is vast (Lakonishok, Shleifer and Vishny, 1994; Shleifer and Vishny, 1997; Daniel and Titman, 1997; Fama and French, 2004) and focuses primarily on equities while studies on other asset classes are rare and more recent (Asness, Moskowitz and Pedersen, 2013). In equity, researchers investigate the value effect analysing the relation between asset prices and fundamental measures (Stattman, 1980; Rosenberg, Reid and Lanstein, 1985; Fama and French, 1992; Asness, Moskowitz and Pedersen, 2013). Arguably, the most common value indicators for stocks are the ratio of the market price to its book value (P/B) or earnings (P/E), see Williamson, (1971), Basu (1977), Fama and French (1992), Lakonishok, Shleifer and Vishny (1994), Chan and Lakonishok (2004), Anderson and Brooks (2006) and Qian, Sorensen and Hua (2009). Alternative value measures are the price-to-cash flow and the dividend-to-price (Arshanapalli, Fabozzi and Nelson, 2006). P/E ratios are particularly common among investors. They define how much investors are willing to pay per dollar of earnings and are usually referred to as multiples (Kane, Marcus and Noh, 1996). Defining value measures for other asset classes is more difficult. Government bonds and commodities do not have financial metrics such as book value while the fragmentation and scarcity of data has often been cited as the reason for the more limited research in credit markets (Campbell and Taksler, 2003).

The literature on value investing for corporate bonds primarily compares market spreads to spreads fitted with structural models (L'Hoir and Boulhabel, 2010; Correia, Richardson and Tuna, 2012). According to these models, corporate bond's yield spreads over Treasury are a function of the default risk (Flannery and Öztekin, 2012) which depends on the firm's asset leverage, volatility and debt's term to maturity (Merton, 1974; Collin-Dufresne and Goldstein, 2001; Campbell and Taksler, 2003; Avramov, Jostova and Philipov, 2007). This approach is supported by a variety of empirical studies suggesting that spreads are explained by default risk with a more limited contribution from liquidity (Longstaff, Mithal and Neis, 2005; Chen, Lesmond and Wei, 2007) and taxes (Elton et al., 2001). Multi-factor models for credit incorporating a value factor are studied by Houweling and Van Zundert (2016), Israel, Palhares and Richardson (2016) and Bektic et al. (2016). Houweling and Van Zundert (2016) find that factors such as size, low-risk, value and momentum generate statistically significant alphas in the corporate bond market. They identify value investments in credit by comparing the actual spread with a fitted credit spread for each bond. Israel, Palhares and Richardson (2016) identify four characteristics (carry, defensive, momentum and value) to explain cross sectional variation in corporate bonds excess returns using Fama-Macbeth regressions (Fama and MacBeth, 1973). To construct a value signal, the authors compare market spreads with model-implied values using an approach similar to Correia, Richardson and Tuna (2012). Bektic et al. (2016) investigate the impact of Fama-French factors (size, value, profitability and investment) in the U.S. and European credit markets. I could not find studies combining spreads with fundamental measures to define multiples in credit. The only exception is a recent report by Morgan Stanley investigating investment opportunities using a set of different valuation metrics including spread and the fraction of spread over leverage (Low et al., 2017).

3.3 Data

3.3.1 Survey of credit fundamental measures

As the academic literature does not discuss indicators of value opportunities, I focus on what happens in the industry as my starting point. I survey the 2017 credit outlooks of the 10 largest investment banks per revenues generated[3]: Bank of America - Merrill Lynch, Barclays, Citi, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, J.P. Morgan, Morgan Stanley and Royal Bank of Canada (see Table 3.1).

Credit analysts use a variety of different indicators to evaluate credit markets and elaborate their investment recommendations. The measures used can be categorized as technicals and fundamentals. Technicals refer primarily to expectations regarding flows, such as central banks purchases, fund flows and issuance (BofA Merrill Lynch, 2016; Deutsche Bank, 2016; Goldman Sachs, 2016; J.P. Morgan, 2016; Royal Bank of Canada, 2016). To define credit multiples analogously to equity, I focus on Investment Grade (IG) bonds and the fundamental measures used to evaluate them. I find that leverage, defined as the ratio of Debt to EBITDA[4], is used in all credit outlooks. As analysts differentiate between gross debt and net debt (debt net of cash), leverage can be net or gross (Kim, Kraft, and Ryan, 2013). Most analysts use net leverage (BofA Merrill Lynch, 2016; Barclays, 2016; Citi, 2016; Deutsche Bank, 2016; Goldman Sachs, 2016; Royal Bank of Canada, 2016).

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[3] Ranking calculated by Dealogic as of December 2016
[4] Earnings Before Interest, Taxes, Depreciation and Amortization

Table 3.1: Analysts' fundamental measures for credit markets

Table 3.1: **Analysts' fundamental measures for credit markets**

The table reports the fundamental measures used by analysts at the 10 largest banks for the 2017 credit outlooks published at the end of 2016.

Bank	Title	Date	Debt/ EBITDA	EBITDA/ Interest	Debt / Assets	EBITDA-Capex/ Interest	Cash/ Assets	Credit migration	Lending conditions
1. BofA Merrill Lynch	2017 US high grade outlook	Nov 2016	Yes	No	No	No	No	No	No
2. Barclays	Global credit outlook 2017	Dec 2016	Yes	No	No	No	No	No	No
3. Citi	Is the credit cycle dead?	Nov 2016	Yes	Yes	No	No	No	No	No
4. Credit Suisse	US creidt strategy: 2017 outlook	Dec 2016	Yes	Yes	No	No	No	No	No
5. Deutsche Bank	Credit outlook 2017	Nov 2016	Yes	Yes	No	No	No	No	No
6. Goldman Sachs	Global credit outlook 2017	Nov 2016	Yes	Yes	Yes	No	No	Yes	No
7. HSBC	US credit strategy: 2017 outlook	Dec 2016	Yes	Yes	No	Yes	No	No	No
8. J.P. Morgan	High grade bond and CDS 2017 outlook	Nov 2016	Yes	Yes	No	No	No	No	No
9. Morgan Stanley	2017 US credti outlook	Nov 2016	Yes	Yes	No	No	No	No	Yes
10. Royal Bank of Canada	2017 Canadian credit outlook	Dec 2016	Yes	Yes	Yes	No	Yes	No	No
Number of outlooks using the specified measure			**10**	**8**	**2**	**1**	**1**	**1**	**1**

Interest coverage, defined as the ratio of EBITDA to Interest, is the second most frequently used indicator (in eight out of ten outlooks). The importance of both indicators is discussed in literature (Campbell and Taksler, 2003; Baghai, Servaes and Tamayo, 2014; Berg, Saunders and Steffen, 2016). Only two outlooks (Goldman Sachs, 2016; Royal Bank of Canada, 2016) use the ratio of Debt to Assets, while this is one of the most commonly used definitions of leverage in academic literature (Arellano, Bai and Zhang, 2012; Berg, Saunders and Steffen, 2016). Analysts likely prefer the ratio of debt to EBITDA as it focuses on the more dynamic cash flows (EBITDA) rather than Assets (Fabozzi, 2001). Other fundamental measures are rarely used, such as the ratio of EBITA minus CAPEX[5] to Interest (HSBC), Cash to Assets (Royal Bank of Canada, 2016), credit migration (Goldman Sachs, 2016) and lending conditions (Morgan Stanley, 2016). For High Yield (HY) credit, analysts also study default rates, but these are not used for IG bonds. My survey suggests using leverage and interest coverage to define credit multiples. They are well and long established metrics among credit analysists while their use is also supported by their relevance in the assessments of ratings agencies (Kim, Kraft and Ryan, 2013).

3.3.2 Spreads and fundamental measures

My data set consists of the available time series of spreads, excess returns, leverage and interest coverage from 1997 to 2016. I consider in total six groups: U.S. Investment Grade, U.S. High Yield, Euro Investment Grade, Euro High Yield, U.S. Investment Grade single A and U.S. Investment Grade BBB. The two main geographical areas (U.S.A and Europe) represent 88% (respectively 67% and 21%) of the world credit market in 2017 (Bank of America Merrill Lynch

[5] Capital Expenditure

Indices, April 2017). I break down these two areas into Investment Grade (IG.) and High Yield (HY) to investigate bonds of different credit quality (Fabozzi, 2001). Within U.S. IG, I analyse two ratings (A and BBB), for which data on fundamentals is available. I use Bank of America Merrill Lynch spreads and excess returns sourced from Bloomberg (names and codes of the indices used are provided in Appendix, Table A.2.1). Aggregate leverage and interest coverage for the six groups are calculated by Merrill Lynch Bank of America and Morgan Stanley. Spreads and fundamental measures exclude financials for which EBITDA is not calculated[6].

Summary statistics are presented in Table 3.2. Spreads range from a minimum of 48 for Euro Investment Grade in 2004 to a maximum of 2081 for Euro High Yield in 2008 at the peak of the financial crisis. The highest variability, measured using standard deviation, is for European High Yield (321). As expected, spreads for single A companies are consistently lower than for BBB. Leverage varies significantly across areas and ratings, with the highest value for U.S. High Yield (4.2) and the lowest for U.S. Investment Grade and single A (1.1). The interest coverage ratio varies from 2.7 for U.S. High Yield (at the lowest of the dot-com market turmoil) to 13.7 for single A which also has the highest average.

[6] EBITDA is not representative for financials whose financial results are heavily dependent on interests

Table 3.2: **Summary statistics**

The table reports summary statistics for spreads, leverage and interest coverage by area/type and rating. Spreads are sourced from Bank of America Merrill Lynch Indices. Leverage and interest coverage are sourced from Bank of America Merrill Lynch and Morgan Stanley. Fundamental measures are available from 1997 to 2016 with the exception of Euro Investment grade (from 1999) and Euro HY (from 2003).

	Spreads				Leverage				Interest Coverage			
Asset Class	**Average**	**Min**	**Max**	**St. Dev.**	**Average**	**Min**	**Max**	**St. Dev.**	**Average**	**Min**	**Max**	**St. Dev.**
Panel A: Investment Grade												
U.S.	157	58	547	76	1.5	1.1	2.1	0.2	10.0	7.3	12.5	1.5
A	121	54	431	60	1.6	1.1	2.6	0.3	10.5	7.2	13.7	1.8
BBB	199	76	695	97	2.3	1.8	2.9	0.3	6.7	4.8	9.4	1.3
Euro	122	48	367	60	1.8	1.4	2.4	0.2	7.4	5.4	9.5	1.1
Panel B: High Yield												
U.S.	586	260	1'755	266	3.5	2.8	4.2	0.3	3.7	2.7	5.0	0.6
Euro	539	214	2'081	321	3.3	2.4	3.9	0.3	3.6	2.9	4.7	0.4

The analysis shows that spreads of U.S. Investment Grade are generally higher than in Euro Investment Grade despite lower leverage and higher interest coverage. The same is not true in HY where European leverage is lower than in the U.S. Across ratings, as expected, the higher quality of Single A translates in lower leverage than for BBB while interest coverage is higher.

3.4 Value indicators

3.4.1 Definitions

In this section, I identify indicators which may be suitable to detect value opportunities in credit markets. In particular, I investigate alternatives to simple spreads by examining fundamental measures. In analogy to equity ratios (such as price-to-book and price-to-earnings), I introduce two credit ratios that use the two fundamental measures identified in the literature review: leverage (defined as net debt over EBITDA) and interest coverage (defined as the fraction of

EBITDA over interest). These two measures have opposite effects on spreads. The higher the leverage, the riskier is the investment and the higher is expected to be the credit spread. Conversely, the higher the interest coverage, the better is the credit quality of the investment and the lower is likely to be the credit spread. Accordingly, I define spread over leverage (SL) as the number which needs to be multiplied by leverage to obtain the spread:

$$spread = \frac{spread}{leverage} \cdot leverage = SL \cdot leverage = SL \cdot \left(\frac{Net\ Debt}{EBITDA}\right) \tag{3.1}$$

A second ratio, termed spread over leverage and the inverse of interest coverage (SLC) is also introduced:

$$spread = \frac{spread}{Leverage + \frac{1}{Interest\ Coverage}} \cdot \left(Leverage + \frac{1}{Interest\ Coverage}\right)$$

$$= SLC \cdot \left(Leverage + \frac{1}{Interest\ Coverage}\right) = SLC \cdot \left(\frac{Net\ Debt + Interest}{EBITDA}\right) \tag{3.2}$$

These formulas ensure that, for a given ratio (SL or SLC), high leverage and low interest coverage imply high credit spreads.

3.4.2 Visual Analysis

A visual comparison of credit multiples is provided in Figure 3.1 to Figure 3.3. Figure 3.1 shows that spreads (S) and SL ratios have different scales but move closely. By construction, spreads are the main driver of SL and SLC ratios as accounting measures change less frequently than market spreads. A similar consideration can be made for equity multiples such as price-to-book ratios. There are however some divergent behaviours between spreads and credit multiples. For example, the SL and SLC ratios for U.S. IG and U.S. single A in Q3 2016 are as expensive (i.e. low) as in Q2 2014 when spreads where instead lower (see circled areas in Figure 3.1). This may suggest that the higher spreads of Q3 2016 are not an investment opportunity but rather the consequence of a deteriorated quality of credit, as represented by leverage and interest coverage. The charts also shows that spreads and SL ratios can diverge for several years but they tend to realign over the longer time horizons. Therefore, the graphical analysis suggests that SL and SLC ratios may be better indicators than spreads to identify value opportunities. An investor might profit from using SL ratios instead of spreads (S) to decide when to buy or sell corporate bonds. In the example, using SL ratios, an investor should sell corporate credit bonds in Q3 2016 rather than buying as simple spreads might suggest. In section 3.5, I investigate the use of these new indicators by comparing the performance of value strategies based on S, SL and SLC ratios.

In Figure 3.2, I compare SL and SLC ratios across areas and ratings. By dividing spreads by leverage (SL), I normalize credit spreads and identify how much income investors require per unit of leverage. SLC ratios further enhance this measure and define how much spread investors receive per unit of leverage and the reciprocal of interest coverage. By construction, SLC ratios are lower than SL ratios.

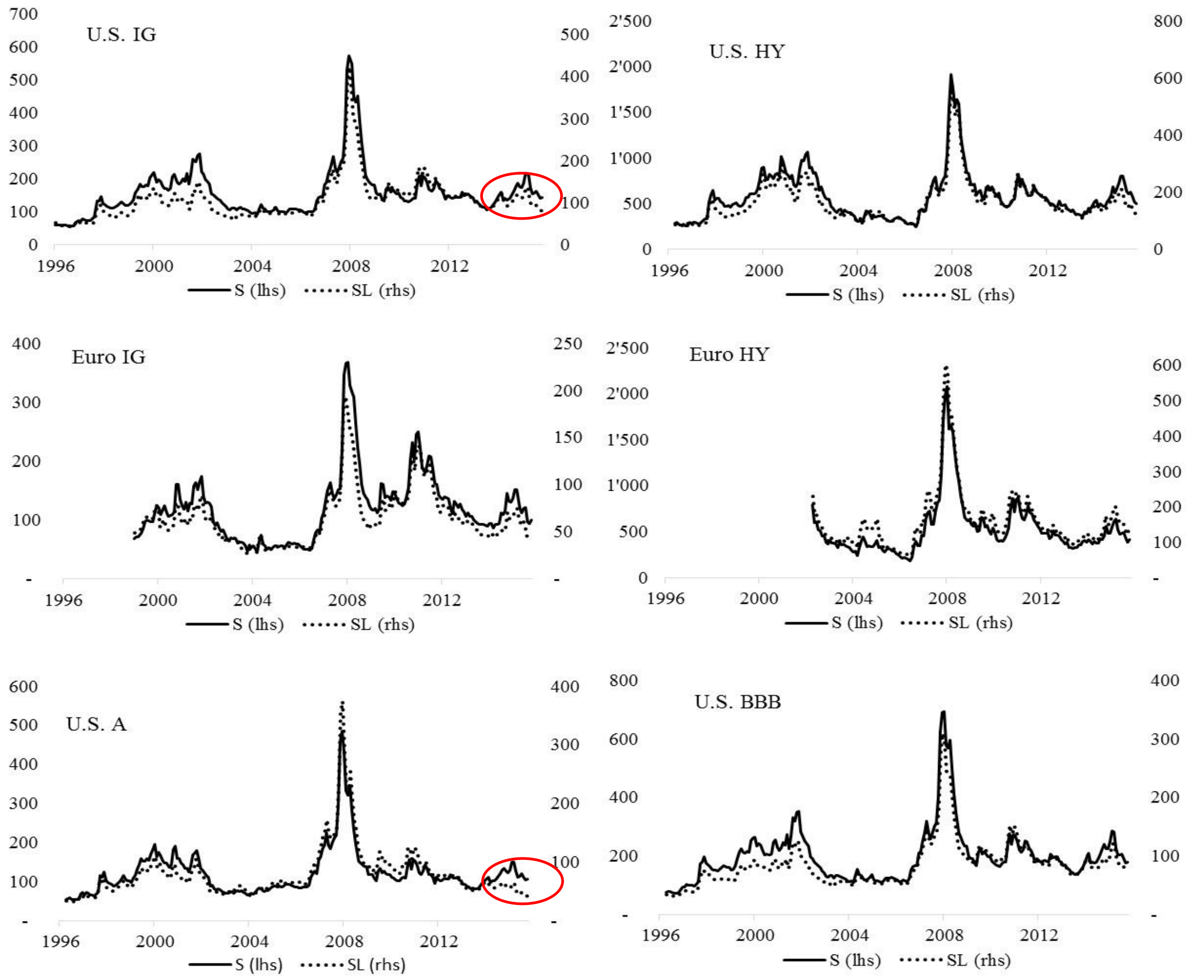

Figure 3.1: **Spreads and SL ratios**

The charts report spreads (S) and SL ratios for (U.S. Investment Grade, U.S. High Yield, Euro Investment Grade, Euro High Yield, U.S. Investment Grade A and U.S. Investment Grade BBB).

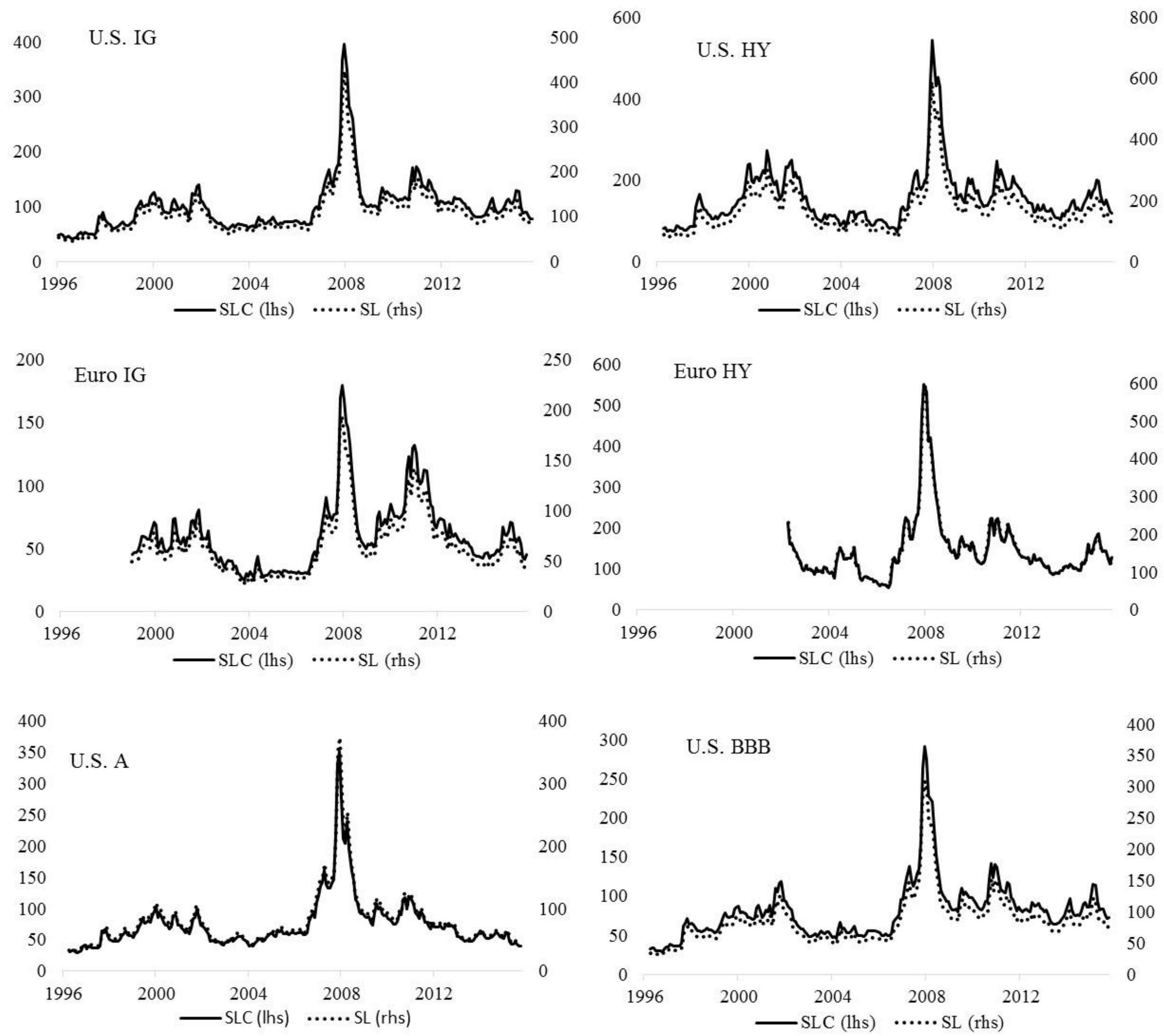

Figure 3.2: **SLC and SL ratios**

The charts report the SLC and SL ratios for (U.S. Investment Grade, U.S. High Yield, Euro Investment Grade, Euro High Yield, U.S. Investment Grade A and U.S. Investment Grade BBB).

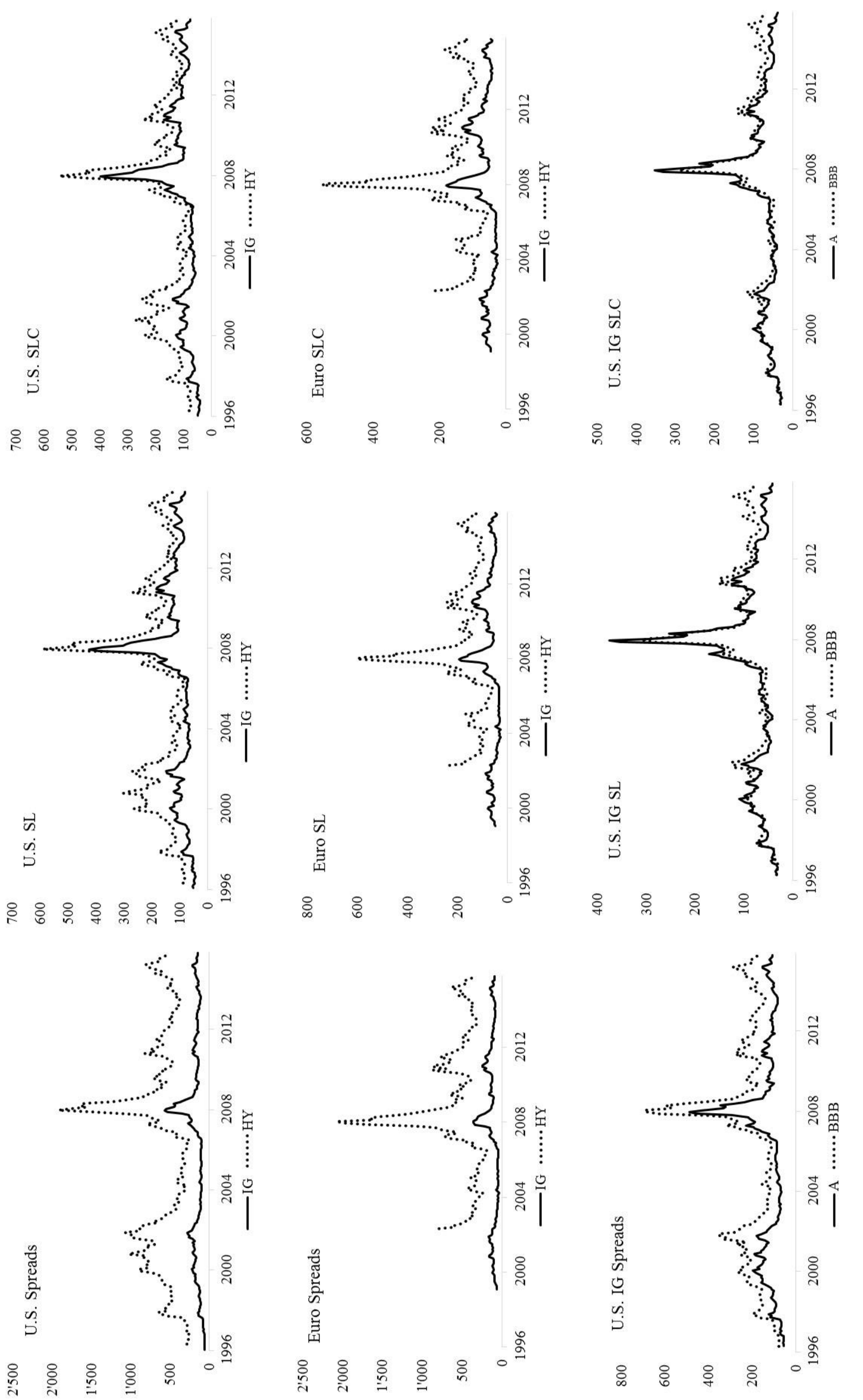

Figure 3.3: **Spreads, SL and SLC ratios across areas and ratings**

The charts compare S, SL and SLC ratios of different rating groups: a) IG (U.S. and Euro) compared to HY and b) single A compared to BBB (U.S.)

In Figure 3.3, I compare spreads, SL and SLC ratios for credit investments in the same area (U.S.A. and Euro) but of different credit quality. This illustrates whether credit multiples can be used as a measure to compare corporate bonds with different rating. The charts show that credit multiples can be used to compare U.S. corporate bonds rated single A with those rated BBB. While spreads for U.S. single A are constantly above those for U.S. BBB, both SL and SLC ratios are similar and can be used to detect which bond type offer a better reward to investors per unit of leverage and interest coverage.

However, credit multiples do not work equally well when comparing investment grade (IG) and high yield (HY) bonds. The charts highlight that credit multiples are always higher for HY securities which suggests that they are consistently a better rewarded investment than IG bonds. This evidence is not surprising as the two rating groups of IG and HY are often treated as separate asset classes both among practitioners and in literature. In particular, Houweling and Van Zundert (2016) report that the existence of this market segmentation and regulatory constraints can affect investors' willingness to invest in HY bonds and thus affect security spreads. This can create some structural biases which make HY spreads higher than what is implied by fundamentals. Figure 3.3 suggests that credit multiples could be successful in comparing investment grade bonds of different rating. This property and the ability of credit multiples to identify value opportunities is investigated in the following sections.

3.5 Value strategies

3.5.1 Performance by quintile

In this section, I study the performance of a value strategy which buys corporate credit bonds when spreads are in different quintiles (Low, 2, 3, 4 and High). I rank corporate bonds in quintiles. This approach has been widely adopted in literature of value investing since the seminal paper of Basu (1977). Quintiles are commonly used in factor analysis (Fama and French, 1993; Fama and French, 2012). However, their use extends also to other area of literature and remains widespread in a variety of recent studies (Ang, Briere and Signori, 2012).

Every month I compare the aggregate spread of each group of bonds with their five-year history and I rank them in quintiles. Then I average the performances based on which quintiles the spreads were in at inception of the strategy. I perform this analysis for six different groups of bonds: U.S. Investment Grade, U.S. single A, U.S. BBB, Euro Investment Grade, U.S. High Yield, and Euro High Yield. I calculate the performance over eight time horizons (3-month, 6-month, 9-month, 1-year, 2-year, 3-year, 4-year and 5-year). The use of a five-year rolling window for historical quintiles is standard in industry (Asness, Moskowitz and Pedersen, 2013). The performance of the strategy is calculated as spread changes (L'Hoir and Boulhabel, 2010; Houweling and Van Zundert, 2016) but also as excess returns (L'Hoir and Boulhabel, 2010; Correia, Richardson and Tuna, 2012) to take into account not only the market movements but also the incremental income provided by holding credit bonds (see Table 3.3).

Results show that spreads tend to revert to the mean (Dufee, 1999; Castagnetti and Rossi, 2013). The longer the investment horizon, the more spreads widen in the low quintile and tighten in the highest quintile. The largest widening is of +462 basis points for U.S. HY over the five-year horizon while the largest tightening is for Euro HY at -697 basis points. Buying corporate bonds when spreads are in the lowest quintile delivers negative performance over time horizons longer than four years with the exception of Euro IG. Conversely, a strategy that buys corporate bonds with spreads in the highest quintiles delivers on average a positive performance for periods longer than six months. The most negative performance of -4.7% is for U.S. single A after four years when spreads are purchased in the lowest quintile. The highest five-year performance of +59.3% is for Euro HY when spreads are in the highest quintile. The *t*-test analysis shows that the performance of the strategies is significantly different from zero primarily over the longer time horizons (in 26 out of 29 cases over five years).

Table 3.3: ***Spreads and excess performance by quintile***

The table reports spreads changes and excess returns when spreads are in different quintiles (Low, 2, 3, 4, High) calculated over a 5-year period. Performance is calculated as difference between Option Adjusted Spreads (OAS or, simply, spread) or the excess returns over government bonds. The investment time horizons considered are: 3-month (3m), 6-month (6m), 9-month (9m), 1-year (1yr), 2-year (2yr), 3-year (3yr), 4-year (4yr) and 5-year (5yr). The investment universe ranges across areas and ratings: U.S. Investment Grade (U.S. IG), U.S. Investment Grade single A. U.S. Investment Grade BBB, Euro Investment Grade (Euro IG), U.S. High Yield (U.S. HY), and Euro High Yield (Euro HY). The significance of the t-test analysis shows whether the excess performance is significantly different from zero.

	Spread Changes (basis points)								**Excess Peformance (%)**							
Quintile	**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**	**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**
Panel A - U.S. IG																
Low	4	8	14	17	55	109	145	136	-0.1	-0.2	-0.4	-0.6	-2.1 **	-4.0 **	-4.5 **	-2.8 *
2	-1	3	7	12	58	35	37	67	0.2	0.2	0.2	0.2	-1.3	0.8	1.6 *	0.7
3	-1	-6	-2	1	12	-6	-17	15	0.4	1.1 *	1.1	1.3 *	2.0 *	4.1 **	5.9 **	4.7 **
4	-14	-17	-24	-29	-42	-54	-41	-26	1.1 *	1.5 *	2.2 **	2.8 **	5.0 **	6.5 **	6.3 **	6.8 **
High	8	5	-26	-26	-122	-117	-114	-128	-0.4	0.4	2.2	2.8	9.5 **	10.0 **	10.9 **	13.6 **
Panel B - U.S. - A																
Low	1	1	3	5	14	35	148	157	0.2	0.3 *	0.3 *	0.4	0.5 *	0.2	-4.7 **	-4.4 **
2	2	7	7	6	1	28	33	38	-0.1	-0.2	-0.1	0.2	1.3 **	0.6	0.9	1.3 **
3	0	-2	3	7	60	53	-3	18	0.2	0.5 *	0.4	0.4	-1.6	-0.5	3.5 **	2.9 **
4	-3	-5	-6	-5	18	-18	-19	-23	0.4	0.6	0.8	0.8	0.2	3.4 **	4.0 **	5.1 **
High	1	-	-32	-45	-105	-102	-102	-111	0.3	0.7	2.5	3.6	8.2 **	8.8 **	9.6 **	11.3 **

	Spread Changes (basis points)								Excess Peformance (%)							
Quintile	**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**	**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**
Panel C - U.S. - BBB																
Low	5	10	18	26	90	118	166	190	-0.0	-0.2	-0.6	-1.0 *	-3.8 **	-3.8 **	-4.4 **	-3.8 *
2	1	7	12	11	61	75	77	81	0.1	0.0	-0.1	0.2	-1.1	-0.7	0.7	1.4 *
3	-5	-12	-11	-2	-11	-18	-28	11	0.7	1.6 **	2.0 **	1.9 *	4.4 **	5.9 **	8.0 **	6.6 **
4	-18	-22	-30	-35	-43	-63	-49	-34	1.5 *	1.9 *	2.8 **	3.6 **	6.0 **	8.2 **	8.0 **	9.1 **
High	10	13	-18	-17	-147	-140	-131	-155	-0.3	0.4	2.3	3.2	12.0 **	12.8 **	13.8 **	17.5 **
Panel D - Euro IG																
Low	2	7	14	18	51	110	135	100	0.0	-0.1	-0.2	-0.2	-0.8	-2.3 *	-2.3 *	0.6 **
2	-3	-4	-7	-8	63	74	92	109	0.4 *	0.7 **	1.2 **	1.5 **	-0.6	-0.3	0.1	0.7
3	9	26	28	34	23	-6	-22	12	-0.1	-0.5	-0.0	0.1	2.5 *	5.2 **	7.4 **	6.6 **
4	-2	-3	4	23	12	-24	-25	-10	0.5	1.1 *	1.1 *	0.6	2.7 **	6.0 **	7.4 **	8.2 **
High	-0	3	-16	-21	-63	-51	-39	-73	0.5	0.8	2.0	2.6	6.0 **	7.1 **	8.0 **	11.7 **
Panel E - U.S. HY																
Low	-1	3	20	36	255	351	446	462	0.9 **	1.7 **	1.9 **	2.2 **	-2.2	-2.7	-2.9	-0.7
2	20	39	47	25	-85	-45	89	226	0.4	0.5	1.0	2.7	12.6 **	14.2 **	11.2 **	8.1 **
3	-33	-55	-42	-13	-133	-186	-174	-4	2.3 *	4.3 **	4.7 *	4.5 *	14.1 **	21.1 **	24.7 **	20.4 **
4	7	46	-3	10	-56	-149	-152	-136	0.1	-0.6	2.4	3.5	9.2 **	18.1 **	22.4 **	25.5 **
High	-52	-73	-72	-118	-446	-452	-469	-494	2.8	5.5	7.2	10.4	27.2 **	31.8 **	39.3 **	46.8 **
Panel F - Euro HY																
Low	-4	0	6	3	61	46	NaN	NaN	1.2 **	2.2 **	3.1 **	4.2 **	6.4 **	10.9 **		
2	43	118	127	119	-25	-67	-26	120	-0.4	-1.8	-0.8	0.9	10.9 **	16.8 **	21.9 **	19.6 **
3	5	-23	-22	31	-35	-137	-151	-71	1.0	3.4 **	4.4 **	3.6	12.3 **	22.0 **	26.9 **	30.3 **
4	-50	-93	-123	-195	-105	-227	-255	-265	3.0 **	5.8 **	8.4 **	12.9 **	15.0 **	25.9 **	32.4 **	39.8 **
High	-172	-86	-115	-253	-566	-481	-493	-697	8.0 *	8.7	10.4	15.2	32.8 **	34.6 **	43.3 **	59.3 **

** and * indicate statistical significance at the 0.05 and 0.10 level, respectively

3.5.2 Performance differential by quintile

I next quantify the value effect by calculating the performance of a strategy that buys corporate bonds when the aggregate spreads are in the highest quintile (High) and sells when spreads are in the lowest quintile (Low), see Israel, Palhares and Richardson (2016). I also study 1) a strategy that buys in the fourth quintile and sells in the second and 2) a strategy that buys in the higher quintiles (High and 4) and sells in the lower quintiles (Low and 2). I perform the analysis using quintiles based on spreads but also SL and SLC ratios. In particular, I investigate whether there is any improvement in considering fundamentals (leverage and interest coverage) in conjunction with spreads as value indicators. In Table 3.4, I report the *p*-value of a *t*-statistic checking whether strategies based on SL and SLC ratios perform significantly different from those based on simple spreads.

The strategies reported in Table 3.4 show significant positive performance over the longer time horizons with returns different from zero for all time periods greater than three years (162 cases). The positive performance is stronger for strategies buying in the higher quintile (High) and selling in the lower quintile (Low), see Panel A. Over a five-year period, returns range from a minimum of +4.9% for Euro IG and single A to a maximum of +64.6% for Euro HY. In Panel B, over a five-year period returns range from +1.6% to +16.1% while in Panel C the performance varies from +4.9% to +37.2%. Strategies based on SL and SLC ratios deliver generally higher returns, however the outperformance compared to strategies based on simple spreads is often statistically insignificant (in 30 out of 36 cases with 10% confidence). Over a five-year period, strategies based on SL or SLC ratios outperform strategies based on spreads with the exception of Euro IG and Euro HY in Panel B. For High minus Low, SL and SLC based strategies (Panel A) outperform between +1.2% (using SL and SLC for U.S. single A) and +5.3% (using SL or SLC based strategies for Euro HY). Strategies based on SL and SLC ratios post similar returns with neither indicator clearly outperforming the other. This suggests that there is only limited benefit in adding interest coverage and using SLC ratios.

Table 3.4: **Value effect using credit multiples**

The table reports the average performance of strategies buying in the higher quintiles and selling in the lower quintiles. In Panel A the strategy buys in the highest quintile and sells in the lowest. In Panel B, the strategy buys in the fourth quintile and sells in the second quintile. In Panel C, the strategy buys in the higher quintiles (High and 4) and sells in the lower (Low and 2).The performance is measured both in spread changes and excess returns over eight different time horizons. In brackets are reported the *p*-values of a *t*-statistic testing the whether the performance of strategies based on SL and SLC significantly differ from the performance based on simple spreads.

		Spread Changes (basis points)								**Excess Peformance (%)**							
Quintile		**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**	**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**
Panel A - High Minus Low																	
U.S. IG	S	1	-3	-18	-21	-80	-112	-132	-133	-0.1	0.3	1.1	1.3	4.7 **	6.4 **	7.3 **	7.4 **
	SL	-10	-7	-21	-23	-52	-70	-152	-172	0.5	0.5	1.4	1.6	3.7 **	5.0 **	9.8 **	11.1 **
										(0.11)	(0.60)	(0.95)	(0.92)	(0.00)	(0.00)	(0.20)	(0.42)
	SLC	-10	-7	-21	-23	-52	-70	-152	-172	0.5	0.5	1.4	1.6	3.7 **	5.0 **	9.8 **	11.1 **
										(0.32)	(0.22)	(0.51)	(0.57)	(1.00)	(0.01)	(0.01)	(0.01)
U.S. A	S	-0	-1	-13	-19	-43	-59	-128	-137	-0.0	0.1	0.6	0.9	2.1 **	3.1 **	6.9 **	7.4 **
	SL	-1	-2	-14	-19	-42	-57	-110	-143	-0.0	0.1	0.6	0.9	2.1 **	3.1 **	6.3 **	8.6 **
										(0.98)	(0.91)	(0.70)	(0.70)	(0.94)	(0.76)	(0.03)	(0.57)
	SLC	-1	-2	-14	-19	-42	-57	-110	-143	-0.0	0.1	0.6	0.9	2.1 **	3.1 **	6.3 **	8.6 **
										(0.35)	(0.71)	(0.35)	(0.62)	(0.09)	(0.42)	(0.01)	(0.33)
U.S. BBB	S	1	-2	-18	-23	-107	-126	-153	-176	-0.1	0.3	1.2	1.6	6.3 **	7.0 **	8.0 **	9.2 **
	SL	-5	-6	-21	-28	-88	-113	-147	-189	0.2	0.5	1.3	1.8	5.7 **	7.2 **	9.3 **	11.4 **
										(0.10)	(0.45)	(0.62)	(0.54)	(0.74)	(0.61)	(0.35)	(0.13)
	SLC	-6	-9	-23	-28	-87	-108	-155	-191	0.3	0.7	1.6	2.0	5.8 **	7.1 **	9.8 **	11.7 **
										(0.40)	(0.74)	(0.94)	(0.93)	(0.63)	(0.46)	(0.22)	(0.53)
Euro IG	S	-2	-3	-15	-19	-56	-82	-86	-88	0.1	0.3	0.8	1.0 *	2.8 **	4.5 **	5.2 **	4.9 **
	SL	2	4	-6	-7	-40	-62	-77	-74	-0.0	0.0	0.5	0.6	2.5 **	4.5 **	6.4 **	6.6 **
										(0.05)	(0.13)	(0.11)	(0.12)	(0.28)	(0.28)	(0.83)	(0.59)
	SLC	1	2	-6	-7	-37	-63	-77	-70	0.0	0.1	0.5	0.7	2.4 **	4.7 **	6.7 **	6.8 **
										(0.72)	(0.66)	(0.46)	(0.08)	(0.00)	(0.05)	(0.20)	(0.28)
U.S. HY	S	-17	-25	-35	-59	-308	-383	-455	-474	0.3	0.6	0.8	1.2	9.2 **	12.1 **	16.5 **	17.9 **
	SL	-11	-23	-52	-62	-312	-325	-430	-482	0.3	0.8	1.6	1.8	10.1 **	11.5 **	17.2 **	20.2 **
										(0.90)	(0.79)	(0.27)	(0.53)	(0.82)	(0.35)	(0.63)	(0.94)
	SLC	-10	-23	-49	-62	-316	-326	-432	-487	0.3	0.9	1.6	1.9	10.4 **	11.7 **	17.5 **	20.7 **
										(0.25)	(0.62)	(0.50)	(0.42)	(0.13)	(0.06)	(0.21)	(0.51)
Euro HY	S	-61	-32	-44	-91	-260	-315	-493	-697	2.2	1.8	1.6	2.6	9.0 *	17.3 **	43.3 **	59.3 **
	SL	-52	-31	-56	-104	-265	-315	-635	-806	1.3	1.0	1.2	2.0	7.9	14.0 *	49.5 **	64.6 **
										(0.19)	(0.53)	(0.90)	(0.86)	(0.68)	(0.45)	(0.87)	(0.66)
	SLC	-52	-31	-56	-104	-265	-315	-635	-806	1.3	1.0	1.2	2.0	7.9	14.0 *	49.5 **	64.6 **
										(0.19)	(0.17)	(0.28)	(0.57)	(0.32)	(0.61)	(0.95)	(0.79)

		Spread Changes (basis points)								Excess Peformance (%)							
Quintile		**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**	**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**
Panel B - Four Minus Two																	
U.S. IG	S	-4	-8	-13	-18	-55	-41	-38	-54	0.2	0.4	0.6	0.8	2.5 **	1.7 *	1.4	1.6
	SL	-9	-13	-14	-18	-46	-62	-56	-60	0.6 *	0.9 *	0.8	1.1 *	3.1 **	4.3 **	4.2 **	4.0 **
										(0.11)	(0.62)	(0.96)	(0.86)	(0.00)	(0.00)	(0.20)	(0.42)
	SLC	-8	-13	-15	-19	-37	-64	-56	-59	0.5 *	0.9 *	0.9 *	1.2 *	2.6 **	4.3 **	4.1 **	3.8 **
										(0.02)	(0.08)	(0.65)	(0.83)	(0.04)	(0.32)	(0.05)	(0.12)
U.S. A	S	-47	-104	-125	-157	-53	-110	-175	-207	0.2	0.4	0.4	0.3	-0.6	1.3 *	1.6 **	2.0 **
	SL	-55	-124	-144	-167	-121	-149	-168	-223	0.0	0.2	0.0	0.0	-2.2 *	0.8	3.1 **	2.2 **
										(0.98)	(0.91)	(0.70)	(0.70)	(0.94)	(0.76)	(0.03)	(0.57)
	SLC	-65	-136	-148	-176	-107	-137	-172	-231	0.0	0.3	0.1	0.1	-2.0 *	0.7	3.1 **	2.2 **
										(0.38)	(0.74)	(0.33)	(0.67)	(0.05)	(0.39)	(0.07)	(0.40)
U.S. BBB	S	-47	-104	-125	-157	-53	-110	-175	-207	0.5	0.7	1.1 *	1.1 *	2.8 **	3.5 **	3.1 **	2.2 *
	SL	-55	-124	-144	-167	-121	-149	-168	-223	0.4	1.2 **	1.4 **	1.5 *	3.4 **	4.2 **	4.5 **	2.8 *
										(0.01)	(0.16)	(0.40)	(0.45)	(0.56)	(0.85)	(0.16)	(0.12)
	SLC	-65	-136	-148	-176	-107	-137	-172	-231	0.3	0.9 *	1.2 *	1.3 *	3.6 **	4.7 **	4.2 **	2.8 *
										(0.22)	(0.15)	(0.36)	(0.33)	(0.93)	(0.34)	(0.03)	(0.06)
Euro IG	S	0	-0	6	16	-21	-45	-46	-47	0.1	0.3	0.0	-0.4	1.8 *	3.6 **	5.1 **	4.9 **
	SL	-0	-1	0	0	-42	-64	-61	-63	0.1	0.2	0.3	0.3	2.7 **	4.1 **	4.9 **	4.3 **
										(0.20)	(0.31)	(0.21)	(0.21)	(0.23)	(0.53)	(0.59)	(0.63)
	SLC	1	0	1	1	-50	-64	-62	-67	0.0	0.1	0.2	0.2	2.8 **	3.9 **	4.6 **	4.2 **
										(0.09)	(0.14)	(0.44)	(0.82)	(0.03)	(0.02)	(0.02)	(0.04)
U.S. HY	S	-6	3	-25	-8	12	-57	-126	-175	-0.2	-0.5	0.7	0.4	-1.2	2.7	6.8 *	10.8 **
	SL	9	-17	-45	-53	-78	-222	-241	-268	-0.8	0.2	1.4	1.8	2.5	8.5 **	11.3 **	11.7 **
										(0.89)	(0.69)	(0.34)	(0.50)	(0.79)	(0.32)	(0.64)	(0.99)
	SLC	8	-13	-48	-53	-83	-225	-243	-267	-0.8	-0.1	1.4	1.6	2.3	8.2 **	11.0 **	11.1 **
										(0.36)	(0.28)	(0.08)	(0.08)	(0.04)	(0.31)	(0.39)	(0.53)
Euro HY	S	-47	-104	-125	-157	-53	-110	-175	-207	1.9 *	4.1 **	4.8 **	6.0 **	4.6	8.8	16.9 **	16.1
	SL	-55	-124	-144	-167	-121	-149	-168	-223	2.4 **	5.4 **	6.3 **	7.4 **	8.2 *	11.6 *	16.1 **	15.0
										(0.19)	(0.53)	(0.90)	(0.86)	(0.68)	(0.45)	(0.87)	(0.66)
	SLC	-65	-136	-148	-176	-107	-137	-172	-231	2.7 **	5.7 **	6.4 **	7.6 **	7.5 *	10.8 *	15.9 *	15.8
										(0.62)	(0.85)	(0.67)	(0.87)	(0.52)	(1.00)	(0.98)	(0.84)

Quintile		Spread Changes (basis points) 3m	6m	9m	1yr	2yr	3yr	4yr	5yr	Excess Peformance (%) 3m	6m	9m	1yr	2yr	3yr	4yr	5yr
Panel C - Higher Minus Lower																	
U.S. IG	S	-1	-5	-16	-19	-70	-81	-92	-102	0.0	0.3	0.9 *	1.1 *	3.7 **	4.3 **	4.7 **	5.2 **
	SL	-10	-10	-18	-21	-50	-66	-102	-116	0.5 *	0.7	1.1 *	1.4 *	3.4 **	4.6 **	6.9 **	7.5 **
										(0.24)	(0.25)	(0.71)	(0.68)	(0.70)	(0.01)	(0.01)	(0.01)
	SLC	-9	-10	-18	-21	-45	-67	-101	-114	0.5 *	0.7	1.2 *	1.4 *	3.1 **	4.6 **	6.8 **	7.4 **
										(0.03)	(0.07)	(0.52)	(0.80)	(0.03)	(0.36)	(0.06)	(0.15)
U.S. A	S	-1	-3	-11	-13	-22	-43	-80	-91	0.1	0.2	0.5	0.6	1.0 *	2.3 **	4.4 **	5.1 **
	SL	-1	-3	-8	-10	-4	-33	-76	-82	0.0	0.2	0.4	0.5	0.2	2.0 **	4.6 **	5.1 **
										(0.28)	(0.63)	(0.22)	(0.44)	(0.06)	(0.47)	(0.00)	(0.29)
	SLC	-1	-3	-9	-11	-6	-34	-77	-84	0.0	0.2	0.4	0.6	0.3	2.0 **	4.6 **	5.2 **
										(0.46)	(0.82)	(0.52)	(0.88)	(0.08)	(0.34)	(0.10)	(0.47)
U.S. BBB	S	-3	-6	-18	-22	-84	-100	-113	-132	0.2	0.5	1.1 *	1.4 *	4.8 **	5.4 **	5.8 **	6.3 **
	SL	-5	-11	-22	-26	-78	-96	-119	-138	0.3	0.8	1.4 *	1.7 **	4.8 **	5.9 **	7.1 **	7.8 **
										(0.69)	(0.32)	(0.58)	(0.60)	(0.79)	(0.68)	(0.13)	(0.40)
	SLC	-5	-11	-21	-25	-78	-97	-120	-139	0.3	0.8	1.4 *	1.7 *	4.9 **	6.0 **	7.3 **	7.9 **
										(0.13)	(0.13)	(0.34)	(0.39)	(0.89)	(0.32)	(0.03)	(0.07)
Euro IG	S	-1	-2	-7	-5	-42	-65	-68	-71	0.1	0.3	0.5	0.4	2.4 **	4.1 **	5.2 **	4.9 **
	SL	1	2	-3	-3	-41	-63	-68	-68	0.0	0.1	0.4	0.4	2.6 **	4.3 **	5.6 **	5.3 **
										(0.91)	(0.87)	(0.26)	(0.02)	(0.01)	(0.01)	(0.06)	(0.18)
	SLC	1	1	-3	-4	-43	-64	-69	-68	0.0	0.1	0.4	0.4	2.6 **	4.3 **	5.5 **	5.3 **
										(0.07)	(0.17)	(0.44)	(0.82)	(0.02)	(0.03)	(0.04)	(0.09)
U.S. HY	S	-13	-16	-32	-41	-208	-269	-332	-378	0.1	0.2	0.7	0.9	5.9 **	8.8 **	12.8 **	15.6 **
	SL	-4	-20	-50	-59	-238	-288	-357	-401	-0.1	0.6	1.6	1.8	7.6 **	10.4 **	14.9 **	17.0 **
										(0.31)	(0.41)	(0.56)	(0.37)	(0.12)	(0.07)	(0.21)	(0.45)
	SLC	-3	-19	-48	-59	-238	-288	-357	-401	-0.1	0.5	1.5	1.8	7.6 **	10.4 **	14.9 **	17.0 **
										(0.32)	(0.36)	(0.10)	(0.08)	(0.04)	(0.31)	(0.39)	(0.53)
Euro HY	S	-54	-66	-82	-120	-171	-203	-296	-414	2.0 **	2.9	3.1	4.1 *	7.1 *	12.7 **	27.0 **	34.3 **
	SL	-53	-71	-94	-130	-203	-225	-319	-479	1.8 *	2.8	3.4	4.2 *	8.0 *	12.7 **	26.9 **	36.8 **
										(0.49)	(0.25)	(0.20)	(0.53)	(0.14)	(0.37)	(0.87)	(0.72)
	SLC	-57	-75	-95	-133	-198	-220	-326	-484	1.9 *	3.0	3.4	4.2 *	7.7 *	12.3 **	27.1 **	37.2 **
										(0.90)	(0.74)	(0.73)	(0.89)	(0.76)	(0.71)	(0.83)	(0.77)

** and * indicate statistical significance at the 0.05 and 0.10 level, respectively

Over a five-year period, value strategies in HY outperform those in IG to a greater extent in Euro than in the U.S.A. This is possibly related to the lower liquidity of HY bonds in Euro than in the U.S. market (Financial Times, 2005; Houweling, Mentink and Vorst, 2005).

In Table 3.5, I investigate the risk of value strategies using the maximum drawdown (Pedersen and Rudholm-Alfvin, 2003; Eling, 2008; Madhavan, 2012; Buraschi, Kosowski and Sritrakul, 2014), defined as the smallest return recorded for each time horizon (Chekhlov, Uryasev and Zabarankin, 2005). The analysis shows that, on aggregate, drawdowns over the five years occur for High minus Low strategies with returns as negative as -12.5% for U.S. HY and for Four minus Two strategies with returns as negative as -22% for Euro HY. Looking at spreads, drawdowns are higher close to 1-year horizon with the largest increase for Euro. HY +1'403 basis points.

Table 3.5: **Drawdown analysis**

The table reports the drawdown of credit spreads and excess returns of two strategies: High minus Low and Four minus Two based on simple spreads.

	Drawdown								Drawdown (%)							
Quintile	**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**	**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**
Panel A - High Minus Low																
US IG	310	354	216	391	56	24	61	24	-15.3	-17.2	-11.4	-18.7	-3.1	-2.0	-3.6	-4.5
US A	267	301	148	337	41	10	29	7	-13.5	-15.0	-8.3	-16.4	-2.6	-2.6	-3.7	-2.2
US BBB	377	432	316	482	80	39	109	36	-17.9	-20.1	-14.6	-21.9	-4.1	-2.7	-5.0	-6.1
EU IG	213	229	183	262	56	56	148	76	-9.1	-9.5	-7.2	-9.9	-3.6	-4.8	-1.8	-2.6
US HY	774	1'290	1'168	1'358	160	186	193	11	-24.0	-36.9	-32.9	-37.2	-13.3	-20.3	-17.7	-12.5
EU HY	410	1'403	1'278	945	113	75	206	-140	-13.8	-39.0	-34.6	-28.5	-13.8	-13.7	3.0	20.9
Panel B - Four Minus Two																
US IG	70	84	102	120	78	58	54	85	-4.4	-4.2	-4.4	-5.5	-6.2	-6.2	-5.3	-4.8
US A	38	74	136	139	260	102	41	65	-2.2	-3.5	-6.9	-6.9	-13.1	-4.2	-4.8	-3.0
US BBB	92	118	127	151	129	86	81	83	-5.7	-6.0	-5.4	-7.1	-6.5	-8.2	-6.4	-6.3
EU IG	92	110	86	266	131	71	124	119	-4.1	-3.8	-3.1	-10.0	-5.5	-3.8	-1.7	-2.8
US HY	286	384	344	1'118	419	240	412	200	-16.5	-19.5	-14.4	-31.8	-19.6	-20.5	-21.8	-16.2
EU HY	119	143	185	178	286	142	47	-19	-5.1	-6.9	-8.6	-10.7	-17.0	-20.5	-22.5	-22.0

3.5.3 Robustness

The robustness of the results is assessed in Table 3.6 by performing the analysis using quantiles formed over 4 years (Panel A), 3 years (Panel B) and using quarterly data (Panel C). In Table 3.6, I report the results for strategies of the type High minus Low.

In Panel A for strategies formed over 4 years, spread tighten or are unchanged across all time horizons. The largest spread changes are for Euro High Yield over the 5-year horizon (-485). The smallest spread change is for Euro IG over the 6-month horizon (0 basis points). Strategies based on SL and SLC ratios show larger spread contractions over the horizons longer than 3 years except for U.S. A and U.S. High Yield over the 4-year horizon. The strategy delivers positive returns across all time horizons with the exception of U.S. High Yield over the 3-month horizon which has also the lowest performance (-0.4%). The highest most significant performance is recorded over the 5-year horizon for Euro High Yield (+27.6%). Strategies based on SL and SLC ratios outperform strategies based on simple spreads on the longer horizons (4-year and 5-year) with the exception of U.S. A over 4 years.

In Panel B, the strategies formed over 3 years show spread tightening across the longest horizons. The largest spread tightening is for U.S. High Yield over 5-years. There are some instances where spreads widen for U.S. A, U.S. BBB and U.S. High Yield. The largest widening is for U.S. High Yield over 3 months (+19 basis points). Excess returns are always positive over the longer horizons (3-year, 4-year and 5-year). There are some negative returns over the shorter time horizons with the largest for U.S. High Yield (-1.6%). However, the negative returns are never significant. On average, strategies based on SL and SLC ratios perform better than strategies based on simple spreads over the longer horizons. Over the 5-year period, strategies based on simple spreads work better for U.S. A.

In Panel C for strategies based on quarterly observations, spreads contract across all time horizons with the exception of the 6-month where spreads widen in some instances for U.S. BBB, Euro IG and Euro HY (+8 basis points). The largest spreads tightening is for Euro High Yield over 5 years (-540 basis points). Excess performance is always positive for horizons longer than one year. The largest positive performance is recorded for Euro High Yield over 5 years (+51.3%). The most negative performance is for Euro High Yield over 1 year (-0.8%).

The robustness analysis confirms the findings from Table 3.4 with value strategies posting significant and positive performance over the longer horizons. In particular, the spread changes over the longer horizon (5-year) are smaller when the period over which the quintiles are calculated is shorter (3-year). Spread changes for horizons smaller than one year are greater than 1% only for Euro High Yield. Performance over 2-year is always positive with the exception of U.S. A (Panel B). The performance of strategies is particularly significant for the longer investment horizon (over 5 years in 44 out 54 cases). Strategies based on quintiles formed over 5 years outperform those formed over 4 and 3 years in all instances. On average, strategies based on quarterly observations outperform those based on monthly observations over the longer horizons. However, the outperformance is not consistent across asset classes.

Table 3.6: **Robustness**

The table reports the performance of the strategies using different time windows: 4-year and 3-year in addition to quarterly data frequency.

		Spread Changes (basis points)								Excess Peformance (%)							
Quintile		**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**	**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**
Panel A - High Minus Low 4 yr																	
US IG	S	-2	-4	-15	-26	-65	-90	-117	-127	0.1	0.3	0.8	1.4 *	3.4 **	4.6 **	5.8 **	6.3 **
	SL	-12	-12	-22	-25	-52	-68	-155	-177	0.7	0.8	1.3	1.5	3.3 **	4.2 **	9.1 **	10.3 **
	SLC	-12	-12	-21	-25	-54	-69	-155	-177	0.7	0.9	1.3	1.6	3.4 **	4.4 **	9.1 **	10.3 **
US A	S	-2	-6	-15	-21	-34	-46	-97	-110	0.1	0.3	0.7	0.9	1.3 *	2.0 **	4.9 **	5.8 **
	SL	-1	-3	-10	-13	-9	-38	-79	-97	0.0	0.2	0.5	0.6	0.3	1.9 **	4.6 **	6.0 **
	SLC	-1	-3	-11	-13	-9	-38	-80	-99	0.0	0.2	0.5	0.6	0.2	1.9 **	4.5 **	6.0 **
US BBB	S	-3	-4	-18	-30	-93	-116	-140	-166	0.1	0.3	1.0	1.7 *	5.1 **	5.9 **	6.7 **	7.9 **
	SL	-5	-6	-18	-28	-75	-110	-153	-195	0.2	0.5	1.1	1.7	4.6 **	6.6 **	9.0 **	11.1 **
	SLC	-6	-9	-20	-29	-74	-110	-159	-194	0.3	0.7	1.2	1.9	4.6 **	6.6 **	9.4 **	10.9 **
EU IG	S	-2	-1	-10	-18	-46	-56	-91	-112	0.1	0.1	0.5	0.8	2.1 **	2.8 **	4.4 **	4.9 **
	SL	-0	0	-9	-17	-31	-45	-104	-119	0.0	0.0	0.5	0.8	1.8 **	3.1 **	6.1 **	6.5 **
	SLC	-0	0	-9	-16	-32	-49	-103	-118	0.0	0.0	0.5	0.8	1.8 **	3.2 **	5.9 **	6.3 **
US HY	S	-9	-18	-49	-69	-268	-316	-415	-470	-0.3	-0.3	0.3	0.2	5.9 **	7.5 **	11.9 **	15.2 **
	SL	-1	-18	-51	-60	-281	-296	-409	-481	-0.4	0.0	0.6	0.3	6.8 **	7.6 **	12.6 **	16.9 **
	SLC	-0	-17	-50	-60	-278	-294	-409	-483	-0.4	0.0	0.5	0.4	6.8 **	7.6 **	12.8 **	17.4 **
EU HY	S	-54	-63	-116	-117	-321	-231	-260	-464	1.5	2.2	3.1	2.5	8.2 *	7.7	14.8	24.3 *
	SL	-54	-69	-100	-91	-331	-246	-282	-485	1.4	2.3	2.9	2.0	9.2 *	8.8	17.3 *	27.6 **
	SLC	-48	-60	-88	-79	-307	-230	-282	-485	1.2	1.9	2.3	1.4	7.9 *	7.5	17.3 *	27.6 **
Panel B - High Minus Low 3 yr																	
US IG	S	3	-1	-14	-25	-52	-69	-102	-124	-0.2	0.1	0.7	1.4 *	2.6 **	3.3 **	4.7 **	5.8 **
	SL	-5	-4	-10	-15	-28	-45	-113	-152	0.2	0.4	0.6	1.0	1.8	2.8 *	6.7 **	8.7 **
	SLC	-5	-3	-11	-16	-29	-45	-113	-152	0.3	0.3	0.7	1.0	1.9	2.9 *	6.7 **	8.7 **
US A	S	5	1	-7	-12	-10	-11	-66	-86	-0.3	0.0	0.4	0.7	0.2	0.2	3.3 **	4.6 **
	SL	3	3	-2	-4	7	-17	-57	-74	-0.2	-0.1	0.1	0.2	-0.6	0.7	3.1 **	4.4 **
	SLC	4	3	-2	-5	6	-13	-58	-76	-0.3	-0.1	0.1	0.2	-0.5	0.5	3.2 **	4.5 **
US BBB	S	4	2	-11	-24	-59	-88	-117	-150	-0.3	0.0	0.7	1.5	3.2 **	4.0 **	5.1 **	6.6 **
	SL	-0	-3	-13	-24	-50	-73	-126	-171	-0.0	0.3	0.8	1.5	3.0 **	4.2 **	7.2 **	9.8 **
	SLC	-0	-3	-13	-22	-49	-74	-128	-174	0.0	0.4	0.9	1.5	3.1 **	4.4 **	7.4 **	10.1 **
EU IG	S	-1	-1	-10	-14	-31	-35	-73	-107	0.0	0.1	0.4	0.5	1.2 *	1.4 *	3.1 **	3.6 **
	SL	-0	3	-3	-9	-20	-30	-80	-109	0.0	-0.0	0.2	0.5	1.1	2.0 **	4.6 **	5.3 **
	SLC	-0	2	-3	-9	-20	-30	-80	-109	0.0	0.0	0.2	0.5	1.1	2.0 **	4.6 **	5.3 **
US HY	S	8	15	-13	-33	-185	-213	-321	-413	-1.0	-1.6	-1.2	-1.4	1.4	1.2	5.0	9.9 **
	SL	18	16	-10	-24	-206	-228	-325	-431	-1.2	-1.4	-1.1	-1.3	2.8	2.9	6.7 *	12.4 **
	SLC	19	16	-12	-26	-215	-225	-324	-433	-1.3	-1.4	-1.0	-1.2	3.0	2.8	6.6 *	12.5 **
EU HY	S	-27	-18	-86	-115	-417	-284	-158	-318	0.5	0.2	1.9	2.4	9.4 **	7.5	3.2	7.4
	SL	-29	-31	-71	-86	-432	-322	-216	-375	0.5	0.8	1.7	1.5	10.5 **	9.3 *	7.4	11.2
	SLC	-29	-32	-74	-90	-437	-331	-227	-389	0.5	0.8	1.8	1.7	10.8 **	9.9 **	8.4	12.5
Panel C - High Minus Low Quarterly																	
US IG	S	-1	3	-10	-29	-93	-120	-129	-117	-0.0	-0.2	0.4	1.5	5.0 **	6.1 **	6.0 **	5.2 *
	SL	-7	-4	-13	-22	-43	-66	-151	-169	0.4	0.5	0.9	1.6	3.1	4.7 *	9.9 **	10.9 *
	SLC	-8	-5	-13	-24	-48	-69	-151	-169	0.5	0.6	1.0	1.7	3.6	5.1 *	9.9 **	10.9 *
US A	S	-6	-1	-8	-16	-38	-59	-132	-133	0.2	-0.1	0.2	0.4	1.3	2.5	6.3 **	6.3 **
	SL	-4	-0	-5	-16	-26	-52	-128	-134	0.1	-0.1	-0.0	0.5	0.8	2.2	6.2 *	6.4 *
	SLC	-4	-0	-5	-16	-26	-52	-128	-134	0.1	-0.1	-0.0	0.5	0.8	2.2	6.2 *	6.4 *
US BBB	S	-3	2	-7	-14	-113	-131	-130	-165	0.1	-0.1	0.4	1.0	6.6 **	7.1 **	6.5 *	8.4 **
	SL	-5	-1	-15	-29	-69	-138	-148	-187	0.1	0.2	0.8	1.6	4.4 *	8.0 **	8.5 *	10.2 *
	SLC	-4	-5	-12	-9	-43	-58	-86	-75	0.2	0.3	0.6	0.5	2.1	3.3 *	5.1 **	4.0
EU IG	S	-1	1	-4	-1	-27	-58	-89	-67	0.1	0.0	0.2	0.1	1.2	3.1 *	5.3 **	3.5
	SL	-1	1	-4	-1	-27	-58	-89	-67	0.1	0.0	0.2	0.1	1.2	3.1 *	5.3 **	3.5
	SLC	-9	-5	-18	-33	-83	-128	-151	-178	0.3	0.4	0.9	1.8	4.9 *	7.0 *	7.9 *	8.6 *
US HY	S	-10	-16	-35	-56	-304	-381	-455	-452	-0.1	0.0	0.2	0.5	7.9 *	10.2 *	13.6 *	13.4 *
	SL	-22	-25	-51	-66	-351	-345	-473	-458	0.4	0.5	1.1	1.3	10.1 *	10.3 *	15.2 *	15.7
	SLC	-27	-37	-59	-76	-326	-327	-485	-489	0.7	1.2	1.7	2.0	9.8 *	10.2 *	17.0 *	18.2 *
EU HY	S	-21	8	-9	26	-219	-267	-308	-540	0.8	0.8	-0.0	-0.8	6.9	15.6	34.9	51.3
	SL	-21	8	-9	26	-219	-267	-308	-540	0.8	0.8	-0.0	-0.8	6.9	15.6	34.9	51.3
	SLC	-21	8	-9	26	-219	-267	-308	-540	0.8	0.8	-0.0	-0.8	6.9	15.6	34.9	51.3

** and * indicate statistical significance at the 0.05 and 0.10 level, respectively

3.5.4 Out-of-sample analysis

To ensure that the analysis is not affected by in-sample fitting, I test my results with three different criteria: 1) I run the strategy using different quintiles calculated over alternative formation periods, 2) I report a graphical analysis of out of sample spread changes and returns over the entire sample and 3) I produce a break-point analysis. In Table 3.6 I have shown the results of the analysis using quintiles calculated over three alternative formation periods: 3-year and 4-year. Here, I report the spread changes and excess returns of the strategy for each quarter. The strategy uses quintiles formed over the previous five years and calculates the returns over the following eight periods (3-month. 6-month, 9-month, 1-year, 2-year, 3-year, 4-year and 5-year). Accordingly, all the spread changes and returns reported in Figure 3.4 and Figure 3.5 are out-of-sample, see Ang, Briere and Signori (2012). This out of sample analysis confirms my main finding that spreads generally tighten over the longer horizons. In particular, the changes in spreads (Figure 3.4) do not show a clear bias for short investment periods (3-month). The longer the time horizons, the more spreads tighten. Over 5 years, spread changes are generally negative with larger differences around periods of markets turmoil (2003 and 2009). I produce a similar analysis investigating out-of-sample excess returns in Figure 3.5. Over the shorter horizons, excess returns do not show a clear pattern. The performance of the strategy is progressively more positive for longer time horizons. Over the 5-year period, returns are mostly positive and show limited drawdowns

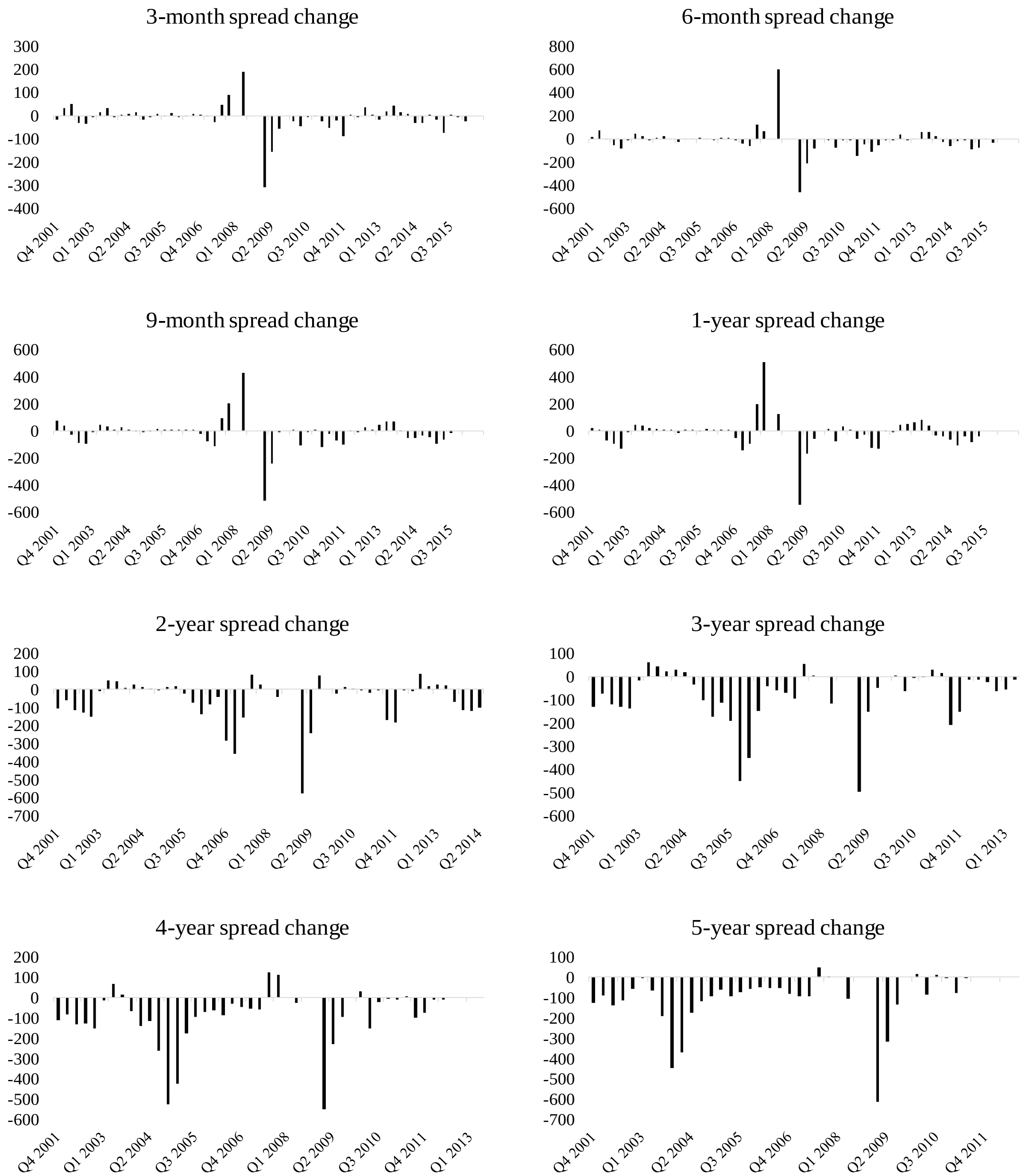

Figure 3.4: **Out-of-sample spread changes**

Charts with out-of-sample spread changes over 3-month, 6-month, 9-month, 1-year, 2-year, 3-year, 4-year and 5-year. Strategy on quarterly data based on SL ratios at aggregate level across asset classes.

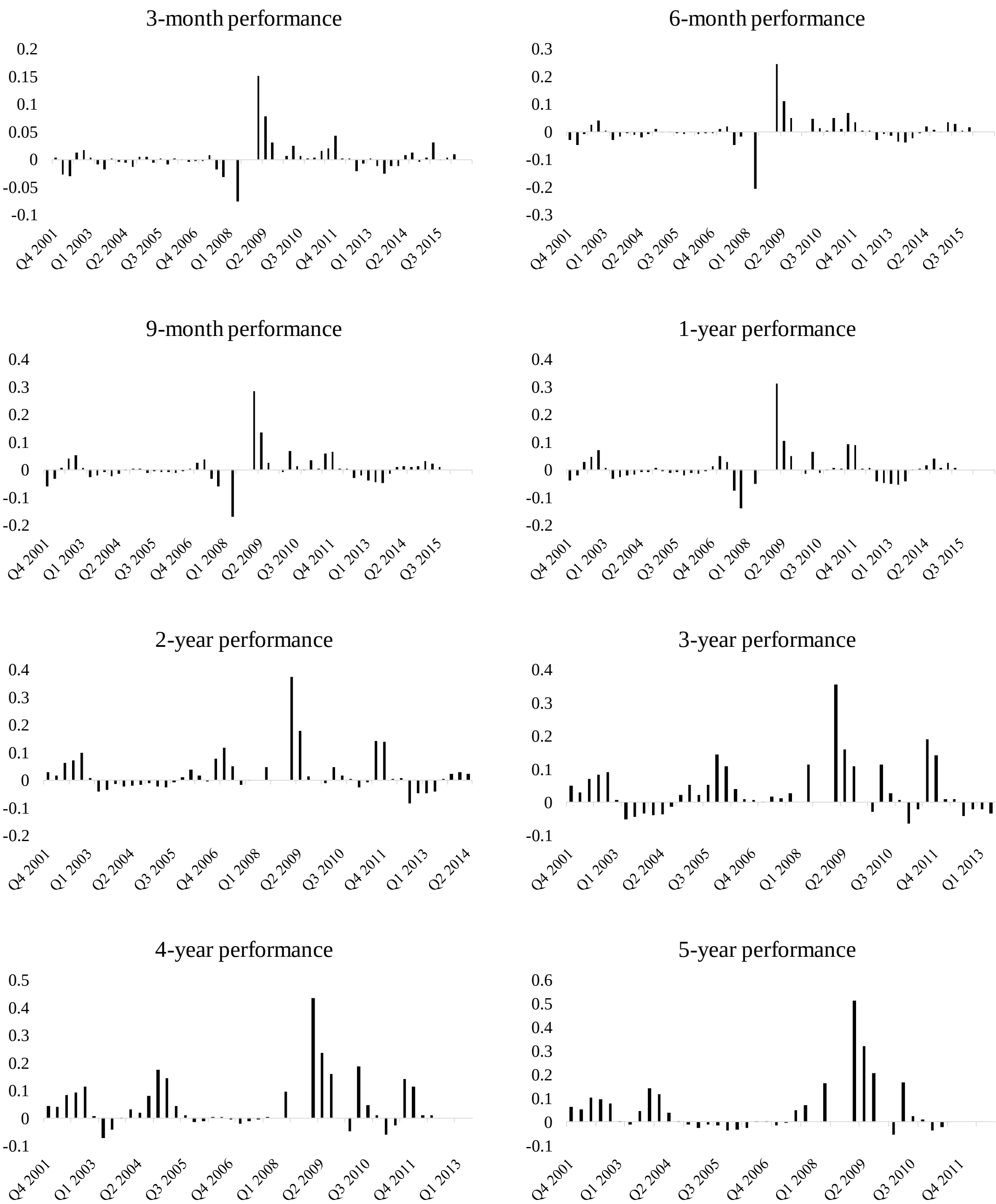

Figure 3.5: **Out-of-sample performance**

Charts with out-of-sample returns over 3-month, 6-month, 9-month, 1-year, 2-year, 3-year, 4-year and 5-year. Strategy on quarterly data based on SL ratios at aggregate level across asset classes.

Lastly, based on the graphical analysis of spreads (O'Hagan and Berrill, 2016), I break down the strategy in three sub-periods (Figure 3.6): pre-GFC (December 1996 – March 2007, GFC

(June 2007 – March 2010) and Post-GFC (June 2010 – September 2016). That further ensures that robustness of the results over the entire sample, which represents all the available data for the investigated asset classes.

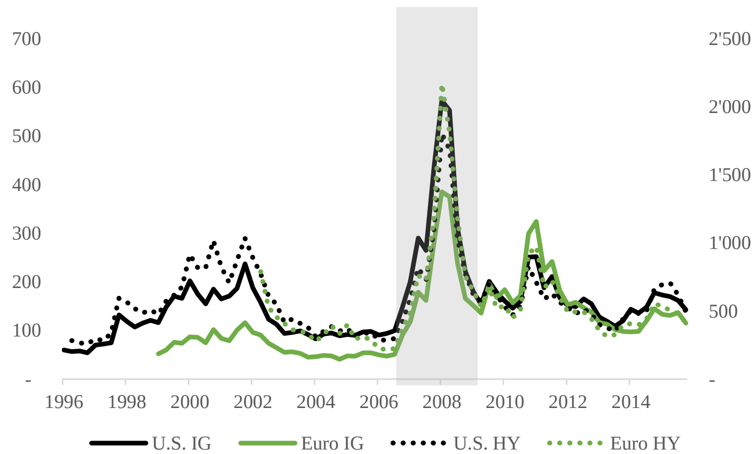

Figure 3.6: **Credit spreads sub-periods**

Charts with credit spreads and sub-periods: pre-GFC, GFC and post-GFC

The analysis by sub-periods confirm the results obtained over the larger sample (Table 3.7). Over the longer time horizons (3-year, 4-year and 5-year) the overlay strategy delivers positive returns with the exception of Euro High Yield before and after the GFC and U.S. High Yield after the GFC. On average, strategies based on SL and SLC outperform strategies based on spreads over the 5-year. In conclusion, in this section, I show that my results are not a function of the formation period of the quintiles. Additionally, out-of-sample spread changes and returns confirm my findings, which remain valid also in different sub-periods.

Table 3.7: **Strategy sub-periods analysis**

This table reports the performance of the overlay strategy in the three sub-periods: pre-GFC, GFC and post-GFC.

		Excess Peformance (%)							
Quintile		**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**
Panel A - Pre GFC									
US IG	S	0.2	0.2	0.7	1.2	4.3**	4.7**	3.1*	2.2
	SL	0.3	0.3	0.6	1.0	3.1	4.6*	3.9*	3.3
	SLC	0.3	0.3	0.5	0.9	3.0	4.9*	3.7*	3.0
US HY	S	-0.3	-0.3	-0.1	0.1	7.5	8.9*	6.6	6.6
	SL	-0.3	-0.2	-0.1	0.2	7.8	9.0*	6.9	7.7
	SLC	-0.3	-0.2	-0.1	0.2	7.8	9.0*	6.9	7.7
EU IG	S	0.1	0.1	0.0	-0.2	2.2*	3.0**	1.0	-0.8
	SL	-0.0	-0.1	-0.1	-0.4	1.9	3.4**	1.4	-1.4**
	SLC	-0.0	-0.1	-0.1	-0.4	1.9	3.4**	1.4	-1.4**
EU HY	S	5.0	7.4	6.4	6.3	16.9	27.3	-4.4	
	SL	4.9	7.3	5.3	4.0	15.8	27.3	-4.4	
	SLC	5.1	8.3	6.5	6.0	20.3	27.3	-4.4	
US A	S	-0.0	-0.1	-0.1	0.1	0.5	2.2	3.2*	3.3*
	SL	0.0	0.2	0.1	0.2	-1.2	1.1	3.5**	2.9*
	SLC	-0.0	0.3	0.2	0.5	-0.5	1.2	3.5**	3.0**
US BBB	S	0.3	0.4	0.6	0.8	5.7**	5.8**	3.4	2.2
	SL	0.3	0.5	1.1	1.5	5.6**	6.0**	3.8*	2.7
	SLC	0.5	0.6	1.2	1.6	5.5**	5.8**	3.9	2.8
Panel B- GFC									
US IG	S	0.7	0.9	1.6	1.9	3.6	4.5	6.4	12.3*
	SL	0.7	0.7	1.2	1.5	4.7	8.4**	10.1*	15.0*
	SLC	0.7	0.7	1.2	1.5	4.7	8.4**	10.1*	15.0*
US HY	S	1.0	1.3	1.7	0.5	5.6	12.4	21.5*	34.2*
	SL	1.0	1.9	2.3	1.3	11.4	18.7*	25.6*	35.3*
	SLC	1.0	1.9	2.3	1.3	11.4	18.7*	25.6*	35.3*
EU IG	S	0.1	0.2	0.3	0.0	3.4*	5.6**	5.8**	8.6**
	SL	-0.2	-0.2	-0.1	-0.2	3.2*	5.9**	5.8*	8.5*
	SLC	-0.2	-0.2	-0.1	-0.2	3.2*	5.9**	5.8*	8.5*
EU HY	S	1.8	3.0	3.0	2.9	10.9	18.4*	29.5*	39.8*
	SL	1.6	2.2	1.9	0.7	8.9	13.8	18.3	35.7*
	SLC	1.5	2.4	2.3	1.2	10.0	16.4*	24.2	35.7*
US A	S	0.2	0.0	-0.0	0.2	1.5	3.4	5.6	9.5*
	SL	0.1	0.1	0.1	0.7	1.1	4.3	6.4*	10.2*
	SLC	0.1	0.1	0.1	0.7	1.1	4.3	6.4*	10.2*
US BBB	S	0.8	1.3	1.5	1.2	5.2	7.4*	10.6*	15.9*
	SL	0.9	1.2	1.9	1.8	5.7	8.6*	11.4*	16.6*
	SLC	0.9	1.2	1.9	1.8	5.7	8.6*	11.4*	16.6*
Panel C - Post GFC									
US IG	S	0.2	0.8	0.9	1.0	0.7	0.1	-0.5	-2.3*
	SL	0.2	0.7	1.0	0.9	1.7	3.7*	6.8*	4.9
	SLC	0.2	0.7	1.0	0.9	1.7	3.7*	6.8*	4.9
US HY	S	0.1	0.7	0.9	0.2	-1.6	-3.0	-0.5	-0.1
	SL	0.5	1.8	1.7	1.3	3.3	6.1	13.3	11.6
	SLC	0.2	1.4	1.3	1.2	3.3	6.1	13.3	11.6
EU IG	S	0.1	0.5	0.3	0.2	1.8	4.8*	9.1**	7.6*
	SL	-0.3	-0.2	-0.2	-0.2	1.5	4.4*	8.7**	7.5**
	SLC	-0.3	-0.2	-0.2	-0.2	1.5	4.4*	8.7**	7.5**
EU HY	S	0.7	1.5	0.7	0.0	-1.0	0.5	12.2	-1.5
	SL	0.9	1.3	0.5	-0.5	-1.4	-1.4	5.3	-9.4
	SLC	0.7	1.5	0.7	0.0	-1.0	0.5	12.2	-1.5
US A	S	-0.0	0.2	0.1	0.1	-0.5	-1.2	-1.3	-2.2*
	SL	-0.3	-0.1	-0.0	-0.0	-0.8	-0.8	-0.3	0.1
	SLC	-0.3	-0.1	-0.0	-0.0	-0.8	-0.8	-0.3	0.1
US BBB	S	0.5	1.3	1.3	1.5	1.5	2.1	3.2	1.4
	SL	0.4	1.2	1.1	0.7	1.7	3.3	6.2	4.0
	SLC	0.4	1.1	1.1	0.7	1.7	3.3	6.2	4.0

** and * indicate statistical significance at the 0.05 and 0.10 level, respectively.

3.6 Discussion of SL and SLC ratios

The results of the analysis in sections 3.4 and 3.5, suggest that further investigation into the use of SL and SLC ratios as indicators of value opportunities is required. In this section, I attempt to identify subsets of U.S. Investment Grade bonds where credit multiples successfully normalize spreads by fundamentals and can be used to study the value effect. I also discuss the limits and challenges in using SL and SLC ratios.

The calculations in sections 3.4 and 3.5 are based on aggregate spreads, leverage and interest coverage calculated by Bank of America Merrill Lynch and Morgan Stanley. However, to create subsets, I need to build a unique database with the same information at single bond level. My dataset comprises the constituents of the Merrill Lynch U.S. Investment Grade Non-Financial Corporate Bond Index at the end of each quarter from December 1996 until September 2016. For each bond, I use the Option Adjusted Spread (OAS), defined as the number of basis points the fair value government spot curve needs to be shifted to match the present value of discounted cash flows to the bond's price (Bank of America Merrill Lynch, 2012). The dataset includes only bonds without optionality to have a homogeneous sample. I match each bond with the leverage of the related parent company as provided by Bloomberg. The numerator of the leverage is given by the net debt, obtained by netting the value of a company's liabilities and debts with its cash and other similar liquid assets. The denominator of leverage and the numerator of interest coverage are the trailing 12-month EBITDA. The denominator of the interest coverage is the trailing 12-month total interest that includes interest charged to income statement and interest capitalized. This information is publicly available only for listed companies. My final sample contains a total of 722 U.S. companies and 60'902 bond observations for the period of analysis

(Table 3.7). As spreads are a function of both the riskiness of the company and the duration of the investment (Merton, 1974; Collin-Dufresne and Goldstein, 2001; Fabozzi, 2001), I partition the sample in subsets by rating and maturity. I use the Bank of America Merrill Lynch composite ratings calculated as the simple averages of ratings from three agencies (Moody's, S&P and Fitch). To have a sufficiently large number of observation for each subset, I identify three groups of ratings: AA (which includes AAA, AA1, AA2, AA3), A (which includes A1, A2, A3) and BBB (which includes BBB1, BBB2 and BBB3). The AA group has 7'317 observations, A has 24'282 and BBB 29'303. Except for 1996 (for which I have data only for the last quarter), the smallest number of observations is in 2005 (1'581) and the largest in 2013 (5'168).

Table 3.8: **Number of observations by year, rating, sector and maturity**

The table reports the number of observations by year and Bank of America Merrill Lynch composite rating and Level 2 sector. Panel C reports the breakdown by maturity into Short (2-7 years), Medium (7-15 years) and Long (15+ years)

	Years																					
	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Total
Panel A - By Rating																						
AA	**85**	**389**	**345**	**303**	**280**	**272**	**270**	**249**	**241**	**207**	**208**	**230**	**251**	**331**	**366**	**449**	**515**	**528**	**613**	**604**	**581**	**7'317**
AAA	10	44	2	21	48	49	43	40	52	28	29	33	32	32	68	115	114	113	118	137	121	1'249
AA1	11	42	20	6	32	1	4					2						12	31	64	91	316
AA2	28	151	162	150	101	93	72	62	65	77	79	93	101	80	84	114	109	109	112	102	83	2'027
AA3	36	152	161	126	99	129	151	147	124	102	100	102	118	219	214	220	292	294	352	301	286	3'725
A	**206**	**911**	**1'117**	**1'048**	**858**	**650**	**535**	**665**	**678**	**560**	**769**	**870**	**1'045**	**1'375**	**1'674**	**1'884**	**1'945**	**2'095**	**2'004**	**1'784**	**1'609**	**24'282**
A1	89	326	261	358	386	242	209	183	183	115	162	201	170	247	351	442	371	296	281	310	404	5'587
A2	73	374	562	439	335	220	177	247	254	284	362	458	615	809	887	903	929	896	898	924	776	11'422
A3	44	211	294	251	137	188	149	235	241	161	245	211	260	319	436	539	645	903	825	550	429	7'273
BBB	**190**	**852**	**1'027**	**944**	**775**	**716**	**776**	**893**	**1'023**	**818**	**905**	**1'050**	**1'252**	**1'580**	**1'931**	**2'165**	**2'438**	**2'545**	**2'434**	**2'555**	**2'434**	**29'303**
BBB1	85	427	499	309	213	209	200	190	218	303	323	319	438	480	595	739	901	951	841	1'005	1'023	10'268
BBB2	75	280	334	444	365	328	435	424	505	289	356	445	512	676	800	852	984	888	955	919	909	11'775
BBB3	30	145	194	191	197	179	141	279	300	226	226	286	302	424	536	574	553	706	638	631	502	7'260
Total	**481**	**2'152**	**2'489**	**2'295**	**1'913**	**1'638**	**1'581**	**1'807**	**1'942**	**1'585**	**1'882**	**2'150**	**2'548**	**3'286**	**3'971**	**4'498**	**4'898**	**5'168**	**5'051**	**4'943**	**4'624**	**60'902**
Panel B - By sector																						
Industrials	434	1'978	2'304	2'173	1'816	1'561	1'495	1'662	1'732	1'415	1'642	1'894	2'172	2'696	3'267	3'793	4'239	4'577	4'530	4'462	4'191	54'033
Utility	47	174	185	122	97	77	86	145	210	170	240	256	376	590	704	705	659	591	521	481	433	6'869
Total	**481**	**2'152**	**2'489**	**2'295**	**1'913**	**1'638**	**1'581**	**1'807**	**1'942**	**1'585**	**1'882**	**2'150**	**2'548**	**3'286**	**3'971**	**4'498**	**4'898**	**5'168**	**5'051**	**4'943**	**4'624**	**60'902**
Panel C - By maturity																						
Short	242	1'087	1'228	1'099	889	751	716	734	671	427	441	466	642	1'050	1'540	2'151	2'732	3'064	3'108	3'070	2'848	28'956
Medium	136	534	540	423	284	224	200	331	493	549	721	848	934	1'132	1'172	1'043	846	770	639	536	466	12'821
Long	103	531	721	773	740	663	665	742	778	609	720	836	972	1'104	1'259	1'304	1'320	1'334	1'304	1'337	1'310	19'125
Total	**481**	**2'152**	**2'489**	**2'295**	**1'913**	**1'638**	**1'581**	**1'807**	**1'942**	**1'585**	**1'882**	**2'150**	**2'548**	**3'286**	**3'971**	**4'498**	**4'898**	**5'168**	**5'051**	**4'943**	**4'624**	**60'902**

In Panel B, I create sub-sets by industry using Bank of America Merrill Lynch Level 2 industry classifications which categorizes bonds in Utilities (6'869 observations) and Industrials (54'033 observations). In Panel C, I report the breakdown by maturity with the largest number of observations in the Short group (28'956) followed by Long (19'125) and Medium (12'821)

I divide each of the three rating groups into sub-sets by duration. Following Duffee (1998) and Fabozzi (2001), I group bonds by maturity classifying them as short term if they have 2-7 years remaining to maturity, medium-term if they have 7-15 years to maturity, and long term if they have more than 15 years to maturity. For each sub-set I report the aggregate spreads, SL, SLC, leverage and interest coverage (Table 3.8).

Table 3.9: **Spreads, SL, SLC, leverage and interest coverage**

The table reports the average spreads, SL, SLC, leverage and interest coverage by rating-duration and sectors.

	Rating	**Short**	**Medium**	**Long**		**Sector**	**Aggregate**
Spreads	AA	54.7	75.7	103.0	Spreads	Industrials	142.5
	A	90.0	112.3	142.1		Utilities	132.7
	BBB	171.5	185.8	207.1			
SL	AA	56.9	85.9	112.9	SL	Industrials	63.2
	A	58.2	70.0	79.7		Utilities	37.6
	BBB	51.6	61.3	80.7			
SLC	AA	54.4	82.7	107.8	SLC	Industrials	61.4
	A	55.5	66.9	76.5		Utilities	35.6
	BBB	49.8	58.9	77.0			
Leverage	AA	1.0	1.0	1.1	Leverage	Industrials	2.3
	A	1.8	1.8	1.9		Utilities	3.5
	BBB	3.3	3.4	2.7			
Interest Coverage	AA	27.0	29.6	27.6	Interest Coverage	Industrials	15.4
	A	18.3	14.6	14.6		Utilities	4.9
	BBB	9.1	9.1	8.1			

The analysis shows that spreads increase with maturity and lower rating. The minimum spread is for AA Short (54.7) and the largest is for BBB Long (207). By construction, SL and SLC ratios also increase with maturity as leverage and interest ratios do not change. However, SL and SLC ratios are similar for groups with different ratings. This confirms my earlier results. The analysis by sectors highlights that both Industrials and Utilities have similar spreads. However, Industrials have a lower leverage (2.3) and higher interest coverage (15.4) than Utilities. As such, the SL ratio and particularly the SLC ratio suggest that Industrials offer a better risk-reward than Utilities. This anomaly is persistent over time (Figure 3.4) and may be related to the steadier business of Utilities which are capital intensive firms but have less volatile revenues than other industries (Stickney and McGee, 1982; Giesecke, Longstaff, Schaefer and Strebulaev, 2014).

The graphical analysis presented in Figure 3.4 shows the historical evolution of spreads and SL ratios and confirms the results in Table 3.8. Interestingly, the SL ratio is more volatile for the AA group. This is related to the low leverage of this group and, particularly, of its higher rated bonds with AAA having a leverage of -0.5 and AA1 of -0.68. In SL and SLC ratios, leverage can be small and negative. This is not dissimilar to equities' Price-Earnings (P/Es) where earnings can be small and negative. However, leverage has an additional complexity as it can be negative both because the net debt is negative and because EBITDA is negative. A negative net debt is typical of the highest rated companies. In my dataset, net debt is negative for example for Apple (rated AA1). Apple has cash in excess of debt, however, it prefers to issue bonds to finance buybacks rather than repatriating its significant cash holdings which would be subject to taxes (Financial Times, 2017). A negative EBITDA is a sign of financial distress. In my dataset, this is the case for example for Apache Corp and Devon Energy, two BBB rated companies operating in the energy sector which recorded negative earnings in 2015 due to declining oil prices.

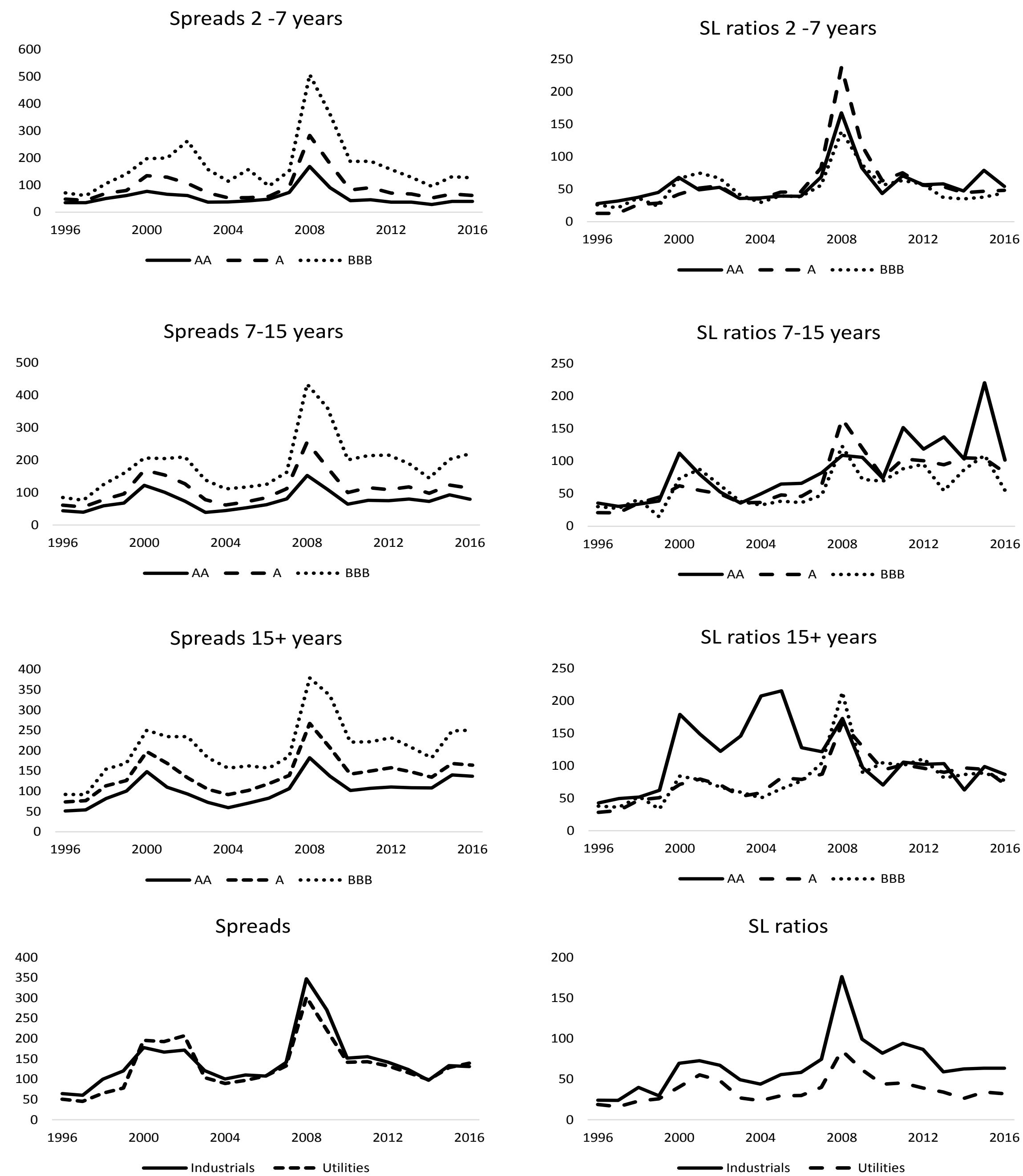

Figure 3.7: **Spreads and SL ratios by rating-maturity and sectors**

The charts show spreads and SL ratios for AA, A and BBB rating groups across maturities (2-7 year, 7-15 year and 15+ year).

3.7 Empirical implementation

To show the relevance of the approach, I apply value investing to credit markets in an empirical setting. In particular, I investigate a strategy that buys (sells) credit bonds in the higher (lower) quintiles on a quarterly basis across all six groups (U.S. Investment Grade, U.S. single A, U.S. BBB, U.S. High Yield, Euro Investment Grade, Euro High Yield). I choose a quarterly frequency (instead of more frequent rebalancing) as this more closely reflects what can be effectively implemented in practice, where corporate bonds liquidity may be limited (Bessembinder, Maxwell, and Venkataraman, 2006; Long, Lesmond, and Wei, 2007; Bao, Jun, and Jiang, 2011). The empirical setting is ensured by the use of actual trading costs. Costs play a major role in the performance of an investment strategy. In literature, transaction costs are typically separated into two major components: explicit costs and implicit costs (Hafner et al, 2003; Keim and Madhovan, 1998). Explicit costs are the direct costs of trading such as bid-ask spreads. Generally known in advance, they are expressed as a percentage of the traded value. Explicit costs are easily observable while it is more difficult to quantify implicit costs such as market impact and opportunity costs as they depend on sizes traded and execution types (Haafner, Puetz, and Werner, 2003; Keim and Madhavan, 1998). Because of these reasons, I use only bid-ask spreads and leave the modelling of implicit costs to future research. Bid-ask spreads have been historically considered as the market remuneration for providing liquidity. They can vary significantly and are mostly a reflection of the securities market capitalization and market stress conditions. To quantify the historical costs, I use the time series of bid-ask calculated by the IMF (2016), see Table 3.10. The average costs are significantly higher for U.S. High Yield (0.9%) than U.S. Investment Grade (0.57%). Trading is significantly more expensive before 2004 and during the Global Financial Crisis (GFC). The maximum costs are on average 0.5% wider than minimum costs and record the highest values for U.S. High Yield (1.1%). IMF estimates show that costs are 0.1% higher on average for the smaller and less liquid European corporate bonds market (Biswas, Nikolova, and Stahel, 2015). Where available, I also cross check costs with the estimates provided by MarketAxess Bid-Ask Spread Index (BASI).

Table 3.10: **U.S. Corporate bond trading costs**

This table reports costs from IMF estimates for U.S. Investment Grade (IG) and U.S. High Yield (HY).

Asset Class	Average	Min	Max	Stdev
U.S. IG	0.57%	0.40%	0.90%	0.12%
U.S. HY	0.90%	0.60%	1.10%	0.19%

I implement the strategy as an overlay to a long only portfolio. This avoids short selling, a trading strategy difficult to implement for credit bonds and whose costs are difficult to observe and quantify. The performance of the overlay strategy is reported in Table 3.11.

Table 3.11: **Overlay strategy performance**

This table reports the performance of an overlay strategy that buys corporate bonds in the higher quintiles and sells in the lower. Figures are comprehensive of historical transaction costs.

		Excess Peformance (%)							
Quintile		**3m**	**6m**	**9m**	**1yr**	**2yr**	**3yr**	**4yr**	**5yr**
US IG	S	0.1	0.2	0.7	1.1	3.1 **	3.8 **	3.8 **	3.8 *
	SL	0.1	0.3	0.6	0.9	2.6 *	4.6 **	5.9 **	6.1 **
	SLC	0.1	0.3	0.6	0.9	2.5 *	4.8 **	5.7 **	5.7 **
US HY	S	-0.5	-0.6	-0.3	-0.2	4.4	6.9 *	10.4 *	12.9 **
	SL	-0.3	-0.2	0.1	0.3	6.5 *	9.3 **	12.2 **	14.4 **
	SLC	-0.5	-0.3	-0.0	0.2	6.5 *	9.3 **	12.2 **	14.4 **
EU IG	S	-0.0	0.1	0.2	0.1	2.1 *	3.7 **	4.6 **	3.8 **
	SL	-0.2	-0.1	-0.0	-0.1	1.7 *	3.9 **	5.2 **	4.0 **
	SLC	-0.2	-0.1	-0.0	-0.1	1.7 *	3.9 **	5.2 **	4.0 **
EU HY	S	1.4	2.2	1.9	1.6	4.7	10.5	23.8 *	30.3 *
	SL	1.4	2.2	1.5	0.8	4.3	8.0	18.3	22.8
	SLC	1.3	2.3	1.7	1.3	4.9	9.8	23.0	29.7
US A	S	-0.1	-0.1	-0.1	0.0	0.1	1.4	3.3 **	4.1 **
	SL	-0.1	-0.1	-0.1	0.0	-1.1	0.8	3.6 **	4.0 **
	SLC	-0.2	-0.1	-0.0	0.2	-0.6	0.8	3.6 **	4.1 **
US BBB	S	0.2	0.4	0.6	0.9	4.4 **	5.2 **	5.1 **	5.3 *
	SL	0.2	0.4	0.9	1.2	4.3 **	5.5 **	6.0 **	5.7 **
	SLC	0.3	0.5	1.0	1.3	4.1 **	5.4 **	6.2 **	6.0 **

** and * indicate statistical significance at the 0.05 and 0.10 level, respectively.

Results confirm that overlay strategies are profitable also in an empirical setting with effective trading costs. For time horizons longer than one year, the strategy delivers positive returns with the only exception of U.S. A for the 2-year period. The overlay strategy delivers higher returns over the longer time horizons and for higher yielding bonds: over the 5-year period Euro HY +30.3% and U.S. High Yield +14.4%. The positive returns are significant over the longer time horizons with the exception of Euro HY using SL and SLC ratio. Over the 5-year and 4-year horizons, the strategies based on SL and SLC ratios deliver significant and higher returns than those based on simple spreads with the exception of Euro HY.

3.8 Conclusions

This chapter identifies indicators of value opportunities in credit markets by surveying the investment outlooks of the largest investments banks. Their credit analysts assess the quality of credit investments focusing on leverage and interest coverage. Using these two fundamental measures, I define two ratios: 1) the fraction of spread over leverage (SL) and 2) the fraction of spread over leverage and the reciprocal of interest coverage (SLC). These ratios represent the spread that investors are willing to pay for a credit investment with a given leverage and interest coverage. I use SL, SLCs and spreads as indicators to identify value opportunities in credit. In particular, I investigate the performance from buying corporate bonds when value indicators are in the higher (lower) quintiles calculated over eight different time horizons (3-month, 6-month, 9-month, 1-year, 2-year, 3-year, 4-year and 5-year). My dataset includes corporate bonds in four credit areas (U.S. Investment Grade, U.S. High Yield, European Investment Grade and European High Yield) and two rating grades (A and BBB). The performance is studied both through spread changes and excess returns while risk is identified as the maximum drawdown.

Buying corporate bonds when spreads are high (i.e. prices are low) is a value opportunity. The average returns are higher for longer time horizons. Value strategies perform better if based on credit multiples (SL and SLC) than with simple spreads, however this performance is often statistically insignificant. SL and SLC ratio deliver similar performance, suggesting a limited contribution of interest coverage. Results are consistent across rating, geographical areas and data frequency. Value strategies in HY post a stronger performance than in IG, particularly in Europe. I find that credit multiples can be used to compare investment grade bonds with different ratings. High yield bonds provide a better spread per unit of leverage than investment grade bonds. Similarly, Industrials bonds have higher credit multiples than Utilities.

My analysis has several implications for investors. First, I find that value investing works better over longer time horizons (three years or longer). Second, I find that strategies based on credit multiples perform better than those based on single spreads but the outperformance is not statistically significant. My results suggest that researchers should further investigate the use credit multiples to identify value opportunities and build value factors in credit markets. My analysis also suggests that value investors should differentiate between Euro and U.S. credit markets and be aware that drawdowns can be significant, particularly during the first year of implementation.

4 What Is Statistical Arbitrage?

4.1 Introduction

The concept of arbitrage is fundamental in financial literature and has been used in classical analysis of market efficiency (Fama, 1969; Ross, 1976), whereby arbitrage opportunities are quickly exploited by investors. However, pure arbitrage opportunities are unlikely to exist in a real trading environment (Shleifer and Vishny, 1997; Alsayed and McGroarty, 2014). An arbitrageur typically engages in a trade that involves some risks. In the specific case where these risks are statistically assessed, then it is appropriate to use the term statistical arbitrage (SA). SA has been broadly investigated in literature, however scholars either focus on definitions or on developing and testing investment strategies, while I am not aware of any attempt to reconcile these two areas of research. On the one hand, several studies introduce definitions extending the concept of arbitrage through statistics but with little emphasis on strategies (Ledoit, 1995; Chochrane and Saa-Requejo, 1998; Bernardo and Ledoit, 2000; Bertsimas, Kogam and Lo, 2001; Carr, Geman and Madan, 2001; Bondarenko, 2003; Hogan et al., 2004). On the other hand, research on statistically determined arbitrage strategies focus on models and investment opportunities (Vidyamurthy, 2004; Stefanini, 2006; Pole, 2007) with little or no discussion on definitions and theoretical framework. This leads me to my research question. What is SA?

This chapter addresses this question with an in-depth investigation of SA. I begin by reviewing existing definitions of arbitrage which are reduced to a common notation and framework to analyse and compare them. I survey statistically determined arbitrage strategies analysing both the academic and financial industry research. In total, I review 165 articles on the subject, published between 1995 and 2016 (see full list in Appendix A.3). Particular attention is paid to hedge funds techniques, market neutral investment strategies and algorithmic trading. The strategies are discussed in a standardized way analysing equity, fixed income and, for the first time, commodity. I find that these strategies show significant similarities and common features that define them. The comparison of theoretical definitions and strategies' key features indicates that no available definition appropriately describes SA strategies. To bridge this gap, I propose a general definition, which more closely reflects investors' strategies. In addition, I suggest that, instead of searching for a definitive theoretical definition of SA, scholars should instead agree on a classification system that encompasses the current forms of SA while facilitating the inclusion of new types as they emerge. I propose a simple system for classifying strategies that takes into account the strategies' risk and return profile. I illustrate the advantages of this approach by demonstrating how it can guide theoretical development and empirical testing. I also provide examples of potential future research directions.

I make several contributions to the existing literature. I identify a general definition, which encompasses all SA strategies and introduce a classification system that facilitates their study. This is achieved through an innovative investigation of SA both in academic and financial industry research. In my review, for the first time, I analyses SA across all asset classes (equity, fixed income and commodity) to identify common features and defining elements. My analysis brings clarity in SA investing and allows investors to have a common framework to assess different investment opportunities.

The chapter is organized as follows. In section 4.2, I review existing definitions of SA producing a comprehensive mapping. In section 4.3, I report a survey of statistically determined arbitrage strategies. In section 4.4, I identify the key features which are common to the various strategies. I combine the findings of the previous sections and propose a general definition and classification system. Section 4.5 concludes the chapter.

4.2 Review of definitions

It is commonly accepted that Statistical Arbitrage (SA) started with Nunzio Tartaglia who, in the mid-1980s, assembled a team of quantitative analysts at Morgan Stanley to uncover statistical mispricing in equity markets (Gatev, Goetzmann and Rouwenhorst, 2006). However, SA came to the fore as a result of Long-Term Capital Management (LTCM), a hedge fund founded in 1994, where Nobel Prize winners Scholes and Merton both worked. The company developed complex SA strategies for fixed income (Duarte, Longstaff and Yu, 2006) which were initially extremely successful. However, in 1998, as a result of the financial crises in East Asia and Russia, LTCM's arbitrage strategies started producing large losses which endangered global markets and forced the Federal Reserve Bank of New York to organise a bailout in order to avoid a wider financial collapse. Nevertheless, SA continued to grow in popularity with applications progressively expanding to all asset classes. SA has become one of the main investment strategies in investment banks and particularly for hedge funds (Preqin, 2016). In particular, the term SA is used to denote hedge funds that aim to exploit pricing anomalies in equity markets (Hedge Fund Research, 2016). Technological developments in computational modelling have also facilitated the use of SA in high frequency trading and with the so-called machine learning methods, such as neural networks and genetic algorithms (Brogaard, Hendershott and Riordan, 2014; Chaboud et al., 2014; Ortega and Khashanah, 2014; Payne and Tresl, 2015). In more recent years, SA has seen renewed interest in emerging areas such as bitcoin (Brandvold et al., 2015; Lintilhac and Tourin, 2016), *big data* (McAfee et al., 2012; Lazer et al., 2014; Nardo, Petracco and Naltsidis, 2016) and factor investing (Maeso and Martellini, 2017).

The literature on the limits of arbitrage is quite broad and provides some insights on why SA opportunities exist. Mou (2010) reports how arbitrageurs have to face three different types of risks: fundamental risk (Shleifer and Vishny, 1997), noise trader risk (De Long et al., 1990) and synchronization risk (Abreu and Brennermeier, 2002). Duffie (2010) describes the risks arising from inattentive investors. Finally, behavioural effects can generate additional risk and asset bubbles. On the one hand, these risks create SA opportunities. On the other hand, the same risks can undermine arbitrageurs' efforts and cause delays in correcting market anomalies. I discuss the above risks more in detail in the Appendix.

In this section, I review all definitions of arbitrage available in literature which may be suitable to define SA. My analysis encompasses both alternative definitions of arbitrage as well as definitions of statistical arbitrage. Before reviewing the various definitions, I briefly recall the four types of definitions that are commonly used: 1) lexical, 2) conceptual, 3) abstract and 4) operational (Borsodi, 1967; Aggarwal et al., 2011). Lexical definitions use simple terms for a wide audience. Conceptual definitions describe a concept in a way that is compatible with a measurable occurrence. Abstract definitions are used when the meaning cannot be measured empirically. Finally, operational definitions provide a clear and concise meaning of a concept in a way that can be measured. Operational definitions clearly specify the object and criteria of measurement which makes them particularly suitable for scientific investigation. I find that existing definitions can be categorized as lexical, conceptual or operational.

4.2.1 Lexical definitions of SA

Some lexical definitions tend to be vague and lack formalism because traders, for good commercial reasons, tend to be obscure about their investment methods. Pole (2007) for example writes that SA uses mathematical models to generate returns from systematic movements in securities prices. According to Avellaneda and Lee (2008), the term statistical arbitrage encompasses a variety of strategies characterised by systematic trading signals, market neutral trades and statistical methods. Montana (2009) defines SA as an investment strategy that exploits patterns detected in financial data streams. Burgess (2000) defines statistical arbitrage as a framework for identifying, modelling and exploiting small but consistent regularities in asset price dynamics. Other definitions are centred on the concept of mispricing. Thomaidis and Kondakis (2006) define SA as an attempt to profit from pricing discrepancies that appear in a group of assets. Do, Faff and Hamza (2006) claim that SA is an equity trading strategy that employs time series methods to identify relative mispricings between stocks. Burgess (2000) also describes statistical arbitrage as a generalisation of a traditional arbitrage where mispricing is statistically determined through replicating strategies. In using derivatives, Zapart (2003) describes statistical arbitrage as an investment opportunity when perfect hedging is not possible.

A general definition of SA strategy should describe what SA is and its objectives. I find instead that some definitions focus on specific implementations and techniques. In particular, in a broad range of papers, SA is associated with pairs trading (Nath, 2003; Vidyamurthy, 2004; Elliott, Van Der Hoek and Malcom, 2005; Gatev, Goetzmann and Rouwenhorst, 2006; Bolgün, Takasbank and Güven, 2010; Cummins, 2010; Meucci, 2010; Reiakvam and Thyness, 2011) and cointegration (Alexakis, 2010; Chiu and Wong, 2013; Chen and Zhu, 2015; Mighri and Mansouri, 2016; Rad, Low, and Faff, 2016)

4.2.2 Conceptual definitions of SA

Another set of definitions can be classified as conceptual as they can be associated with specific measures. In reviewing Hedge Funds (HFs) strategies, Connor and Lasarte (2003) use the probability of a loss in defining SA as a zero-cost portfolio where the probability of a negative payoff is very small but not exactly zero. Stefanini (2006) uses the expected value in noting that SA seeks to capture imbalances in expected value of financial instruments, while trying to be market neutral. For Saks and Maringer (2008), SA accepts negative payoffs as long as the expected positive payoffs are high enough and the probability of losses is small enough. Focardi, Fabozzi and Mitov (2016) focus on uncorrelated returns reporting that SA strategies aim to produce positive, low-volatility returns that are uncorrelated with market returns.

4.2.3 Operational definitions of arbitrage

I next discuss the various extensions of arbitrage available in the literature that are used mainly in asset pricing. All definitions can be classified as operational and are mathematically formulated. Here, I provide a description of the various arbitrages while I leave a more rigorous formulation to the section 4.2.4.

I first introduce the classical definition of arbitrage, defined as a zero-cost trading strategy with positive expected payoff and no possibility of a loss. The absence of arbitrage is a necessary condition for equilibrium models, however this condition alone is often too weak to be practically useful for certain applications such as option pricing (Bondarenko, 2003).

A first attempt to provide a new definition of arbitrage is made by Ledoit (1995) who defines δ-Arbitrage (δA) using the Sharpe ratio (Sharpe, 1964; Lo, 2002). Ledoit (1995) defines δA as an investment strategy having a Sharpe ratio above a constant and strictly positive level δ. In the context of incomplete markets, Chochrane and Saa-Requejo (1998) independently apply the same concept as Ledoit to derivatives. They define a strategy as a Good Deal (GD) if its market price lies outside the range of plausible prices as determined by the various discount factors *m*.

Bernardo and Ledoit (2000) introduce the Approximate Arbitrage (AA) as they note that the Sharpe ratio is not a good measure of the attractiveness of an investment opportunity. If returns are not normally distributed strategies can have arbitrarily low Sharpe ratios, hence the introduction of a gain-loss ratio. AA is defined as an investment strategy whose maximum gain-loss ratio is above a predefined constant value. Instead of using the Sharpe ratio or the gain-loss ratio, Carr, Geman, and Madan (2001) base their definition of Acceptable Opportunity (AO) on two distinct sets of probability measures (valuation and stress measures). AO is defined as an investment strategy having a non-negative expected value under each valuation measure and losses capped under a set of stress measures. In other words, AO is an investment opportunity acceptable to a wide variety of reasonable individuals as it has expected non-negative payoff with losses capped under probability measures reflecting stressed conditions (stress measures). Bertsimas, Kogam and Lo (2001) introduce ε-Arbitrage (εA) referring to replication strategies. Pricing through εA involves finding the least costly optimal replication strategy. Accordingly, an ε A strategy Z_t invests in the spread $V_t - F_t$ whenever the price of a derivative F_t significantly differs from the least costly optimal replication strategy V_t.

In the literature, there are two definitions of Statistical Arbitrage (SA) which differ significantly from each other. Bondarenko's SA is a trading strategy which can have negative payoffs, as long as the average payoff is non-negative. Key in the definition is the introduction of the augmented information set, which, in addition to the market information at time *t*, also includes the knowledge of the final price. (Hogan et al., 2004) provide an alternative definition of SA which focusses on long horizon trading opportunities. Hogan's SA is a long horizon trading opportunity that, at the limit, generates a risk-less profit. According to this definition SA satisfies four conditions (i) it is a zero-cost, self-financing strategy, that in the limit has (ii) positive expected discounted payoff, (iii) a probability of a loss converging to zero, and (iv) a time averaged variance converging to zero if the probability of a loss does not become zero in finite time. The fourth condition only applies when there always exists a positive probability of losing money.

4.2.4 Mathematical formulations of operational definitions

In reporting the following definitions, I use a common notation which replicates the original versions as closely as possible. Let X_t be the asset price and $Z_t = Z(X_0, \dots, X_t)$ denote the price of a strategy which is a function of X_t. Assume there are no trading costs and the risk-free interest rate is r_f.

Definition of Pure Arbitrage (PA). A zero-cost strategy Z_t is called a PA if

$$E[Z_T] > 0 \tag{4.1}$$

$$Z_T \geq 0, \forall X_T$$

where $E[Z_T]$ is the expected value of the strategy price Z_T on the underlying asset X_t (Bondarenko, 2003).

Definition of δ-Arbitrage (δA). A strategy is called a δA if exists $\delta \in R^+$ such that

$$\frac{E[R_T - r_f]}{\sigma[R_T - r_f]} \geq \delta \tag{4.2}$$

where R_T is the return of the strategy Z_t at time T, $E[R_T - r_f]$ is the expected excess return over the risk free r_f and $\sigma[R_T - r_f]$ is the standard deviation of the excess return (Ledoit, 1995).

Definition of Good Deal (GD). Let m be a generic discount factor, $C \in R^+$ and Z_t a strategy function of X_t, then Z_t is a GD if

$$Z_t \notin [Z_{min,t}, Z_{max,t}] \tag{4.3}$$

where $Z_{min,t} = \min_m E[mZ_T]$, $Z_{max,t} = \max_m E[mZ_T]$, $\forall m$ such that $X_t = E(mX_T)$, $m \geq 0$ and $\sigma(m) \leq {}^{C}/_{r_f}$. The expression $\min_m E[mZ_T]$ indicates the minimum expected value of the value of the strategy Z_T at maturity discounted by m. Analogously the expression $\max_m E[mZ_T]$ indicates the maximum expected value of the value of the strategy Z_T at maturity discounted by m. By $\sigma(m)$, I refer to the standard deviation of the discount factor m. The condition $X_t = E(mX_T)$ with positive discount factor constraint $(m \geq 0)$ rules out arbitrage opportunities. The volatility constraint $\sigma(m) \leq {}^{C}/_{r_f}$ reduces the set of discount factors and hence sharpens price bounds. Hansen and Jagannathan (1991) show that GD applies the same concept of δA to derivatives. Indeed they prove that imposing $\sigma(m) \leq {}^{C}/_{r_f}$ implies that no portfolio priced by *m* can have a Sharpe ratio greater than δ (Chochrane and Saa-Requejo, 1998).

Definition of Approximate Arbitrage (AA). A strategy Z_t is called an AA if $\exists C \in [1, +\infty)$ such that

$$Gain - Loss\ ratio = \frac{E\left[max\left(Z_T - \left(1 + r_f\right) \cdot Z_t\right)\right]}{E\left[min\left(Z_T - \left(1 + r_f\right) \cdot Z_t\right)\right]} > C \tag{4.4}$$

where $E\left[max\left(Z_T - \left(1 + r_f\right) \cdot Z_t\right)\right]$ is the expected maximum excess profit of the strategy Z_t and similarly $E\left[min\left(Z_T - \left(1 + r_f\right) \cdot Z_t\right)\right]$ is the expected minimum excess loss (Bernardo and Ledoit, 2000).

Definition of Acceptable Opportunity (AO). Consider $M \geq 1$ probability measures P_m with: a) P_m a stress measure with floor $C_m < 0$, $\forall m \in [1, \ldots, l]$ and $l \leq M - 1$ and b) P_m a valuation measure with floor $C_m = 0$, $\forall m \in [l + 1, \ldots, M]$. Let Ω_m^S be the set of states charged with positive probability mass by the mth stress measure and Ω_m^V be the set of states charged with positive probability mass by the mth valuation measure. A zero-cost strategy Z_t is called an AO if

$$E^{P_m}[Z_T] \geq C_m \tag{4.5}$$

$\forall m \in [l + 1, \ldots, M]$ with $\Omega_m^S \subseteq \Omega_m^V$. The expression $\mathrm{E}^{\mathrm{P_m}}[\mathrm{Z_T}]$ is the expected value of the strategy $\mathrm{Z_t}$ under probability measure $\mathrm{P_m}$.The condition $l \leq M - 1$ assumes that there is at least one valuation measure. The condition $\Omega_m^S \subseteq \Omega_m^V$ implies that stress measures evaluate outcomes believed possible by some valuation test measure. Otherwise one would accept opportunities which generate acceptable losses under the stress measure, even though such opportunities may have non-positive cash flows over all states (according to valuation measures), see Carr, Geman, and Madan (2001).

Definition of ε-Arbitrage (εA). Consider a portfolio V_t aiming to replicate as close as possible the payoff at maturity of a derivative $F_t$with underlying X_t. Define $V_t = \vartheta_t X_t + B_t$ where ϑ_t is the number of shares held in X_t and B_t the value of bonds held. Let ϑ_t be a self-financing strategy after initial cost V_0. The ε-arbitrage price of F_t is obtained by solving

$$\varepsilon = \min_{V_0} \sqrt{\min_{\vartheta_0} E\,\{[V_T - F_T]^2\}} \tag{4.6}$$

For in depth analysis, please see Bertsimas, Kogam and Lo (2001).

In the literature, there are two extensions of the concept of arbitrage to Statistical Arbitrage (SA).

Definition of Statistical Arbitrage (SA) - Bondarenko's version. Let $I_t^{X_T} = (X_0, \dots, X_t; X_T)$ denote the augmented information set, then a zero-cost strategy Z_t is called a Statistical Arbitrage (SA) if $\forall X_T$

$$E[Z_T|\, I_0] > 0 \tag{4.7}$$

$$E\left[Z_T|\, I_0^{X_T}\right] \geq 0$$

Implicit in the definition of SA is the assumption that there are many different histories I_T corresponding to a given final state X_T, which means that a path-dependent strategy may have uncertain payoffs in X_T. $E[Z_T|\, I_0]$ is the expected value conditional on the information set I_0 available at inception. $E\left[Z_T|\, I_0^{X_T}\right]$ is the expected value conditional on the information set $I_0^{X_T}$available at inception plus the knowledge of the final state X_T (Bondarenko, 2003).

Definition of Statistical Arbitrage (SA) – Hogan's version. Let $t \in [0, +\infty)$ then a zero-cost, self-financing strategy Z_t is called a Statistical Arbitrage (SA) if

a) $Z_0 = 0$ (4.8)

b) $\lim_{T \to +\infty} E[Z_T] > 0$

c) $\lim_{T \to +\infty} P(Z_T < 0) = 0$

d) $If\, P(Z_T < 0) > 0, \forall T < \infty, \lim_{T \to +\infty} {\sigma^2[Z_T]}/{T} = 0$

$Z_0 = 0$ indicates that the strategy is zero cost. Condition b) indicates that the strategy has a positive expected payoff at the limit. Condition c) states that the probability of the strategy producing a loss goes to zero with time. The fourth condition introduces a cap to the variance of the strategy which is allowed to increase with time but with a growth less than linear. This definition was further extended by Jarrow et al. (2012) altering the fourth condition as $\lim_{T \to \infty} Var[\Delta Z_T | \Delta Z_T < 0] = 0$ to limit the variance only of negative incremental trading profits (Hogan et al., 2004).

As a summary, I provide a high-level description of all the reviewed arbitrage definitions in Table 4.1.

Table 4.1: **Definitions of arbitrage**

Author/Name	**Definition**
Panel A: Lexical definitions	
Burgess (2000)	SA is a framework for identifying, modelling and exploiting small but consistent regularities in asset price dynamics
Zapart (2003)	SA is an investment opportunity arising from the choice of models for hedging
Do et al. (2006)	SA is an equity trading strategy that employs time series methods to identify relative mispricing between stocks
Thomaidis and Kondakis (2006)	SA is an attempt to profit from pricing discrepancies that appear in a group of assets
Pole (2007)	SA uses mathematical models to generate returns from systematic movements in securities prices
Avellaneda and Lee (2008)	SA encompasses a variety of strategies characterized by: i) systematic trading signals, ii) market neutral trades and iii) statistical methods
Montana et al. (2008)	SA is an investment strategy that exploits patterns detected in financial data streams
Panel B: Conceptual definitions	
Connor and Lasarte (2003)	SA is a zero-cost portfolio where the probability of a negative payoff is very small but not exactly zero
Stefanini (2006)	SA seeks to capture imbalances in expected value of financial instruments, while trying to be market neutral
Saks and Maringer (2008)	SA accepts negative pay-outs with a small probability as long as the expected positive payouts are high enough and the probability of losses is small enough
Focardi, Fabozzi and Mitov (2016)	SA strategies aim at producing positive, low-volatility returns that are uncorrelated with market returns
Panel C: Operational definitions	
δ - Arbitrage (Ledoit, 1995)	Is a strategy with a Sharpe ratio above a constant and positive δ
Good Deal (Cochrane and Saa-Requejo,1998)	Consists in buying (selling) securities whose market price lies outside a range of plausible prices
Approximate Arbitrage (Bernardo and Ledoit, 2000)	Is a strategy whose gain-loss ratio is above a predefined constant value
Acceptable Opportunity (Carr et al., 2001)	Is a strategy with a non-negative expected value under each valuation measure and losses capped under the set of stress measures
ε - Arbitrage (Bertsimas et al., 2001)	Consists in buying (selling) those derivatives strategies whose price significantly differs from the least costly optimal replication strategy
SA (Bondarenko, 2003)	Is a strategy with expected positive payoff and expected non-negative payoff conditional on the augmented information set
SA (Hogan et al., 2004)	With time the strategy has positive expected payoff, probability of a loss which tends to zero and time averaged variance which converges to zero

4.3 Literature review of strategies

4.3.1 Literature review

The existing literature on SA includes a small number of reviews of arbitrage strategies which cover only single asset classes. In fixed income, Duarte, Longstaff and Yu (2006) conduct an analysis of the risk and return characteristics of the most widely-used fixed income arbitrage strategies. In equity, Do, Faff and Hamza (2006) analyse different approaches to pairs trading: distance approach, cointegration approach, stochastic spread approach and stochastic residual spread approach. Again, focussing on equities, Pole (2007) elaborates on pairs trading as well as statistical models for time series analysis. There are no reviews for commodities, where studies primarily focus on modelling spreads and term structures for single commodities (Lautier, 2005).

In my review, for the first time, I look at SA across all asset classes to identify common features and defining elements. I review the existing literature on statistically determined arbitrage strategies and, particularly, on those labelled as SA. I identify 165 articles in literature discussing SA strategies spanning from 1995 to 2016 (see Table 4.2). The surveyed studies focus on equities (104 studies), followed by bonds (40) while other asset classes appear only in a small number of articles: commodities (9), volatility (9) and FX (1). Just two articles discuss pairs trading across asset classes (mix): investment grade credit default swaps versus equity (Gadiraju, 2009) and gold miners versus gold (Yu and Wang, 2014).

Table 4.2: **Studies on arbitrage strategies**

The table reports the breakdown by asset class of existing studies on statistically determined arbitrage opportunities.

SA strategy	Equities	Bonds	Commodities	Volatility	FX	Mix	Total
Pairs trading	103		6		1	2	112
Capital structure arbitrage		30					30
Volatility Arbitrage				9			9
Term Structure Arbitrage	1	4	3				8
Swap Spread Arbitrage		3					3
Mortgage Arbitrage		3					3
Total	**104**	**40**	**9**	**9**	**1**	**2**	**165**

I categorize the various strategies based on the classification proposed by Duarte, Longstaff and Yu (2006) who identify five different types of SA strategies in fixed income: 1) swap arbitrage strategies, 2) term structure arbitrage (or yield curve arbitrage), 3) mortgage arbitrage, 4) volatility arbitrage and 5) capital structure arbitrage. I add equity pairs trading to the classification for fixed income of Duarte, Longstaff and Yu (2006). The term SA is used very frequently in particular in relation to pairs trading (112) which includes pairs trading between indices (13), ETFs (4) and spread trading between commodities (6). Various articles focus on cointegration (21), the Ornstein-Uhlenbeck[7] stochastic process (10) and, more recently, high frequency trading (9). Pairs trading is predominantly an equity strategy (103). Capital structure arbitrage is the second most documented strategy (30) which includes primarily convertible arbitrage strategies (19). Term structure strategies are documented only in eight studies of which four analyse bonds. Swap spread arbitrage and mortgage arbitrage are discussed in three studies each.

[7] Ornstein-Uhlenbeck is a model used to describe the multivariate dynamics of financial variables (Meucci, 2010)

4.3.2 Review of strategies

I next describe the six identified trading strategies. Pairs trading is a SA strategy which is particularly popular in equity (Vidyamurthy, 2004). In its simplest formulation, pairs trading aims to identify pairs of stocks whose prices have historically moved together. When the spread between the two components of the pair significantly widens, the strategy sells the best performing security to buy the laggard. If the spread reverts to the mean the trade will be profitable regardless of market trends. This strategy relies on the assumption of a (long-term) equilibrium in the investigated spreads (Ardeni, 1989) which can be detected through a variety of statistical methods (Nath, 2003; Vidyamurthy, 2004; Elliott, Van Der Hoek and Malcom, 2005; Do, Faff and Hamza, 2006; Gatev, Goetzmann and Rouwenhorst, 2006; Avellaneda and Lee, 2008; Do and Faff, 2010). Long and short positions can be combined in a ratio which makes the trade market-neutral (with a neutral beta position versus the market) or dollar-neutral. The use of pairs trading is not limited to stocks. There are applications to other areas such as spreads between different commodities (Monroe and Cohn, 1986; Barrett and Kolb, 1995; Cummins and Bucca, 2012), commodity future contracts (Cui, Huang, and Cai, 2015) and freight markets (Roehner, 1996; Alizadeh and Nomikos, 2002). Pairs trading can also be used to model the spread between different portfolios (Alexander, Dimitriu, and Malik, 2005; Cheng, Yu, and Li, 2011; Acosta-Gonzalez, Armas-Herrera, and Fernandez-Rodriguez, 2015).

Term structure arbitrage is a common SA strategy which typically involves taking market-neutral long-short positions at different points of a term structure as suggested by a relative value analysis (Duarte, Longstaff and Yu, 2006). Positions are held until the trade converges and the mispricing disappears. Term structure arbitrage is particularly common in fixed income (also called yield curve arbitrage) and commodities. In spite of being one of the most common SA strategies, the literature on implementations of yield curve arbitrage is quite limited and mostly focuses on interest rates models (Fabozzi, 2001; Duarte, Longstaff and Yu, 2006). Term structure arbitrage in commodities uses models (similar to the one used in rates) to identify relative value opportunities across the curve (Lautier, 2005). An implementation of term structure arbitrage in commodities is described by Mou (2010) who identifies investment opportunities arising from the futures rolling of the main commodity indices. In credit, SA opportunities in the term structure of CDS are studied by Jarrow, Li and Ye (2009).

Volatility arbitrage is a popular and widely used strategy (Belton and Burghardt, 1993; Ammann and Herriger, 2002; Ahmad and Willmott, 2005; Jena and Tankov, 2011; Baik, Kang and Kim, 2013). Its implementations are structured to be pure bets on volatility and should not be influenced by the actual direction of the underlying. Similarly to other types of arbitrage, volatility arbitrage refers to a wide range of different strategies which can be classified into 1) gamma trading, 2) volatility surface arbitrage, 3) cross asset volatility trading and 4) dispersion trading. Gamma trading plays the implied volatility versus historical volatility on the same asset across different strike prices and maturities (Carr, Geman and Madan, 2001; Ahmad and Willmott, 2005). Volatility surface arbitrage is a relative value strategy trading the implied volatilities on the same underlying in different points of the volatility surface (Sinclair, 2008). Cross-asset volatility trading plays the implied volatility of an asset versus the implied volatility of another asset through traditional long-short trades. Finally, dispersion trading (also known as decorrelation trading) trades the volatility of a basket of securities against the volatilities of the components of the same basket (Sinclair, 2008).

Swap spread arbitrage is another popular fixed income strategy which bets on the difference between a fixed and a floating yield (Duarte, Longstaff and Yu, 2006; Krishnamurthy, 2008). It is structured in two parts. On the one hand, the arbitrageur enters a par interest rate swap paying a fixed coupon rate SR and receiving the floating LIBOR rate L_t. On the other hand, the arbitrageur buys a treasury bond, with the same maturity as the swap, with the money borrowed through a repurchase agreement known as repo. Entering this part of the trade the arbitrageur earns the treasury rate TR and pays the repo rate r_t. The overall cash flow of the trade is $(L_t - r_t) - (SR - TR)$ where *SR*-*TR* is the fixed interest rate component (also known as swap spread) and $L_t - r_t$ is the floating rate part which needs to be rolled periodically (typically every three months). The strategy generates a positive income as long as the floating yield exceeds the fixed one. Swap spread arbitrage is immune from interest rate risk if both the repo rate and LIBOR (which generally have the same maturity and rolling dates) react similarly to a move in rates.

Mortgage arbitrage consists of buying mortgage-backed securities (MBSs) while hedging their interest rate exposure primarily through derivatives (Biby, Modukuri and Hargrave, 2001). The strategy provides a positive carry as the yield on MBSs is typically higher than that of comparable treasury bonds. As the spread earned is generally small, arbitrageurs use leverage to enhance returns. Mortgage arbitrage strategies can be classified based on the different types of MBS used. A popular implementation of the strategy is with pass-through MBSs which pass all of the interest and principal cash flows of a pool of mortgages to the pass-through investors (Stefanini, 2006).

Capital structure arbitrage involves taking long and short positions in the various instruments of a company's capital structure (Yu, 2005; Duarte, Longstaff and Yu, 2006; Driessen and Van Hemert, 2012; Kapadia and Pu, 2012; Calice, Chen and Williams, 2013). This includes a variety of strategies between equity, debt and credit instruments of a given company. Some of the most popular strategies are credit arbitrage and convertible arbitrage. Credit arbitrage (also known as capital structure arbitrage) usually refers to strategies that aim to exploit mispricing between a company's credit default swap (CDS) and its equity. Arbitrageurs use the information on the equity price and the capital structure of an obligor to compute its theoretical CDS spread. The theoretical CDS is then compared with the level quoted in the market. If the market spread is higher (lower) than the theoretical spread, then the strategy goes short (long) on the CDS contract while simultaneously hedging the equity with a short (long) position (Schaefer and Strebulaev, 2006).

Convertible Arbitrage is one of the most popular capital structure strategies and involves buying a portfolio of convertible bonds while selling short the underlying stocks (Agarwal et al., 2006; Yan, Yang and Zhao, 2016). Intuitively, if the stock increases in price, the bonds will appreciate and if the stock falls the short position will profit. In some versions, the interest rate risk is hedged with treasury futures or interest rate swaps. In addition to credit arbitrage and convertible arbitrage, other capital structure arbitrage strategies focus on the spread between bonds and equities of the same company. In particular Schaefer and Strebulaev (2006) show that structural models provide accurate predictions of the sensitivity of corporate bond returns to changes in the value of equity (hedge ratios). Other strategies instead focus on the spread between CDS and corporate bonds or different types of credit default swaps (Mayordomo, Ignacio and Romo, 2014; Leccadito, Tunaru and Urga, 2015).

This review allows me to identify the defining features of the different strategies across asset classes. They are summarized in Table 4.3.

Table 4.3: **Arbitrage trading strategies**

The table reports the defining features of the surveyed strategies

Strategy	**Descriptoins**
Pairs trading	Plays mean reversion in the spreads of two securities
Term structure arbitrage	Takes long-short positions across the term structure
Volatility arbitrage	Plays the spread of implied vs. realised volatility of the same security or implied vs. implied volatility of the same or different securities
Swap spread arbitrage	Profits from the spread between a fix and a floating leg by entering a short (long) Treasury position and simultaneously buying (selling) an IRS
Mortgage arbitrage	Buys MBS hedging the interest rates exposure
Capital structure arbitrage	Takes long-short positions on different instruments of a company (credit arbitrage and convertible arbitrage)

4.4 What is SA?

In this section, I define SA strategies. I identify those features which are common to the surveyed arbitrage strategies. I compare them with the available definitions and provide a new definition in conjunction with a classification scheme. The new definition incorporates all strategies' key elements and the classification scheme encompasses the important dimensions of SA while being flexible and easy to use.

4.4.1 Strategies key features

All strategies aim to exploit relative value opportunities through the implementation of long-short positions. Pairs trading invests in the spread between two stocks. Term structure models the spread between yields or future prices. Volatility arbitrage identifies relative value opportunities between volatilities. Swap spread plays a fixed spread versus a floating spread. Mortgage arbitrage models the spread of MBS over treasury. Capital structure arbitrage profits from the spread between various instruments of the same company. Spreads trading involves taking long-short positions in order to profit from spreads or simply to bet on a security while being market-neutral.

However, not all strategies need mean reversion. Pairs trading and term structure arbitrage need spreads to revert to their mean to be profitable. Other strategies instead need a persistent positive spread-carry: between implied and realised volatility (volatility arbitrage), between the fixed and the floating spread (swap spread arbitrage), in the MBS spread over treasury (mortgage arbitrage) and between various instruments of the same company (capital structure arbitrage). If spreads narrow these strategies are less profitable and can turn into a loss. In addition, not all strategies are zero-cost. This is not only due to market frictions or trading costs but it is true by construction. For example, pairs trading (in the market-neutral form) may require a net payment and mortgage arbitrage requires the purchase of MBSs.

Not all strategies are "market-neutral" but rather invest in some risk factors while hedging others. For example, term structure arbitrage may hedge only against parallel shifts of the term structure. Volatility arbitrage hedges against movements of the underlying but not of the underlying volatility. Swap spread arbitrage hedges against changes in treasury and swap rates but not against credit risk. Mortgage arbitrage hedges against movements in treasury rates but not mortgage spreads. More generally, it depends on the definition of market. If we assume that markets are defined by various risk factors then the reviewed strategies cannot be considered market-neutral. Furthermore, all strategies require exposure to some sources of risks which represent their set of investment opportunities or, in other words, their market.

Not all strategies guarantee gains but rather offer positive expected excess returns with an acceptably small potential loss. Arbitrageurs require a positive expected excess return over the risk free to compensate for risk. The potential loss must be acceptably small in order to qualify the strategy as arbitrage rather than simple investment. Although not all the academic literature reports it, trades always have a stop loss resulting from investors' risk tolerance. A stop loss is mostly exogenous to the models underlying the strategy and relies on investors' risk appetite. All strategies have embedded a take profit whenever the trade does not offer any more potential upside. A take profit is triggered in case there is reversion to the mean (pairs trading, term structure arbitrage, volatility arbitrage and capital structure arbitrage) or when the positive carry disappears (swap spread arbitrage and mortgage arbitrage). More generally, each strategy is closed at a profit or at a loss at maturity.

From the previous analysis, it is possible to conclude that four key factors define statistically determined arbitrage opportunities: 1) relative value, 2) positive expected excess returns with an acceptably small potential loss, 3) take profit and 4) stop loss (see Table 4.4).

Table 4.4: **Key features of statistically determined arbitrage strategies**

For each trading strategy, the table reports whether the listed features are present or not. Where there is no clear assessment (-) is reported.

Main Features by strategy	Pairs trading	Term structure arbitrage	Volatility arbitrage	Swap spread arbitrage	Mortgage arbitrage	Capital structure arbitrage
Relative value	Yes	Yes	Yes	Yes	Yes	Yes
Mean reversion	Yes	Yes	-	No	No	-
Market neutral	-	-	-	-	-	-
Zero cost	-	-	-	Yes	No	-
Expected positive excess return	Yes	Yes	Yes	Yes	Yes	Yes
Acceptably small potential loss	Yes	Yes	Yes	Yes	Yes	Yes
Take profit	Yes	Yes	Yes	Yes	Yes	Yes
Stop loss	Yes	Yes	Yes	Yes	Yes	Yes

4.4.2 Definition of SA strategy

From the review of strategies and definitions, I find that both in the definitions and strategies, statistics are used to explain securities mispricing. In particular, they focus on the same observable phenomenon but from different perspectives. Definitions focus primarily in strengthening the concept of arbitrage introducing additional constraints that can make theory more consistent with financial markets. In some cases, they use tools common to practitioners, such as the Sharpe ratio in δA. In other cases, instead the focus is more on the theoretical framework, such as in the augmented information set in Bondarenko's (2003) definition. Strategies instead use quantitative models as a tool to have a more efficient approach to uncover mispricing. Starting from the empirical evidence of market inefficiency, investors use different techniques to identify “arbitrages” with a given statistical confidence. It is evident how both academics and practitioners look at the same issue: academics rule out those investment opportunities which are not compatible with a rigorous pricing, while investors try to identify investment opportunities resulting from inaccurate pricing. In both cases statistical methods have been used. Now the question is: do they come to the same conclusions? And more particularly, is there a definition of SA which encompasses the various strategies?

I aim to create a definition which is measurable. That rules out lexical definitions which focus generically on systematic strategies (Burgess, 2000; Pole, 2007; Avellaneda and Lee, 2008; Montana, 2009) and relative value (Zapart, 2003; Do et al., 2006; Thomaidis and Kondakis, 2006). I compare the key features of SA strategies with conceptual and operational definitions (see Table 4.5). The available conceptual definitions do not capture all key features: Connor and Lasarte (2003) and Saks and Maringer (2008) do not mention relative value, while Stefanini (2006) and Focardi, Fabozzi and Mitov (2016) do not require small potential losses. The analysis of available operational definitions reveals that, singularly, no definition requires long-short trading nor spread modelling. More generally, with the exception of εA no definition refers to relative value analysis. Only δA, GD and AA incorporate the feature of positive excess returns while the other definitions generically refer to positive expected returns as there is no initial cost involved. AA embeds the feature of acceptably small potential loss but this is limited to a specific measure (gain-loss ratio). AO limits losses through the use of generic stress measures. Hogan’s SA partially requires acceptably small potential losses as the probability of a loss converges to zero with time. All definitions embed the concept of take profit as long as it is assumed that a strategy is closed at maturity T or when the expected returns are no longer positive (at a generic time t). AOs can be closed in stop loss if the realised loss is higher than what is acceptable according to the stress measures. Hogan's SA has the concept of stop loss if it is assumed that a strategy is closed when the constraints on the probability of a loss are no longer satisfied. AA trades are closed in stop loss only if the gain-loss ratio is lower than 1. According to the other definitions instead a trade is closed only when the defining criteria are no longer met and this does not necessarily involve a stop loss. In conclusion, there are some differences across definitions. Although some definitions are compatible with various strategies' common features, nevertheless they fail to incorporate all of them as defining elements.

Table 4.5: **SA definitions versus strategies' key features**

Key Features	**Relative value**	**Expecxted positive excess return**	**Acceptably small potential loss**	**Take profit**	**Stop loss**
Panel A: Conceptual definitions					
Connor and Lasarte (2003)	No	-	Yes	Yes	Yes
Stefanini (2006)	Yes	Yes	No	Yes	No
Saks and Maringer (2008)	No	Yes	Yes	Yes	Yes
Focardi et al. (2016)	-	Yes	-	Yes	No
Panel B: Operational definitions					
δ - Arbitrage (Ledoit, 1995)	No	Yes	No	Yes	No
Good Deal (Cochrane and Saa-Requejo,1998)	No	Yes	No	Yes	No
Approximate Arbitrage (Bernardo and Ledoit, 2000)	No	Yes	Yes	Yes	-
Acceptable Opportunity (Carr et al., 2001)	No	-	Yes	Yes	Yes
ε - Arbitrage (Bertsimas et al., 2001)	Yes	-	No	Yes	No
SA (Bondarenko, 2003)	No	-	No	Yes	No
SA (Hogan et al., 2004)	No	-	Yes	Yes	Yes

As no available definition fully captures what is done in practice, I identify a conceptual definition that incorporates all strategies' key elements. I choose to use a conceptual definition as it clearly defines SA while leaving each analyst to select the most appropriate measure as explained below.

I define a SA strategy as a relative value strategy with a positive expected excess return and an acceptably small potential loss. I note the following in relation to my proposed new definition. First, SA is a relative value strategy. This reflects the fact that all the reviewed strategies play the spread of a security against another one. It should be noted that, while the concept of relative value is universally accepted, its boundaries are not clearly defined. A priori a total return strategy can be considered a relative value strategy of an investment against the overnight rate (which is close to zero). It is using the common understanding that I refer to relative value strategies as strategies aiming to find mispricing using historical relationships. As a relative value strategy, SA requires that the underlying securities are combined in a long-short portfolio. This allows to more accurately isolate some sources of risk (expected to deliver positive excess returns) while hedging others. The underlying securities may or may not belong to the same asset class.

Another element is given by the expected positive excess return. This part of the definition incorporates two features. The first one is given by the fact that the strategy focuses on the expected return. This differs from the definition of arbitrage where the strategy has no admissible possible negative outcomes. Losses are allowed in my definition of SA. The second one is given by the excess return. This reflects the fact that every arbitrageur embarks on a strategy involving some risk only if there are expectations of returns higher than the risk free whenever an initial investment is required.

The last requirement is given by the acceptably small potential loss. This element is fundamental in order to differentiate SA from a simple investment strategy. To be called arbitrage, a strategy needs to have a constrained loss profile. A strategy is closed whenever the defining criteria are no longer satisfied: a) in stop loss, if the loss is no longer acceptably small or b) in take profit, if the performance is positive and the expected excess return is no longer positive.

This definition cannot be operational unless I define how to measure a "positive expected excess return" and an "acceptably small potential loss". The need for clarity on this issue is critical. However, the complex and dynamic landscape of financial markets suggests that no definitive theoretical or operational definition of SA is likely to be agreed. Because of this I propose to use the definition in conjunction with a classification scheme.

A positive expected excess returns requires defining the risk free and a probability measure. The risk free can be the cost of financing (for unfunded strategies) or the cash rate (for funded strategies). In the case of a zero-cost trading strategy, the risk free is equal to zero. Defining an acceptably small potential loss requires identifying a set of suitable risk measures and criteria to establish what is acceptably small. Examples of risk measures are the probability of a loss, the Value at Risk (VaR) and the Conditional Value at Risk (CVaR), see Duffie and Pan (1997), Rockafellar and Uryasev (2000), Jorion (2007) and Wang and Zhao (2016). It is left to each investor to define what is acceptably small according to his utility function.

This classification scheme aims to be sufficiently detailed to encompass the important dimensions of SA while at the same time being intuitive and easy to use. To be widely accepted, a definition should also appeal to practitioners and other stakeholders by reflecting the world as it is perceived. My definition, with annexed classification scheme, satisfies the four canons of a good definition: adequacy, differentiation, impartiality and completeness (Borsodi, 1967). It is adequate as it clarifies a substantial portion of the meaning of SA. It shows differentiation as it eliminates confusions including all the terms which distinguish SA from a generic investment strategy. Impartiality in the definition is guaranteed as all key elements receive similar significance while assuring the necessary completeness.

My definition of SA compares favourably to existing SA definitions and clearly differentiates from them. There are two operational definitions of SA provided by Bondarenko (2003) and Hogan (2004). The definition of Bondarenko (2003) is not suitable to describe this wider range of strategies as it requires the knowledge of the value of underlying variables at maturity. Hogan's SA definition instead seems to be more focused on investors' strategies and this is reflected by its broader use in more recent literature (Goncu, 2015; Focardi, Fabozzi and Mitov, 2016). However, Hogan's definition does not emphasize the need for positive excess return and the peculiarity of relative value, which are instead defining elements in my definition. Additionally, it is not flexible enough to include SA strategies based on specific ratios, see for example the Sharpe ratios used by Bertram (2010), Cummins and Bucca (2012) and Goncu (2015). Compared to the other existing operational definitions of arbitrage, my definition is more generic and does not focus on a single indicator like the Sharpe ratio (for δ-arbitrage and Good Deal) or the gain-loss ratio (for Approximate Arbitrage). This allows flexibility in choosing the classification system to measure the strategies' risk and return profile. Additionally, my definition is not limited to derivatives (like ε-arbitrage), nor requires the specification of a-priori valuation and stress measures (Acceptable Opportunity). Compared to the other conceptual definitions, my definition reformulates Saks and Maringer (2008) adding relative value. This addition is fundamental to rule out investing in short term government bonds (with positive expected return and low probability of a loss) as a SA strategy. My definition does not require a strategy to be zero-cost (Connor and Lasarte, 2003), market neutral (Stefanini, 2006), nor with returns uncorrelated to markets (Focardi, Fabozzi and Mitov, 2016) but more generically focus on relative value. Compared to lexical definitions, my formulation of SA is compatible with a measurable occurrence. To discuss my definition in a financial context, in the next section I produce an investigation of SA for hedge fund strategies.

My definition and classification system could guide future research. For example, the use of a common classification system allows investigating the profitability and riskiness of SA strategies across asset classes and time. This enables mapping pricing anomalies and can provide directions on how to improve pricing models. The existence of persistent SA opportunities in selected strategies can be used as an indicator to direct future research to less studied asset classes and instruments. Having a framework brings transparency to the term SA, helping investors in making investment decisions. For example, my definition of SA can be used in the hedge funds industry where there is no agreement on a standardized classification system of strategies (Baquero and Verbeek, 2008). This can help address the issue of a lack of uniform definitions in hedge funds where several classification systems are still in use with significant differences among them (Indjic and Heen, 2003; AIMA, 2012).

4.5 Empirical implementation

I apply the new definition of SA to hedge funds arbitrage strategies to show its benefits in an empirical setting (see Table 4.6). I use a dataset including the four leading indices providers for hedge funds strategies: Bloomberg's Active Indices for Funds (BAIF), Hedge Fund Research (HFRX), Credit Suisse Sector Invest and Barclay Hedge (Das, 2003; Fung and Hsieh, 2004). BAIF indices represent a composite of hedge funds included in the Bloomberg databases and domiciled globally. HFRX indices are designed to be representative of the overall composition of the hedge funds universe and are comprised of all eligible hedge funds strategies. The Credit Suisse Sector Invest indices are asset-weighted indices derived from the Credit Suisse database of more than 5'000 funds. The Barclay Hedge Fund indices are the arithmetic average of the net returns of all the 2'866 funds in the Barclay database as of March 2018. I investigate all arbitrage strategies with the exclusion of risk and merger arbitrage, which are not statistically determined but qualitatively assessed. For all selected strategies, I calculate the expected excess performance and the 90% Conditional Value at Risk (CVaR) expressed in percentages (Duffie and Pan, 1997; Rockafellar and Uryasev, 2000; Jorion, 2007; Wang and Zhao, 2016). I use three different data frequencies: monthly, quarterly and yearly.

Table 4.6: **Hedge fund indices**

This table reports the dataset of indices representative of hedge funds arbitrage strategies.

Indices	Ticker	Start Date	End Date
BAIF capital structure and credit arbitrage hedge funds index	BBHFCRED	Dec-05	Dec-17
BAIF convertible arbitrage hedge funds index	BBHFCARB	Jan-05	Dec-17
BAIF equity statistial arbitrage hedge funds index	BBHFSTAT	Feb-05	Dec-17
BAIF fixed income arbitrage hedge funds index	BBHFFARB	Feb-05	Dec-17
BAIF mortgage-backed arbitrage hedge funds index	BBHFMARB	Feb-05	Dec-17
HFRX relative value fixed income convertible arbitrage index	HFRXCA	Jan-98	Dec-17
HFRX relative value arbitrage index	HFRXRVA	Jan-98	Dec-17
Credit Suisse Sector Invest convertible arbitrage index	SECTCONV	Sep-04	Dec-17
Credit Suisse Sector Invest fixed income arbitrage index	SECTFIAR	Oct-04	Dec-17
BarclayHedge convertible arbitrage index	BGHSARBT	Dec-96	Dec-17
BarclayHedge fixed income arbitrage index	BGHSFIAR	Dec-96	Dec-17

The analysis is reported in Table 4.7 and shows that expected excess returns are positive for all strategies with the exception of Credit Suisse fixed income arbitrage. This strategy has negative expected excess returns with quarterly and yearly observations and cannot be considered a SA. Losses can be significant across strategies. Excluding BAIF equity statistical arbitrage, the worst returns range from -11% for BAIF mortgage-backed arbitrage with monthly data to -58.6% of HFRX convertible arbitrage with yearly data. Analogously, the cVaR shows significant negative values ranging from -2.4% of Barclay Hedge fixed income arbitrage with monthly data to -34% of HFRX convertible arbitrage with yearly data. This finding suggests that these strategies are not arbitrage opportunities. Only BAIF equity SA with yearly observations shows features compatible with my definition of SA as losses are limited (minimum returns of -2.3% and cVaR of -2.2%) while expected excess returns are significantly positive (+8.3%).

Table 4.7: **Arbitrage strategies analysis**

This table reports summary statistics, expected excess returns and cVaR expressed in percentages for HFs relative value arbitrage strategies.

	BAIF Capital and credit arbitage	BAIF Convertible arbitrage	BAIF Equity statistical arbitrage	BAIF Fixed income arbitrage	BAIF Mortgage-backed arbitrage	HFRX Convertible artrbitrage	HFRX Relative value arbitrage	Credit Suisse Convertible arbitrage	Credit Suisse Fixed income arbitrage	BarclayHedge Convertible arbitrage	BarclayHedge Fixed income arbitrage
Panel A - Monthly											
Min	-12.9	-13.0	-5.8	-11.7	-11.0	-34.8	-14.3	-20.3	-20.6	-13.9	-13.7
Max	6.6	5.1	7.7	3.6	6.3	6.7	6.8	6.5	10.0	7.1	4.2
Stdev	7.1	6.6	8.4	5.5	6.3	10.4	6.4	9.6	8.1	5.9	4.9
Exp. Excess Ret.	2.0	1.9	2.4	1.6	1.8	3.0	1.9	2.8	2.3	1.7	1.4
cVaR	-3.5	-3.5	-3.7	-3.0	-2.5	-4.9	-3.7	-4.8	-4.2	-2.7	-2.4
Panel B - Quarterly											
Min	-17.6	-14.1	-6.5	-15.1	-7.9	-45.1	-23.2	-22.2	-30.6	-15.3	-19.2
Max	17.0	11.2	11.2	7.3	14.5	14.0	14.6	17.9	11.2	15.9	8.5
Stdev	10.1	8.4	8.2	6.7	8.2	13.1	8.8	12.1	10.3	8.0	6.3
Exp. Excess Ret.	1.3	1.1	1.8	0.8	2.2	0.5	0.7	0.5	-0.2	1.6	1.3
cVaR	-8.4	-7.6	-5.0	-6.6	-5.1	-11.9	-8.2	-12.4	-11.2	-5.5	-4.8
Panel C - Yearly											
Min	-30.9	-24.8	-2.3	-19.7	-16.6	-58.6	-37.9	-45.1	-38.1	-27.9	-25.5
Max	36.3	28.1	18.8	11.2	45.3	42.5	38.5	55.5	17.2	53.6	19.8
Stdev	15.6	12.4	7.0	8.3	15.4	18.5	14.0	21.2	12.5	14.2	8.7
Exp. Excess Ret.	6.2	5.2	8.3	4.0	10.7	3.5	4.2	3.9	-0.4	7.6	6.0
cVaR	-16.0	-13.3	-2.2	-9.8	-9.4	-34.0	-20.9	-23.7	-20.8	-15.7	-13.2

4.6 Conclusions

In this chapter, I investigate the concept of statistical arbitrage (SA). As there is no agreement in literature on a common definition, I review both the theoretical and empirical work on SA since its introduction. In particular, I look at all those definitions, which may be suitable to identify this class of strategy. I produce a review of all strategies which may be associated with the concept of statistically determined arbitrage opportunities. I identify those common features which define the concept embedded in investors thinking. As no definition is suitable to describe this type of strategies I introduce a general definition and propose a classification system that encompasses the current forms of SA strategies while facilitating the inclusion of new types as they emerge.

My study makes several contributions to the existing literature. I bridge the gap existing between the literature on arbitrage definitions and SA strategies. I perform an innovative investigation of SA both in academic and financial industry research analysing, for the first time, SA across all asset classes (equity, fixed income and commodity). I find a general definition, which includes all SA strategies and propose a classification system measuring the strategies' risk and return profile. This facilitates the inclusion of new strategies and measures as they emerge. My analysis allows investors to have a common framework to evaluate investment opportunities and brings clarity in SA investing, guiding theoretical development and empirical testing. I also provide examples of potential future research directions.

5 Conclusions

5.1 Introduction

Factor models have been extensively studied in academia (Fama and French, 2015; Clarke, De Silva and Thorley, 2016) with factor-based strategies becoming increasingly popular in the financial industry (Citi, 2016). Literature focuses on equity markets with fewer studies on industry specific factors (such as mining stocks) and other asset classes (such as credit markets), see Asness, Moskowitz and Pedersen (2013). Factors are used particularly by sophisticated investors in the broader context of statistical arbitrage (Maeso and Martellini, 2017), a common financial strategy for which there is still no clarity in literature (Hogan et al., 2004). In this thesis, I contribute to the literature in these areas of Finance with three individual studies. The first studies the sensitivity of mining stocks to metals using multifactor models. The second investigates value investing opportunities in credit markets combining credit spreads with fundamentals. The third provides an alternative definition of statistical arbitrage through a comparison of arbitrage strategies across asset classes.

The chapter is organized as follows. In section 5.2, I detail my main findings. In section 5.3, I report the main contributions. In section 5.4, I discuss the limitations and directions for future research. Section 5.5 concludes the chapter.

5.2 Main Findings

In the first study, I investigate the sensitivity of world mining stocks to precious and industrial metals. My sample consists of all investible mining firms classified into three groups for precious metals (gold, silver and platinum) and four groups for industrial metals (steel, iron ore, copper and aluminium). I investigate the sensitivity of mining stocks to metals by adding a metal factor to four models: the Capital Asset Pricing Model (CAPM), the Fama-French 3-factor model (FF3), the Fama-French 4-factor model (FF4) and the Fama-French 5-factor model (FF5) (Fama and French, 1993; Fama and French, 2012 and Fama and French, 2015). I use both panel data and time series regressions on equal and value weighted portfolios. I also study subsets by location (North America, developed markets and emerging markets) and size (large and small cap) while the robustness of my results is ensured by using spot and futures prices, monthly and weekly data, trimming the dataset and performing a sub-period analysis.

I find that the metal factor is fundamental in explaining the returns of all mining stocks with a stronger effect on companies domiciled in developed markets. Metals significantly increase the performance of my models and their significance is higher for precious metals. In particular, gold is the most significant metal, possibly due to its role as a safe haven and countercyclical nature. Stocks of industrial metals are more influenced by the market factor as they are arguably more sensitive to economic growth. Fama-French factors are less relevant and only marginally increase the significance of the models.

In the second study, I investigate value opportunities in credit markets across geographical areas (U.S.A. and Euro Zone) and ratings (Investment Grade and High Yield). I use two financial ratios: leverage and interest coverage. Their relevance has been largely discussed in literature

(Collin-Dufresne and Goldstein, 2001; Campbell and Taksler, 2003; Flannery and Öztekin, 2012; Kim, Kraft and Ryan, 2013; Berg, Saunders and Steffen, 2016) while they are the main measures used by credit analysists at the largest banks. Using these two fundamental measures, I introduce two ratios: 1) the fraction of spread over leverage (or SL) and 2) the fraction of spread over leverage and the reciprocal of interest coverage (or SLC). In analogy to equity, I refer to SL and SLC as credit multiples and I use them to investigate value opportunities in credit. I compare the average performance from buying corporate bonds when their multiples rank in different quintiles calculated over periods of different length (three-year, four-year and five-year periods). The performance of strategies performance is measured using both spread changes and excess returns while their risk is assessed through the maximum drawdown.

I find that average returns are higher when spreads are in the higher quintiles and the effect is statistically relevant over the longer time horizons (three to five years). Value strategies perform better if based on SL and SLCs but this outperformance is not statistically significant in several instances. By normalizing spreads with leverage and interest coverage, credit multiples can be used as a measure to identify value opportunities within investment grade bonds.

In the third study, I investigate statistical arbitrage (SA), a common financial term for which there is no agreed definition in literature. On the one hand, I review and compare all the definitions, which may be suitable to identify this class of investment techniques. On the other hand, I survey 165 articles on SA strategies published in the academic and financial industry research between 1995 and 2016. This review covers equity, fixed income and, for the first time, commodity.

I find that SA strategies share similarities and common features which are not appropriately captured by existing definitions. To bridge this gap, I provide a general definition and propose a classification system that takes into account the strategies' risk and return profile. My new definition encompasses current strategies and facilitates the inclusion of new ones.

5.3 Contributions

This thesis makes several contributions to the academic literature and provides investors with practical advice in several areas of Finance.

My first study contributes to the literature on factor models for mining stocks. I extend the existing research on gold to mining firms of all available metals, both precious and industrial. My data set encompasses all investable miners domiciled both in developed and emerging markets while previous research studied only stocks in selected countries. I perform an original investigation by adding a metal factor to Fama-French models. My results show that Fama-French factors are less relevant than the metal factor which is particularly significant for stocks of precious metals. This finding has practical implications and suggests that investors should treat mining stocks differently than firms in other industries. Investors should also distinguish between stocks of precious and industrial metals.

In addressing my second research question, I make several contributions to the literature on value investing. I study spreads in conjunction with fundamentals (leverage and interest coverage) to identify value opportunities in credit markets. By doing so, I introduce credit multiples in analogy to equity multiples. I originally study value opportunities in credit markets using different time horizons (three months, six months, nine months, one year, two years, three years, four years and five years) and quintiles calculated over different periods (three years, four years and five years). My investigation spans across areas and ratings covering the majority of the world credit market: U.S. Investment Grade, U.S. High Yield, Euro Investment Grade and Euro High Yield. I also analyse two separate rating groups within U.S. Investment Grade: A and BBB. Finally, I complement existing literature by providing a novel review of value indicators used by credit analysts at the largest investment banks. My results suggest that credit multiples should be further investigated to build value factors for corporate bonds.

My third study makes several contributions to the literature on statistical arbitrage. For the first time, I perform a cross-asset review of SA strategies encompassing equity, fixed income and commodity. This survey provides an original and comprehensive mapping of SA literature and techniques including recent market innovations and technological advances such as algorithmic trading. The standardised framework of the review allows me to identify the key features and defining elements of SA across asset classes. Through an innovative comparison of SA definitions and strategies I find that no definition appropriately describes SA strategies. As a result, I introduce a novel definition and classification system which can guide future research. My analysis has practical implications as it provides investors with a framework to evaluate existing and future investment strategies. My study brings clarity to SA investing, an area which to date has been characterized by a significant lack of transparency.

5.4 Limitations and directions for future research

My study on metals could be enhanced by investigating the relevance of hedging for mining stocks. Some firms sell forward part of their metal production to fix future prices and reduce the volatility of their financial results (Tufano, 1998), making them less sensitive to fluctuations of metal prices. Future research could investigate levels of hedging among a sample of firms and the impact of this hedging on financial performance. I find that industry specific factors can be more relevant than broader factors for specific group of securities (Heston and Rouwenhorst, 1995). Following my finding, future research could follow an industry specific approach in building factor models. For example, investments in credit bonds significantly impact the investment results and profitability of insurers (Cummins, 2000; Sherris, 2006). Future research could investigate the influence of credit factors on insurance stocks.

In my second study, I find that credit multiples can be used as value indicator to rank investment grade bonds of similar maturity. As a result, future analysis could use credit multiples to build value factors also in credit markets in a similar fashion to equity. This would extend existing research where credit spreads are valued based on the comparison between model-based spreads and market spreads. Some of the shortcomings of SL and SLC ratios could be addressed using for example a different definition of leverage where the numerator is the total debt instead of the debt net of cash. This would reduce the effectiveness of leverage as measure of creditworthiness but would avoid having negative debt. Alternatively the use of total debt to assets could be also contemplated in analogy to the price-to-book ratio in equity. This definition of leverage has assets at the denominator that make this indicator more stable. Credit multiples have the same sensitivity to earnings as price-earnings. This enables to use multiples as a tool to compare equity prices and credit spreads based on firms' earnings expectations. Empirical research could investigate the use of this framework and its effectiveness for asset allocation.

In my third study, I identify a framework to classify statistical arbitrage strategies. This classification system could be used to map how statistical arbitrage opportunities and their drivers have evolved in time. For example, future research could identify which SA strategies deliver the higher risk-adjusted returns in different phases of the business cycle and what are the driving factors. This could develop into a dynamic allocation model for statistical arbitrage strategies. Empirical research could also use my classification system to screen hedge funds and identify those which do not show a compatible risk-return profile. This analysis could benefit investors, further enhancing market transparency.

5.5 Conclusions

This chapter provides a summary of main findings, contributions, limitations and direction of future research. My thesis is structured in five chapters. In Chapter 1, I provide an introduction to the three research topics. In Chapter 2, I discuss the sensitivity of mining stock to metals by adding a metal factor to CAPM and Fama-French models. In Chapter 3, I investigate value opportunities in credit markets by combining credit spreads to fundamentals. In Chapter 4, I discuss statistical arbitrage strategies with a comparison of academic and financial industry literature across all asset classes (equity, fixed income and commodity). Chapter 5 concludes the thesis.

Appendix

A.1 Appendix to Chapter 2

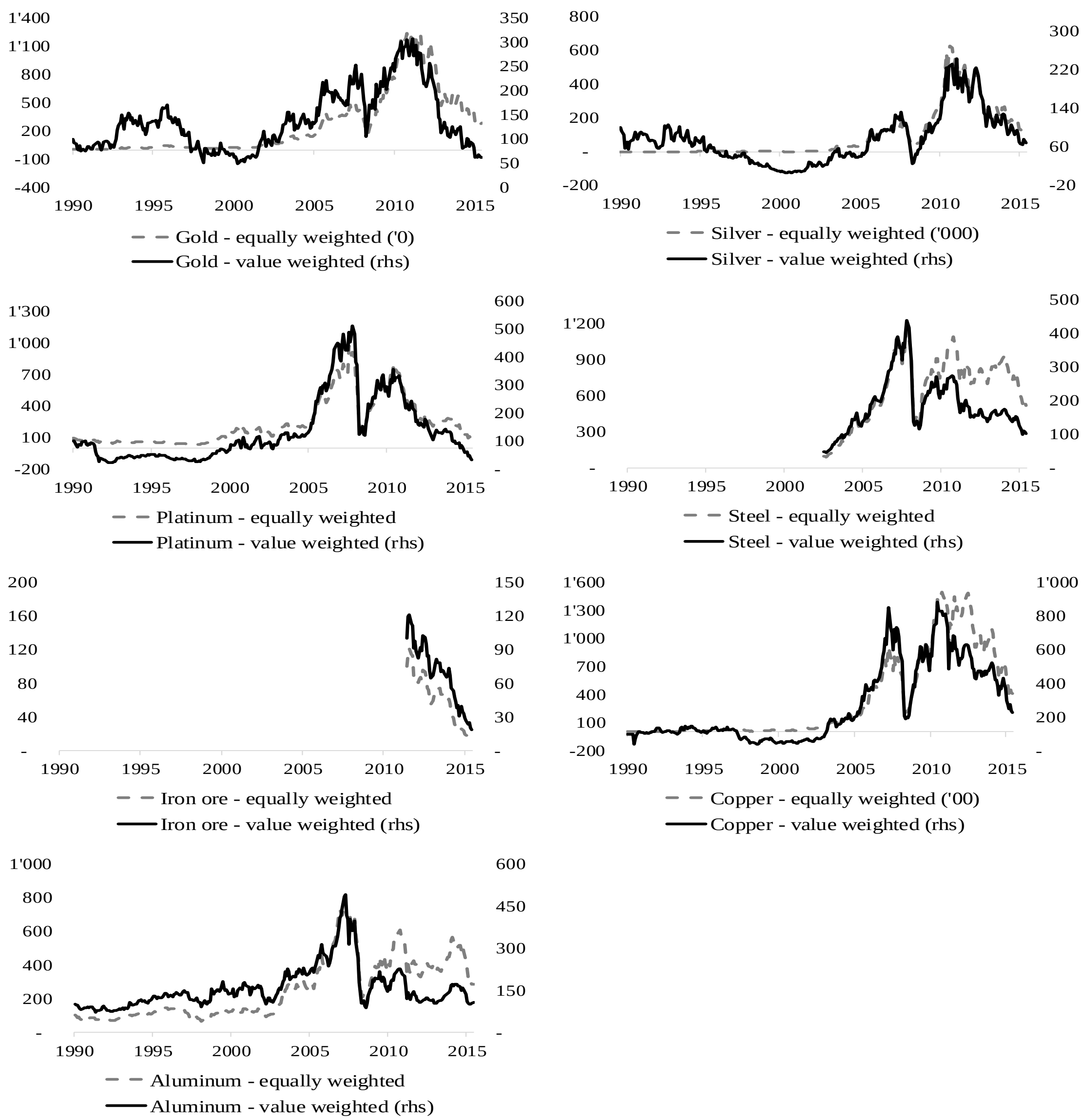

Figure A.1.1: **Charts of equally and value weighted portfolios of miners**

The charts show the cumulative performance of equally and value weighted portfolios of miners grouped by metals.

The graphical analysis illustrates how both types of portfolios tend to move together.

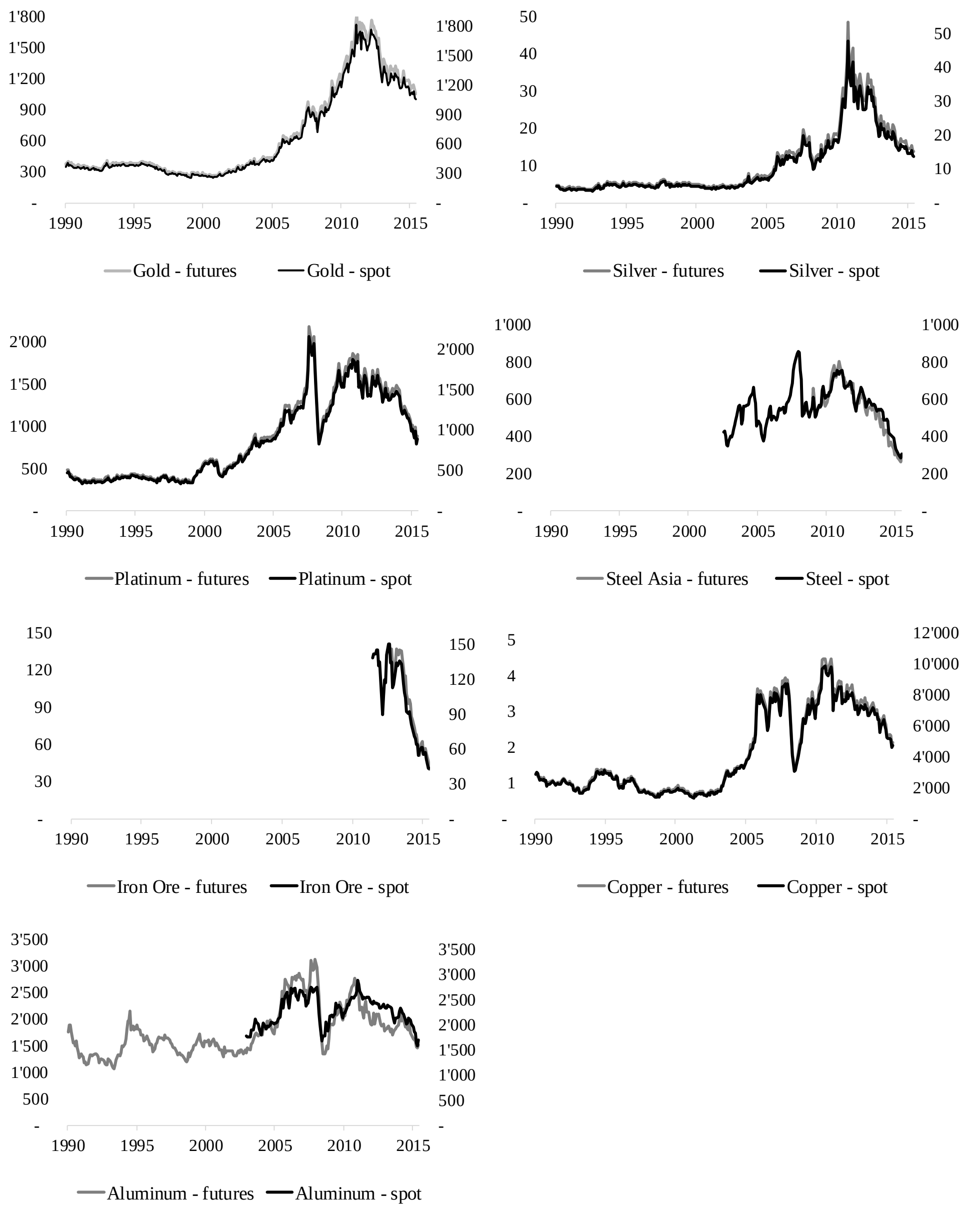

Figure A.1.2: **Charts of futures and spot prices**

In Figure A.1.2 I show the cumulative performance of futures (lhs) and spot (rhs) prices. The graphical analysis shows that both types of portfolios tend to move together.

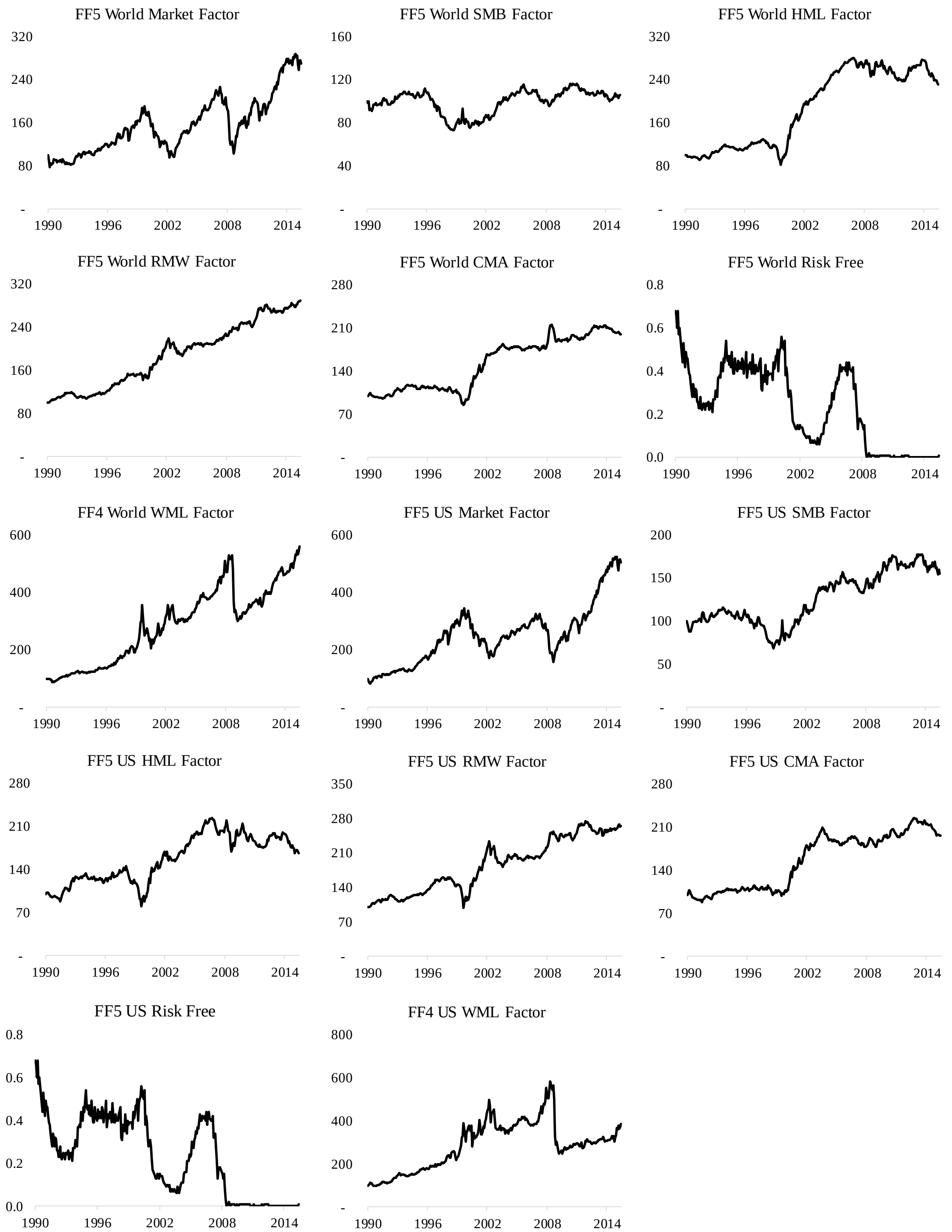

Figure A.1. 1: **Charts of Fama-French factors**

Table A.1.1

Correlations with spot metal prices

The table reports the correlations among the time series of all factors used in the analysis and spot metal prices

		Metals							FF3			FF4				FF5				
Type	**Metal/Factors**	**Gold**	**Silver**	**Platinum**	**Copper**	**Aluminum**	**Iron Ore**	**Steel**	**R_M-R_F**	**SMB**	**HML**	**R_M-R_F**	**SMB**	**HML**	**WML**	**R_M-R_F**	**SMB**	**HML**	**RMW**	**CMA**
Metals	Gold	1.00	0.85 **	0.76 **	0.32 *	-0.10	0.11	0.05	0.23	0.28	-0.01	0.23	0.28	-0.01	-0.31 *	0.23	0.28	-0.01	-0.18	-0.26
	Silver		1.00	0.78 **	0.42 **	-0.03	-0.01	0.08	0.30 *	0.24	-0.08	0.30 *	0.24	-0.08	-0.37 *	0.30 *	0.24	-0.08	-0.21	-0.38 **
	Platinum			1.00	0.55 **	0.02	0.15	0.30 *	0.46 **	0.09	0.25	0.46 **	0.09	0.25	-0.52 **	0.46 **	0.09	0.25	-0.34 *	-0.09
	Copper				1.00	0.39 **	0.27	0.48 **	0.50 **	0.16	0.27	0.50 **	0.16	0.27	-0.55 **	0.50 **	0.16	0.27	-0.54 **	-0.24
	Aluminum					1.00	0.11	0.39 **	0.01	0.01	0.01	0.01	0.01	0.01	0.04	0.01	0.01	0.01	-0.07	-0.06
	Iron						1.00	0.63 **	0.10	0.26	0.42 **	0.10	0.26	0.42 **	-0.20	0.10	0.26	0.42 **	-0.33 *	0.36 *
	Steel							1.00	0.20	0.14	0.32 *	0.20	0.14	0.32 *	-0.31 *	0.20	0.14	0.32 *	-0.31 *	0.26
FF3	RM-RF								1.00	-0.18	0.24	1.00 **	-0.18	0.24	-0.44 **	1.00 **	-0.18	0.24	-0.40 **	-0.17
	SMB									1.00	-0.02	-0.18	1.00 **	-0.02	-0.01	-0.18	1.00 **	-0.02	-0.45 **	-0.19
	HML										1.00	0.24	-0.02	1.00 **	-0.46 **	0.24	-0.02	1.00 **	-0.45 **	0.49 **
FF4	RM-RF											1.00	-0.18	0.24	-0.44 **	1.00 **	-0.18	0.24	-0.40 **	-0.17
	SMB												1.00	-0.02	-0.01	-0.18	1.00 **	-0.02	-0.45 **	-0.19
	HML													1.00	-0.46 **	0.24	-0.02	1.00 **	-0.45 **	0.49 **
	WML														1.00	-0.44 **	-0.01	-0.46 **	0.45 **	0.14
FF5	RM-RF															1.00	-0.18	0.24	-0.40 **	-0.17
	SMB																1.00	-0.02	-0.45 **	-0.19
	HML																	1.00	-0.45 **	0.49 **
	RMW																		1.00	0.15
	CMA																			1.00

** and * indicate statistical significance at the 0.05 and 0.10 level, respectively

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Table A.1.2

Correlations with futures metal prices

The table reports the correlations among the time series of all factors used in the analysis and futures metal prices

		Metals							FF3			FF4				FF5				
Type	**Metal/Factors**	**Gold**	**Silver**	**Platinum**	**Copper**	**Aluminum**	**Iron Ore**	**Steel**	**R_M-R_F**	**SMB**	**HML**	**R_M-R_F**	**SMB**	**HML**	**WML**	**R_M-R_F**	**SMB**	**HML**	**RMW**	**CMA**
Metals	Gold	1.00	0.83 **	0.74 **	0.10	0.23	0.40 *	-0.21	0.08	0.19	0.07	0.08	0.19	0.07	-0.08	0.08	0.19	0.07	0.07	-0.12
	Silver		1.00	0.69 **	0.19	0.13	0.30	-0.15	0.13	0.18	-0.05	0.13	0.18	-0.05	-0.05	0.13	0.18	-0.05	0.14	-0.26
	Platinum			1.00	0.39 *	0.29	0.25	0.04	0.25	-0.01	0.30	0.25	-0.01	0.30	-0.31	0.25	-0.01	0.30	0.02	0.09
	Copper				1.00	0.47 **	0.10	0.21	0.35 *	0.06	0.37 *	0.35 *	0.06	0.37 *	-0.37 *	0.35 *	0.06	0.37 *	-0.36 *	-0.07
	Aluminum					1.00	-0.10	0.17	0.19	-0.04	0.23	0.19	-0.04	0.23	-0.27	0.19	-0.04	0.23	0.08	0.02
	Iron						1.00	-0.05	-0.08	0.21	0.16	-0.08	0.21	0.16	0.07	-0.08	0.21	0.16	-0.10	0.19
	Steel							1.00	0.21	-0.08	0.04	0.21	-0.08	0.04	-0.15	0.21	-0.08	0.04	0.00	0.26
FF3	RM-RF								1.00	-0.29	0.21	1.00 **	-0.29	0.21	-0.23	1.00 **	-0.29	0.21	-0.17	-0.22
	SMB									1.00	-0.01	-0.29	1.00 **	-0.01	0.23	-0.29	1.00 **	-0.01	-0.48 **	-0.17
	HML										1.00	0.21	-0.01	1.00 **	-0.57 **	0.21	-0.01	1.00 **	-0.33	0.39 *
FF4	RM-RF											1.00	-0.29	0.21	-0.23	1.00 **	-0.29	0.21	-0.17	-0.22
	SMB												1.00	-0.01	0.23	-0.29	1.00 **	-0.01	-0.48 **	-0.17
	HML													1.00	-0.57 **	0.21	-0.01	1.00 **	-0.33	0.39 *
	WML														1.00	-0.23	0.23	-0.57 **	0.00	-0.10
FF5	RM-RF															1.00	-0.29	0.21	-0.17	-0.22
	SMB																1.00	-0.01	-0.48 **	-0.17
	HML																	1.00	-0.33	0.39 *
	RMW																		1.00	0.29
	CMA																			1.00

A.2 Appendix to Chapter 3

Table A.2.1: **Indices used in the analysis**

Index Name	Ticker	Fields used
Merrill Lynch U.S. Investment Grade Non Financial	CF0X	Excess Return and Option Adjusted Spread
Merrill Lynch U.S. High Yield Non Financial	H0NF	Excess Return and Option Adjusted Spread
Merrill Lynch Euro Investment Grade Non Financial	EN00	Excess Return and Option Adjusted Spread
Merrill Lynch euro High Yield Non Financial	HNE0	Excess Return and Option Adjusted Spread
Merrill Lynch U.S. A Non Financial	C30X	Excess Return and Option Adjusted Spread
Merrill Lynch U.S. BBB Non Financial	C4NF	Excess Return and Option Adjusted Spread

A.3 Appendix to Chapter 4

Literature on risks involved in SA

In this appendix, I discuss some of the risks that characterize SA opportunities: fundamental risk (Shleifer and Vishny, 1997), noise trader risk (De Long et al., 1990), synchronization risk (Abreu and Brennermeier, 2002) and the risks arising from inattentive investors Duffie (2010).

Shleifer and Vishny (1997) argue that market anomalies arise from the failure of investors in recognizing potential opportunities. Arbitrageurs often concentrate on the same markets where they are more confident leaving other asset classes unexplored. Also volatility may keep arbitrageurs away, should the alpha not increase proportionally to volatility. Finally, they observe that the investment time horizon plays a major role. If the long run ratio of expected alpha to volatility is high but the ratio over a shorter horizon is low, arbitrageurs may not engage in a trade.

De Long et al. (1990) define noise traders as those traders who act irrationally on the back of erroneous stochastic believes driving prices away from fair value. Their unpredictability creates a risk which deters rational arbitrageurs from entering a corrective trade. As a result prices can significantly diverge from fair value also for a prolonged time. They observe that it may happen that arbitrage trades do not eliminate the effects of noise as noise itself creates risks. De Long et al. (1990) identify an additional risk to arbitrage strategies. In extreme situations, arbitrageurs can increase market anomalies instead of correcting them. This happens when arbitrageurs get involved in trades posting excessive losses. If prices move against the arbitrage trade, then arbitrageurs may be forced to liquidate their positions exactly when they offer the greatest opportunity. The results of the liquidation will be to increase mispricing instead of rectifying it. Traders may also be forced to liquidate before the mispricing is corrected as they have mostly short term investment horizons which are determined on the basis of endogenous reasons.

Abreu and Brunnermeier (2002) explain why mispricing can persist even when professional arbitrageurs are present in the market. They offer a new reason called synchronization risk which considers temporal risk. To correct an arbitrage, arbitrageurs need to deploy enough capital to rectify market imbalances. This requires time as arbitrageurs become sequentially aware of mispricing. Early informed arbitrageurs will act more quickly than others. That generates uncertainty about the timing of the price correction. This is the so called synchronization risk. According to their model, market imbalances are eventually corrected but that occurs with a delay. Abreu and Brunnermeier (2002) also note that holding costs may limit the capacity of arbitrageurs to hold a trade long enough to eliminate market anomalies. Additionally, the fundamentals of the strategy may change over the time and arbitrageurs may close a trade to deploy capital in new and more profitable opportunities.

Duffie (2010) criticizes neoclassical dynamic asset pricing noting that investors are not focused at all time in adjusting their portfolios. In reality many market participants are likely to spend a significant amount of time on other tasks. This investors' inattention for asset price dynamics reduces the amount of capital available making markets thinner (and so less efficient) over the short run. Duffie also identifies trading opportunities in the price dynamics caused by the slow movement of investment capital. Duffie observes that prices react sharply to supply-demand shocks because of the relatively small capital available to absorb the impact over the short term.

When capital becomes available, the price pattern tends to reverse. Capital movements can be slow because of various reasons such as time to raise capital by intermediaries and costs for searching trading counterparties.

A possible reason why arbitrage persists is that not all market participants are fully rational. For example behavioural traders can act on the back of market sentiment instead of fundamental information. Bubbles are a special form of mispricing. There are various papers on the subject. Bubbles can last because traders prefer to enjoy their returns (Abreu and Brunnermier, 2002). Bubbles can also be created by rational investors to push up prices and induce a behavioural feedback (De Long et al., 1990).

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