THREE ESSAYS ON FINANCIAL MARKETS

by

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ABSTRACT OF THE DISSERTATION

Three Essays on Financial Markets

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The first essay examines the momentum phenomenon in the sovereign CDS market. We find that from 2001 to 2015, the portfolio of sovereign CDS past three-month winners outperforms the portfolio of past three-month losers by 0.53% per month after adjusting for risk factors. The excess returns of the long-short portfolio increase with the holding period for up to 20 months, and there is no sign of mean reversion. This evidence is consistent with investors' initial underreaction to public information, as in Barberis, Shleifer, and Vishny (1998).

The second essay studies the macro-informational role of the sovereign CDS market and the way in which macro information flows between sovereign CDS market and stock and bond markets. We find that the sovereign CDS market can predict future stock index returns, government bond yields, and real economic activities. For example, a strategy that buys stock indices of countries in the top quintile (whose creditworthiness improved the most in the previous quarter according to sovereign CDSs) and sells indices from the bottom quintile generates an average return of 15% per year. Moreover, the information is flowing one way, from sovereign CDS market to stock and bond markets, but not the other way around. Our evidence suggests that stock and bond markets gradually

"catch up" with the sovereign CDS market, especially during the days surrounding credit rating or outlook changes. The predictive power of sovereign CDS returns is almost entirely from their global, rather than country-specific, component.

The third essay investigates the investment performance of US ethical equity mutual funds relative to the market and their traditional counterparts using a survivorship-bias-free database. We detect selectivity and market timing performance of fund managers using the models of Treynor and Mazuy (1966) and Bhattacharya and Pfleiderer (1983). Our empirical results indicate that ethical funds perform no worse than their traditional counterparts, although neither type of funds outperforms the market. We find some evidence of superior security selection and/or market timing skill among a small number of ethical and traditional funds. Matching traditional funds have slightly more abnormal performance than ethical funds.

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Last but not least, thank myself for continuous believing in life even when it was extremely tough.

Dedication

To my parents.

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Chapter 1 Introduction

Since the development of the financial derivatives in 1970s, the information aggregation in derivative market has been widely analyzed. While existing studies primarily focus on firm-level information and microstructure issues, we add to this literature by focusing on macro variables.

My dissertation contains three essays on financial markets. In my first essay, I examine the momentum phenomenon in the sovereign CDS market. Although momentum has been examined extensively in the literature, this essay offers a new angel. A number of behavioral models of momentum rely on the interaction of private and public information. One prominent exception is Barberis, Schleifer and Vishny (1998), where there is only public information. The sovereign CDS market offers a nice setup to analyze the mechanism in Barberis, Shleifer, and Vishny (1998), since most of the information in this market is macro information, and is arguably publicly available. It is also worth noting that investors in sovereign CDS markets are supposedly sophisticated institutions. This is important because it is often considered that behavioral biases are less relevant for sophisticated institutions. In prior studies, even in derivative markets and currency markets, naïve retail investors can be quite active. This chapter focuses on the sovereign CDS market, to which retail investors do not have access.

We find robust cross-sectional momentum in sovereign CDS market. For example, in our sample from 2001 to 2015 the sovereign CDS portfolio of past three-month winners outperforms the portfolio of past three-month losers by 0.53% per month after adjusting for known risk factors, such as sovereign CDS market factor, Fama-French three factors, stock market momentum factor and global value and momentum factors as in Asness et al. (2013). The excess returns of the long-short portfolio increase with the holding period for up to 20 months, and there is no sign of mean reversion. The evidence in this essay is consistent with investors' initial underreaction to public information, as in Barberis, Shleifer, and Vishny (1998).

The second essay studies the macro-informational role of the sovereign CDS market and the way in which macro information flows between sovereign CDS market and stock and bond markets. This is a long-standing question. However, most of the previous studies are based on micro-level information at high frequency. By focusing on macro information, our study can potentially shed new light on this long-standing issue. Conceptually, there might be difference between information aggregated at micro-level and at macro-level. For micro information, the private information is more important, for example, some investors may have better access to private information about a specific company. However, for macro information, since the information is publicly available, there is little role of private information. What differs investors is their ability to analyze the data.

The sovereign CDS market has been developing rapidly since the early 2000s. By 2015, the market has an aggregate notional amount of around $2 trillion, and covers 91 countries. Our conjecture is that sovereign CDS market can predict stock and bond markets. Our conjecture is motivated by the fact that the investors in the sovereign CDS market are sophisticated investors and in stock and bond markets are predominately local. We find strong evidence consistent with the conjecture. We sort the countries into 5 quintiles based on past 3-month sovereign CDS performances. The sovereign creditworthiness of quintile-

1 countries has improved the most according to the sovereign CDS market, while that of quintile-5 countries has deteriorated the most. Presumably, the sovereign CDS market indicates good news during the past 3 months for quintile-1 countries, and bad news for quintile-5 ones. If this information is not fully reflected in stock prices, the stock indices of quintile-1 countries would outperform those of quintile 5 in the coming months. We find that a long-short strategy that buys stock indices in the quintile 1 and sell stock indices in quintile 5 generate an average return of 15% per year. Similarly, we find sovereign CDS market can predict bond returns. Our evidence suggests that the sovereign CDS can also predict the real economics activities, such as GDP and PMI. Furthermore, the information flow appears to be one way, from sovereign CDS market to stock and bond markets. We did not find any evidence that stock and bond markets can predict sovereign CDS returns. Our evidence also suggests that stock and bond markets gradually "catch up" with the sovereign CDS market, especially during the days surrounding credit rating or outlook changes. The predictive power of sovereign CDS returns is almost entirely from the global, rather than country-specific, component.

The third essay investigates the investment performance of US ethical equity mutual funds relative to the market and their traditional counterparts using a survivorship-bias-free database. Ethical investing, more popularly known as sustainable, socially conscious, "green" or socially responsible investment (SRI), is the application of ethical as well as financial considerations or screens in investment decision-making. It is an investment strategy based on normative ethical and social values. Ethical investing aims at rewarding ethical corporate behavior through positive screening and discouraging unethical corporate behavior through negative screening. The demand for ethical investment opportunities has been growing very rapidly. According to Global Sustainable Investment Alliance (GSIA), assets under management (AUM) of global ethical investment funds climbed to $13.6 trillion at the start of 2012, a 22 percent increase since 2010. This represents 21.8 percent of the total global AUM (Global Sustainable Investment Alliance, 2013). In the US alone, sustainable, responsible, and impact investing assets have expanded 76 percent in two years: from $3.74 trillion at the start of 2012 to $6.57 trillion at the start of 2014, according to the US SIF Foundation's latest biennial survey, the Report on US Sustainable, Responsible, and Impact Investing Trends 2014. As a result, AUM of US ethical funds now accounts for more than one out of every six dollars under professional management in the US (USSIF, 2014). The purpose of this paper is to examine the investment performance of ethical equity mutual funds in the US using a comprehensive and integrated model. This paper fills the void in the literature by examining the investment performance of a sample of ethical funds in the US using the Bhattacharya-Pfleiderer model. We detect selectivity and market timing performance of fund managers by first using Treynor-Mazuy's (1966) model to determine these performances from a quadratic regression of fund returns on market returns. Secondly, we use a comprehensive and integrated model derived by Bhattacharya and Pfleiderer (1983) and Lee and Rahman (1990) to simultaneously capture stock selection and market timing skill of fund managers. Our empirical results indicate that ethical funds perform no worse than their traditional counterparts, although neither type of funds outperforms the market. We find some evidence of superior security selection and/or market timing skill among a small number of ethical and traditional funds. Matching traditional funds have slightly more abnormal performance than ethical funds in our sample.

Chapter 2 Momentum in the Sovereign CDS Market

2.1 Introduction

Since Jegadeesh and Titman (1993), there has been a large literature examining the so-called momentum strategy, which buys assets that performed well recently and sells those performed poorly recently. The excess returns from momentum strategies, according to Eugene Fama, are "the biggest embarrassment to the Efficient Market Hypothesis." Naturally, many of the explanations have been based on behavioral ideas, such as underreaction to public information, as analyzed in Barberis, Shleifer, and Vishny (1998), initial overreaction followed by more overreaction, as in Daniel, Hirshleifer, and Subrahmanyan (1998), and initial underreaction and delayed overreaction to private information, as in Hong and Stein (1999).

In this chapter, I analyze momentum in a setup where the investors are *exclusively* sophisticated institutions. This is important because it is often considered that behavioral biases are less relevant for sophisticated institutions. In prior studies, even in derivative markets and currency markets, naïve retail investors can be quite active. This chapter focuses on the sovereign CDS market, to which retail investors do not have access.

More importantly, analyzing momentum in this market also helps to shed light on the theories of momentum. Among the three most influential models of momentum, Daniel, Hirshleifer, and Subrahmanyan (1998) and Hong and Stein (1999) focus on *private information*. In contrast, Barberis, Shleifer, and Vishny (1998) focus on *public information*. In the sovereign CDS market, since the main variable is the creditworthiness of sovereign governments, it is perhaps reasonable to assume that private information plays a minor role. Therefore, the relevant mechanism for momentum is more likely to be driven by public information, as in Barberis, Shleifer, and Vishny (1998). It is certainly true that a number of prior studies have documented momentum at the "aggregate level", e.g., aggregate stock market indices and currencies etc. However, there is an important conceptual difference: If naïve investors play an important role in the market, the difference between public and private information is no longer meaningful. For instance, although macro variables are announced publicly, it is conceivable that naïve investors may not have the capacity to analyze the effect of those variables on the aggregate stock market, or they may not even pay attention to those numbers. Hence, the public information essentially becomes sophisticated investors' private information. In the CDS market, however, this is less of an issue to the extent that all investors are sophisticated institutions. Since all investors are on a "level playing field," it is perhaps more appropriate to treat the macro information as public information, instead of sophisticated investors' private information.

We obtain sovereign CDS market data on 91 countries during January 2001 to September 2015 from Markit. Following O'Kane (2008), we construct the monthly sovereign CDS returns. To examine the momentum effect in the sovereign CDS market, we sort countries into 5 quintiles based on their past n-month sovereign CDS returns. Quintile-1 countries have the lowest sovereign CDS return, i.e., their credit worthiness improved the most according to the sovereign CDS market, while quintile-5 countries have the highest sovereign CDS returns.

We find strong evidence for momentum in the sovereign CDS market: quintile-5 portfolio will "outperform" quintile-1 portfolio in the coming h months, i.e., the sovereign CDS return of quintile 5 will be higher than that of quintile 1 in the coming h months. For example, for the case of n=3 and h=1, for each quintile, we form an equal-weighted portfolio of sovereign CDS. During the month after the sorting, the quintile-5 portfolio outperforms the quintile-1 portfolio by 0.56% per month (t = 3.31). The return of the long-short strategy increases when we increase the holding period. For instance, the cumulative return is 1.44% per month (t = 2.03) if the holding period is 6 months, and is 2.16% per month (t = 1.63) if we hold it for 12 months. There is no sign of reversal even if we further increase the holding period. For example, the cumulative return is 3.24% (t = 0.87) when we increase the holding period to 36 months. We also vary the sorting period n from one month to 36 months, and the results remain similar. After accounting for the factors of sovereign CDS market return, Fama-French three factors, and the global value and momentum factors in Asness, Moskowitz and Pederson (2013), the long-short return is still 0.53% per month (t = 2.66).

Those results are consistent with investor underreaction that the momentum returns for sovereign CDS are significantly positive up to 6 months, the returns continue over 24 months, and do not reverse over the longer horizon. This phenomenon is different from the momentum in equity markets, where the long-short returns reverse over longer horizons.

If we interpret the momentum strategy profits as the consequence from underreaction to fundamental information, then the momentum strategy should be more profitable when the fundamental information becomes public so that the sovereign CDS price catches up with the reality. Hence, this interpretation predicts that the momentum strategy should be more profitable around the time when credit rating or outlook changes are announced.

What is the nature of the information that contains in sovereign CDS spreads? Is it country specific information, or is it more about the influences of the world economy on each country? To address this question, we decompose the monthly sovereign CDS returns into a “systematic” component and an “idiosyncratic” component by regressing sovereign CDS returns on the average sovereign CDS returns across all countries in our sample. That is, the idiosyncratic component captures a country’s change in credit worthiness that is related to country-specific events, while the systematic component is related to the average change of credit worthiness across all countries. Which component explains the momentum in sovereign CDS returns? Our evidence shows that the momentum in sovereign CDS returns can be explained by both the systematic component and the idiosyncratic component. That is, this phenomenon is due to the underreaction to both the systematic and the idiosyncratic components.

We follow Moskowitz et al. (2012) to examine the time series momentum in the sovereign CDS market. The time series momentum is constructed by selling the sovereign CDS with negative past returns and buying the sovereign CDS with positive past returns. We find robust time series momentum in sovereign CDS. The time series momentum profit is significant up to 6-month formation periods and 3-month holding periods.

This chapter adds to the large literature on momentum. Jegadeesh and Titman (1993) first document the momentum strategies in US common stock returns from 1965 to 1989 by sorting on past returns of three to 12 months and find winners outperform subsequently. They also find similar results in the more recent sample from 1990 to 1998 (Jegadeesh and Titman, 2001). Moskowitz et al. (1999) document a strong industry momentum effect. An industry momentum investment strategy that buys stocks from past winning industries and sells stocks from past losing industries generates significant profits after controlling for size and book-to-market. Momentum phenomenon appears to exist globally within and across all major different asset classes. By investigating the value and momentum returns jointly, Asness et al. (2013) find evidence that there is a strong common global factor structure that can be used to explain the comovement and the cross section of average returns both globally across asset classes and within an asset class. For example, Menkhoff et al. (2012) investigate the momentum strategies in the foreign exchange market and provide evidences that there is a significant cross-sectional excess return of up to 10% per annum and as in Jegadeesh and Titman (2001) the return continues and subsequently reverses over longer horizons of up to 36 months. Lee et al. (2014) show evidences that a 3-month formation and 1-month holding period CDS momentum strategy generates monthly return of 0.52% and by incorporating the past CDS information the traditional stock momentum profit increases by 1.04% per month. Moskowitz et al. (2012) find significant time series momentum returns by selling equity index, currency, commodity, and bond futures (the most 58 liquid instruments) with negative past returns and buying those 58 instruments with positive past returns and show evidence consistent with previous studies that momentum returns are persistent for one-to-12 months and reverses over longer horizons. More recently, Moskowitz (2016) analyzes value and momentum in sports betting markets, and concludes that they are consistent with the delayed overreaction behavioral models.

Theories that explain momentum primarily focus on behavioral biases. For example, in Barberis, Shleifer, and Vishny (1998) momentum is due to the underreaction to public information and is the systematic errors investors make by using the public information to forecast the expectation of future cash flows. Their model incorporates two behavioral biases conservatism and representativeness and the momentum is due to the conservatism that underweight the new information relative to the past information. In Daniel, Hirshleifer, and Subrahmanyan (1998), the momentum is due to the initial overreaction followed by even more overreaction to the private information by incorporating two behavioral biases, overconfidence and self-attribution bias. In Hong and Stein (1999) model, momentum is due to the initial underreaction by "Newswatcher" and delayed overreaction by "Momentum trader" relying on positive feedback trading. That is, when information diffuses slowly into price, the investors tend to underreact to the information and they may chase returns and eventually drive prices above the fundamental value, leading to delayed overreaction. The evidence in our study is consistent with investors' initial underreaction to public information, as in Barberis, Shleifer, and Vishny (1998).

2.2 Data

A sovereign CDS contract allows market participants to purchase and sell protection against the risk of default of a sovereign government. During the term of the Sovereign CDS contract, the buyer makes quarterly payments, the CDS coupon/spread, to the seller in exchange for the seller's promise of protection. The Sovereign CDS spreads are paid on the 20th day of March, June, September and December. If a credit event occurs, the protection buyer will be compensated by the loss of the credit event.[1] The credit event includes failure to pay, moratorium, obligation acceleration, and restructuring, and is determined by the ISDA Determinations Committee.

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[1] In most cases, the parties use "cash settle" with an auction process, in which the CDS seller make a cash payment based on an auction-generated market price of certain eligible debt obligation of the sovereign government. An alternative settlement is the "physical settle", in which the protection buyers tender an eligible bond to the sellers and receive the par value of the bond.

The market for sovereign CDS has been growing fast in the past decade, especially during the recent sovereign debt crisis. According to the Depository Trust & Clearing Corporation, the aggregate notional amount of sovereign CDS contracts is around $2 trillion in 2015, accounting for around 15% of all credit derivatives.

The data in our analysis come from several sources. Our sovereign CDS data are from the Markit Group, which collects daily sovereign CDS quotation data from major SCDS dealers to publish the average CDS spread. Our sample covers 91 sovereign countries, from January 2001 to September 2015.As shown in Figure 2.1, there are 29 countries with active sovereign CDS markets in our sample in 2001. This number has been increasing steadily and is 91 by 2015. We focus US dollar denominated CDS contracts with a five-year maturity and default tier being Senior Unsecured Debt, as these contracts are most widely traded and have the highest market liquidity.

Following O'Kane (2008), we calculate the "CDS return" as the profit/loss (P&L) of buying $1 notional protection, which is estimated based on the widely used ISDA CDS model.[2] This computation is standard in the industry and the details are described in O'Kane (2008). However, two practical issues are worth noting. First, there are four premium payment dates, the so-called IMM dates, each year: March 20, June 20, September 20 and December 20. All five-year contracts initiated between two IMM dates expire on the same date. After each IMM date, contracts with a new maturity date start trading. These new contracts are said to be "on-the-run" until the next IMM date. Our sovereign CDS spread data are based on on-the-run contracts. Hence, to make sure that the

[2] To implement the valuation model, we assume a constant hazard rate and a 40% the recovery rate, and use the LIBOR term structure as the discount rates.

CDS spreads are comparable, we compute the monthly CDS return based on the running spreads on the 20th of the month and on the 19th of the next month. Second, there are two credit events in our sample, one for Greece and one for Argentina. Both were auction-settled and the recovery rates are 21.5% and 39.5% for Greece and Argentina, respectively. These two large monthly returns are included in our analysis. Given our large sample size, these two observations have only a negligible influence on our estimates.

Table 2.1 provides summary statistics of our sovereign CDS data from January 2001 to September 2015. The average CDS spread is 241 bps with a standard deviation of 556 bps. The monthly average SCDS return is -0.02%, with a standard deviation of 2.59%.

2.3 Empirical Results

In this section, we examine the momentum returns of sovereign CDS. We obtain sovereign CDS market data on 91 countries during January 2001 to September 2015 from Markit. Following O'Kane (2008), we construct the monthly returns. To examine the momentum effect in the sovereign CDS market, we sort countries into 5 quintiles based on their past 3-month sovereign CDS returns. Quintile-1 countries have the lowest sovereign CDS return, i.e., their credit worthiness improved the most according to the sovereign CDS market, while quintile-5 countries have the highest sovereign CDS returns.

We find strong evidence for momentum in the sovereign CDS market: quintile-5 portfolio "outperform" quintile-1 portfolio by 0.56% per month (t = 3.31), or 6.72% per year in the coming month.

Table 2.2 presents summary of characteristics for the momentum quintile portfolios over the sample period from January 2001 to September 2015. The average return of the loser portfolio (quintile 1) is -0.26% per month, while that of the winner portfolio (quintile

5) is 0.3% per month. The winner portfolio outperforms the loser portfolio by 0.56% per month, or 6.72% per year, with a t-statistic of 3.31. As motivated by Moskowitz et.al (2016), we calculate the skewness of the monthly log returns to the portfolios. We did not find any evidence of momentum crash by using skewness measure in our sovereign CDS sample. Panel A of Table 2.3 presents the Sovereign CDS momentum monthly returns for various formations (n = 1, 3, 6, and 9) and holding periods (h = 1, 3, 6, and 9). The momentum returns for sovereign CDS are significantly positive up to 6 months and do not reverse over the longer horizon. In panel B of Table 2.3, we extend the sorting periods to 48 months and find no return reversals. Figure 2.2 also shows the cumulative returns of long-short sovereign CDS portfolios sorting by past 3-month and with different holding periods up to 36 months. The cumulative monthly returns increase when the holding period increases to over 16 months, and increase slows down when the holding period increases further. However, the cumulative monthly returns do not reverse. This is consistent with the underreaction interpretation that sovereign CDS market gradually incorporates information into prices.

To account the risk factors in the existing literature, we regress this long-short strategy return on numbers of factors. Panel C of Table 2.3 shows the regression results by first regressing our long-short returns (i.e., quintile 1 minus quintile 5) on sovereign CDS monthly equally-weighted portfolio, denoted by MKT_SCDS. The coefficient of MKT_SCDS is 0.86 (t = 1.95). The alpha is 0.57% per month (t = 3.61) and it is approximately the same as the long-short returns. Previous studies including Lakonishok et al. (1994), Asness (1995), and Fama and French (1996) have shown that momentum is correlated with size and value. Hence, we include the Fama-French three factors, stock market returns denoted by MKT_stock, Small-minus-Big denoted by SMB, High-minus-Low denoted by HML, and Carhart momentum factor denoted by Carhart_MOM. We also include the momentum of the stock, denoted by MOM_stock. We construct the MOM_stock by sorting countries into five quintiles based on their past three-month stock index returns and compute the one-month return of the portfolio that is long in the top quintile countries and short in the bottom quintile countries, both equal-weighted. These five risk factors cannot explain the long-short strategy and the alpha is 0.52% per month (*t* =2.78). In the last two columns, we include the global value and momentum factors in Asness, Moskowitz and Pederson (2013), VAL_global and MOM_global, which are obtained from AQR data library. The alphas from our long-short strategy appear largely independent of these factors.

Asness et al. (2013) find evidence that momentum is significantly negatively related to recessions for particularly nonstock asset classes. Therefore, the exposure to business cycle state variables might help to explain the sovereign CDS momentum returns. To examine if the momentum return in the sovereign CDS market can be explained by the risk exposure to business cycle, we plot the cumulative momentum returns over time for three momentum strategies MOM (1,1), MOM (3,1), and MOM (6,1) in Figure 2.3. The shaded areas correspond to NBER recessions. The striking pattern in the figure is that the momentum strategy returns tend to increase significantly. Therefore, the business cycle risk cannot explain the sovereign CDS momentum returns. We find that the correlation between momentum returns in sovereign CDS and momentum returns in stock index is 0.12 and the correlation between momentum returns in sovereign CDS and momentum returns in bond index is 0.18. Figure 2.4 shows the 24-month rolling window correlation between momentum returns in sovereign CDS and momentum returns in stock index and between momentum returns in sovereign CDS and momentum returns in bond index.

What is the information that the sovereign CDS spreads are underreacting to? A natural candidate is the sovereign creditworthiness. When should that information be incorporated into prices? A conjecture is perhaps when that information becomes public, i.e., when credit rating or outlook changes are announced. This interpretation implies that the momentum strategy should be more profitable around the time when credit rating or outlook changes are announced. To test the implication, we run a panel regression with an interaction term. Specifically, we regress the return of sovereign CDS of country *i* in month *t* on a momentum return predictor, which is constructed from sovereign CDS data during months *t-3* to *t-1*, and a credit event dummy variable, which is 1 if country *i* has a credit rating or outlook change in month *t* and 0 otherwise. Our focus is on the coefficient of the interaction term of the predictor and this credit event dummy. As shown in the second column of Table 2.5, the coefficient of I_CDS_{it} is 0.10 (t=1.31). The coefficient of the interaction term $I\_CDS_{it} \times D_{it}$ is 1.42 ($t=3.24$), which is more than 14 times the coefficient for I_CDS_{it}. That is, the CDS market's predictive power is more than 14 times stronger during announcement months than during other periods. Our estimates show that the interaction coefficient is 14 times larger than the coefficient of the predictor. That is, the sovereign CDS momentum profit is 14 times stronger during credit-event months than during other periods and the information in past sovereign CDS spreads is ultimately incorporated into prices when there is a public announcement of credit rating or outlook change.

We also investigate the time series momentum, which is related to, but different from the cross-sectional momentum. The cross-sectional momentum is detected by finding securities that recently outperformed their peers over the past one-to-n months continue to outperform their peers on average over the next several months. The time-series momentum focuses purely on a security's own past return and it is detected by buying the securities with positive past returns and selling the securities with negative past returns. Moskowitz et al. (2012) find that the existence and significance of time series momentum is robust when the formation and holding periods are 12 months or less and across asset classes. We conduct this analysis on the sovereign CDS markets. We sort the sovereign CDS returns of each country into two groups based on their past 3-month sovereign CDS returns. Group-1 contains all past 3-month negative sovereign CDS returns and group-2 contains all positive returns. Then, we form a portfolio for each country that buys the group-2 sovereign CDS with past 3-month positive returns and sells the group-1 sovereign CDS with past 3-month negative returns in the coming month. Then, we equal-weighted average the long-short portfolios across all countries in our sample. The return from this strategy is the return from the time series momentum with 3-month formation period and 1-month holding period. As shown in Table 2.6, the long-short strategy is 0.24% ($t = 2.81$) per month. We also repeat our analysis by varying the sorting period n from one to 9 months and the holding period h from one to 9 months. As shown in Table 2.6, the long-short return is significantly positive up to 6 months.

2.4 Conclusion

In this chapter, I analyze the momentum phenomenon in the sovereign CDS market. I find robust cross-sectional momentum in sovereign CDS market. For example, in the sample from 2001 to 2015 the sovereign CDS portfolio of past three-month winners outperforms the portfolio of past three-month losers by 0.53% per month after adjusting for known risk factors, such as sovereign CDS market factor, Fama-French three factors, stock momentum factor and global value and momentum factors as in Asness et al. (2013). The excess returns of the long-short portfolio increase with the holding period for up to 20 months, and there is no sign of mean reversion. The evidence in this essay is consistent with investors' initial underreaction to public information, as in Barberis, Shleifer, and Vishny (1998) and the information in past sovereign CDS spreads is ultimately incorporated into prices when there is a public announcement of credit rating or outlook change.

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Chapter 3 The Macro-Informational Role of Derivatives: Evidence from the Sovereign CDS Market[1]

Modern markets show considerable micro efficiency … In no contradiction to the previous sentence, I had hypothesized considerable *macro* [emphasis added] inefficiency, in the sense of long waves in the time series of aggregate indexes of security prices below and above various definitions of fundamental values.

—Paul Samuelson[2]

3.1 Introduction

Ever since the launch of modern financial derivative markets in the 1970s, significant efforts have been made to examine the informational role of derivatives. While existing studies primarily focus on firm-level information and microstructure issues, we add to this literature by focusing on macro variables.

As indicated by Paul Samuelson's hypothesis in the opening quote, there might be important differences between aggregating micro and macro information. For the former, private information perhaps plays an important role. For the latter, however, since arguably most of the information is publicly available, investors' sophistication and information-processing capacity is likely to be more important. Hence, studying the macro-informational role of derivatives can potentially shed new light on this long-standing question. This analysis becomes possible thanks to the rapid development of the sovereign

[1] This essay is based on a joint work with Hongjun Yan, Depaul University and Jinfan Zhang, Chinese University of Hong Kong (Shenzhen)

[2] This is from a private letter from Paul Samuelson to John Campbell and Robert Shiller, and is discussed in Shiller (2001, p. 243).

CDS market since the early 2000s. By 2015, the market has an aggregate notional amount of around $2 trillion, and covers 91 countries.[3]

We first examine whether the sovereign CDS market can predict future stock index returns. Specifically, we sort countries into 5 quintiles based on their past 3-month sovereign CDS performances. The sovereign creditworthiness of quintile-1 countries has improved the most according to the sovereign CDS market, while that of quintile-5 countries has deteriorated the most. Presumably, the sovereign CDS market indicates good news for quintile-1 countries, and bad news for quintile-5 ones. If this information is not fully reflected in stock prices, the stock indices of quintile-1 countries would outperform those of quintile 5 in the coming months.

This is indeed the case. Specifically, we first form an equal-weighted portfolio of stock indices for each quintile, and construct their dollar-denominated returns. During the month after the sorting, the quintile-1 portfolio outperforms the quintile-5 portfolio by 1.25% per month (t=3.80), or 15% per year. Similarly, the market-capitalization-weighted portfolio of quintile 1 outperforms that of quintile 5 by 1.10% per month (t=2.43). After accounting for the factors of international stock and currency markets, this return difference is still 1.00% per month (t= 2.83) for the equal-weighted portfolio, and 0.89% (t=2.17) for the value-weighted portfolio.

Similarly, if sovereign bond markets do not fully reflect the good news from the sovereign CDS market regarding quintile-1 countries, their bond prices will tend to go up in the coming months, i.e., their yields will fall. On the other hand, the bond yields for

[3] Based on the data from the Depository Trust & Clearing Corporation (DTCC) and Markit Inc.

quintile-5 countries will tend go up. Indeed, during the month after the sorting, the average of 5-year sovereign bond yield indices for quintile-1 countries decreases by 7.04 basis points while that for quintile-5 countries increases by 4.9 basis points. The difference in the bond yield changes across these two quintiles is 11.87 basis points per month (t=3.15). After accounting for market and momentum factors in bond markets, this difference in yield changes is still 6.85 basis points per month (t=2.26). Without the data on the size of sovereign bond markets, we construct the value weighted average of yield changes based on each country's GDP. The difference in this value-weighted average bond yield changes across the top and bottom quintiles is 6.42 basis points per month (t=2.37), and is 4.45 basis points per month (t=2.06) after accounting for market and momentum factors in bond markets.

Moreover, our evidence suggests that the predictability appears to be mostly one way. While the sovereign CDS market has strong predictive power for future stock index returns and sovereign bond yields, there is little, if any, evidence that stock or bond markets have predictive power for future sovereign CDS spreads.

Our interpretation of these results is that the sovereign CDS market is more efficient at aggregating certain macro information (e.g., sovereign creditworthiness). Stock and bond markets only gradually "catch up" with the sovereign CDS market, i.e., the information in the sovereign CDS market is gradually incorporated into stock and bond prices.

This interpretation is motivated by the fact that the investors in the sovereign CDS market are mostly sophisticated financial institutions, while those in the stock and bond markets are predominately local investors. For firm-level variables, some local investors might have better access to private information, which can potentially overcome their disadvantage relative to sophisticated institutions. For macro variables, however, since arguably most of the information is publicly available, sophistication and information-processing capacity plays a more important role. Hence, in our context, the market for sophisticated investors (i.e., the sovereign CDS market) might be able to aggregate information more efficiently. Moreover, our interpretation is also motivated by the insight in Black (1975) that derivatives often have embedded leverage, allowing investors to trade on their information more aggressively.

We have five pieces of evidence that support this interpretation. First, the cumulative alphas of the long-short strategies in both stock and bond markets increase with the holding period, and do not mean revert. For instance, when the holding period increases to one year, the cumulative alphas are around 6% and 30 basis points for stock and bond markets, respectively. There is no sign of reversal when we further increase the holding period. This is consistent with our interpretation that stock and bond markets gradually catch up with the information in the sovereign CDS market, and that there is no overshooting and reversal.

Second, stock and bond prices appear to catch up with the sovereign CDS market "at the right time." Recall that our interpretation is that the sovereign CDS market contains some information that is not fully reflected in stock and bond prices. What kind of information? A natural candidate is perhaps the information on the creditworthiness of sovereign governments. When should that information be incorporated into stock and bond prices? A reasonable conjecture is perhaps when that information becomes public, i.e., when credit rating or outlook changes are announced. Hence, our interpretation implies that the previously described long-short strategies should be *more* profitable during the months when credit rating or outlook changes are announced and so stock and bond prices catch up with the sovereign CDS market.

To test this conjecture, we run a panel regression of the stock index return of country *i* in month *t* on a return predictor, which is constructed from sovereign CDS data during months *t-3* to *t-1*, and a credit event dummy variable, which is 1 if country *i* has a credit rating or outlook change in month *t* and 0 otherwise. Our primary focus is on the coefficient for the interaction term of the predictor and this credit event dummy. Our estimates show that the interaction coefficient is twice as large as the coefficient of the predictor. That is, the sovereign CDS market's predictive power for stock returns is two times stronger during credit-event months than during other periods. We also run similar panel regressions for bond markets and find that the sovereign CDS market's predictive power for future bond yield changes is 5 to 7 times stronger during credit-event months than during other periods.

Third, stock and bond prices appear to catch up with the sovereign CDS market "in the right direction." Specifically, our interpretation implies asymmetry between positive and negative information. If stock and bond prices fail to reflect the information in the sovereign CDS market, arbitrageurs can profit from trading stocks and bonds. Due to short sales constraints, however, it is more costly for arbitrageurs to exploit negative, rather than positive, information. Hence, less negative information is incorporated into stock and bond prices, and when it eventually becomes public, stock and bond prices will respond more strongly. In other words, the catchup to negative information should be stronger. Consistent with this prediction, we find that when a credit rating or outlook change is announced, stock and bond prices respond strongly if the sovereign CDS market has been anticipating negative news. In contrast, the responses are statistically insignificant if the sovereign CDS market has been anticipating positive news.

Fourth, we utilize daily data (as opposed to monthly ones in previous tests) to conduct a more granular analysis of the timing of the information flow from the sovereign CDS market to stock and bond markets. Specifically, for credit rating and outlook changes, stock and bond markets should be able to catch up with the sovereign CDS market during the few *days* around announcements. Indeed, we find that the previous long-short strategies are especially profitable during the several days around announcements. For example, the average daily long-short strategy return is 48.04 basis points on credit event days, but is only 2.22 basis points on other days. This return difference decays quickly towards zero if we expand the event window. For instance, the average daily long-short strategy return is 24.08 basis points (t=1.76) higher during the three-day window around credit events than on other days. Once we expand the window to 11 days, this return difference is merely 5.20 basis points, and is statistically insignificant. A similar pattern exists for bond markets. Moreover, as is the case in the previous analysis based on monthly data, the results are also mostly due to catching up with the negative news in the sovereign CDS market.

Fifth, what is the nature of the information that is more efficiently aggregated by the sovereign CDS market than local stock and bond markets? Is it country-specific, or is it world-wide? A natural conjecture is that sovereign CDS investors' advantage, over local stock and bond investors, is probably their superior capacity in analyzing global, rather than country-specific, information. In our earlier analysis of credit rating and outlook changes, for example, while some of the changes might be country specific, many others are systematic in nature. For instance, the prospects of the global economy and the monetary policy in the U.S. can have significant implications the creditworthiness of countries around the world. Sovereign CDS investors' advantage is perhaps their better understanding of these global implications, rather than their country specific knowledge.

One might think that this interpretation is somewhat inconsistent with our early evidence on credit rating and outlook changes since one might think that those changes are mostly country specific. However, this clearly is not the case. For example, Longstaff et al (2011) find that the first principal component of sovereign credit spreads explains 64% the credit spread variations in their sample. This first principle component is highly correlated with the U.S. market, and has a correlation of −74% with U.S. stock market returns, and a correlation of 61% percent with changes in the VIX index. That is, sovereign credit risks have a large systematic component. Intuitively, the monetary policy in the U.S. can significantly affect the creditworthiness of countries around the world. The growth of the global economy has great influences on the balance sheets of energy and raw material exporting countries. Even for the influence of natural disasters, rating agencies have long recognized its systematic nature.[4] Our conjecture is that sovereign CDS investors' advantage is their better understanding of these global implications on the creditworthiness of individual countries, rather than their country specific knowledge.

To test this conjecture, we decompose the monthly sovereign CDS spreads into a "systematic" component and an "idiosyncratic" component, and examine which component has predictive power for future stock and bond returns. Consistent with the

[4] See, e.g., *Climate Risk: Rising Tides Raise the Stakes*, Standard and Poor's, *Insights*, December 2015.

conjecture, our evidence shows that sovereign CDSs' forecasting power is almost entirely from its systematic component. This evidence is consistent with the view in Longstaff et. al. (2011) that "global investors play a predominant role" in the sovereign CDS market.[5] Our study adds to this view by showing that those global investors appear to be more capable of processing world-wide information whose implications for stock and bond markets are only gradually appreciated by local investors.

In addition to the forecasting power for financial variables, the sovereign CDS market also has forecasting power for future real economic activities. Specifically, we run panel regressions of GDP growth and PMI index on the returns in stock, bond, and sovereign CDS markets during the previous quarter. Our evidence shows that the sovereign CDS market does possess unique predictive power for future GDP growth and PMI index. Interestingly, as in the case of forecasting financial variables, this predictive power for future real economic activities is also almost entirely from the systematic component of sovereign CDS spreads.

There is a large literature on the informational role of derivative markets. These studies primarily focus on firm-level information,[6] and the evidence is often mixed. For example, a number of studies have examined the lead-lag relation between individual stock and option prices. While many studies (e.g., Chakravarty, Gulen, and Mayhew (2004)) conclude that option prices lead stock prices, Muravyev, Pearson, and Broussard (2013) reach the opposite conclusion using a different methodology. This literature often utilizes intra-day data to examine price discovery in order to address the asynchronous trading

[5] See, also, Pan and Singleton (2008) and Ang and Longstaff (2013).

[6] Several studies analyze index futures and options, e.g., Kawaller, Koch, and Kock. (1987), Chan, Chan, and Karolyi (1991), and Chordia et al. (2016).

issue. Several studies show that individual options can predict future stock returns at monthly frequencies (e.g., Cremer and Weinbaum (2010) and An, Ang, Bali, and Cakici (2014)), and that options trading volume can predict future stock returns (e.g., Easley, O'Hara and Srinivas (1998) and Pan and Poteshman (2006)). But Goyal and Saretto (2009)) find that underlying stock prices lead option prices. The direction of the information flow between the individual stocks and corporate CDSs is also mixed. Acharya and Johnson (2007) find that the CDS market appears to be able to forecast future negative credit news. Lee, Naranjo, and Sirmans (2014) find that the corporate CDS market can improve the momentum trading strategy in the stock market. However, Hilscher, Pollet, and Wilson (2014) find that information flows from the equity to the CDS market. The lead-lag relations have also been analyzed between corporate CDSs and corporate bonds (Blanco et al. (2005)), CDOs versus stocks (Longstaff (2010)).

Our paper adds to this literature by analyzing the market for *macro* information. In our context, private information is perhaps less important. Instead, investors' sophistication and information-processing capacity plays a more prominent role. This feature allows our analysis to shed new light on the long-standing question. Moreover, our setup also enables us to study the nature of the information that is better aggregated by derivatives, and the informational role for real macroeconomic activities.

3.2 Data

A sovereign CDS contract allows market participants to purchase or sell protection against the risk of default of a sovereign government. During the term of the contract, the buyer makes quarterly payments, which are called CDS coupons or spreads, to the seller in exchange for the seller's promise of protection. The Sovereign CDS spreads are paid on the 20th day of March, June, September and December. If a credit event occurs, the protection buyer will be compensated by the seller for the loss during the credit event.[7] The market for sovereign CDS has been growing rapidly in the past decade, especially during the recent sovereign debt crisis. According to the Depository Trust & Clearing Corporation, the aggregate notional amount of sovereign CDS contracts was around $2 trillion in 2015, accounting for around 15% of all credit derivatives.

Our sovereign CDS data are from the Markit Group, which collects daily sovereign CDS quotation data from major dealers to publish the average CDS spread. Our sample covers 91 sovereign countries, from January 2001 to September 2015. As shown in Figure 3.1, there are 29 countries in our sample in 2001. This number has been growing steadily and reaches 91 by 2015. The list of countries and the starting dates of the data for each country are listed in the appendix. We focus on US dollar denominated contracts with a five-year maturity with the default tier being senior unsecured debt, which are most actively traded and have the highest market liquidity.

Following O'Kane (2008), we define the "return" of a CDS contract during a period of time as the ratio of the mark-to-the-market profit/loss during that period of time relative to the notional amount. The mark-to-the-market profit/loss is estimated based on the widely used ISDA CDS model, which is standard in the industry and is described in detail in

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[7] The credit event includes failure to pay, moratorium, obligation acceleration, and restructuring, and is determined by the ISDA Determinations Committee. In most cases, the parties use "cash settlement" with an auction process, in which the CDS seller makes a cash payment based on an auction-generated market price of certain eligible debt obligation of the sovereign government. An alternative settlement is the "physical settlement," in which the protection buyers tender an eligible bond to the sellers and receive the par value of the bond.

O'Kane (2008).[8] Several points are worth noting. First, the sovereign CDS return increases when the underlying country's creditworthiness deteriorates, that is, a higher sovereign CDS return indicates bad news. Second, there are four premium payment dates, the so-called IMM dates, each year: March 20, June 20, September 20 and December 20. All contracts initiated between two IMM dates expire on the same day. After each IMM date, contracts with a new maturity date start trading. These new contracts are said to be "on-the-run" until the next IMM date. Our sovereign CDS data are based on on-the-run contracts. We compute the monthly CDS return based on the spreads on the 20th of a month and on the 19th of the next month to make sure that these two spreads are for the same CDS contract. Third, there are two credit events in our analysis, one for Greece and one for Argentina. Both were auction-settled and the recovery rates are 21.5% and 39.5% for Greece and Argentina, respectively.[9] They led to two large monthly returns, which are included in our analysis. Due to our large sample size, these two observations have only a negligible influence on our estimates. Table 3.1 provides summary statistics of our sovereign CDS data from January 2001 to September 2015. The average CDS spread is 241 bps with a standard deviation of 556 bps. The monthly average SCDS return is -0.02%, with a standard deviation of 2.59%.

For each country, we obtain, from Bloomberg, the daily returns of its main stock index, which is denominated in U.S. dollars and includes dividends. As illustrated in Figure 3.1, the total number of countries for which we have both CDS and stock data is 28 in 2001

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[8] To implement this valuation model, we assume a constant hazard rate and a 40% recovery rate, and use the LIBOR term structure as the discount rates.

[9] The credit event for Ecuador in 2008 is not in our sample due to the lack of data for its stock and bond indices.

and 75 in 2015. The complete list of countries and stock indices is provided in the appendix. To be consistent with our CDS return data, we construct the monthly stock index return as the return from the 20th of a month to the 19th of the next month from daily stock index returns. As shown in Table 3.1, the average monthly stock index return is 1%, with a standard deviation of 7.99%.

We obtain daily yield to maturity of 5-year domestic-currency-denominated sovereign bonds from Bloomberg. As illustrated in Figure 3.1, the number of countries with both bond yields and CDS data has grown from 17 in 2001 to 51 by 2015. The complete list of countries and bond indices is provided in the appendix. The monthly yield changes are calculated based on the yield on the 20th of a month and that on the 19th of the next month. The average monthly yield change is -2 bps, with a standard deviation of 54 bps.

The rating and outlook of senior unsecured foreign currency debt are obtained from Standard and Poor's. They cover all the countries on which we have sovereign CDS data. The median rating for all the observations is BBB+.

Finally, we obtain the quarterly year-over-year GDP growth data from IMF World Economic Outlook Database, and collect the seasonally adjusted Product Manager Index (PMI) data from Markit Group. PMI is a key economic indicator derived from monthly surveys of private sector companies in six different categories: production level, new orders from customers, speed of supplier deliveries, inventories, order backlogs and employment level. If the PMI index is larger (smaller) than 50, it implies that the economy is expanding (contracting). To ensure the consistency of the methodology for the data construction across countries we focus on the production level sub-PMI index. Nevertheless, we also repeat our analysis based on the broader headline PMI index and the results are very similar. Towards the end of our sample, we have 38 countries with both the PMI and CDS data. The detailed list of countries and the starting time for each country is in the appendix. The mean and standard deviation of the GDP growth rate are 3.12% and 4.13%, respectively. The average PMI is 52.9 with a standard deviation of 6.3.

3.3 Main Results

3.3.1 Using the sovereign CDS market to predict stock returns

We first examine whether the sovereign CDS market contains information that can predict future stock returns. This is motivated by the fact that the investors in the sovereign CDS market are mostly sophisticated financial institutions, while those in the stock and bond markets are predominately local investors. For firm-level variables, some local investors might have better access to private information, which can potentially overcome their disadvantage relative to sophisticated institutions. For macro variables, however, since arguably most of the information is publicly available, sophistication and information-processing capacity plays a more important role. Hence, in our context, the market with sophisticated investors (i.e., the sovereign CDS market) should be able to aggregate information more efficiently. In the presence of market frictions, stock market prices may fail to fully reflect the information in sovereign CDS market prices. Hence, sovereign CDS market prices might be able to predict future stock market returns.

To test this conjecture, we sort countries into five quintiles based on their past 3-month sovereign CDS returns, and update the quintiles every month. The countries in quintile 1 have the lowest CDS returns, i.e., according to the sovereign CDS market, their credit worthiness improved the most. Countries in quintile 5 have the highest CDS returns, i.e., their credit worthiness deteriorated the most. That is, the sovereign CDS market indicates that, during the prior three months, quintile-1 countries had good news while quintile-5 countries had bad news. If stock markets do not fully reflect the information in the sovereign CDS market, we would find that the stock markets in quintile 1 would, on average, outperform those in quintile 5 in the coming months.[10]

That is indeed what we find. For each quintile, we form an equal-weighted portfolio of the stock indices of its countries. Panel A of Table 3.2 reports the average excess return of each portfolio over the 1-month US Treasury yield. In our full sample, as shown in the first row, the excess return of the quintile-1 portfolio is 1.34% per month, while that of the quintile-5 portfolio is only 0.09%. The difference is 1.25% per month, or 15% per year, with a *t*-statistic of 3.80. We then form a market-capitalization-weighted portfolio for each quintile, and find that quintile-1 portfolio outperforms quintile-5 portfolio by 1.10% per month (t=2.43).

To account for the risk factors in the literature, we construct a number of factors. We first compute the global stock market factor as the equal weighted return of all stock indices. Secondly, our long-short return should have a positive loading on the international momentum factor (Anthony (1997), Rouwenhorst (1998)), because the good news in the sovereign CDS market about a country is likely accompanied by high stock returns in that country. Hence, we construct the stock index momentum strategy return factor, MOM_stock, as follows. We sort countries into five quintiles based their past three-month

[10] One might be concerned that quintiles 1 and 5 might be dominated by emerging countries since their sovereign CDS returns are more volatile than those of developed countries. However, this is not the case. Every country in our sample has been sorted into each of the 5 quintiles at some point in time.

stock index returns. MOM_stock is computed as the one-month return of the portfolio that is long in the top quintile countries and short in the bottom quintile countries, both equal weighted. Finally, since our stock index returns are denominated in U.S dollars, foreign exchange exposures might have contributed to our long-short portfolio return. Hence, we obtain the two currency factors in Lustig, Roussanov and Verdelhan (2011), MKT_FX and HML_FX, which are currency market factor and the carry trade risk factor, respectively, from the author's website. We also construct the currency momentum return factor, MOM_FX, based on a momentum trading strategy in the currency market with a 3-month formation period and a 1-month holding period.

We regress our long-short returns (i.e., quintile 1 minus quintile 5) on the above factors. The results based on the equal-weighted portfolios are reported in the first column of Panel B of Table 3.2. As expected, our long-short strategy return has a strong positive loading on the momentum factor. Nevertheless, the resulting alpha of our long-short strategy remains highly significant, and is 1.01% per month (t=2.89). In the second column, we include the global value and momentum factors in Asness, Moskowitz and Pederson (2013), VAL_global and MOM_global, which are obtained from AQR data library. Our long-short strategy return has insignificant loadings on these factors, and the resulting alpha is 1.27% per month (t=3.50). The results based on the market-cap-weighted portfolios are reported in the third and fourth columns. The alphas are somewhat smaller, but remain statistically significant.

We conduct subsample analyses by partitioning our sample by time. The first half of the sample covers the data from January 2001 to December 2007, and the second half January 2008 to September 2015. The results are reports in Panel A. The second and third rows report the results based on equal weighted portfolios. They show that sovereign CDS markets have predictive power in stock markets in both subsample periods. The long-short strategy return is 1.94% per month (*t*=3.51) for the first half of the sample, and 0.58% per month (*t*=2.10) for the second half. As shown in the last two rows of Panel A, the results based on value weighted portfolios, reported are qualitatively similar.

The above analysis is based on sorting by a three-month sorting period and holding on a one-month holding period. To examine the robustness of those results, we repeat the analyses by varying the sorting and holding periods. The upper part of Panel C reports the results based on equal-weighted portfolios. It shows that, for the one-month holding period, the long-short strategy alphas are significant when we vary the sorting period from one month to six months. For example, the long-short strategy alpha is 0.83% per month (*t*=2.71) when the sorting period is 6 months and the holding period is one month. On the other hand, the long-short strategy decreases with the holding period. For example, when the sorting period is three months, the long-short strategy alpha is 0.45% and 0.32% per month when the holding period is 3 months and 6 months, respectively. The value-weighted results, reported in the lower part of Panel C, are similar.

3.3.2 Using the sovereign CDS market to predict bond yields

We now examine whether the sovereign CDS market contains information that can predict future bond returns. Our bond data from Bloomberg provides the yield to maturity, but not returns, of the 5-year domestic sovereign bond index. Since the return of a bond is approximately the negative of yield change multiplied by its duration, we simply use yield changes to approximate bond returns.[11] To simplify our discussion, when there is no potential for confusion, we will refer to yield changes as if they are bond returns.

As in the previous section, to test if the sovereign CDS market can predict future bond returns, we sort countries into 5 quintiles based on their past 3-month sovereign CDS returns, and update the quintiles every month. The creditworthiness of the countries of quintile 1 improved the most, while that of quintile 5 deteriorated the most. If the good news about quintile-1 countries has not been fully reflected in the bond markets, we would expect the borrowing costs of the governments in those countries to go down in the future. Similarly, we would expect the future borrowing costs of the governments of quintile-5 countries to go up.

This conjecture is also confirmed by our evidence. Specifically, we compute the equal-weighted average of bond yield changes for the countries in each quintile. As shown in the first row of Panel A in Table 3.3, on average, the bond yield of quintile-1 countries decreases by 7.04 basis points, while that of quintile-5 countries increases by 4.90 basis points. The difference between the two yield changes is 11.87 basis points, with a *t*-statistic of 3.15. Ideally, we prefer to weight yield changes by the market capitalization of the sovereign bond markets. Since the market capitalization data are not available for enough countries, we construct GDP-weighted average of yield changes instead. As expected, the value weighted result is qualitatively similar but smaller in magnitude. The difference in weighted average yield changes is 6.42 basis points (*t*=2.37).

[11] As a robustness check, we obtain monthly excess returns of U.S. dollar-denominated sovereign bonds of developing countries from Borri and Verdelhan (2015). The analysis based on this smaller sample leads to similar results.

In order to control for the factors that might have contributed to the bond return (yield change) difference, we regress it on a market factor, MKT_bond, which is computed as the equal weighted yield changes across all countries, and the momentum factor, MOM_bond, which is the counterpart of the momentum return in the sovereign bond market, with a 3-month formation period and a 1-month holding period, whereby we use yield changes as if they are bond returns.

As shown in the first column of Panel B of Table 3.3, the market and momentum factors cannot account for the difference in bond yield changes between quintiles 1 and 5. In the regression with both factors, the estimated "alpha" is 6.85 basis points (t=2.26). That is, if the duration of the five-year bonds is 4 years, then the alpha from the long-short strategy in the sovereign bond markets is roughly 27.4 (=6.85×4) basis points per month. In the second column, we find that the global value and momentum factors in Asness, Moskowitz, and Pedersen (2013) cannot explain the difference in bond yield changes either. The estimated alpha is 11.16 basis points, with a t-statistic of 2.47. The value-weighted results, reported in the last two columns of the Panel B, are weaker but qualitatively similar.

We repeat our analysis for the two subsample periods, January 2001 to December 2007 and January 2008 to September 2015. The second and third rows of Panel A of Table 3.3 show that the sovereign CDS market has predictive power in the sovereign bond markets for both periods. The difference in the yield changes between the top and bottom quintiles is 7.75 basis points per month (t=1.75) for the first half of the sample, and 15.63 per month (t=2.82) for the second half. The value-weighted results are reported in the last two rows of the Panel A, and are weaker but qualitatively similar. We also repeat our analysis by varying the sorting period n and holding period h. The results, reported in Panel

C, remain quite similar. For example, as shown in upper half of Panel C, which reports the results based on equal weighted portfolios, for the case of 3-month sorting period (n=3), the long-short strategy alpha is 5.33 basis points (t=2.49) when the holding period is 3 months, and 4.54 basis points (t=2.19) when the holding period is 6 months. The results based on value-weighted portfolios, reported in the lower half of Panel C, are also quite similar.

3.3.3 The direction of information flow

Our previous evidence shows that the sovereign CDS market appears to contain information that can predict future stock index and sovereign bond returns. So, a natural question is whether there is information dissemination in the opposite direction. That is, can stock or bond markets predict future returns in the sovereign CDS market?

Note that there is momentum in all three markets. To examine if market A has marginal predictive power for market B, it is important to control for the past return in market B. Hence, to examine the direction of information flow, we conduct the following sequential sorting. We first sort countries into 5 quintiles based on their past 3-month stock index returns. Then, for each quintile, we sort countries into 2 halves based on their past 3-month sovereign CDS returns, and compute the return from the equal-weighted long-short portfolio that buys stock indices of countries with low past CDS returns and sells those of countries with high past CDS returns. We then compute the equal-weighted average return across the 5 long-short portfolios. That is, the return from this strategy reflects sovereign CDS markets' power to predict future stock returns, after controlling for the past stock returns. As shown in Panel A of Table 3.4, for our full sample, the strategy return is 51 basis points per month (t=3.17). After controlling for the market factor, the alpha remains at 49 basis points per month (t=2.75). This is consistent with our evidence in Table 3.2 that the sovereign CDS market can predict future stock returns. Columns two and three report the strategy returns for the first and second half of our sample, and demonstrate that the predictive power of Sovereign CDS markets is present in both subsamples.

We now examine whether there is information flowing along the opposite direction, that is, if stock returns can predict future sovereign CDS returns after controlling for past CDS returns. We conduct similar 5 by 2 sequential sorting, first based on the past 3-month CDS returns and then based on the past 3-month stock returns. As we can see from the last three columns of Panel A, the average strategy returns are very close to zero, for both the full sample and the two subsamples. The largest t-statistic is merely 0.55. Hence, we don't find any evidence that stock markets have marginal predictive power for future sovereign CDS returns.

Our analyses of the direction of the information flow between sovereign CDS markets and bond markets are based on similar 5-by-2 sequential sorting. As shown in Panel B of Table 3.4, the sovereign CDS market has strong predictive power for future bond yield changes, after controlling for past bond yield changes. The alpha for our full sample is 5.73 basis points per month with a t-statistic of 2.88. On the other hand, the predictive power of bond yields for sovereign CDS returns is marginal. The t-statistic for the alpha is 1.68 for the full sample, and the predictive power is mostly concentrated in the second half of the sample.

Panels C and D analyze the direction of information flow using a different methodology. In Panel C, we run Fama-MacBeth regressions of stock index returns and bond yield changes on the previous 3-month sovereign CDS returns. As shown in the first column, after controlling for the previous 3-month stock index return, the coefficient for the sovereign CDS return is -0.12 (*t*=2.12), indicating that sovereign CDS returns can predict future stock index returns. Similarly, the second column shows that the sovereign CDS return has predictive power for future bond yield index changes, after controlling for the yield change in the previous 3 months. In contrast, Panel D shows that stock index returns and bond yield changes do not appear to have predictive power for future sovereign CDS returns once we control for the previous 3-month sovereign CDS return.

In summary, our evidence suggests that there is information flowing from the sovereign CDS market to stock and bond markets. But there is little, if any, evidence of information flowing the other way.

3.3.4 Interpretation

Our interpretation of the above results is as follows. Relative to stock and bond markets, the sovereign CDS market is better at aggregating certain information about its underlying countries. When this information gradually becomes public, stock and bond prices catch up with the sovereign CDS market.

This interpretation is motivated by the fact that the investors in the sovereign CDS market are mostly sophisticated financial institutions, while those in the stock and bond markets are predominately local investors, as is known in the international finance literature.[12] For firm-level variables, certain local investors might have better access to private information, which can potentially overcome their disadvantage relative to sophisticated investors. This may explain the mixed results in the literature on whether

[12] See Karolyi and Stulz (2003) for a review.

local investors know more.[13] For macro variables, however, sophistication and information-processing capacity plays a more important role, since arguably most of the information is publicly available. Hence, in our macro information setup, the market for sophisticated investors (i.e., the sovereign CDS market) would aggregate information more efficiently. Moreover, our interpretation is also motivated by the insight in Black (1975) that derivatives often have embedded leverage, allowing investors to trade on their information more aggressively. We have the following five pieces of evidence that is consistent with this interpretation.

3.3.4.1 Persistence

Our interpretation suggests that the sovereign CDS market contains information that is only gradually incorporated into stock and bond prices over time. That is, stock and bond markets gradually "catch up" with the sovereign CDS market. This interpretation implies that when we increase the holding period of the long-short portfolios in Tables 3.2 and 3.3, the cumulative alphas should increase and stabilize, but not revert back to zero.

This is indeed the case. We repeat the analysis in Table 3.2 by extending the holding period, and the results are summarized in Panel A of Figure 3.2. It shows that the cumulative alpha of the long-short strategy in stock markets gradually increases when the holding period increases to around 6 months, and the increase slows down when the holding period increases further. However, the cumulative alpha does not revert back to zero. Similarly, we repeat the bond market analysis in Table 3.3 by extending the holding period. As shown in Panel B of Figure 3.2, the cumulative yield change difference

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[13] See, for example, Bae, Stulz, and Tan (2008) and its references.

gradually increases when the holding period increases to around 6 months, and then stays roughly there when we further increase the holding period.

3.3.4.2 Timing of the predictability

Our interpretation is that the sovereign CDS market contains some information that is not fully reflected in stock and bond prices. What kind of information? A natural candidate is perhaps the creditworthiness of sovereign governments. When should that information be incorporated into stock and bond prices, i.e., when should stock and bond prices catch up? A natural conjecture is perhaps when that information becomes public, e.g., when credit rating or outlook changes are announced.

This conjecture implies that the previously described long-short strategies in stock and bond markets should be *more* profitable during the months when credit events occur and so stock and bond markets catch up with the sovereign CDS market. In other words, one reason that our long-short strategies in stock and bond markets are profitable is that the sovereign CDS market can anticipate future credit events and position the portfolios in advance, which reap profits when those credit events eventually become public.

To test this implication, we run a panel regression of the stock index return of country *i* in month *t* on an indicator variable, I_CDS_{it}, a dummy variable D_{it}, and their interaction term. The indicator variable I_CDS_{it} is set to 1 if country *i* is in quintile 1 according to the sorting based on sovereign CDS returns during months *t-3* to *t-1* (i.e., the CDS market indicates that the creditworthiness of country *i* improved during the previous 3 months), is set to *-1* if country *i* is in quintile 5, and is set to 0 if country *i* is in the other three quintiles. The dummy variable D_{it} is 1 if there is a credit rating change or outlook change for country *i* in month *t* according to Standard & Poor's, and is 0 otherwise. Our interpretation implies that the sovereign CDS market has a stronger predictive power for stock returns in credit-event months, and hence the coefficient of the interaction term should be positive.

This is indeed the case. As shown in the first column of Panel A Table 3.5, the coefficient of I_CDS_{it} is 0.38 (t=2.18). The coefficient of the interaction term $I\_CDS_{it} \times D_{it}$ is 0.84 (t=*1.70*), which is more than twice the coefficient for I_CDS_{it}. That is, the CDS market's predictive power is more than two times stronger during credit-event months than during other periods. In column two, we control for the stock momentum by including a momentum indicator variable I_MOM_{it}, which is 1 if country i is in the top quintile based on the stock returns in the past 3 months, is -1 if country i is in the bottom quintile, and is 0 otherwise. The interaction coefficient is still twice as large as the coefficient for I_CDS_{it}.[14]

We run similar panel regressions for bond yield changes. Since yield change and bond return are negatively related, our interpretation implies that the coefficient of the interaction term should be negative. Indeed, as shown in the third column, the coefficient for $I\_CDS_{it} \times D_{it}$ is -29.28 (t=2.36) and that for I_CDS_{it} is -4.11 (t=1.51). That is, the sovereign CDS market's predictive power for future bond yield changes is 7 times stronger during credit-event months than other periods. The last column shows that the results remain similar after controlling for the bond market momentum.

In summary, the above evidence lends further support to our interpretation by showing that stock and bond markets catch up with the sovereign CDS market at the "right time"—when credit-related information becomes public. In the next section, we examine whether they catch up with the sovereign CDS market "in the right direction."

[14] The interaction coefficient is statistically insignificant. This is perhaps because, as shown in Panel B of Table 3.5, the sovereign CDS market's predictive power in stock markets appears to be mostly from bad news.

3.3.4.3 Asymmetry in predictability

Our interpretation implies asymmetry between catching up with positive and negative news. If stock and bond prices fail to reflect the information in the sovereign CDS market, arbitrageurs can profit from trading stocks and bonds. Due to short sales constraints, however, it is more costly to exploit negative information than positive. Hence, less negative information is incorporated into stock and bond prices, and when it eventually becomes public, stock and bond prices should respond more strongly. In other words, catchup to negative information should be stronger.

To test this implication, we decompose the indicator I_CDS_{it} into two variables. The first one, $Good\_CDS_{it}$, is set to 1 if the sovereign CDS market indicates "good news" for country *i* in the previous three months. That is, $Good\_CDS_{it}$ is 1 if country *i* is in quintile 1 in month *t* according to the sorting based on sovereign CDS returns during the prior three months, and is 0 otherwise. The second variable, Bad_CDS_{it}, is set to -1 if country *i* is in quintile 5, and is 0 otherwise. Note that I_CDS_{it} is the sum of $Good\_CDS_{it}$ and Bad_CDS_{it}. Hence, one can view the earlier regressions in Panel A as restricted regressions where the coefficients for $Good\_CDS_{it}$ and Bad_CDS_{it} are restricted to be the same; and the coefficients for $Bad\_CDS_{it}\times D_{it}$ and $Good\_CDS_{it}\times D_{it}$ are restricted to be the same. We now allow these coefficients to be different. Our interpretation that catchup to bad news is stronger implies that the coefficient for $Bad\_CDS_{it}\times D_{it}$ should be larger than that for $Good\_CDS_{it}\times D_{it}$.

Our evidence is consistent with this implication. For stock markets, as shown in the first column of Panel B of Table 3.5, the coefficient of $Bad\_CDS_{it}\times D_{it}$ is 2.46 (t=2.48) while that of $Good\_CDS_{it}\times D_{it}$ is -0.82 (t=1.08). This is consistent with the interpretation that stock markets catch up with bad news more strongly. A similar pattern exists for the bond markets. Since yield change and bond return are negatively related, our interpretation implies that the two interaction coefficients should be negative and that the coefficient of $Bad\_CDS_{it}\times D_{it}$ should be smaller. Indeed, as shown in the column three, the coefficient of $Bad\_CDS_{it}\times D_{it}$ is -50.47 (t=2.25) while that of $Good\_CDS_{it}\times D_{it}$ is -4.26 (t=0.47). Finally, we control for momentum in the regressions, and the results, reported in columns two and four, remain very similar.

In summary, stock and bond prices appear to catch up with the sovereign CDS market "in the right direction." When a credit event becomes public, stock and bond prices respond strongly if the sovereign CDS market was anticipating negative news. In contrast, the responses are largely insignificant if the sovereign CDS market was anticipating positive news.

3.3.4.4 Daily analysis

Our evidence so far has been based on monthly data, which do not allow for detailed analysis on the timing of the responses of stock and bond prices. In this section, we utilize daily data to conduct more granular analysis on the timing of stock and bond markets catching up with the sovereign CDS market.

Specifically, we run the regressions in Panel A of Table 3.5 at daily frequency. The indicator variable $\mathrm{I\_CDS}_{it}$ and the dummy variable D_{it} are now replaced by their daily-frequency counterparts, $\mathrm{I\_CDS}_{it}^{d}$ and D_{it}^{n}. For country i on day t, we have $\mathrm{I\_CDS}_{it}^{d} = \mathrm{I\_CDS}_{im}$, if day t is in month m. For $n=0,1,2\ldots$, the dummy variable D_{it}^{n} is 1 if country i has an S&P credit rating change or outlook change during the (2n+1)-day window (t-n, t+n), and is 0 otherwise.

The idea is to examine whether stock and bond prices catch up with the sovereign CDS market during the $(2n+1)$-day window around the credit event day. We run a number of regressions by varying the value of n from 0 to 20. In the case of $n=0$, the coefficient of the interaction term captures the effect on credit event days only. When we increase the value of n, the event window gets longer. In the case of $n=5$, for example, the interaction coefficient captures the average effect during the 11-day window around credit event days.

Note that the interaction coefficient captures the extra return from the long-short strategy during the event window relative to other periods. If stock and bond markets catch up quickly with the sovereign CDS market after the announcement of credit rating or outlook changes, the interaction coefficient should be large for narrow event windows surrounding announcement days (i.e., when n is small), but decays towards zero when the event window expands (i.e., when n increases).

This is exactly what we find. For the case n=0 in stock return regressions, as shown in Panel A of Table 3.6, the coefficients of $\mathrm{I\_CDS}_{it}^{d}$ and the interaction term $\mathrm{I\_CDS}_{it}^{d} \times D_{it}^{n}$ are 1.11 (t=2.37) and 22.91 (t=1.69), respectively. That is, the sovereign CDS market's predictive power for stock returns is over 20 times stronger on credit event days than on other days. This extra predictive power decays quickly when we expand the event window. For example, during the 3-day window around the credit event day (i.e., $n=1$), the interaction coefficient is 12.04 basis points (t=1.76), suggesting that the sovereign CDS market's predictive power is around 12 times stronger during the 3-day window. For the case of n=5, for example, the interaction coefficient is only 2.60, and is insignificantly different from zero. A similar pattern exists for bond markets. Since yield change and return are negatively related, the interaction coefficient is negative, and converges to zero when n increases. For example, the interaction coefficient is -4.74 (t=2.77) for the case of $n=0$, is -2.58 (t=2.58) for the case of n=1, and is only -1.01 (t=1.46) for the case of n=5.

As is the case in the analysis based on monthly data, the results are also mostly due to catching up with bad news. Specifically, we run the regressions in Panel B of Table 3.5 at daily frequency. The indicator Good_CDS_{it} and Bad_CDS_{it} are now replaced by their daily-frequency counterparts, Good_CDS_{it}^{d} and Bad_CDS_{it}^{d}. For country i on day t, we have $\text{Good\_CDS}_{it}^{d} = \text{Good\_CDS}_{im}$ and $\text{Bad\_CDS}_{it}^{d} = \text{Bad\_CDS}_{im}$ if day t is in month m.

As shown in Panel B of Table 3.6, the coefficient for $\text{Bad\_CDS}_{it}^{d} \times D_{it}^{n}$ is 37.97 (t=1.53) for the case of $n=0$. That is, if a country is in the bottom quintile based on its sovereign CDS return in the previous three months, then its stock index return is, on average, 37.97 basis points lower on credit-event days than on other days. The low statistical significance is likely due to the noise in daily stock returns. Note that the amount of noise decreases when the event window expands. Hence, although the interaction coefficient is expected to decrease as the event window expands, its statistical significance may increase. Indeed, for the case of $n=5$, for example, the average daily stock index return is only 11.17 basis points lower during the 11-day window surrounding credit event days, but the t-statistic increases to 2.08. For the case of $n=20$, this effect is only 5.32 basis points per day but has a t-statistic of 2.04. In contrast to these results, the catching up with good news is not detectable: the coefficient estimates for $\text{Good\_CDS}_{it}^{d} \times D_{it}^{n}$ are insignificantly different from 0. Similar patterns hold for bond markets. As shown in Panel D, the coefficients for the interaction term $\text{Bad\_CDS}_{it}^{d} \times D_{it}^{n}$ are highly significant and they decay towards zero when n increases. Moreover, the coefficients for $\text{Good\_CDS}_{it}^{d} \times D_{it}^{n}$ are insignificantly different from zero.

In summary, our evidence is consistent with the interpretation that when a sovereign credit rating or outlook change is announced, stock and bond prices catch up with the sovereign CDS market, mostly for bad news, and that most of the action occurs during the few days surrounding the credit event.

3.3.4.5 Systematic vs. idiosyncratic

What is the nature of the information that is more efficiently aggregated by the sovereign CDS market than local stock and bond markets? Is it country-specific information, or is it world-wide? A natural conjecture is that sovereign CDS investors' advantage, over local stock and bond investors, is probably their understanding of the global economy, rather than their country specific knowledge. Hence, the predictive power of the sovereign CDS market is perhaps due to its superior capacity in digesting world-wide, rather than country-specific, information.

One might think that this interpretation is somewhat inconsistent with our early evidence on credit rating and outlook changes since one might think that those changes are mostly country specific. However, this clearly is not the case. For example, Longstaff et al (2011) find that the first principal component of sovereign credit spreads explains 64% the credit spread variations in their sample. This first principle component is highly correlated with the U.S. market, and has a correlation of −74% with U.S. stock market returns, and a correlation of 61% with changes in the VIX index. That is, sovereign credit risks have a large systematic component. Intuitively, the monetary policy in the U.S. can significantly affect the creditworthiness of countries around the world. The growth of the global economy has great influences on the balance sheets of energy and raw material exporting countries. Even for the influence of natural disasters, rating agencies have long recognized its systematic nature.[15] Our conjecture is that the sovereign CDS market's advantage over local stock and bond markets is its capacity to aggregate world-wide, rather than country specific, information.

To test our conjecture that the sovereign CDS market's advantage over local stock and bond markets is its capacity to aggregate world-wide, rather than country specific, information, we decompose the monthly sovereign CDS returns into a "systematic" component and an "idiosyncratic" component, and examine which component has predictive power for future stock and bond returns. Specifically, we regress sovereign CDS returns on the average sovereign CDS returns across all countries in our sample. The regression residual is classified as the idiosyncratic component of a sovereign CDS return, which captures country-specific information. The remaining portion of the CDS return is the systematic component, which reflects world-wide information. Which component has predictive power for future stock and bond returns? To answer this, we repeat our analyses in Tables 3.2 and 3.3, using the two components as predictors. The results are summarized in Table 3.7.

As shown in the first row of Panel A, the systematic component of the CDS returns can predict future stock returns. The long-short strategy sorted by the systematic component generates 81 basis points per month (t=3.20). Adjusting for the factors in the literature leads to an alpha of 69 basis points per month (t=2.75). In contrast, there is no evidence that the idiosyncratic component has predictive power for future stock index returns. As shown in the second row of Panel A, the long-short strategy sorted by the

[15] See, e.g., *Climate Risk: Rising Tides Raise the Stakes*, Standard and Poor's, *Insights*, December 2015.

idiosyncratic component has a return of -7 basis points per month (*t*=0.21), and an alpha of 4 basis points per month (*t*=0.12). As a comparison, we report in the third row the returns of the portfolios sorted by total CDS returns.[16] It shows that both the long-short return and alpha are virtually the same as those from the sorting based on the systematic components. In other words, the predictive power of sovereign CDS returns is almost entirely from the systematic, rather than country-specific, component.

Similar results hold for bond markets. As shown in Panel B of Table 3.7, if we sort countries based on the systematic component of CDS returns, the difference in bond yield changes between the top and bottom quintiles is 11.61 basis points per month (*t*=2.78), and is 7.77 basis points per month (*t*=2.84) after accounting for known factors. In contrast, this difference in bond yield changes is 6.11 basis points (*t*=1.71), and is 3.28 basis points (*t*=1.06) after adjusting for risk factors. As a comparison, we report in the third row the results from total-CDS-return-based sorting. Similar to the results for stock returns, the comparison shows that the predictive power of the sovereign CDS return is almost entirely from its systematic component.

Our previous evidence suggests that the predictive power of the sovereign CDS market is mostly from its advantage in world-wide information. This interpretation further implies that the predictive power of the sovereign CDS market should come mostly from its ability to predict the "systematic" component, rather than the "idiosyncratic" component, of future stock and bond returns. To test this, we decompose stock and bond returns using

[16] The only difference between this row and the analysis in Table 3.2 is that the sample period here is set to be the same as that for the first two rows to make the results comparable. Since we need 12 months of data to estimate the beta for our decomposition, the sample period for this table is January 2002 to September 2015.

a simple market model. Specifically, we regress excess stock index returns on the excess returns of the global stock index, which are obtained from Kenneth French's website. The idiosyncratic component is the regression residual and the remaining portion of the stock index return is the systematic component. Similarly, the bond yield change decomposition is based on a regression of bond yield changes on the bond yield changes in the U.S., which serves as a proxy for the global market factor.[17] Consistent with our interpretation, the bottom two rows of Panels A and B show that the predictive power of the sovereign CDS returns comes almost entirely from their ability to forecast the systematic components of future stock and bond returns.

The above evidence supports the view in Longstaff, Pan, Pedersen, and Singleton (2011) that "global investors play a predominant role" in the sovereign CDS market. Our results suggest that those global investors appear to be more capable of processing world-wide information, whose implications on local stock and bond markets are only gradually appreciated by local investors.

3.4 Using the sovereign CDS market to predict real economic activities

In this section, we examine whether the sovereign CDS market can predict future real economic activities. Specifically, we run panel regressions of quarterly year over year GDP growth on the returns in the stock, bond, and sovereign CDS markets during the previous quarter, after controlling for the GDP growth in the previous quarter. The results are reported in Table 3.8. In the first column of Panel A, the coefficient for CDS return is -

[17] We also explored alternative market factors in our decomposition. For example, we used the equal weighted average return of all stock indices in our sample as the market factor for our stock regressions, and the average bond yield change across all countries in our sample as the market factor for our bond regressions. The results based on the alternative decompositions remain very similar.

1.18 (t=2.03), suggesting that sovereign CDS returns have marginal predictive power for future GDP growth. Interestingly, the coefficients for Stock return and ΔYield are 0.97 (t=2.05) and -13.66 (t=1.12). That is, the stock markets possess additional information that is relevant for predicting future GDP growth, but the information in bond markets barely has additional predictive power.

Following the analysis in the previous section, we decompose sovereign CDS returns into systematic and idiosyncratic components. Under the hypothesis that sovereign CDS investors have an advantage in analyzing world-wide information and its implications on individual countries, the marginal predictive power of sovereign CDS returns should come mostly from their systematic component. This implication is confirmed by the results in the second column. It shows that the coefficients for the systematic and idiosyncratic components of the sovereign CDS return are -4.98 (t=1.71) and 1.58 (t=0.91), respectively. That is, the unique information in the sovereign CDS return is mostly embedded in its systematic component.

We run similar regressions for the Purchasing Managers' Index (PMI), which is a monthly indicator of the manufacturing activity in private sectors. As shown in column one of Panel B, the coefficient for the CDS return is -6.10 (t=3.55). It suggests that sovereign CDS returns contain unique information that has predictive power for future PMI index. The deterioration of the creditworthiness in the sovereign CDS market predicts that the manufacturing activity will slow down in the future. Column two shows that the coefficients for the systematic and idiosyncratic components of the sovereign CDS return are -14.23 (t=2.18) and -2.29 (t=1.01), respectively. That is, similar to the result in the analysis for GDP, the unique information in the sovereign CDS return that can predict future PMI is also mostly from its systematic component.

3.5 Conclusion

We have shown that sovereign CDS markets can predict future stock returns and government bond yields. The predictive power is partly due to the sovereign CDS markets' ability to anticipate future credit rating or outlook changes, especially deterioration. Our evidence is consistent with the interpretation that the sovereign CDS market contains information, especially world-wide information, which is only gradually appreciated by stock and bond markets, especially during the few days around credit rating or outlook changes. Finally, our evidence also suggests that sovereign CDS markets contain information that can forecast future real economic activities, such as GDP growth and PMI.

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Appendix: List of countries and indices

Country	CDS	Stock		Bond		PMI	GDP
		Index name	Start	Index name	Start		
Algeria	Sep-2008						2008Q1
Angola	Oct-2009						2009Q1
Argentina	Apr-2001	MERVAL	Apr-2001				2001Q1
Austria	Jul-2001	ATX	Jul-2001	GAGB5YR	Jul-2001	Jul-2001	2001Q1
Australia	Oct-2003	AS51	Oct-2003	GACGB5	Oct-2003	Oct-2003	2003Q1
Barbados	Jul-2006						2006Q1
Belgium	Mar-2001	BEL20	Mar-2001	GBGB5YR	Mar-2001		2001Q1
Bulgaria	May-2001	SOFIX	May-2001	GBBP05	Aug-2008		2001Q1
Bahrain	Aug-2004	BHSEASI	Aug-2004				2004Q1
Belize	Jan-2010						2010Q1
Brazil	Feb-2001	IBOV	Feb-2001	GEBR5Y	Feb-2007	Feb-2001	2001Q1
Tunisia	Dec-2003	TUSISE	Dec-2003				2003Q1
Canada	Oct-2003	SPTSX	Oct-2003	GCAN5YR	Oct-2003	Oct-2003	2003Q1
Chile	Mar-2002	IGPA	Mar-2002	CLGB5Y	Jul-2014		2002Q1
China	Feb-2001	SHSZ300	Feb-2001	GCNY5YR	Jul-2005	Feb-2001	2001Q1
Hong Kong	Sep-2004	HSCI	Sep-2004	HKGG5Y	Sep-2004	Sep-2004	2004Q1
Colombia	Apr-2001	COLCAP	Apr-2001	COGR5Y	Dec-2009		2001Q1
Costa Rica	Sep-2003	CRSMBCT	Sep-2003				2003Q1
Croatia	Feb-2001	CRO	Feb-2001	HRKGGR05	Aug-2008		2001Q1
Cyprus	Aug-2002	CYSMMAPA	Aug-2002				2002Q1
Czech	Apr-2001	PX	Apr-2001	CZGB5YR	Apr-2001	Apr-2001	2001Q1
Germany	Nov-2002	DAX	Nov-2002	GDBR5	Nov-2002	Nov-2002	2002Q1
Denmark	Dec-2002	KFX	Dec-2002	GDGB5YR	Dec-2002	Dec-2002	2002Q1
Dominica	Aug-2003						2003Q1
Ecuador	Jul-2003						2003Q1
Egypt	Apr-2002	HERMES	Apr-2002			Apr-2002	2002Q1
El Salvador	Jul-2003						2003Q1
Estonia	Jul-2004	TALSE	Jul-2004				2004Q1
Fiji	Jul-2007						2007Q1
Finland	Aug-2002	HEX	Aug-2002	GFIN5YR	Aug-2002		2002Q1
France	May-2002	CAC	May-2002	GFRN5	May-2002	May-2002	2002Q1
Greece	Feb-2001	ASE	Feb-2001	GGGB5YR	Feb-2001	Feb-2001	2001Q1
Guatemala	Sep-2003						2003Q1
Iceland	Apr-2004						2004Q1
India	Aug-2003	TOTMKIN	Aug-2003	GIND5YR	Aug-2003	Aug-2003	2003Q1
Indonesia	Jan-2002	JCI	Jan-2002	GIDN5YR	Feb-2003	Jan-2002	2002Q1
Iraq	Mar-2006						2006Q1
Ireland	Feb-2003	ISEQ	Feb-2003	GIGB5YR	Feb-2003	Feb-2003	2003Q1
Israel	May-2001	TA-25	May-2001	GISR5YR	Jul-2001	May-2001	2001Q1
Italy	Mar-2001	FTSEMIB	Mar-2001	GBTPGR5	Mar-2001	Mar-2001	2001Q1
Jamaica	Oct-2003	JMSMX	Oct-2003				2003Q1
Japan	Feb-2001	TPX	Feb-2001	GJGB5	Feb-2001	Feb-2001	2001Q1
Jordan	Oct-2003	JOSMGNFF	Oct-2003				2003Q1
Kazakhstan	Feb-2004	KZKAK	Feb-2004				2004Q1
South Korea	May-2001	KRX100	May-2001	GVSK5YR	May-2001	May-2001	2001Q1

Latvia	Sep-2004	RIGSE	Sep-2004				2004Q1
Lebanon	Apr-2003	BLOM	Apr-2003			Apr-2003	2003Q1
Lithuania	May-2002	VILSE	May-2002				2002Q1
Malaysia	May-2001	TOTMKMY	May-2001	MGIY5Y	Aug-2005	May-2001	2001Q1
Malta	Aug-2004	MALTEX	Aug-2004				2004Q1
Macedonia	Oct-2011		Oct-2011				
Mexico	Feb-2001	MEXBOL	Feb-2001	GMXN05YR	Jun-2001	Feb-2001	2001Q1
Morocco	May-2001	MCSINDEX	May-2001				2001Q1
Netherlands	Sep-2003	AEX	Sep-2003	GNTH5YR	Sep-2003	Sep-2003	2003Q1
Nigeria	Jan-2007	NGSEINDX	Jan-2007			Jan-2007	2007Q1
Norway	Nov-2003	OBX	Nov-2003	GNOR5YR	Nov-2003		2003Q1
New Zealand	Jan-2004	NZSE50FG	Jan-2004	GNZGB5	Jan-2004	Jan-2004	2004Q1
Oman	Dec-2008	MSM30	Dec-2008				2008Q1
Pakistan	Aug-2004	KSE100	Aug-2004	PKRF/5Y	Aug-2004		2004Q1
Panama	Mar-2002	BVPSBVPS	Mar-2002				2002Q1
Peru	Mar-2002	SPBLPGPT	Mar-2002	GRPE5Y	Nov-2007		2002Q1
Philippines	Apr-2001	PSECOMP	Apr-2001	PDSR5YR	Apr-2001	Apr-2001	2001Q1
Poland	Feb-2001	WIG	Feb-2001	POGB5YR	Feb-2001	Feb-2001	2001Q1
Portugal	Mar-2002	BVLX	Mar-2002	GSPT5YR	Mar-2002		2002Q1
Qatar	Oct-2001	DSM	Oct-2001				2001Q1
Hungary	Apr-2001	BUX	Apr-2001	GHGB5YR	Apr-2001		2001Q1
Georgia	Jul-2015						2015Q1
Romania	Apr-2002	BET	Apr-2002	ROMGGR05	Aug-2011		2002Q1
Ghana	Jun-2008	GGSECI	Jun-2008				2008Q1
Russia	Oct-2001	INDEXCF	Oct-2001	RUGE7Y	Oct-2001	Oct-2001	2001Q1
Saudi Arabia	Mar-2007	SASEIDX	Mar-2007			Mar-2007	2007Q1
Singapore	Aug-2003	SGX	Aug-2003	MASB5Y	Aug-2003	Aug-2003	2003Q1
Slovakia	Jun-2001	SKSM	Jun-2001	GRSK5Y	Sep-2007		2001Q1
Slovenia	Mar-2002	TOP40					2002Q1
South Africa	Feb-2001	EZA	Feb-2001	GSAB5YR	Feb-2001	Feb-2001	2001Q1
Spain	Mar-2001	IBEX	Mar-2001	GSPG5YR	Mar-2001	Mar-2001	2001Q1
Serbia	Jul-2006	BELEXLN	Jul-2006				2006Q1
Sri Lanka	Jan-2008	CSEALL	Jan-2008	GGRSL5Y NTBA	Aug-2011		2008Q1
Sweden	Jul-2001	OMX	Jul-2001	GSGB5YR	Jul-2001		2001Q1
Switzerland	Jul-2007	SMI	Jul-2007	GSWISS05	Jul-2007	Jul-2007	2007Q1
Taiwan	Sep-2006	TWSE	Sep-2006	GVTW5YR	Sep-2006	Sep-2006	2006Q1
Thailand	Apr-2001	SET	Apr-2001	GVTL5YR	Apr-2001	Apr-2001	2001Q1
Trinidad and Tobago	Dec-2004						2004Q1
Turkey	Feb-2001	XU100	Feb-2001	IECM5Y	Aug-2007	Feb-2001	2001Q1
UAE	Mar-2007	DFMGI	Mar-2007			Mar-2007	2007Q1
United Kingdom	Apr-2006	UKX	Apr-2006	GUKG5	Apr-2006	Apr-2006	2006Q1
Ukraine	Oct-2002	UX	Oct-2002	GUAU5YR	Apr-2011		2002Q1
Uruguay	Jun-2002						2002Q1
US	Jan-2004	SPX	Jan-2004	USGG5YR	Jan-2004	Jan-2004	2004Q1
Venezuela	Mar-2001						2001Q1
Vietnam	Sep-2002	HCMNVNE	Sep-2002	GGVF5YR BIDV	Feb-2007	Sep-2002	2002Q1

Chapter 4 The Investment Performance, Attributes, and Investment Behavior of "Ethical" Equity Mutual Funds in the US: An Empirical Investigation[1]

4.1 Introduction

Ethical investing, more popularly known as sustainable, socially conscious, "green" or socially responsible investment (SRI), is the application of ethical as well as financial considerations or screens in investment decision-making. It is an investment strategy based on normative ethical and social values. According to Cowton (1994), ethical investing is "the exercise of ethical and social criteria in the selection and management of investment portfolios." Ethical investment has been defined as putting your money where your morals are, or investing according to your beliefs (Brownlow, 2009). Traditional investment is driven by only financial considerations, such as maximizing return or wealth, diversifying risk, and maintaining liquidity. Ethical investing is driven by societal needs and benefits and takes into account non-financial criteria, such as certain attributes of the companies in which money is invested, in addition to the financial considerations of traditional investors. Ethical considerations may include, among others, religious affiliations, beliefs, or values.[2] Knoll (2002) pointed out that ethical considerations might be a screening process or a variable in the selection process. Screens can be either negative (exclusionary) or positive

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[1] This essay is based on a joint work with Cheng-few Lee, Rutgers University and Shafiqur Rahman, Portland State University.

[2] It is notable that the roots of socially responsible investing seem to have stemmed from a religious connection – they have been traced back to the 1920s when the Methodist Church of Great Britain wished to invest in the UK stock market while avoiding companies involved in alcohol and gambling (Brownlow, 2009).

(inclusionary). Negative screening excludes companies that are incompatible with the investors' ethical values, while positive screening seeks out companies that act in a manner consistent with the investors' ethical values. Examples of negative screening are excluding companies that are engaged in gambling, pornography, production and distribution of alcohol, tobacco, and weapons, employing under-age workers, damaging the environment, and exploiting animals for cosmetics and apparels. Examples of positive screening include investing in companies that promote environmental improvement, pollution control, community engagement, energy conservation, sustainability, consumer protection, human rights, diversity, and such other stakeholder-friendly activities as well as companies serious about product safety, improved working condition for employees, seeking renewable energy to replace fossil fuels, *etc*. Ethical investing aims at rewarding ethical corporate behavior through positive screening and discouraging unethical corporate behavior through negative screening. The demand for ethical investment opportunities has been growing very rapidly. According to Global Sustainable Investment Alliance (GSIA), assets under management (AUM) of global ethical investment funds climbed to $13.6 trillion at the start of 2012, a 22 percent increase since 2010. This represents 21.8 percent of the total global AUM (Global Sustainable Investment Alliance, 2013). In the US alone, sustainable, responsible, and impact investing assets have expanded 76 percent in two years: from $3.74 trillion at the start of 2012 to $6.57 trillion at the start of 2014, according to the US SIF Foundation's latest biennial survey, the Report on US Sustainable, Responsible, and Impact Investing Trends 2014. As a result, AUM of US ethical funds now accounts for more than one out of every six dollars under professional management in the US (USSIF, 2014).

The purpose of this paper is to examine the investment performance of ethical equity mutual funds in the US using a comprehensive and integrated model. Several prior studies examined investment performance of ethical mutual funds and unit trusts in the US (Hamilton, Jo, and Statman, 1993, Statman, 2000, Bauer, Koedijk, and Otten, 2005, and Benson and Humphrey, 2008) and other countries (Mallin, Saadouni, and Briston, 1995, Gregory, Matatko, and Luther, 1997, Cummings, 2000, Tippet, 2001, Bauer, Koedijk, and Otten, 2005, Kreander, Gray, Power, and Sinclair, 2005, Beurden and Gossling, 2008, Jones, Laan, Frost, and Loftus, 2008, Renneboog, Horst, and Zhang, 2008a, and Cortez, Silva, and Areal, 2009).[3] Most of these studies examined investment performance of ethical funds employing unconditional risk-adjusted performance measures such as Sharpe's (1966) reward-to-variability ratio, Treynor's (1965) reward-to-volatility ratio, and Jensen's (1969) alpha or its multi-factor version based on Fama and French (1993) and Carhart (1997). One weakness of all these measures is their focus on the fund managers' security selection or selectivity skill only, while totally disregarding the managers' ability to time the market. A few studies examined fund managers' market timing skill using a rudimentary market timing model of Treynor and Mazuy (1966) [Gregory and Whittaker, 2007 and Renneboog, Horst, and Zhang, 2008a] or a less sophisticated model of Henriksson and Merton (1981) [Kreander, Gray, Power, and Sinclair, 2005]. However, the studies using the Treynor-Mazuy model did not correct for heteroscedasticity of regression residuals resulting from the fund manager's attempt to time the market. A comprehensive and integrated model to simultaneously capture stock selection and market timing skill has

[3] See Beurden and Gossling (2008) and Renneboog, Horst, and Zhang (2008b) for surveys of these studies.

been developed by Jensen (1972) by extending the Treynor-Mazuy model. Bhattacharya and Pfleiderer (1983) further refined the Treynor-Mazuy model, and Lee and Rahman (1990) developed the econometric methodology to apply the model in empirical investigation. This refined model has been used to examine investment performance of US equity mutual funds (Lee and Rahman, 1990, 1991) and US equity pension funds (Coggin, Fabozzi, and Rahman, 1993). These studies found evidence of security selection and/or market timing skill in a small number of funds. There is no prior research work in the extant literature examining the investment performance of ethical funds using such a refined model. This paper fills the void in the literature by examining the investment performance of a sample of ethical funds in the US using the Bhattacharya-Pfleiderer model. Another weakness of the majority of previous studies is survivorship-bias. These studies excluded funds that disappeared via merger, acquisition or liquidation. In their empirical investigation, Grinblatt and Titman (1989) and Brown and Goeszmann (1995) found survivorship-bias of approximately 0.5 percent per year, and this could overstate the performance measures to some extent. This paper is free from survivorship-bias as it uses a survivorship-bias-free database. Intuitively, we investigate the ethical mutual fund performance by developing two hypotheses:

Hypothesis 1: The ethical mutual funds tend to have a higher return by strictly screening. However, the additional ethical research requires a higher fee than that of the traditional funds. Furthermore, the ethical mutual funds tend to be managed by small mutual fund companies, therefore, the economies of scale is hard to be utilized by mutual fund managers. We will include the mutual funds' expense ratios to rule out this influence, the expense ratios can be calculated as the ratio of fund's operating expense and average dollar value of its asset under management;

Hypothesis 2: Since the high turnover ratio equates to higher brokerage transaction fees. The investment on ethical mutual funds with clear purpose should have a lower turnover rate, which is associated with a higher return. Therefore, the insignificant abnormal performance associated with ethical mutual funds may due to the effect offset by these two hypotheses.

This paper is organized as follows: section II briefly traces the development of the Bhattacharya-Pfleiderer model and discusses its superiority over other competitive models and justification for using this model in empirical investigation of investment performance of managed portfolios. Section III discusses the data and econometric methodology used in this paper, section IV discusses the empirical results, and section V concludes the paper

4.2 A Model for Security Selection and Market Timing Skill

The unconditional risk-adjusted performance measures of Sharpe's (1966) reward-to-variability ratio, Treynor's (1965) reward-to-volatility ratio, and Jensen's (1969) alpha assume that the risk level of managed portfolio under consideration is stationary through time, and these measures ignore the manager's market timing skill (*i.e.*, ability to shift the overall risk composition of the portfolio by moving into and out of segments of the market). Selling "winners" for realizing capital gains or "losers" for tax purposes and reinvesting the proceeds (not necessarily in the stocks of same risk-class) is another reason risk as measured by standard deviation (in Sharpe's reward-to-variability ratio) or beta (in Treynor's reward-to-volatility ratio) changes. Portfolio turnover of mutual funds also causes the risk of the portfolio to change. Mutual funds have an average turnover rate (*i.e.*, the percentage of a fund's holdings that change every year) of approximately 85 percent, meaning that funds are turning over or selling nearly all of their holdings every year (Barker, n.d). This results in violation of the stationarity assumption of risk made in Sharpe's or Treynor's measure. When fund managers adopt a market-timing strategy, the unconditional measure of Jensen's alpha becomes biased. Jensen (1968) acknowledged the ability of the fund managers to change the risk level of their portfolios in anticipation of broad market movements. Fama (1972) and Jensen (1972) addressed this issue and suggested a somewhat finer breakdown of performance. Fama (1972) suggested that the portfolio manager's forecasting skill could be partitioned into two distinct components: (1) forecasts of price movements of selected individual stocks (selectivity or micro-forecasting), and (2) forecasts of price movements of the general stock market as a whole (market timing or macro-forecasting). This partitioning of forecasting skills is also evident in Treynor and Black (1973) who have shown that portfolio managers can effectively separate actions related to security analysis from those related to market timing. When managers successfully time the market, the measures without controlling for market timing behavior are biased (Ferson and Schadt, 1996). Jensen (1968) demonstrated that, in the presence of market timing ability, the estimated measure of systematic risk or beta would be biased downward and the estimated performance measure (Jensen's alpha) will be biased upward. Grant (1978) explained how market timing actions would affect the results of empirical tests that focus only on micro-forecasting skill. He noted that potential market timing ability would cause the Jensen's alpha to be downward-biased and the measure of systematic risk to be upward-biased.

Admati and Ross (1985) discussed the failure of traditional measures based on CAPM (Treynor's reward-to-volatility ratio and Jensen's alpha) to evaluate the fund manager's performance in the presence of changing risk level and information asymmetry. When there is information asymmetry, the manager changes the composition of the portfolio in response to the private information he or she receives. Based on the information signal received, the manager forms his or her posterior distribution of assets' returns that is unknown to others and varies over time (depending on what the information happens to be). The true and relevant risk actually carried by the manager now changes over time though other parameters are stationary (Lee and Rahman, 1994). Admati and Ross (1985) showed that the weakness of CAPM-based measures also affects Sharpe's reward-to-variability ratio that is independent of CAPM. Intuitively, although better information implies higher expected returns, it also leads to a larger variance resulting in a lower reward-to-variability ratio for well-informed fund managers.

It is apparent that fund managers be evaluated by both selection ability and timing skill. This necessitates modeling selection and timing skill simultaneously. Market timing is common among fund managers. Same fund managers manage ethical and traditional funds, and while managing ethical funds, they are primarily driven by investment objectives and constraints of respective funds rather than their own ethical belief. They are more likely to try to time the market (in traditional as well as ethical funds) to increase portfolio returns. That means fund managers time the market for both traditional funds and ethical funds although fund managers who manage only the ethical funds may not time the market efficiency due to their own beliefs about a specific ethical mutual fund. It is, therefore, appropriate to simultaneously examine selectivity and market timing skill of ethical fund managers so that there is no model misspecification error leading up to biased estimates. However, whether they are successful market timer is an empirical question.

Using the option-pricing model, Merton (1981) and Henriksson and Merton (1981) developed a measure that permits detection and separation of selectivity and timing skills of fund managers. In their model, the fund manager forecasts whether the stock market will provide a return that is higher or lower than the risk-free rate. The forecaster does not attempt or is not able to predict by how much stocks will outperform or underperform the risk-free rate. Based on their forecasts, fund managers adjust the relative weight of the market portfolio and the risk-free asset. Merton (1981) demonstrated that the returns on the portfolio using the indicated market timing rule is the same as those that would be generated by a strategy of investing in the market portfolio and risk-free asset and acquiring free put options on the market portfolio with an exercise price equal to the risk-free rate. The forecasters in this model are not as sophisticated as those of Jensen (1972) where the fund managers have the ability to forecast how much better the superior investment will perform. The Henriksson-Merton model, on the other hand, assumes that the managers have a coarse information structure in which binary signals (up or down) are only indicative of the sign or direction (and not the size) of the excess of the market return over the risk-free rate. One weakness of the Henriksson-Merton model is that although information is measured, there is no test of whether information is being used properly (Dybvig and Ross, 1985). In their empirical analysis, Chang and Lewellen (1984) and Henriksson (1984) found a large number of negative timing coefficients reflecting irrational behavior on the part of the fund managers. In order to generate a negative timing coefficient, fund managers must possess superior information and employ it irrationally, that is, raise (lower) market risk when the signal indicates that the market will fall (rise). Connor and Korajczyk (1991) termed this behavior *perverse timing*.

Treynor and Mazuy (1966) observed that if the fund managers can forecast market returns, they will hold more high-beta stocks or a greater portion of the market portfolio when they expect the market to go up in order to increase portfolio return. Conversely, they will hold more low-beta stocks or a smaller portion of the market portfolio when they expect the market to go down in order to reduce capital losses. Thus, the portfolio return will be a nonlinear function of the return on the market portfolio. To capture this, the authors added a quadratic excess market return term to standard CAPM:

$$R_{pt} = \alpha_p + \beta_p R_{mt} + \mu_{pt} \tag{1}$$

$$R_{pt} = \alpha_p + \beta_p R_{mt} + \gamma(R_{mt})^2 + \varepsilon_{pt} \tag{2}$$

where R_{pt} is the excess (net of risk-free rate) return on the fund, R_{mt} is the excess (net of risk-free rate) return on the market portfolio, α_p is a measure of security selection skill, β_p measures the sensitivity of the fund return to the market return, γ measures fund manager's market timing skill, and μ_{pt} and ε_{pt} are random error with an expected value of zero. Thus, the fund return will be a convex function of the excess market return. Using annual returns for fifty-seven open-end mutual funds, they found that the hypothesis of no market-timing skill can be rejected with 95 percent confidence for only one of the funds.

Jensen (1972) developed a model similar to the Treynor-Mazuy model to detect selectivity and timing skill of fund managers. Jensen's measure of market timing performance calls for the fund manager to forecast the deviation of the market return from its consensus expected return. In the Jensen analysis, the forecasted return and actual return on the market are assumed to have a joint normal distribution. The fund manager receives information (not available to others in the market) about the returns to be earned on the market portfolio next period. On the basis of this information, the manager forecasts the market return. Whenever the manager's expectations concerning the market return are identical to the consensus of all market participants, the manager selects a target risk level. Whenever the manager's information is different from the consensus, the manager will revise the risk level up or down in anticipation of market movement to earn abnormal return. Jensen showed that the fund manager's market timing skill could be measured by the correlation between the forecasted and actual market return.

Bhattacharya and Pfleiderer (1983) corrected an error in Jensen's model and showed that one could use a regression technique to detect selectivity and timing. While Jensen (1972) assumes that the manager uses the unadjusted forecast of the market return, Bhattacharya and Pfleiderer (1983) assume that the manager receives a signal at the beginning of the period about the expected market return with a nonzero forecasting error and the manager adjusts the forecast to minimize the variance of the forecast error. This assumption allowed them to detect the manager's market timing ability from the correlation between the manager's forecast and the excess market return.[4] They specify a relationship in terms of observed variables that is somewhat similar to the Treynor-Mazuy model:

$$R_{pt} = \alpha_p + \theta E(R_{mt})(1 - \Psi)R_{mt} + \Psi\theta(R_{mt})^2 + \theta\Psi\varepsilon_t R_{mt} + \omega_{pt} \tag{3}$$

where

θ = the fund manager's response to information

$E(R_{mt})$ = expected excess market return

[4] See Lee and Rahman (1990) and Coggin, Fabozzi, and Rahman (1993) for details.

Ψ = the coefficient of determination (R^2) between the manager's forecast and excess market return

ε_{pt} = the error of the manager's forecast

The quadratic regression of R_{pt} on R_{mt} and $(R_{mt})^2$ allows us to detect a manager's selectivity skill from α_p. Bhattacharya and Pfleiderer (1983) show that α_p is an accurate measure of security selection ability. A manager having no security specific information will earn $\alpha_p = 0$. In this model, managers who have security specific information may also have information that permits them to time the market. The error term of eq. (3):

$$\omega_t = \theta\Psi\varepsilon_t R_{mt} + \mu_{pt} \tag{4}$$

provides the information to detect the manager's timing skill. The first term in ω_t contains the information needed to quantify the manager's timing ability. We can extract this information by regressing $(\omega_t)^2$ on $(R_{mt})^2$:

$$(\omega_t)^2 = \theta^2\Psi^2\sigma^2_{\varepsilon}(R_{mt})^2 + \zeta_t \tag{5}$$

where

$$\zeta_t = \theta^2\Psi^2(R_{mt})^2[(\varepsilon_t)^2 - (\sigma_\varepsilon)^2] + (\mu_{pt})^2 + 2\,\theta\Psi R_{mt}\varepsilon_t\mu_{pt} \tag{6}$$ [5]

This regression produces a consistent estimator of $\theta^2\Psi^2\sigma^2_{\varepsilon}$, where σ^2_{ε} is the variance of the manager's forecast error. We now divide $\theta^2\Psi^2\sigma^2_{\varepsilon}$ by the square of $\theta\Psi$, which is the estimated coefficient of $(R_{mt})^2$ in eq. (3), to obtain an estimate of σ^2_{ε}. This combined with σ^2_{π}, the variance of excess market return, allows us to estimate $\Psi = (\sigma^2_{\pi})/[\sigma^2_{\pi} + \sigma^2_{\varepsilon}] = \rho^2$, where ρ is the correlation coefficient between the manager's forecast and excess return on

[5] See Lee and Rahman (1990) for details.

the market.[6] Then we estimate ρ, which is a measure of the quality of the manager's timing skill. This model is an enhancement of the Treynor-Mazuy model, and it is the first model that analyzes the error term to detect a manager's macro-forecasting or timing skill. Such a refinement makes the model more powerful than other competitive models.

4.3 Data and Methodology

The dataset for this study consists of monthly returns for the period January 2004 through December 2013 (120 months) for a sample of sixty-seven ethical equity mutual funds in the US with no missing data for the entire sample period or until it disappeared before December 2013 due to merger, acquisition, or liquidation, or since inception through December 2013 for those funds that started after January 2004. This resulted in a maximum number of 120 monthly observations and a minimum number of 49 monthly observations. The list of funds came from US SIF – the Forum for Sustainable and Responsible Investment, and the monthly return observations and monthly total net assets were collected from the CRSP survivorship-bias-free US mutual fund database. The monthly returns are net of all management expenses and 12b-1 fees, but before deducting front- and back-end load fees. These returns are appropriate when evaluating the investment performance of fund managers without regard to whether the managed funds are load or

[6] The correlation coefficient between managers' forecast of market return and realized market return, ρ, is analogous to the Pearson product-moment correlation coefficient. We test the significance of the manager's timing skill using the following t-test for the significance of the Pearson product-moment correlation coefficient:

$$t = \rho[(n - 2)/(1 - \rho^2)]^{½}$$

This statistic is distributed approximately as t with (n – 2) degrees of freedom, where n is the number of observations based on which ρ is calculated. See Harnett and Soni (1991), pp. 503-504, for details.

no-load funds. The fund managers do not control load fees which are decided by the fund administrators, and the fund managers should not be evaluated based on returns net of load fees, if there is any. A matched sample of another sixty-seven traditional equity funds was generated from the CRSP mutual fund database to compare the performance of each ethical fund with that of a traditional counterpart. Each ethical fund was matched with a traditional fund based on asset size and investment objective. Bollen (2007) used risk exposure and age or phase of a fund's life cycle to match SRI funds with conventional funds. Funds with same investment objectives are likely to be in the same risk class and apparently have the same risk exposure. However, it makes more sense to match funds and compare and contrast investment performance of fund managers based on asset size or AUM rather than fund age. The matched sample is also free from survivorship-bias as the sample includes funds that disappeared from the database before December 2013—the end of sample period—because of merger, acquisition, or liquidation. Sixty-seven ethical funds along with their investment objectives are listed in Table 4.1 and sixty-seven traditional funds along with their investment objectives are listed in Table 4.2. The monthly return on the CRSP value-weighted index including dividends is used for market return. Monthly observations of the 91-day Treasury bill rate are used as a proxy for the risk-free rate.

To compare results, we examined the fund managers' investment performance using both the Treynor-Mazuy and the Bhattacharya-Pfleiderer model. It is necessary to correct for heteroscedasticity in both models. In the Treynor-Mazuy model, the error term exhibits conditional heteroscedasticity because of the fund manager's attempt to time the market, even though security returns are assumed to be independent and identically distributed through time. To correct this, following Breen, Jagannathan, and Ofer (1986), and Lehmann and Modest (1987), Coggin, Fabozzi, and Rahman (1993) used heteroscedasticity-consistent covariance matrix estimators proposed by White (1980), Hansen (1982), and Hsieh (1983). Long and Ervin (2000) found this estimator to have weak small sample properties often resulting in incorrect inferences. MacKinnon and White (1985) introduced three alternative heteroscedasticity-consistent covariance matrix estimators that are all asymptotically equivalent to the estimator proposed by White (1980) but typically have strong small sample properties. MacKinnon and White (1985) and Long and Ervin (2000) examined the performance of these estimators in small samples using Monte Carlo simulations in regression models and strongly recommended using the alternative known as HC3 if the sample size is less than 250. We used the HC3 estimator to correct for heteroscedasticity in the Treynor-Mazuy model. (See appendix B for the formula for HC3). In the Bhattacharya-Pfleiderer model, the disturbance terms in eq. (3) and (4) are heteroscedastic, and standard regression technique does not produce the most efficient estimates. Following Lee and Rahman (1990), we use the GLS procedure to obtain efficient estimates of parameters by taking into account the changing variances of the error terms. First, we divide all the variables of eq. (3) by the variance of error term in eq. (3) and all the variables of eq. (4) by the variance of error term in eq. (4).[7] We then apply OLS regression to the transformed observations of eq. (3) and (4) to obtain more efficient estimates. The significance tests reported in the next section are based on heteroscedasticity-adjusted t-statistics.

One weakness of the Bhattacharya-Pfleiderer model is its failure to detect negative or inferior market timing (Hunter and Coggin, 1993). Bhattacharya and Pfleiderer (1983)

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[7] These variances are presented in the Appendix A.

argued that negative correlation between the prediction and realization of market would imply that the fund manager possessed timing information that had positive value but that the manager was misguided by its application. Another manager would do well by shorting the position of the well-informed but misguided manager. Similar to Coggin, Fabozzi, and Rahman (1993), we rule out the possibility of presence in the market of well-informed but foolish managers and as such ignore the negative market timing. Similar to Coggin, Fabozzi, and Rahman (1993), we resolve this issue by examining the sign of the coefficient of the squared excess market return in eq. (3). Intuitively, in the spirit of the Treynor-Mazuy model, the sign of this coefficient is indicative of the nature of the fund manager's timing skill. If this coefficient is negative, we designate timing skill (as measured by ρ) to be poor or negative. This modification makes the model more realistic. A similar adjustment of the Bhattacharya-Pfleiderer model was implicitly introduced in Jagannathan and Korajczyk (1986).

4.4 Empirical Results

Table 4.3 presents descriptive statistics – average returns, betas, variances, skewness and kurtosis of monthly returns for the ethical funds in our sample and their matching traditional funds. Mean value of average monthly returns for all ethical funds is 0.7506 percent which is higher than that of average monthly returns of 0.6317 percent for all traditional funds. Average returns of ethical funds vary from 0.3575 percent to 1.5403 percent, while average returns of traditional funds vary from -1.8826 percent to 1.7975 percent. Mean value of variances of returns for traditional funds (0.003017239) is higher than that for ethical funds (0.002387104). These variances range from 0.000305 to 0.004678 for ethical funds and from 0.000109 to 0.018142 for traditional funds. Mean value of betas of ethical and traditional funds are 1.000964179 and 0.965604627, respectively. These betas range from 0.94844 to 1.06081 for ethical funds and from 0.70893 to 1.20816 for traditional funds. Mean value of skewness of returns for traditional funds (-0.63075) is lower than that for ethical funds (-0.75332). Average skewness varies from -1.89976 to 0.050448 for ethical funds and from -1.46823 to 0.770109 for traditional funds. Mean value of kurtosis of returns for ethical funds (2.36682) is higher than that for traditional funds (1.720394). Average kurtosis varies from 0.069931 to 8.462671 for ethical funds and from -0.65102 to 4.282699 for traditional funds. It appears that the ethical funds in our sample have in general higher average returns, lower variances, higher betas, higher skewness and higher kurtosis than their traditional counterparts. The difference in those statistics may due to different reasons, for example, the matching criteria for matching ethical mutual funds to the traditional mutual funds.

As discussed earlier, the risk dimension (systematic as well as total risk) of a mutual fund changes over time because of portfolio turnover resulting from the search for mispriced securities and/or market timing efforts. Betas and variances of funds presented in Table 4.3 are calculated assuming stationarity of risk measures during the sample period. It is not worthwhile to compare and contrast the ethical and traditional funds based on these static measures and an average return without adjusting for a time-varying risk measure. Now we turn to a more meaningful comparison of performance of the ethical funds and their traditional counterparts based on dynamic risk-adjusted measures that allow for nonstationarity of risk measures.

Table 4.4 presents summary empirical results from employing the Treynor-Mazuy model and the Bhattacharya-Pfleiderer model to the time series of monthly returns of the ethical and traditional equity mutual funds. These results show some evidence of selectivity and market timing at the individual fund level. There are some noticeable differences between the Treynor-Mazuy model and the Bhattacharya-Pfleiderer model in detecting abnormal performance of ethical as well as traditional funds. Thirty-three out of sixty-seven ethical funds have a positive selectivity measure of the Treynor-Mazuy model, only two of which are statistically significant at the .05 level. Twenty-three out of sixty-seven traditional funds have a positive selectivity measure of the Treynor-Mazuy model, only five of which are statistically significant at the .05 level. Thirty-four ethical and forty-two traditional funds have a negative selectivity measure of the Treynor-Mazuy model, and these measures are statistically significant at the .05 level for seven ethical and seventeen traditional funds. Twenty-seven ethical and thirty-seven traditional funds have a positive timing measure of the Treynor-Mazuy model, and these measures are statistically significant at the .05 level for two ethical and ten traditional funds. For the Bhattacharya-Pfleiderer model, thirty-five ethical funds have a positive selectivity measure, only two of which are statistically significant at the .05 level, and twenty-nine traditional funds have a positive selectivity measure, only six of which are statistically significant at the .05 level. Thirty-two ethical and thirty-eight traditional funds have a negative selectivity measure of the Bhattacharya-Pfleiderer model, and these measures are statistically significant at the .05 level for seven ethical and seventeen traditional funds. Twenty-seven ethical and thirty-seven traditional funds have a positive timing measure of the Bhattacharya-Pfleiderer model, and these measures are statistically significant at the .05 level for nine ethical and eighteen traditional funds. Fifteen ethical funds have both a positive selectivity and timing measure of the Treynor-Mazuy model, and two of those funds have a statistically significant selectivity and timing measure. Twenty-two traditional funds have both a positive selectivity and timing measure of the Treynor-Mazuy model, and three of those funds have a statistically significant selectivity and timing measure. Thirteen ethical funds have both a positive selectivity and timing measure of the Bhattacharya-Pfleiderer model, and only one of those funds has a statistically significant selectivity and timing measure. Twenty-two traditional funds have both a positive selectivity and timing measure of the Bhattacharya-Pfleiderer model, and six of those funds have a statistically significant selectivity and timing measure. The result that a small number of ethical and traditional funds have a statistically significant selectivity and timing measure in either model implies that the funds do exhibit some degree of specialization in one or the other forecasting skill. These results complement those of Baker *et al.* (2010), Fama and French (2010), Berk and Binsbergen (2015), and Pastor *et al.* (2015) who provide evidence for the existence of investment skill among fund managers and Kacperczyk *et al.* (2014) who provide evidence that managers demonstrate timing skill in bad times and selectivity skill in good times.

The results show that traditional funds have more abnormal (superior as well as inferior) selectivity performance than their ethical counterparts. Restricted investment opportunities because of screening criteria require managers of the ethical funds to be more efficient and disciplined in picking "winners" and avoiding "losers" to keep their transaction costs low and portfolio return reasonably high.[8] The enlarged boundary of the unrestricted feasible investment opportunity set makes managers of traditional equity funds

[8] The alternative explanation will be investigated in the future research we have mentioned in the last section. The ethical mutual fund investors tend to be more risk averse and require a higher return. If they select the specific mutual fund by their peculiar beliefs, the transaction fees for the screening should be higher than that of traditional funds.

wander around unsuccessfully searching for mispriced assets and thereby generates too many transaction costs that drives down their portfolio returns. However, ethical funds have less success in market timing than their traditional counterparts in both models. It appears that both traditional and ethical funds do not outperform the market judged by risk-adjusted performance measures, as neither group has a large number of funds demonstrating superior performance on a risk-adjusted basis. Our results are consistent with those of prior studies of investment performance of managed portfolios. (See, for example, Jensen, 1968, Kon, 1983, Chang and Lewellen, 1984, Henrikkson, 1984, Cumby and Glen, 1990, Lee and Rahman, 1990, Connor and Korajczyk, 1991, Coggin, Fabozzi, and Rahman, 1993, Elton *et al.*, 1993, Grinblatt and Titman, 1994, Malkiel, 1995, Carhart, 1997, Daniel *et al.*, 1997, Pollet and Wilson, 2008, and Benos and Jochec, 2011). These results are also consistent with the efficient market hypothesis, which states that no investors (individual or institutions) can consistently generate superior risk-adjusted returns.

In a recent paper, Amihud and Goyenko (2013) show that R^2 from regression of a fund's returns on factor returns in a multifactor model can be used as a proxy for a mutual fund's selectivity performance usually measured by regression intercept or alpha. R^2 is the proportion of the fund return variance that is explained by the variation in these factors; thus, lower R^2 means that the fund tracks them less closely. Selectivity is thus measured by $1 - R^2$, the proportion of the fund's variance that is due to idiosyncratic risk or multifactor tracking error variance. If lower R^2 helps improve the mutual fund managers' selectivity or stock picking performance, R^2 should be negatively related to alpha, and they find a statistically significant negative correlation between R^2 and alpha. They added quadratic excess market return to the multifactor model to test if timing, the other measure of fund performance, and R^2 are any way related. They found no evidence that a fund's lower R^2 reflects market timing and concluded that market timing and R^2 are unrelated. However, they did not examine if adding quadratic excess market return to the multifactor model to account for market timing materially affects the negative correlation between R^2 and alpha. In the presence of market timing, alpha is a biased measure of selectivity performance (Jensen, 1968, Grant, 1978, and Ferson and Schadt, 1996). Another weakness of Amihud and Goyenko's (2013) methodology is that while adding quadratic excess market return to the multifactor model to capture manager's timing skill, they did not correct for heteroscedasticity of regression residuals. In Appendix C, we briefly discuss Amihud and Goyenko's (2013) model and methods for evaluating mutual fund performance. In addition, in this Appendix, we also discuss the weakness of using OLS R-square instead of using GLS R-square as we have done in this paper. As mentioned earlier, the error term in a model with a quadratic term exhibits conditional heteroscedasticity (Lee and Rahman, 1990, and Coggin, Fabozzi, and Rahman 1993). We extend Amihud and Goyenko's (2013) work by examining the correlation between the regression intercept or alpha and R^2 from regression of eq. (2) of the Treynor-Mazuy model and eq. (3) of the Bhattacharya-Pfleiderer model with correction for heteroscedasticity.

Table 4.5 presents the estimated correlation coefficients between alpha and R^2 for alternative models. The results are not decisive; at the best they are mixed. The more specific information for R^2 and alpha for each of ethical and traditional mutual funds are presented in Appendix D. After taking the market timing into consideration, for ethical funds, the correlation between R^2 and alpha is significant negative in the Treynor-Mazuy and the Bhattacharya-Pfleiderer model. These results are consistent with those of Amihud and Goyenko (2013) and imply that the negative relation between R^2 and alpha still holds in the presence of fund manager's market timing activities. However, our results for traditional funds seem inconclusive and are inconsistent with those of Amihud and Goyenko (2013). For traditional funds, the correlation between R^2 and alpha is significant positive in the Treynor-Mazuy model, and negative, but not significant, in the Bhattacharya-Pfleiderer model. Table 4.4 reveals that traditional funds in our sample have more abnormal (superior as well as inferior) performances than their ethical counterparts. It is conceivable that power of R^2 to serve as a proxy for selectivity in the presence of market timing weakens as the sample becomes disperse with more abnormal performances on the upside and downside. There is one caveat worth noting regarding the proxy selectivity. Amihud and Goyenko's (2013) suggestion to consider $1 - R^2$ as an easily calculable and intuitive alternative to directly estimating selectivity using a risk-adjusted performance measure has its shortcoming. The proxy selectivity measure would simply rank funds based on the magnitude of $1 - R^2$ without taking into account whether the abnormal (superior or inferior) performance is statistically significant. It is evident from Table 4.4 that all abnormal performances are not necessarily statistically significant. $1 - R^2$ pays attention to size only, but not the quality of performance. This measure fails to discriminate between statistically significant and insignificant abnormal performance and considerably diminishes the effectiveness of this simple measure in evaluating investment performance of mutual funds.

We employed parametric matched-pairs t-test and nonparametric Wilcoxon matched-pairs signed-rank test to investigate if ethical funds and traditional funds differ significantly in terms of risk-adjusted performance measures. Table 4.6 presents p-values for these tests. Both the matched-pairs t-test and the Wilcoxon matched-pairs signed-rank test fail to reject the null hypothesis of no significance difference between ethical and traditional funds in the timing measure of the Treynor-Mazuy model and both the selectivity and timing measure of the Bhattacharya-Pfleiderer model at the .05 level. However, both the matched-pairs t-test and the Wilcoxon matched-pairs signed-rank test reject the hypothesis of no significant difference between ethical and traditional funds in the selectivity measure of the Treynor-Mazuy model at the .05 level. As discussed earlier, the Bhattacharya-Pfleiderer model of measuring investment performance of managed portfolios is more robust, econometrically and methodologically superior to, and an improvement over the Treynor-Mazuy model. It appears that empirical results based on the Bhattacharya-Pfleiderer model are consistent with those of prior studies (Hamilton, Jo and Statman 1993, Mallin, Saadouni, and Briston, 1995, Goldreyer, Ahmed, and Diltz, 1999, Statman, 2000, Kreander, Gray, Power, and Sinclair, 2005, Geczy, Stambaugh, and Levin, 2006, Bauer, Koedijk, and Otten, 2005, Bauer, Derwall, and Otten, 2007, and Jones, Laan, Frost, and Loftus, 2008), which found that ethical funds perform no worse than their traditional counterparts. However, we observe that there are slightly more outliers (superior and inferior performer) in traditional funds than in ethical funds. The Bhattacharya-Pfleiderer model used in this paper has resolved all methodological and econometric issues that confound the empirical results of the previous studies, and our results are free from any specification error. Moreover, our results are free from survivorship-bias that partially distorts the empirical results of the prior studies.

Ethical mutual funds are at an apparent disadvantage compared to traditional mutual funds because the ethical screening process reduces the set of stocks available for efficient diversification and risk-reduction. It is possible to improve the efficient frontier and further reduce systematic risk by adding stocks from the enlarged global market to the portfolio, because stocks in a larger sample are likely to be uncorrelated, less positively correlated, or somewhat negatively correlated (Solnik, 1974). However, a subset of stocks from the enlarged global market may not pass an ethical fund's screening criteria test, and the manager of an ethical fund may encounter "lost opportunity." This smaller asset universe in the portfolio formation process may negatively affect an investor's efficient frontier and risk-reduction via diversification. The empirical evidence in this paper and other previous studies that ethical funds match the performance of traditional funds on a risk-adjusted basis goes against conventional wisdom, which states that limited opportunity for risk reduction via diversification along with incremental expenses associated with implementing the ethical screening process and monitoring the acceptable companies to ensure reasonable compliance with designated ethical values continuously will result in lower risk-adjusted return for ethical funds compared to traditional funds with unrestricted investment and diversification opportunities. Advocates of ethical investing may argue that competitive returns to ethical funds arise because screening tools allow fund managers to identify the best companies in terms of potential for profits (Cortez, Silva, and Areal, 2009).

The empirical findings of this paper have important implications for investors of ethical funds. Ethical funds may have a diverse clientele base including "devoted" ethical investors who are willing to sacrifice a fraction of risk-adjusted return for ethical values and "profit-maximizing" ethical investors (or so-called "bargain hunters" in ethical investing) who are reluctant to settle for risk-adjusted returns lower than those of a traditional fund in a comparable risk class. The empirical results of this paper are good news for both of these investors. Devoted ethical investors do not have to sacrifice returns to invest in ethical funds, and profit-maximizing ethical investors may also get what they want.

4.5 Summary and concluding remarks

The demand for ethical investing has been growing very fast in recent decades and along with it, assets under management of ethical equity mutual funds are experiencing phenomenal growth. It is of utmost importance to evaluate the performance of managers of ethical funds using risk-adjusted performance measures for managed portfolios so that investors of ethical funds can select appropriate funds based on their risk-tolerance and investment objectives. The performance of ethical funds should be compared to that of traditional funds so that investors can determine if they have to sacrifice a fraction of risk-adjusted return for adhering to cherished ethical values. This paper examines investment performance of a sample of US equity ethical funds and compares their performance to that of a matching sample of traditional funds selected based on fund size and investment objective. This paper employs a sophisticated model that resolves all methodological and econometric issues confounding the empirical results of the previous studies of investment performance. Using a survivorship-bias-free data base from the US market, this paper compares and contrasts investment performance of ethical and traditional funds. The empirical results presented in the paper demonstrate that ethical funds perform no worse than their traditional counterparts, although ethical and traditional funds as a group do not outperform the market, which is consistent with prior studies of mutual fund performance.

The ability of the ethical funds to match the performance of the traditional funds implies that ethical fund investors are not making a financial sacrifice as a price for adhering to their precious ethical values. We also find that not many ethical and traditional funds exhibit superior security selection skill and/or market timing skill, although we notice that traditional funds have more abnormal (superior as well as inferior) performance relative to the market. These results have important implications for investors of ethical funds regardless of their preferred utility maximization formula, *i.e.*, whether they are "dedicated" ethical or "profit-maximizing" ethical investors.

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Appendix A: The derivation of the variances of error terms

This Appendix shows the derivation of the variances of error terms in eq. (3) and eq. (4).

The variance of the error terms in eq. (3) is

$$\sigma^2_{\omega} = \theta^2\Psi^2\sigma^2_{\varepsilon}(R_{mt})^2 + \sigma^2_{\mu} \tag{A1}$$

The variance of the error terms in eq. (4) is

$$\sigma^2_{\zeta} = 2\theta^4\Psi^4\sigma^4_{\varepsilon}(R_{mt})^4 + 2\sigma^4_{\mu} + 4\theta^2\Psi^2\sigma^2_{\varepsilon}(R_{mt})^2\sigma^2_{\mu} \tag{A2}$$

Eq. (A2) is derived as follows:

$$\sigma^2_{\zeta} = [\theta^2\Psi^2(R_{mt})^2]^2\text{var}(\varepsilon_t^2 - \sigma_{\varepsilon}^2) + \text{var}(\mu_{pt})^2] + (2\theta\Psi R_{mt})^2\text{var}(\varepsilon_{pt}\mu_{pt})$$

$$= \theta^4\Psi^4(R_{mt})^4\text{var}(\varepsilon_t^2) + \text{var}(\mu_{pt})^2] + 4\theta^2\Psi^2(R_{mt})^2\sigma^2_{\varepsilon}\sigma^2_{\mu}$$

$$= 2\theta^4\Psi^4\sigma^4_{\varepsilon}(R_{mt})^4 + 2\sigma^4_{\mu} + 4\theta^2\Psi^2\sigma^2_{\varepsilon}(R_{mt})^2\sigma^2_{\mu}$$

See Lee and Rahman (1990) for details.

Appendix B: The alternative methods to deal with heteroscedasticity residuals

This appendix presents the heteroscedasticity consistent covariance matrix estimator, which has been used in recent years to get the consistent estimation of the covariance matrix of the parameter estimates when the heteroscedasticity structure is unknown or misspecified. While (1980) first documented this concept known as HC0. Davidson and MacKinnon (1993) documented HC1, HC2, and HC3, which are the improvements of HC0. The heteroscedasticity consistent covariance matrix estimator can be expressed as

$$\sum = B^{-1}MB^{-1} \tag{B1}$$

Where B is the Hessian matrix and M is the outer product of gradient with or without adjustment.

$$M_{HC0} = \sum_{t=1}^{T} g_t g_t' \tag{B2}$$

Where T is the sample size and g_t is the gradient vector of t th observation.

$$M_{HC1} = \frac{T}{T-k} \sum_{t=1}^{T} g_t g_t' \tag{B3}$$

Where k is the number of parameters.

$$M_{HC2} = \sum_{t=1}^{T} \frac{g_t g_t'}{1 - h_{tt}} \tag{B4}$$

$$M_{HC3} = \sum_{t=1}^{T} \frac{g_t g_t'}{(1 - h_{tt})^2} \tag{B5}$$

Where h_{tt} is the leverage defined as $h_{tt} = j_t'(\sum_{t=1}^{T} j_t j_t')^{-1} j_t$, where j_t is the t th observed regressors in column vector form for OLS model, the derivative vector of the t th residual w.r.t the parameters for AR error model, and the gradient of the t th observation (g_t) for GARCH or heteroscedasticity model. Lee and SIN (2016) have discussed this estimator in further detail.

Appendix C: R-square approach to mutual fund performance[9]

Amihud and Goyenko (2013) use R-square as a predictor of fund performance. They use Fama and French (1993) and Carhart (1997) as a benchmark model, and get R-square estimates:

[9] This Appendix is a methodology summary of Amihud and Goyenko (2013). In addition, we also discuss the potential weakness of using OLS R-square instead of GLS R-square, which is used in this paper.

$$1 - \mathrm{R}^2 = \frac{\mathrm{RMSE}^2}{\mathrm{VARIANCE}} = \frac{\mathrm{RMSE}^2}{\text{Systematic Risk}^2 + \mathrm{RMSE}^2} \qquad (C1)$$

RMSE^2 is the idiosyncratic volatility. The volatility of the residual from the Fama and French (1993) and Carhart (1997) four factors model and Systematic Risk^2 is the return variance that is due to the benchmark indexes' risk. They use $1 - \mathrm{R}^2$ as a measure of selectivity. Therefore, the selectivity is greater if the fund's idiosyncratic volatility is higher relative to its total variance. They found R^2 and measures of market timing are unrelated. The authors examine a strategy that predicts fund performance base on the fund's lagged R-square and alpha. The procedure produces twenty-five portfolios with an equal number of funds in each. As the empirical evidence shows lower R-square produces higher alpha. The long-short portfolio of R-square produces annual alpha 2.052% (t=2.68). When adding back the monthly expenses to the excess returns, the performance is still significantly better for lower R-square funds.

Following Daniel et al. (1997), the authors use two measures of fund performance: (1)"Characteristics Selectivity" (CS), the difference between the weighted average return of the previously disclosed fund stock holdings and the weighted average return on one of the 125 passive benchmark portfolios that is matched to each stock in the fund portfolio based on the market capitalization, B/M and prior-year return, the weights being those of the stocks that constitute the fund's previously-disclosed holdings, and (2) "Characteristics Timing" (CT), the difference between the weighted return on the 125 characteristics portfolios in month t where the weights are those of the stocks with similar characteristics in the fund in month t-1. Thus, if R-square is a measure of the fund manager's selectivity, it should predict performance based on CS not on CT.

The authors use CS as dependent variables to estimate the following regression:

$$CS_{j,t} = \gamma_t TR^2_{j,t-1} + \delta_{1t} Expenses_{j,t-1} + \delta_{2t} log(TNA)_{j,t-1} + \delta_{3t} [log(TNA)]^2_{j,t-1}$$
$$+ \delta_{4t} Turnover_{j,t-1} + \delta_{5t} log(Fund\ Age)_{j,t-1}$$
$$+ \delta_{6t} log(Manager\ tenure)_{j,t-1} + \sum_{n=1}^{9} \lambda_{nt} StyleDummy_{j,n,t-1}$$
$$+ e_t \qquad (C2)$$

Changing $CS_{j,t}$ to $CT_{j,t}$, we can get a similar regression. The logistic transformation is applied:

$$TR^2 = \log\left(\frac{\sqrt{R^2 + c}}{1 - \sqrt{R^2 + c}}\right) \qquad (C3)$$

where c=0.5/n, and n is the sample size. According to the empirical results, the authors find $\gamma < 0$, which confirms that lower R-square indicates greater selectivity enhancing the fund performance measure by CS. No relation is found for γ measuring by CT. By changing the dependent variable from CS or CT to alpha, the author got a regression similar to eq. (20). The empirical results that $\gamma < 0$ and significant for regression when alpha is the dependent variable confirm the hypothesis that alpha is higher for funds with lower a R-square.

After a robustness check, the authors conclude that the fund's R-square is a significant predictor of its subsequent performance, measured by the fund's alpha. In their paper, they use OLS R-square instead of GLS R-square, which is used in our paper. The potential weakness of using OLS R-square is that OLS R-square is larger than GLS R-square. In addition, GLS R-square gives a more precise location estimate than OLS R-square estimate. Lewellen *et al.* (2010) have discussed this issue in some detail.

Appendix D: List of Alpha and R-square estimates

In this Appendix, we present alpha and R-square estimates for both ethical mutual funds and traditional mutual funds as follows:

Ethical Funds	Alpha		R-Square	Traditional Funds	Alpha		R-Square
ADJEX	6.63606		0.9631	ABBIX	-30.0263	*	0.9944
AHRAX	-11.5786		0.9892	ACIIX	-10.6312	*	0.9742
ARGFX	8.31053	*	0.9556	ADJPX	-2.18846		0.9217
CAAAX	-35.9713	*	0.9969	AGWYX	-0.14168		0.8969
CAACX	-14.9299		0.9937	AVGIX	-2.51516		0.9463
CAAPX	12.29666	*	0.9733	BIBDX	0.28681		0.8449
CALCX	-5.53696	*	0.9528	CLGYX	3.30037		0.8956
CCACX	3.17351		0.9685	CLVLX	-72.303	*	0.9972
CCAFX	5.0241		0.9686	CNVBX	-6.98271		0.9556
CCLAX	-4.50814		0.9531	DSCVX	9.68023	*	0.9359
CCVAX	2.9868		0.9701	DXDDX	-2.39284		0.7728
CEGIX	-1.27811		0.9707	EMG	11.99682	*	0.9763
CEYIX	-3.89176		0.9895	EVX	-0.19505		0.9287
CIEYX	13.60922		0.8639	FCLTX	15.23052	*	0.9694
CISIX	-0.43854		0.9931	FGADX	-0.39669		0.5435
CMAAX	-13.7214	*	0.9884	FKASX	8.27699	*	0.9572
CMACX	-16.3186	*	0.9883	FMCAX	5.92561		0.9662
CMICX	-31.5295	*	0.9951	FMDBX	33.88719		0.9795
CMIFX	-20.0464		0.995	FMPTX	5.39997		0.9605
CSCCX	1.41774		0.9718	FSPCX	3.7963		0.9535
CSECX	-12.6955		0.9894	FXZ	1.69134		0.9005
CSIEX	-7.64613		0.9894	GEPSX	6.39836		0.9869
CSVIX	4.60653		0.9719	HAABX	-21.6898		0.996
CSXAX	-5.58447		0.9931	HFMRX	11.72654		0.8022
CSXCX	-15.5304		0.9931	HTCSX	-10.5547		0.9746
CVALX	-14.9001		0.9953	IDROX	1.61461		0.8488
DIEQX	-2.14391		0.9931	IOEIX	-19.0074	*	0.9848
DSEFX	-6.76141		0.9931	IYEAX	-6.82983		0.8552
DSEPX	-0.7823		0.9929	JORRX	17.96206	*	0.9457
DSFRX	-3.0982		0.993	LCEVX	-7.362		0.9845
GCEQX	-17.4146		0.9925	LPCAX	-7.72265	*	0.7793
MGNDX	6.90973		0.9859	LPEIX	-0.40102		0.8031
MMDEX	10.59045		0.9857	LTEIX	-15.7342	*	0.9899
MMSCX	5.629		0.9541	LTWKX	-20.8331	*	0.98
MMSIX	6.539		0.9543	MMUGX	-2.10265		0.9558

MVIAX	-10.2111		0.986	MTHIX	-1.2528		0.8829
MVIIX	-9.24198		0.9847	MTHRX	-2.78872		0.8806
MYPVX	-17.5789		0.995	NECCX	12.21348		0.9928
NBSLX	8.81743		0.9645	NMGAX	3.81623		0.779
NBSRX	-0.34802		0.9868	NMGCX	1.33895		0.7804
NBSTX	-1.31261		0.9867	NYVBX	-25.2271	*	0.9923
NRAAX	21.73388		0.8781	OGNAX	-9.07486	*	0.8842
NRACX	16.92342		0.8781	OGNIX	-8.92855	*	0.8842
NRARX	20.02576		0.8785	OIBHX	-2.65791		0.9824
PARMX	9.12909		0.9817	OISGX	5.81253		0.9709
PARSX	4.67224		0.9494	PIXDX	19.55225	*	0.9841
PARWX	9.8109		0.978	PLVBX	-37.3167	*	0.9888
PRBLX	-4.03993		0.9858	PLVCX	-11.6971		0.9936
PWGIX	5.20472		0.9809	PPXJX	-104.25	*	0.996
PXGRX	2.83316		0.9807	RDLFX	6.63444		0.9771
PXSCX	9.42249		0.826	REDAX	-6.93199		0.9437
PXSIX	9.86835		0.8272	RMOCX	3.79252		0.9444
PXSRX	9.13226		0.8255	RSGEX	1.9977		0.9872
PXWEX	-32.3327	*	0.9888	RYIYX	-3.53106	*	0.5197
PXWGX	6.93467		0.9779	RYMZX	-3.54863	*	0.6551
PXWIX	-32.6699	*	0.9906	RYSJX	-1.84456		0.6805
SRIAX	1.20697		0.9276	SEA	-0.04653		0.4389
SRICX	0.2502		0.9273	SECGX	-7.81029		0.9856
SRIDX	1.44696		0.9281	SEIAX	-61.1464	*	0.991
SRIGX	1.17322		0.9277	SFISX	-7.91687	*	0.9284
TICRX	8.97117		0.9976	SLEAX	-15.4348	*	0.9851
TISCX	6.40618		0.9975	SSCPX	1.29513		0.9729
TRPSX	22.67786		0.9715	STDIX	7.733		0.9548
TRSCX	-0.83191		0.9975	TCGCX	5.82382		0.9686
WAEGX	-0.75311		0.971	TWHIX	1.42919		0.9554
WASOX	8.47049		0.7644	VBCVX	3.47903		0.9711
WSEFX	-13.3194		0.9897	VSOIX	4.73275		0.9351

Table 2. 1 Summary statistics

This table presents the summary statistics of *CDS spread* and *CDS return*. *CDS spread* is the daily sovereign CDS spread, and is from Markit. Following O'Kane (2008), we compute the *CDS return* from the *CDS spreads* on the 20th of a month and on the 19th of the next month.

	Mean	**Std Dev**	**1st**	**25th**	**50th**	**75th**	**99th**	**Obs**
CDS spread (bps)	240.56	555.71	1.74	36.66	119.28	276.43	1960.15	12193
CDS return (%)	-0.02	2.59	-6.64	-0.37	-0.01	0.22	7.83	12065

Table 2. 2 Summary of Characteristics

This table presents characteristics of the excess monthly return of momentum quintile portfolio for formation period – 3 months and holding period – 1 month over the sample period from January 2001 to September 2015. Countries are sorted into 5 groups based on their past 3-month sovereign CDS returns. Countries in group P1 (P5) have lowest (highest) CDS returns, i.e., their creditworthiness improved (deteriorated) the most, according to the sovereign CDS market. Then, for each group, we form an equal-weighted portfolio of stock indices for the countries in the group. The quintile 1 portfolio – the loser portfolio (i.e., the creditworthiness of the underlying countries improved the most), which contains the 20% of sovereign CDS with worst losses, and quintile 5 – winner portfolio (i.e., the creditworthiness of the underlying countries deteriorated the most), which contains the 20% of the sovereign CDS with the largest gains. Long-short is the zero-investment winner-minus-loser portfolio which is long the quintile 5 and short the quintile 1 portfolio. Skewness(m) denotes the full-period realized skewness of the monthly log returns to the portfolios. T-statistics are based on standard errors that are Newey-West (1987) adjusted with 12 lags. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Return statistics	**Momentum quintile portfolios (%)**					**P5 - P1 (%)**	**Market (%)**
	1	*2*	*3*	*4*	*5*		
Mean return	-0.26	-0.075	0.00	0.00	0.30	0.56***	-0.01
σ	0.15	0.07	0.06	0.07	0.22	0.17	0.10
t-statistics	-1.80	-1.01	0.01	0.00	1.37	3.31	-0.10
skewness (m)	-0.76	-0.47	1.62	1.28	2.6	2.42	1.44

Table 2. 3 Cross-sectional momentum strategy of sovereign CDS

Panel A presents average monthly momentum returns (with the t-statistics in the parenthesis) of sovereign CDS for formations periods (*n* = 1, 3, 6, and 9) and holding periods (*h* = 1, 3, 6, and 9). Long-short is the zero-investment winner-minus-loser portfolio which is long the quintile 5 and short the quintile 1 portfolio. The average monthly returns are in percentage. Panel B presents the long-short portfolio returns by extending the formation periods-*n* to 48 months. Panel C reports the results from regressing the monthly returns of the long-short portfolio, P5-P1, on various factors for the full sample. MKT_SCDS is the monthly return of the equal-weighted portfolio of sovereign CDS. MOM_stock is the momentum return for stock indices, with 3-month formation period and 1-month holding period. MKT_stock is the monthly return of the equal-weighted portfolio of stock indices. SMB and HML are the risk factors in Fama and French (1993). SMB is the small-minus-big factor which accounts for the spread in returns between small and large-sized firms based on firms' market capitalization. HML is the high-minus-low factor which accounts for the difference in returns between high book-to-market ratio and low book-to-market ratio firms. VAL_global and MOM_global are the global value and momentum factors in Asness, Moskowitz and Pederson (2013) and are obtained from AQR data library. T-statistics are based on standard errors that are Newey-West (1987) adjusted with 12 lags, and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A. Sovereign CDS momentum monthly returns for various formation and holding periods. n: sorting period, h: holding period (months)

	Long-short portfolio returns (%)			
	n=1	*n=3*	*n=6*	*n=9*
h=1	0.50***	0.56***	0.41**	0.47**
	(2.93)	*(3.31)*	*(2.44)*	*(2.55)*
h=3	0.42***	0.39**	0.39**	0.36
	(3.42)	*(2.80)*	*(2.70)*	*(1.91)*
h=6	0.25***	0.24**	0.23	0.24
	(2.71)	*(2.03)*	*(1.53)*	*(1.38)*
h=9	0.14	0.18	0.17	0.2
	(1.47)	*(1.53)*	*(1.19)*	*(1.14)*

Panel B. Sovereign CDS momentum monthly returns for longer formation periods

	Long-short portfolio returns (%)							
	n=1	*n=3*	*n=6*	*n=9*	*n=12*	*n=24*	*n=36*	*n=48*
h=1	0.50***	0.56***	0.41***	0.47**	0.35	0.35	0.22	0.23
	(2.93)	*(3.31)*	*(2.44)*	*(2.55)*	*(1.62)*	*(1.53)*	*(0.99)*	*(1.13)*
h=3	0.42***	0.39**	0.39**	0.36	0.34	0.33	0.23	0.17
	(3.42)	*(2.80)*	*(2.70)*	*(1.91)*	*(1.67)*	*(1.5)*	*(1.11)*	*(0.84)*

Panel C. Regressions of cross-sectional sovereign CDS momentum returns

	Returns	Returns	Returns	Returns
Alpha (%)	0.57***	0.52***	0.54***	0.53***
	(3.61)	(2.78)	(3.17)	(2.66)
MKT_SCDS	0.86*	1.02*	0.92**	0.98*
	(1.95)	(1.81)	(2.18)	(1.76)
MOM_stock		0.01		0.01
		(0.25)		(0.34)
MKT_stock		0.002		0.001
		(0.04)		(0.02)
SMB		0.01		0.02
		(0.10)		(0.27)
HML		0.17		0.14
		(1.35)		(0.80)
Carhart_MOM		-0.05		-0.002
		(-1.14)		(-0.03)
VAL_global			0.25	0.09
			(1.42)	(0.34)
MOM_global			-0.01	-0.10
			(-0.14)	(-0.67)
Observations	175	175	175	175
R-Square	0.1313	0.1625	0.1576	0.1674

Table 2. 4 Systematic vs. Idiosyncratic

Countries are sorted into 5 quintiles based on the systematic (denoted as Sys.), or idiosyncratic (denoted as Idio.), component of their past 3-month sovereign CDS returns. The CDS return decomposition is based on a 12-month rolling window regression of CDS returns on the average CDS returns across all countries in our sample. The idiosyncratic component is the regression residual and the remaining portion of the CDS return is the systematic component. Quintile 1 (5) countries have lowest (highest) returns, i.e., their credit worthiness improved (deteriorated) the most, according to the sovereign CDS market. For each group, we form an equal-weighted portfolio of sovereign CDS for the countries in the group. It reports the average return of the portfolio (Total) for each of the portfolios for each of the 5 quintiles, and for the long-short portfolio that is long in quintile 1 and short in quintile 5. The "alpha" column reports the alpha of the long-short strategy after adjusting for MKT_stock, MOM_stock, MKT_stock, SMB, HML and all of which are defined in Panel C of Table 2.3. Since we need 12-month data to estimate the regressions, the sample period of the followings is January 2002 to September 2015. T-statistics are based on standard errors that are Newey-West (1987) adjusted with 12 lags, and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Sorting var.	Predicted var.	1	2	3	4	5	5-1	alpha
CDS return	CDS return	(lowest)				(highest)	(%)	(%)
Sys.	Total	-0.25	-0.09	-0.01	0.03	0.19	0.44***	0.34**
		(-1.63)	(-0.95)	(-0.18)	(0.48)	(0.94)	(2.64)	(2.19)
Idio.	Total	-0.19	-0.02	0.00	-0.05	0.12	0.30**	0.32**
		(-1.08)	(-0.27)	(-0.07)	(-0.73)	(0.53)	(2.00)	(2.01)
Total	Total	-0.25*	-0.06	-0.01	0.00	0.27	0.52***	0.51***
		(-1.94)	(-0.82)	(-0.11)	(0.00)	(1.36)	(3.21)	(2.70)

Table 2. 5 The timing of predictability

This table reports results from panel regressions of monthly sovereign CDS returns. I_CDSit is 1, if country i is in quintile 1 in month t according to the sorting based on sovereign CDS returns during months t-3 to t-1, i.e., its creditworthiness improved the most. Similarly, I_CDSit is set to -1 if country i is in quintile 5, and is set to 0 if country i is in the other three quintiles. Dit is 1 if there is a credit rating change or outlook change for country i in month t according to Standard & Poor's, and is 0 otherwise. T-statistics, in parentheses, are based on standard errors that are clustered by month. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

	Return (%)	Return (%)
I_CDS_{it}	0.21**	0.10
	(2.47)	(1.31)
$I\_CDS_{it} \times D_{it}$		1.42***
		(3.24)
D_{it}		0.77***
		(2.97)
Country Fixed Effects	Yes	Yes
Month Fixed Effects	Yes	Yes
Observations	10,168	10,168
R-squared	0.1192	0.1299

Table 2. 6 Time series momentum strategy of sovereign CDS

This table presents average monthly time series momentum returns (with the t-statistics in the parenthesis) of sovereign CDS for formations periods (*n* = 1, 3, 6, and 9) and holding periods (*h* = 1, 3, 6, and 9). Long-short is the strategy involves selling (buying) the sovereign CDS contract with positive past returns and selling the sovereign CDS contract with negative past returns. The average monthly returns are in percent. T-statistics are based on standard errors that are Newey-West (1987) adjusted with 9 lags, and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A. Sovereign CDS momentum monthly returns for various formation (*n*) and holding periods (*h*)

	Long-short portfolio returns (%)			
	n=1	*n=3*	*n=6*	*n=9*
h=1	0.25***	0.24***	0.14*	0.13*
	(2.90)	*(2.81)*	*(1.78)*	*(1.74)*
h=3	0.20***	0.19**	0.18**	0.16**
	(2.74)	*(2.15)*	*(2.17)*	*(2.48)*
h=6	0.11	0.12	0.12*	0.09
	(1.54)	*(1.40)*	*(1.75)*	*(1.21)*
h=9	0.07	0.09	0.06	0.09
	(1.21)	*(1.20)*	*(0.99)*	*(1.47)*

Table 3. 1 Summary statistics

This table presents the summary statistics of main variables in the paper. *CDS spread* is the sovereign CDS spread, and is from Markit. Following O'Kane (2008), we compute the monthly *CDS return* from the *CDS spreads* on the 20th of a month and on the 19th of the next month. *Stock index return* is the monthly US-dollar denominated return of the main stock index of a country, from the 20th of a month to the 19th of the next month, and is from Bloomberg. *Bond yield change* is the monthly yield change, from the 20th of a month to the 19th of the next month, of 5-year local currency denominated sovereign bond index, which is constructed by Bloomberg. The quarterly year-over-year GDP growth data are from the IMF World Economic Outlook Database. The seasonally adjusted Product Manager Index (PMI) data are from Markit Group. The list of stock indices and bond yield indices is reported in the appendix. The sample period is from January 2001 to September 2015.

	Mean	**Std Dev**	**1st**	**25th**	**50th**	**75th**	**99th**	**Obs**
CDS spread (bps)	240.40	556.66	1.74	36.45	118.79	276.17	1975.68	12193
CDS return (%)	-0.02	2.59	-6.64	-0.37	-0.01	0.22	7.83	12065
Stock index return (%)	1.00	7.99	-21.70	-3.01	1.12	5.18	22.14	11196
Bond yield change (bps)	-1.62	54.01	-130.00	-17.00	-2.40	13.30	140.00	6375
PMI	52.57	6.38	31.88	49.41	52.88	56.40	67.59	5051
GDP growth (%)	3.12	4.13	-9.11	1.19	3.09	5.43	12.55	3559

Table 3. 2 Using CDS to predict stock returns

Countries are sorted into 5 quintiles based on their past 3-month sovereign CDS returns. Those in quintile 1 (5) have the lowest (highest) CDS returns, i.e., their credit worthiness improved (deteriorated) the most, according to the sovereign CDS market. Then, for each quintile, we form portfolios of stock indices, one equal weighted and one market-cap weighted. Panel A reports the average excess return over the 1-month US Treasury yield for each of the 5 portfolios, and the long-short portfolio that is long in quintile 1 and short in quintile 5. The first row is for the full sample. The second and third rows are based on subsamples partitioned by time. The first half is from January 2001 to December 2007 and the second half is from January 2008 to September 2015. Panel B reports the results from the regression of the monthly returns of the long-short portfolio on various factors. MKT_stock is the monthly return of the equal-weighted portfolio of all stock indices. MOM_stock is the momentum return for stock indices, with a 3-month portfolio formation period and a 1-month holding period. MOM_FX is the momentum return in the currency market, with a 3-month formation period and a 1-month holding period. MKT_FX and HML_FX are the two currency factors in Lustig, Roussanov and Verdelhan (2011), and are obtained from the authors' website. VAL_global and MOM_global are the global value and momentum factors in Asness, Moskowitz and Pederson (2013), and are obtained from the AQR data library. Panel C reports the alphas from the long-short strategies, which are sorted based on the data from the prior *n* months and have a holding period of *h* months, for various values of *n* and *h*. All *t*-statistics are based on standard errors that are Newey-West (1987) adjusted with 12 lags, and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Returns of stock index portfolios (%)

		1 (good)	2	3	4	5 (bad)	1-5
Equal weight	Full sample	1.34**	1.41**	0.89*	0.76	0.09	1.25***
		(2.34)	(2.46)	(1.73)	(1.53)	(0.15)	(3.80)
	2001-2007	2.56***	2.82***	1.54***	1.73***	0.62	1.94***
		(4.27)	(6.04)	(3.01)	(4.04)	(0.63)	(3.51)
	2008-2015	0.27	0.22	0.38	-0.07	-0.31	0.58**
		(0.36)	(0.30)	(0.47)	(0.10)	(0.40)	(2.10)
Value weight	Full sample	1.14**	0.82*	0.54	0.82	0.04	1.10**
		(2.15)	(1.77)	(1.22)	(1.85)	(0.06)	(2.43)
	2001-2007	2.12***	1.68***	0.92	1.10**	0.44	1.68**
		(2.94)	(2.73)	(1.39)	(2.12)	(0.43)	(1.96)
	2008-2015	0.28	0.15	0.26	0.56	-0.22	0.51*
		(0.33)	(0.21)	(0.31)	(0.9)	(0.28)	(1.77)

Panel B: Dependent variable: return of quintile 1 – quintile 5 (%)

	Equal weight		Value weight	
Alpha	1.01***	1.27***	0.90**	0.99**
	(2.89)	(3.50)	(2.17)	(2.23)
MKT_stock (%)	-0.048	-0.063	0.018	-0.10
	(0.53)	(0.57)	(0.20)	(1.17)
MOM_stock (%)	0.263**		0.32***	
	(2.30)		(4.08)	
MKT_FX (%)	-0.10		-0.30	
	(0.57)		(1.06)	
HML_FX (%)	0.40***		0.060	
	(2.61)		(0.30)	
MOM_FX (%)	-0.155		0.26	
	(1.34)		(1.11)	
VAL_global (%)		0.31		0.66
		(0.69)		(1.23)
MOM_global (%)		-0.040		0.18
		(0.21)		(0.61)
Observations	175	175	175	175
R-Square	0.12	0.02	0.13	0.02

Panel C: Long-short strategy alpha (%) n: sorting period, h: holding period (months)

		h=1	*h*=3	*h*=6
Equal weight	*n*=1	0.59**	0.36*	0.27
		(2.17)	(1.74)	(1.47)
	n=3	1.01***	0.45**	0.32*
		(2.89)	(2.25)	(1.81)
	n=6	0.83***	0.43**	0.32
		(2.71)	(2.00)	(1.51)
Value weight	*n*=1	1.12**	0.66**	0.22
		(2.49)	(2.53)	(1.34)
	n=3	0.90**	0.36	0.11
		(2.17)	(1.54)	(0.38)
	n=6	0.11	-0.23	-0.06
		(0.24)	(0.68)	(0.21)

Table 3. 3 Using CDS to predict bond yield changes

Countries are sorted into 5 quintiles based on their past 3-month sovereign CDS returns. Those in quintile 1 (5) have the lowest (highest) CDS returns, i.e., their credit worthiness improved (deteriorated) the most, according to the sovereign CDS market. Then, for each quintile, we compute equal-weighted and GDP-weighted averages of bond yield changes, ΔYield. Panel A reports ΔYield for each of the 5 quintiles and the difference in ΔYield between quintiles 1 and 5. The first row is for the full sample. The second and third rows are based on subsamples partitioned by time. The first half is from January 2001 to December 2007 and the second half is from January 2008 to September 2015. Panel B reports the results from the regression of monthly difference in ΔYield between quintiles 1 and 5 on various factors. MKT_bond is the monthly equal-weighted yield changes across all countries. MOM_bond is equivalent to the momentum return in the sovereign bond market, with a 3-month formation period and a 1-month holding period, with yield changes as proxies for bond returns. VAL_global and MOM_global are the global value and momentum factors in Asness, Moskowitz and Pederson (2013), and are obtained from the AQR data library. Panel C reports the alphas from the long-short strategies, which are sorted based on the data from the prior *n* months and have a holding period of *h* months, for various values of *n* and *h*. All *t*-statistics are based on standard errors that are Newey-West (1987) adjusted with 12 lags, and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Yield changes of bond index portfolios (bps)

		1 (good)	2	3	4	5 (bad)	5-1
Equal weight	Full sample	-7.04***	-3.85***	-2.28	-3.38*	4.90	11.87***
		(2.76)	(2.59)	(1.61)	(1.87)	(1.46)	(3.15)
	2001-2007	-8.24*	-3.04	-0.42	-1.39	-0.30	7.75*
		(1.78)	(1.26)	(0.20)	(0.58)	(0.15)	(1.75)
	2008-2015	-5.81**	-4.36**	-3.7**	-4.59*	9.82*	15.63***
		(2.32)	(2.32)	(2.10)	(1.77)	(1.73)	(2.82)
Value weight	Full sample	-6.12**	-4.40***	-1.71	-3.15	0.31	6.42**
		(2.38)	(3.01)	(1.26)	(1.44)	(0.14)	(2.37)
	2001-2007	-8.48**	-3.07	-0.38	-1.25	-3.10	5.39*
		(1.96)	(1.49)	(0.18)	(0.45)	(1.02)	(1.72)
	2008-2015	-4.02	-4.68**	-2.38	-4.33	3.73	7.75**
		(1.40)	(2.65)	(1.31)	(1.34)	(1.32)	(2.59)

Panel B: Dependent variable: ΔYield of quintile 5 – ΔYield of quintile 1 (bps)

	Equal weight		Value weight	
Alpha	6.85**	11.16**	4.45**	6.14**
	(2.26)	(2.47)	(2.06)	(2.40)
MKT_bond (%)	14.36	79.51**	18.11	7.99
	0.74	(2.06)	(0.78)	(0.45)
MOM_bond (%)	69.81***		59.67***	
	(6.60)		(8.19)	
VAL_global (%)		6.69***		5.82**
		(2.79)		(1.98)
MOM_global (%)		3.88**		2.18
		(2.32)		(1.19)
Observations	175	175	175	175
R-Square	0.42	0.10	0.32	0.02

Panel C: Long-short strategy alpha (bps) *n*: sorting period, *h*: holding period (months)

		h=1	*h*=3	*h*=6
Equal weight	*n*=1	4.35	3.17*	2.45**
		(1.52)	(1.84)	(2.04)
	n=3	6.85**	5.33**	4.54**
		(2.26)	(2.49)	(2.19)
	n=6	4.76**	4.27**	3.71**
		(2.08)	(2.36)	(2.04)
Value weight	*n*=1	1.36	3.23**	2.16
		(0.69)	(2.29)	(1.61)
	n=3	4.45**	3.60**	3.08*
		(2.06)	(2.15)	(1.80)
	n=6	5.66***	4.59*	3.56
		(2.66)	(1.92)	(1.43)

Table 3. 4 The direction of information flow

Panel A reports the sequential sort results for stock and sovereign CDS markets. In the first 3 columns, we first sort countries into 5 quintiles by their past 3-month stock index returns. Then, for each quintile, we sort countries into 2 halves based on their past 3-month sovereign CDS returns, and compute the return from the equal-weighted stock portfolio that is long in countries with low past CDS returns and short in countries with high past CDS returns. Finally, we compute the equal-weighted average return across the five long-short stock portfolios. The first 3 columns report the average returns and alphas for the full sample and the two subsamples. The first half is from January 2001 to December 2007 and the second half is from January 2008 to September 2015. The results in the last 3 columns are based on similar 5-by-2 sequential sorting for CDS returns, first based on the past 3-month CDS returns and then based on the past 3-month stock returns. The analysis in Panel B is similar to that in Panel A, where bond yield changes replace stock returns. T-statistics are based on standard errors that are Newey-West (1987) adjusted with 12 lags, and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Sovereign CDSs vs. Stocks

	CDSs to Stocks (%)			Stocks to CDSs (%)		
	Full	First	Second	Full	First	Second
Mean	0.51***	0.77***	0.32**	0.01	0.04	-0.02
	(3.17)	(2.82)	(2.08)	(0.15)	(0.46)	(0.20)
Alpha	0.49***	1.03***	0.31**	0.01	0.05	-0.02
	(2.75)	(3.77)	(1.99)	(0.1)	(0.55)	(0.28)

Panel B: Sovereign CDSs vs. Bond yields

	CDSs to Bond Yields (bps)			Bond Yields to CDSs (%)		
	Full	First	Second	Full	First	Second
Mean	5.46***	4.28*	6.59**	0.21*	0.02	0.38*
	(2.96)	(1.68)	(2.53)	(1.72)	(0.8)	(1.74)
Alpha	5.73***	3.55*	7.12***	0.21*	0.02	0.38*
	(2.88)	(1.73)	(2.65)	(1.68)	(0.83)	(1.67)

Panel C: Using sovereign CDSs to predict stocks and bonds

	Return (%)	ΔYield (bps)
CDS return$_{t-3,t-1}$	-0.12**	3.25***
	(2.12)	(2.76)
Stock return $_{t-3,t-1}$	0.03***	
	(3.45)	
ΔYield $_{t-3,t-1}$		0.02
		(0.82)

Panel D: Using stocks and bonds to predict sovereign CDSs

	CDS return (%)	CDS return (%)
Stock return $_{t-3,t-1}$	-0.031	
	(0.09)	
ΔYield $_{t-3,t-1}$		12.22
		(1.60)
CDS return$_{t-3,t-1}$	11.18**	7.74**
	(2.55)	(2.27)

Table 3. 5 The source of predictability

This table reports results from panel regressions of monthly excess stock index returns and changes in 5-year bond yields. I_CDS_{it} is 1, if country *i* is in quintile 1 in month *t* according to the sorting based on sovereign CDS returns during months *t*-3 to *t*-1, i.e., its creditworthiness improved the most. Similarly, I_CDS_{it} is set to -1 if country *i* is in quintile 5, and is set to 0 if country *i* is in the other three quintiles. D_{it} is 1 if there is a credit rating change or outlook change for country *i* in month *t* according to Standard & Poor's, and is 0 otherwise. I_MOM_{it} is an indicator for momentum. For the first two columns, I_MOM_{it} is 1 if the excess return of country *i*'s stock index is in the top quintile portfolio during months *t-3* to *t-1*, is -1 if country *i* is in the bottom quintile, and is 0 otherwise. For the last two columns, I_MOM_{it} is similarly constructed, with yield changes replacing stock returns. $Good\_CDS_{it}$ is 1 if country *i* is in the top quintile based on sovereign CDS returns during months *t-3* to *t-1* (i.e., if the sovereign CDS market indicates "good news" for country *i*), and is 0 otherwise. Bad_CDS_{it} is -1 if country *i* is in the bottom quintile based on sovereign CDS returns during months *t-3* to *t-1*, and is 0 otherwise. $Winner_{it}$ is a dummy variable, which is 1 if country *i* is in the top quintile based on the performance of the dependent variable (i.e., stock index return in the first 2 columns, and yield change in the last 2 columns) during months *t-3* to *t-1*, and is 0 otherwise. Similarly, $Loser_{it}$ is a dummy variable, which is 1 if country *i* is in the bottom quintile based on the performance of the dependent variable during months *t-3* to *t-1*, and is 0 otherwise. T-statistics, in parentheses, are based on standard errors that are clustered by month. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A

	Return (%)	Return (%)	ΔYield (bps)	ΔYield (bps)
I_CDS_{it}	0.38***	0.31**	-4.11	-3.57
	(2.81)	(2.23)	(-1.51)	(-1.49)
$I\_CDS_{it} \times D_{it}$	0.84*	0.59	-29.28**	-20.33**
	(1.70)	(1.10)	(-2.36)	(-1.98)
I_MOM_{it}		0.35*		1.70
		(1.93)		(0.93)
$I\_MOM_{it} \times D_{it}$		0.87		18.55**
		(1.47)		(2.40)
D_{it}	-0.26	-0.19	10.33	8.31
	(0.77)	(0.53)	(1.52)	(1.32)
Country Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	10,161	10,161	5,696	5,696
R-squared	0.4056	0.4071	0.162	0.164

Panel B

	Return (%)	Return (%)	ΔYield (bps)	ΔYield (bps)
	(1)	(2)	(3)	(4)
Bad_CDS_{it}	0.43**	0.35*	-5.73*	-5.30*
	(2.22)	(1.80)	(1.80)	(1.71)
$Bad\_CDS_{it} \times D_{it}$	2.46**	2.12**	-50.47**	-38.40**
	(2.48)	(2.17)	(2.25)	(1.98)
$Good\_CDS_{it}$	0.33	0.27	-2.29	-1.57
	(1.58)	(1.29)	(0.65)	(0.46)
$Good\_CDS_{it} \times D_{it}$	-0.82	-1.00	-4.26	-3.39
	(1.08)	(1.30)	(0.47)	(0.41)
$Winner_{it}$		0.45*		1.33
		(1.85)		(0.38)
$Winner \times D_{it}$		0.76		33.45**
		(0.77)		(2.46)
$Loser_{it}$		-0.24		-2.15
		(1.01)		(1.18)
$Loser_{it} \times D_{it}$		-0.83		2.58
		(0.94)		(0.33)
D_{it}	0.59	0.63	1.18	-7.69
	(1.48)	(1.43)	(0.21)	(1.25)
Country Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	10,161	10,161	5,696	5,696
R-squared	0.406	0.408	0.164	0.167

Table 3. 6 Daily regressions

This table repeats the analysis in columns 2 and 4 of both panels of Table 3.5, but using daily frequency data. The dependent variables are daily stock index returns and changes in 5-year bond yield indices. The dummy variable in Table 3.5, D_{it}, is now replaced by its daily-frequency counterpart, D_{it}^{n}, which is 1 if there is an S&P credit rating change or outlook change for country *i* during day *t-n* to *t+n*, and is 0 otherwise. We adjust all other independent variables in Table 3.5 (I_CDS_{it}, Bad_CDS_{it}, Good_CDS_{it}, Winner_{it} and Loser_{it}) into daily frequency to obtain I_CDS_{it}^{d}, Bad_CDS_{it}^{d}, Good_CDS_{it}^{d}, Winner_{it}^{d} and LoserS_{it}^{d}, respectively For example, for country *i* on day *t*, we set $\text{I\_CDS}_{it}^{d} = \text{I\_CDS}_{im}$, if day *t* is in month *m*. Bad_CDS_{it}^{d}, Good_CDS_{it}^{d}, Winner_{it}^{d} and LoserS_{it}^{d} are defined similarly. The table only reports the estimated coefficients of I_CDS_{it}^{d}, Bad_CDS_{it}^{d}, Good_CDS_{it}^{d}, and the interaction terms for various values of *n*. T-statistics are based on standard errors that are clustered by day. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Dependent variable: daily stock index return (bps)

	***n*=0**	***n*=1**	***n*=2**	***n*=5**	***n*=10**	***n*=20**
I_CDS_{it}^{d}	1.11**	1.07**	1.07**	1.11**	1.01**	0.96**
	(2.37)	(2.29)	(2.28)	(2.36)	(2.16)	(2.03)
$\text{I\_CDS}_{it}^{d} \times D_{it}^{n}$	22.91*	12.04*	7.93*	2.60	3.47	2.06
	(1.69)	(1.76)	(1.65)	(0.84)	(1.55)	(1.32)

Panel B: Dependent variable: daily stock index return (bps)

	***n*=0**	***n*=1**	***n*=2**	***n*=5**	***n*=10**	***n*=20**
Bad_CDS_{it}^{d}	1.48**	0.14**	1.34**	1.32*	1.12*	1.09
	(2.16)	(2.06)	(1.96)	(1.93)	(1.64)	(1.60)
$\text{Bad\_CDS}_{it}^{d} \times D_{it}^{n}$	37.97	23.11*	21.06**	11.17**	10.35***	5.32**
	(1.53)	(1.89)	(2.50)	(2.08)	(2.65)	(2.04)
Good_CDS_{it}^{d}	0.74	0.74	0.79	0.89	0.90	0.83
	(1.04)	(1.04)	(1.11)	(1.23)	(1.25)	(1.13)
$\text{Good\_CDS}_{it}^{d} \times D_{it}^{n}$	8.55	1.13	-5.14	-5.93	-3.33	-1.21
	(0.52)	(0.13)	(-0.81)	(-1.4)	(-1.06)	(-0.54)

Panel C: Dependent variable: daily yield change (bps)

	n=0	*n*=1	*n*=2	*n*=5	*n*=10	*n*=20
$\mathrm{I\_CDS}_{it}^{d}$	-0.15***	-0.15***	-0.14***	-0.14***	-0.12**	-0.13**
	(-2.88)	(-2.74)	(-2.70)	(-2.61)	(-2.32)	(-2.53)
$\mathrm{I\_CDS}_{it}^{d} \times D_{it}^{n}$	-4.74***	-2.58**	-1.57*	-1.01	-0.82*	-0.34
	(-2.77)	(-2.58)	(-1.80)	(-1.46)	(-1.88)	(-1.05)

Panel D: Dependent variable: daily yield change (bps)

	n=0	*n*=1	*n*=2	*n*=5	*n*=10	*n*=20
$\mathrm{Bad\_CDS}_{it}^{d}$	-0.30***	-0.29***	-0.28***	-0.26***	-0.22**	-0.23***
	(-3.35)	(-3.20)	(-3.15)	(-2.88)	(-2.54)	(-2.82)
$\mathrm{Bad\_CDS}_{it}^{d} \times D_{it}^{n}$	-10.42***	-5.55***	-3.52**	-2.94***	-2.27***	-1.13*
	(-2.83)	(-2.85)	(-2.28)	(-2.66)	(-3.05)	(-1.83)
$\mathrm{Good\_CDS}_{it}^{d}$	0.01	0.01	0.00	0.01	0.01	0.02
	(0.07)	(0.08)	(0.07)	(-0.12)	(-0.17)	(-0.29)
$\mathrm{Good\_CDS}_{it}^{d} \times D_{it}^{n}$	1.35	0.37	0.30	0.90	0.64	0.48
	(0.55)	(0.33)	(0.30)	(1.10)	(1.32)	(1.38)

Table 3. 7 Systematic vs. Idiosyncratic

Countries are sorted into 5 quintiles based on their past 3-month sovereign CDS returns, their systematic or idiosyncratic component (denoted as "Sys" and "Idio", respectively). The CDS return decomposition is based on a regression of CDS return on the average CDS return across all countries. The idiosyncratic component is the regression residual and the remaining portion of the CDS return is the systematic component. Quintile-1 (-5) countries have the lowest (highest) returns. In Panel A, for each quintile, we form an equal-weighted portfolio of stock indices. It reports the average excess return of the portfolio over the 1-month US Treasury yield (Total), the average of the systematic and idiosyncratic components of the stock index returns (Sys and Idio) for each of the 5 portfolios, and for the long-short portfolio that is long in quintile 1 and short in quintile 5. The stock index return decomposition is based on a 12-month rolling window regression of excess stock index returns on the excess returns of the global stock index, which are obtained from Kenneth French's website. The idiosyncratic component is the regression residual and the remaining portion of the stock index return is the systematic component. The "alpha" column reports the alpha of the long-short strategy after adjusting for MKT_stock, MOM_stock, MOM_FX, MKT_FX and HML_FX, all of which are defined in Table 3.2. Similarly, Panel B reports the analysis on bond yield changes. The bond yield change decomposition is based on a 12-month rolling window regression of bond yield changes on the U.S. yield changes. The idiosyncratic component is the regression residual and the remaining portion of the yield change is the systematic component. The "alpha" column reports the estimates of the constant term from the regression of the monthly difference in yield changes between quintiles 1 and 5 on MKT_bond and MOM_bond, both of which are defined in Table 3.3. Since we need 12-month data to estimate the decomposition regressions, the sample period of the portfolio returns is from January 2002 to September 2015. T-statistics are based on standard errors that are Newey-West (1987) adjusted with 12 lags, and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Using CDS returns to predict stock returns (%)

Sorting var.	Predicted var.	1	2	3	4	5	1 - 5	alpha
CDS return	Stock return	(good)				(bad)		
Sys	Total	1.51**	1.25**	0.70	0.68	0.69	0.81***	0.69***
		(2.20)	(2.10)	(1.42)	(1.23)	(1.13)	(3.20)	(2.75)
Idio	Total	1.07	0.85	0.82	0.95	1.14	-0.07	0.04
		(1.61)	(1.73)	(1.51)	(1.63)	(1.58)	(0.21)	(0.12)
Total	Total	1.36**	1.42**	0.96*	0.79	0.54	0.81***	0.69**
		(2.23)	(2.34)	(1.77)	(1.50)	(0.97)	(3.82)	(2.37)
Total	Sys	1.65***	1.37***	1.18***	1.03**	0.57	1.08***	0.96***
		(3.08)	(2.76)	(2.83)	(2.27)	(1.07)	(6.83)	(5.15)
Total	Idio	-0.27	0.03	-0.20	-0.26	-0.04	-0.23	-0.26
		(1.26)	(0.16)	(1.03)	(1.44)	(0.15)	(0.84)	(0.82)

Panel B: Using CDS returns to predict bond yield changes (bps)

Sorting var.	Predicted var.	1	2	3	4	5	5 - 1	alpha
CDS return	Yield change	(good)				(bad)		
Sys	Total	-5.35**	-3.68**	-2.64*	-3.42*	6.08	11.61***	7.77***
		(2.41)	(2.45)	(1.71)	(1.76)	(1.48)	(2.78)	(2.84)
Idio	Total	-3.19	-3.65**	-2.20	-3.20**	2.92	6.11*	3.28
		(0.92)	(2.35)	(1.52)	(2.00)	(0.90)	(1.71)	(1.06)
Total	Total	-7.31***	-3.16**	-2.46*	-2.67	6.23*	13.54***	8.51***
		(2.88)	(2.25)	(1.69)	(1.45)	(1.81)	(3.54)	(2.88)
Total	Sys	-5.79***	-3.69***	-1.73*	-1.39	4.42*	10.18***	8.82***
		(3.39)	(4.58)	(1.89)	(1.54)	(1.69)	(4.54)	(5.18)
Total	Idio	-0.87	0.59	-0.69	-1.69	2.33	3.24	-0.60
		(0.37)	(0.46)	(0.67)	(1.10)	(0.84)	(0.88)	(0.19)

Table 3. 8 Predicting Real Economic Activities

This table reports the results from panel regressions. In Panel A, the dependent variable is the quarterly GDP year over year growth rate. CDS return$_{t-1}$, Stock return$_{i,t-1}$, ΔYield$_{i,t-1}$ are country *i*'s sovereign CDS return, stock index return, and 5-year bond yield index change during the previous quarter, respectively. GDP$_{i,t-1}$ is country *i*'s GDP growth rate in the previous quarter. Sys. CDS return$_{i,t-1}$ and Idio. CDS return$_{i,t-1}$ are country *i*'s systematic and idiosyncratic components of the CDS returns in the previous quarter, respectively. The CDS return decomposition is described in Table 3.7. In Panel B, the dependent variable is the monthly PMI index on output. CDS return$_{i,t-3,t-1}$, Stock return $_{i,t-3,t-1}$, ΔYield $_{i,t-3,t-1}$ are country *i*'s sovereign CDS return, stock index return, and change in 5-year bond yield index during the previous three months, respectively. PMI $_{i,t-1}$ is country *i*'s PMI index in the previous month. Sys. CDS return$_{i,t-3,t-1}$ and Idio. CDS return$_{i,t-3,t-1}$ are country *i*'s systematic and idiosyncratic components of its CDS returns during the previous three months. The CDS return decomposition is described in Table 3.7. T-statistics, in parentheses, are based on standard errors that are clustered by country. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: GDP Growth Rate

CDS return$_{i,t-1}$	-1.18**	
	(-2.03)	
Sys. CDS return$_{i,t-1}$		-4.98*
		(-1.71)
Idio. CDS return$_{t,t-1}$		1.58
		(0.91)
ΔYield $_{i,t-1}$	-13.66	-9.57
	(-1.12)	(-0.47)
Stock return $_{i,t-1}$	0.97**	0.79
	(2.05)	(1.50)
GDP$_{i,t-1}$	0.822***	0.83***
	(18.83)	(17.56)
Constant	13.49	10.36
	(1.10)	(0.51)
Country fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Observations	1,891	1,702
R-squared	0.866	0.872

Panel B: PMI

CDS return$_{i,t-3,t-1}$	-6.10***	
	(-3.55)	
Sys. CDS return$_{i,t-3,t-1}$		-14.23**
		(-2.18)
Idio. CDS return$_{i,t-3,t-1}$		-2.29
		(-1.01)
ΔYield $_{i,t-3,t-1}$	-6.33	-2.03
	(-1.05)	(-0.38)
Stock return $_{i,t-3,t-1}$	0.83	0.97
	(1.06)	(1.13)
PMI $_{i,t-1}$	0.61***	0.59***
	(7.84)	(7.81)
Constant	27.53***	27.85***
	(6.72)	(4.91)
Country fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
Observations	3,538	3,215
R-squared	0.754	0.759

Table 4. 1 List of 67 Ethical Mutual Funds and their Investment Objectives

	Fund name	Ticker	Objective Code
1	Ariel Investment Trust: Ariel Fund; Investor Class Shares	ARGFX	EDCS
2	Ariel Investment Trust: Ariel Appreciation Fund; Investor Class Shares	CAAPX	EDCM
3	Azzad Funds: Azzad Ethical Fund	ADJEX	EDYG
4	City National Rochdale Funds: City National Rochdale Socially Responsible Equity Fund; Class N Shares	AHRAX	EDYG
5	Calvert Social Index Series, Inc: Calvert Social Index Fund; Class I Shares	CISIX	EDYG
6	Calvert Social Index Series, Inc: Calvert Social Index Fund; Class C Shares	CSXCX	EDYG
7	Calvert Social Index Series, Inc: Calvert Social Index Fund; Class A Shares	CSXAX	EDYG
8	Calvert Social Investment Fund: Equity Portfolio; Class A Shares	CSIEX	EDYG
9	Calvert Social Investment Fund: Calvert Aggressive Allocation Fund; Class C Shares	CAACX	EDYG
10	Calvert Social Investment Fund: Calvert Aggressive Allocation Fund; Class A Shares	CAAAX	EDYG
11	Calvert Social Investment Fund: Calvert Conservative Allocation Fund; Class C Shares	CALCX	M
12	Calvert Social Investment Fund: Calvert Conservative Allocation Fund; Class A Shares	CCLAX	M
13	Calvert Social Investment Fund: Equity Portfolio; Class C Shares	CSECX	EDYG
14	Calvert Social Investment Fund: Calvert Moderate Allocation Fund; Class C Shares	CMACX	M
15	Calvert Social Investment Fund: Calvert Moderate Allocation Fund; Class A Shares	CMAAX	M
16	Calvert Social Investment Fund: Equity Portfolio; Class I Shares	CEYIX	EDYG
17	Calvert Social Investment Fund: Large Cap Core Portfolio; Class A Shares	CMIFX	EDYG
18	Calvert Social Investment Fund: Large Cap Core Portfolio; Class C Shares	CMICX	EDYG
19	Calvert Impact Fund, Inc: Calvert Small Cap Fund; Class A Shares	CCVAX	EDCS
20	Calvert Impact Fund, Inc: Calvert Small Cap Fund; Class C Shares	CSCCX	EDCS
21	Calvert Impact Fund, Inc: Calvert Small Cap Fund; Class I Shares	CSVIX	EDCS
22	Calvert World Values Fund, Inc: Calvert Capital Accumulation Fund; Class A Shares	CCAFX	EDCM
23	Calvert World Values Fund, Inc: Calvert Capital Accumulation Fund; Class C Shares	CCACX	EDCM
24	Sentinel Group Funds, Inc: Sentinel Sustainable Mid Cap Opportunities Fund; Class A Shares	WAEGX	EDCM

25	Sentinel Group Funds, Inc: Sentinel Sustainable Core Opportunities Fund; Class I Shares	CVALX	EDYG
26	Sentinel Group Funds, Inc: Sentinel Sustainable Core Opportunities Fund; Class A Shares	MYPVX	EDYG
27	Sentinel Group Funds, Inc: Sentinel Sustainable Mid Cap Opportunities Fund; Class I Shares	CEGIX	EDCM
28	Domini Social Investment Trust: Domini Social Equity Fund; Class A Shares	DSEPX	EDYG
29	Domini Social Investment Trust: Domini Social Equity Fund; Institutional Shares	DIEQX	EDYG
30	Domini Social Investment Trust: Domini Social Equity Fund; Investor Shares	DSEFX	EDYG
31	Domini Social Investment Trust: Domini Social Equity Fund; Class R Shares	DSFRX	EDYG
32	Green Century Funds: Green Century Equity Fund	GCEQX	EDYG
33	Praxis Mutual Funds: Praxis Value Index Fund; Class A Shares	MVIAX	EDYB
34	Praxis Mutual Funds: Praxis Value Index Fund; Class I Shares	MVIIX	EDYB
35	Neuberger Berman Equity Funds: Neuberger Berman Socially Responsive Fund; Trust Class Shares	NBSTX	EDYG
36	Neuberger Berman Equity Funds: Neuberger Berman Socially Responsive Fund; Investor Class Shares	NBSRX	EDYG
37	Parnassus Funds: Parnassus Workplace Fund	PARWX	EDYG
38	Parnassus Funds: Parnassus Small-Cap Fund	PARSX	EDCS
30	Parnassus Funds: Parnassus Mid-Cap Fund	PARMX	EDCM
40	Parnassus Income Funds: Parnassus Equity Income Fund; Investor Shares	PRBLX	EDYI
41	Pax World Funds Series Trust I: Pax World Growth Fund; Individual Investor Class Shares	PXWGX	EDYG
42	Pax World Funds Series Trust I: Pax World Growth Fund; Institutional Class Shares	PWGIX	EDYG
43	Pax World Funds Series Trust I: Pax World Growth Fund; Class R Shares	PXGRX	EDYG
44	Pax World Funds Series Trust I: Pax World Global Women's Equality Fund; Individual Investor Class Shares	PXWEX	EF
45	TIAA-CREF Funds: Social Choice Equity Fund; Institutional Class Shares	TISCX	EDYG
46	TIAA-CREF Funds: Social Choice Equity Fund; Retirement Class Shares	TRSCX	EDYG
47	TIAA-CREF Funds: Social Choice Equity Fund; Retail Class Shares	TICRX	EDYG
48	Boston Trust & Walden Funds: Walden Equity Fund	WSEFX	EDYG
49	Pax World Funds Series Trust I: Pax World Global Women's Equality Fund; Institutional Class Shares	PXWIX	EF
50	Neuberger Berman Equity Funds: Neuberger Berman Socially Responsive Fund; Institutional Class Shares	NBSLX	EDYG
51	Pax World Funds Series Trust I: Pax World Small Cap Fund; Individual Investor Class Shares	PXSCX	EDYG
52	Pax World Funds Series Trust I: Pax World Small Cap Fund; Institutional Class Shares	PXSIX	EDYG

53	Pax World Funds Series Trust I: Pax World Small Cap Fund; Class R Shares	PXSRX	EDYG
54	Boston Trust & Walden Funds: Walden Small Cap Innovations Fund	WASOX	EDCS
55	Calvert Social Investment Fund: Equity Portfolio; Class Y Shares	CIEYX	EDYG
56	Praxis Mutual Funds: Praxis Growth Index Fund; Class A Shares	MGNDX	EDYG
57	Praxis Mutual Funds: Praxis Growth Index Fund; Class I Shares	MMDEX	EDYG
58	Praxis Mutual Funds: Praxis Small Cap Fund; Class A Shares	MMSCX	EDCS
59	Praxis Mutual Funds: Praxis Small Cap Fund; Class I Shares	MMSIX	EDCS
60	Gabelli SRI Fund, Inc; Class A Shares	SRIAX	EF
61	Gabelli SRI Fund, Inc; Class C Shares	SRICX	EF
62	Gabelli SRI Fund, Inc; Class I Shares	SRIDX	EF
63	Gabelli SRI Fund, Inc; Class AAA Shares	SRIGX	EF
64	Neuberger Berman Equity Funds: Neuberger Berman Socially Responsive Fund; Class A Shares	NRAAX	EDYG
65	Neuberger Berman Equity Funds: Neuberger Berman Socially Responsive Fund; Class C Shares	NRACX	EDYG
66	Neuberger Berman Equity Funds: Neuberger Berman Socially Responsive Fund; Class R3 Shares	NRARX	EDYG
67	TIAA-CREF Funds: Social Choice Equity Fund; Premier Class Shares	TRPSX	EDYG

Note: The CRSP investment style code consists of up to four characters, with each position defined. Reading left to right, the four codes represent an increasing level of granularity. Codes with less than four characters exist, and it simply means that they are defined to a less granular level. Level 1: Equity (E) or Mixed Fixed-Income and Equity (M), Level 2: Domestic (D) or Foreign (F), Level 3: (1) Sector (S), and corresponding Level 4: (1). Gold (G), Health (H), Financial (F), Natural Resources (N), Real Estate (R), Technology (T), Utilities (U), Commodities (C), Consumer Services (S), Industries (I), Materials (M), and Telecom (A); Level 3: (2) Cap-based (C), and corresponding Level 4: (2). Large Cap (L), Mid Cap (M), Small Cap (S), and Micro Cap (I); Level 3: (3). Style (Y), and corresponding Level 4: (3). Growth (G), Growth & Income (B), Hedge (H), Short (S), and Income (I). For example, EDYG is Equity Domestic Style Grow. Source: Survivor-Bias-Free US Mutual Fund Guide, CRSP

Table 4. 2 List of 67 Traditional Mutual Funds and their Investment Objectives
Source: Survivor-Bias-Free US Mutual Fund Guide, CRSP

	Fund name	Ticker	Objective Code
1	AllianceBernstein Blended Style Series, Inc: US Large Cap Portfolio; Class I Shares	ABBIX	EDYG
2	American Century Capital Portfolios, Inc: Equity Income Fund; Institutional Class Shares	ACIIX	EDYI
3	Allianz Funds: NFJ Dividend Value Fund; Class P Shares	ADJPX	EDYI
4	BlackRock Funds II: Income Builder Portfolio; Institutional Shares	BIBDX	EDYI
5	American Century Variable Portfolios, Inc: VP Income & Growth Fund; Class I Shares	AVGIX	EDYB
6	AIM Funds Group: AIM Select Equity Fund; Class Y Shares	AGWYX	EDYG
7	Calvert Impact Fund, Inc: Calvert Large Cap Growth Fund; Class Y	CLGYX	EDYG
8	Calvert Fund: Calvert New Vision Small Cap Fund; Class B Shares	CNVBX	EDCS
9	Advantage Funds, Inc: Dreyfus Small Company Value Fund	DSCVX	EDCS
10	RidgeWorth Funds: Aggressive Growth Allocation Strategy Fund; Class C Shares	CLVLX	EDYG
11	SPDR Series Trust: SPDR Dow Jones Mid Cap Growth ETF	EMG	EDCM
12	Direxion Funds: Direxion Monthly Dollar Bear 2x Fund; Investor Class Shares	DXDDX	EDYS
13	Federated Equity Funds: Federated Kaufmann Small Cap Fund; Class A Shares	FKASX	EDCS
14	Fidelity Advisor Series I: Fidelity Advisor Mid Cap Fund; Class T Shares	FMCAX	EDCM
15	Fidelity Advisor Series VII: Fidelity Advisor Industrials Fund; Class T Shares	FCLTX	EDSI
16	Franklin Gold & Precious Metals Fund; Advisor Class Shares	FGADX	EDSG
17	Market Vectors ETF Trust: Market Vectors--Environmental Services ETF	EVX	EDSI
18	First American Investment Funds, Inc: Mid Cap Index Fund; Class B Shares	FMDBX	EDCM
19	Fidelity Devonshire Trust: Fidelity Advisor Mid Cap Value Fund; Class T Shares	FMPTX	EDCM
20	Fidelity Select Portfolios: Insurance Portfolio	FSPCX	EDSF
21	GE Institutional Funds: Premier Growth Equity Fund; Service Class Shares	GEPSX	EDYG
22	First Trust Exchange-Traded AlphaDEX Fund: First Trust Materials AlphaDEX Fund	FXZ	EDSM
23	Hartford Mutual Funds, Inc: Hartford Equity Growth Allocation Fund; Class B Shares	HAABX	EDYG
24	ICON Funds: ICON Equity Income Fund; Class I Shares	IOEIX	EDYI
25	ING Equity Trust: ING Real Estate Fund; Class O Shares	IDROX	EDSR
26	Eagle Series Trust: Eagle Large Cap Core Fund; Class R5 Shares	HTCSX	EDYG

27	Hartford Mutual Funds, Inc: Hartford MidCap Fund; Class R3 Shares	HFMRX	EDCM
28	AIM Equity Funds: AIM Diversified Dividend Fund; Class C Shares	LCEVX	EDYG
29	Financial Investors Trust: ALPS/Red Rocks Listed Private Equity Fund; Class I Shares	LPEIX	EDSF
30	Advisors' Inner Circle Fund II: SmartGrowth Lipper Optimal Conservative Index Fund; Class A Shares	LPCAX	EDYB
31	Ivy Funds, Inc: Ivy Tax-Managed Equity Fund; Class A Shares	IYEAX	EDYG
32	Janus Investment Fund: Janus Orion Fund; Class R Shares	JORRX	EDYG
33	AllianceBernstein Blended Style Series Inc: AllianceBernstein 2015 Retirement Strategy; Class I Shares	LTEIX	EDYB
34	MFS Series Trust VI: MFS Utilities Fund; Class R1 Shares	MMUGX	EDSU
35	Manning & Napier Fund, Inc: Target 2010 Series; Class I Shares	MTHIX	EDYB
36	Manning & Napier Fund, Inc: Target 2010 Series; Class R Shares	MTHRX	EDYB
37	AllianceBernstein Blended Style Series Inc: AllianceBernstein 2055 Retirement Strategy; Class K Shares	LTWKX	EDYB
38	Davis New York Venture Fund, Inc: Davis New York Venture Fund; Class B Shares	NYVBX	EDYG
39	Natixis Funds Trust I: Natixis US Diversified Portfolio; Class C Shares	NECCX	EDYG
40	JPMorgan Trust II: JPMorgan Multi-Cap Market Neutral Fund; Class A Shares	OGNAX	EDYH
41	Neuberger Berman Equity Funds: Neuberger Berman Mid Cap Growth Fund; Class A Shares	NMGAX	EDYG
42	Neuberger Berman Equity Funds: Neuberger Berman Mid Cap Growth Fund; Class C Shares	NMGCX	EDYG
43	Optimum Fund Trust: Optimum Small-Mid Cap Growth Fund; Institutional Class Shares	OISGX	EDCS
44	JPMorgan Trust II: JPMorgan Multi-Cap Market Neutral Fund; Select Class Shares	OGNIX	EDYH
45	Old Mutual Funds II: Old Mutual Barrow Hanley Value Fund; Class I Shares	OIBHX	EDYG
46	PIMCO Funds: Fundamental IndexPLUS TR Fund; Class D Shares	PIXDX	EDYG
47	Principal Funds, Inc: LargeCap Value Fund III; Class B Shares	PLVBX	EDYG
48	Principal Funds, Inc: LargeCap Blend Fund I; Class J Shares	PPXJX	EDYG
49	UBS PACE Select Advisors Trust: UBS PACE Large Co Value Equity Investments; Class C Shares	PLVCX	EDYB
50	RS Investment Trust: RS Equity Dividend Fund; Class A Shares	REDAX	EDYI
51	RS Investment Trust: RS MidCap Opportunities Fund; Class C Shares	RMOCX	EDYB
52	RiverSource Investment Series, Inc: RiverSource Disciplined Large Cap Growth Fund; Class R4 Shares	RDLFX	EDYG
53	Russell Investment Company: Russell US Growth Fund; Class E Shares	RSGEX	EDYG
54	Rydex Series Funds: Inverse High Yield Strategy Fund; Class C Shares	RYIYX	EDYS

55	Rydex Series Funds: Managed Futures Strategy Fund; Class C Shares	RYMZX	EDSC
56	Rydex Series Funds: Strengthening Dollar 2x Strategy Fund; C-Class Shares	RYSJX	EDYH
57	Claymore Exchange-Traded Fund Trust 2: Claymore/Delta Global Shipping ETF	SEA	EDSI
58	Saratoga Advantage Trust: Small Capitalization Portfolio; Class I Shares	SSCPX	EDCS
59	Sentinel Group Funds, Inc: Sentinel Capital Growth Fund; Class C Shares	SECGX	EDYG
60	State Farm Mutual Fund Trust: State Farm Equity Fund; Legacy Class A Shares	SLEAX	EDYG
61	SunAmerica Equity Funds: SunAmerica Growth & Income Fund; Class A Shares	SEIAX	EDYB
62	Sun Capital Advisers Trust: SC WMC Large Cap Growth Fund; Service Class Shares	SFISX	EDYG
63	American Century Mutual Funds, Inc: Heritage Fund; Investor Class Shares	TWHIX	EDYG
64	Thornburg Investment Trust: Thornburg Core Growth Fund; Class C Shares	TCGCX	EDYG
65	AIG Retirement Company I: Broad Cap Value Income Fund	VBCVX	EDYB
66	Wells Fargo Funds Trust: Wells Fargo Advantage Discovery Fund; Investor Class Shares	STDIX	EDYG
67	Victory Portfolios: Small Company Opportunity Fund; Class I Shares	VSOIX	EDCS

Table 4. 3 Summary Statistics

Means, Betas, and Variances of Monthly Returns of Sixty-Seven Ethical and Sixty-Seven Traditional Funds. It appears that the ethical funds in our sample have in general higher average returns, lower variances, higher betas, higher skewness and higher kurtosis than their traditional counterparts. The difference in those statistics may due to different reasons, for example, the matching criteria for matching ethical mutual funds to the traditional mutual funds.

	Ethical Funds	Traditional Funds
	Means	
Maximum	0.0154	0.018
Minimum	0.0035	-0.0188
Average	0.0075	0.0063
	Variance	
Maximum	0.0047	0.0181
Minimum	0.0003	0.0001
Average	0.0024	0.003
	Beta	
Maximum	1.0608	1.2082
Minimum	0.9484	0.7089
Average	1.001	0.9656
	Skewness	
Maximum	0.0504	0.7701
Minimum	-1.8998	-1.4682
Average	-0.7533	-0.6308
	Kurtosis	
Maximum	8.4627	4.2827
Minimum	0.0699	-0.651
Average	2.3668	1.7204

Table 4. 4 Summary Statistics of Selectivity and Timing Measure

The table shows the positive and negative selectivity for both models and show how many significant values among them for both ethical and traditional mutual funds. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

	Ethical Funds	Traditional Funds
Treynor-Mazuy Model		
Selectivity Measure		
Positive	33	23
Significant Positive*	2	5
Negative	34	42
Significant Negative*	7	17
Timing Measure		
Positive	27	37
Significant Positive*	2	10
Bhattacrarya-Pfleiderer Model		
Selectivity Measure		
Positive	35	29
Significant Positive*	2	6
Negative	32	38
Significant Negative*	7	17
Timing Measure		
Positive	27	37
Significant Positive*	9	18

Table 4. 5 R^2 and Fund Liquidity

According to Amihud and Goyenko (2013), the Correlation Coefficient Between Regression Intercept (alpha) and R^2 can be measured to illustrate the fund selectivity. After taking the market timing into consideration, for ethical funds, the correlation between R^2 and alpha is significant negative in the Treynor-Mazuy and the Bhattacharya-Pfleiderer model. These results are consistent with those of Amihud and Goyenko (2013) and imply that the negative relation between R^2 and alpha still holds in the presence of fund manager’s market timing activities. For traditional funds, the correlation between R^2 and alpha is significant positive in the Treynor-Mazuy model, and negative, but not significant, in the Bhattacharya-Pfleiderer model. It is conceivable that power of R^2 to serve as a proxy for selectivity in the presence of market timing weakens as the sample becomes disperse with more abnormal performances on the upside and downside. There is one caveat worth noting regarding the proxy selectivity. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

	Fund	
Model	Ethical	Traditional
Treynor-Mazuy Model	-0.4217*	0.3269*
Bhattacharya-Pfleiderer Model	-0.4887*	-0.1607

Table 4. 6 Parametric Matched-Pairs T-test and Nonparametric Wilcoxon Matched-Pairs Signed-Rank Test

P-values are shown for Parametric Matched-Pairs T-test and Nonparametric Wilcoxon Matched-Pairs Signed-Rank Test between ethical and traditional Funds. Both the matched-pairs t-test and the Wilcoxon matched-pairs signed-rank test fail to reject the null hypothesis of no significance difference between ethical and traditional funds in the timing measure of the Treynor-Mazuy model and both the selectivity and timing measure of the Bhattacharya-Pfleiderer model at the .05 level. However, both the matched-pairs t-test and the Wilcoxon matched-pairs signed-rank test reject the hypothesis of no significant difference between ethical and traditional funds in the selectivity measure of the Treynor-Mazuy model at the .05 level. As discussed earlier, the Bhattacharya-Pfleiderer model of measuring investment performance of managed portfolios is more robust, econometrically and methodologically superior to, and an improvement over the Treynor-Mazuy model.

	Matched-Pairs T-test (p-value)	**Wilcoxon Matched-Pairs Signed-Rank Test (p-value)**
	Treynor-Mazuy Model	
Selectivity Measure	0.03	0.03
Timing Measure	0.23	0.36
	Bhattacharya-Pfleiderer Model	
Selectivity Measure	0.19	0.24
Timing Measure	0.97	0.92

Figure 2. 1 Number of countries

This figure plots the number of countries in our sovereign CDS sample from January 2001 to September 2015.

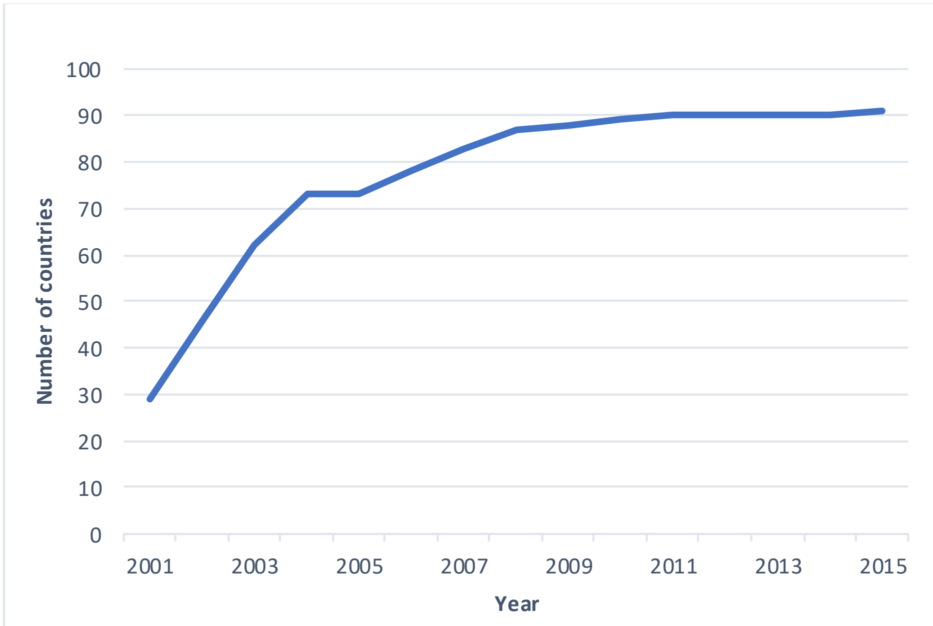

Figure 2. 2 Cumulative monthly returns of sovereign CDS momentum

The figure plots the cumulative alphas of the long-short strategy in sovereign CDS markets, after controlling for MKT_SCDS. All factors are described in Panel C of Table 2. 3

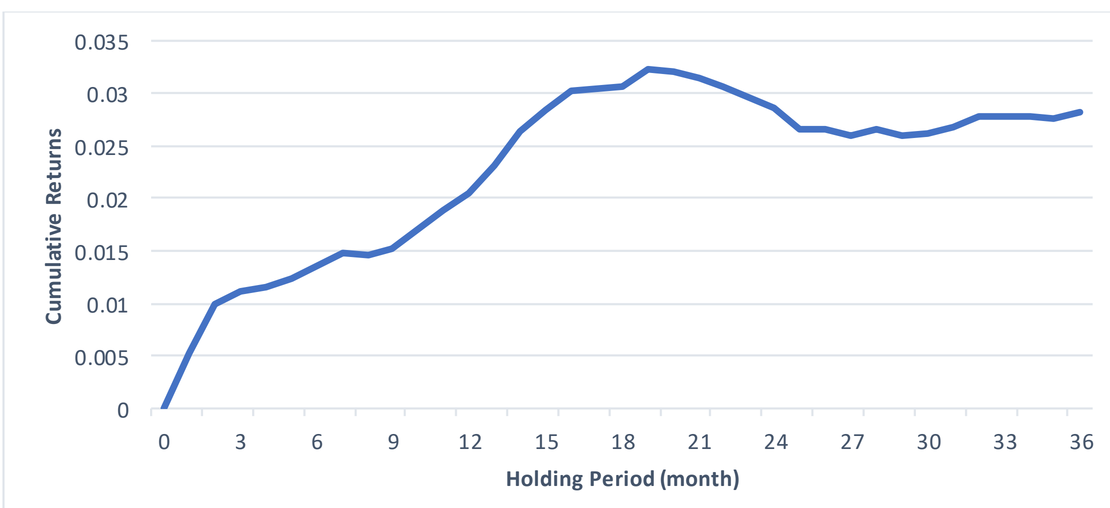

Figure 2. 3 Cumulative monthly returns during recession

This figure shows cumulative monthly returns accruing to three different momentum returns. The momentum strategies are sorted by past returns of 1, 6, and 12 months, respectively, and held by one month. The blue line shows return to the momentum strategy with a one-month formation period, the red line shows return to a strategy with a six-month formation period, whereas the green line shows return to a momentum strategy with a 12-month formation period. Shaded areas correspond to two NBER recessions from March 2001 to November 2001 and from December 2007 to June 2009.

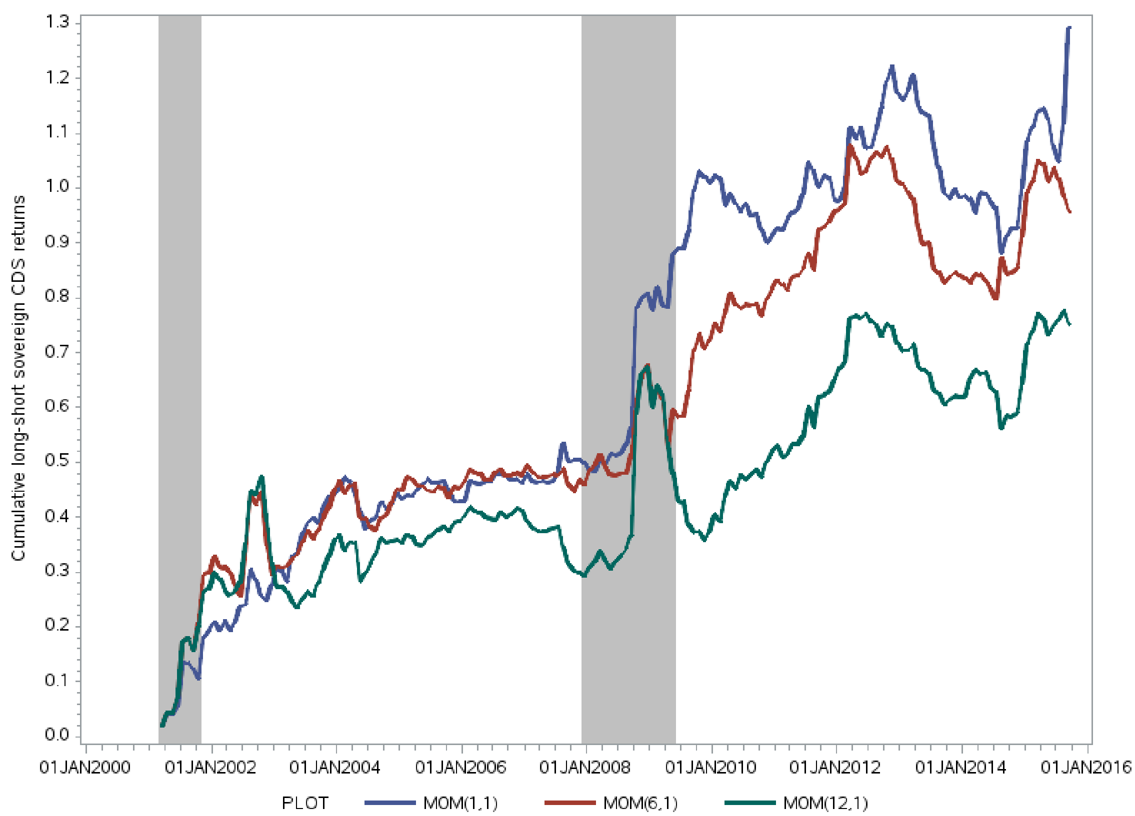

Figure 2. 4 Time series plot of correlation

This figure plots the 24-month rolling window correlation between momentum returns of sovereign CDS returns and momentum returns of stock index returns from April 2001 to September 2015 and the 24-month rolling window correlation between the momentum returns of sovereign CDS returns and momentum returns of bond index from April 2001 to September 2015, as denoted in red line and blue line, respectively. Shaded areas correspond to two NBER recessions from March 2001 to November 2001 and from December 2007 to June 2009.

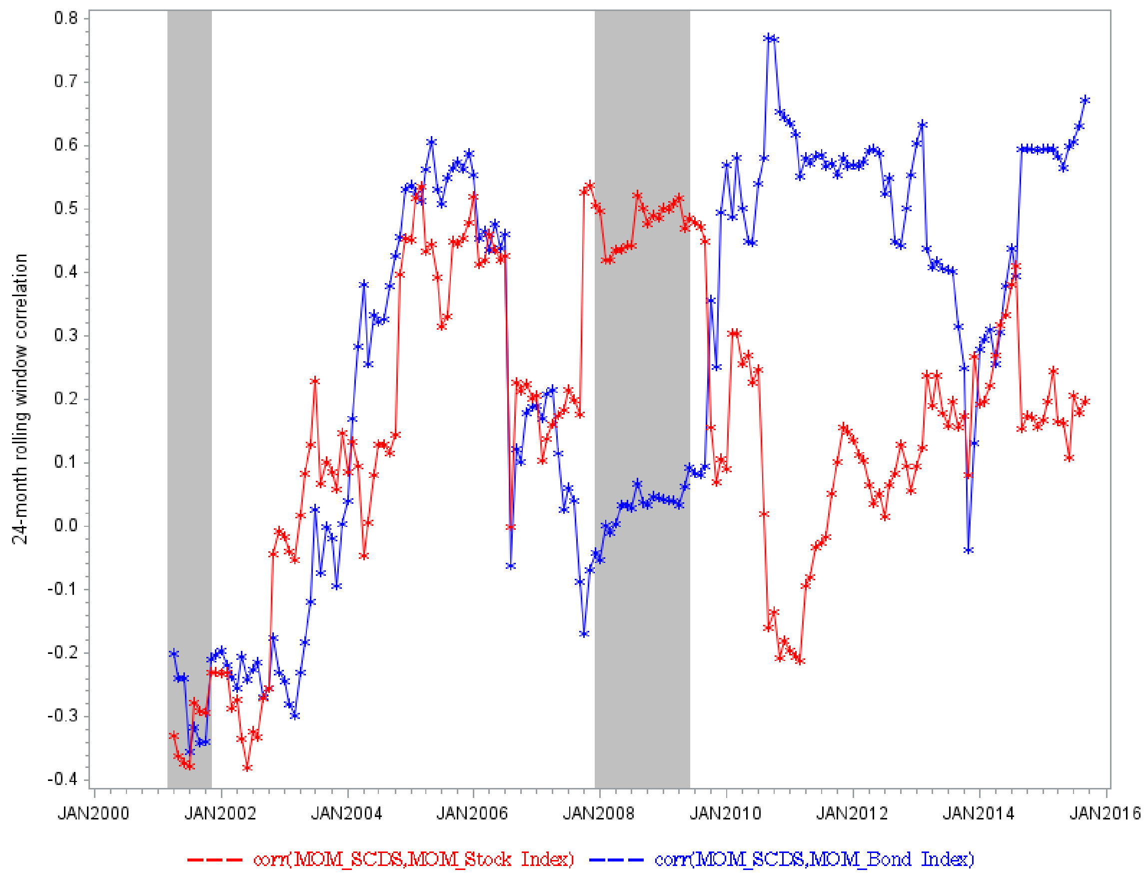

Figure 3. 1 Number of countries

This figure plots the number of countries in our sovereign CDS sample, the sample with both sovereign CDS and stock indices, and the sample for both sovereign CDS and sovereign bonds.

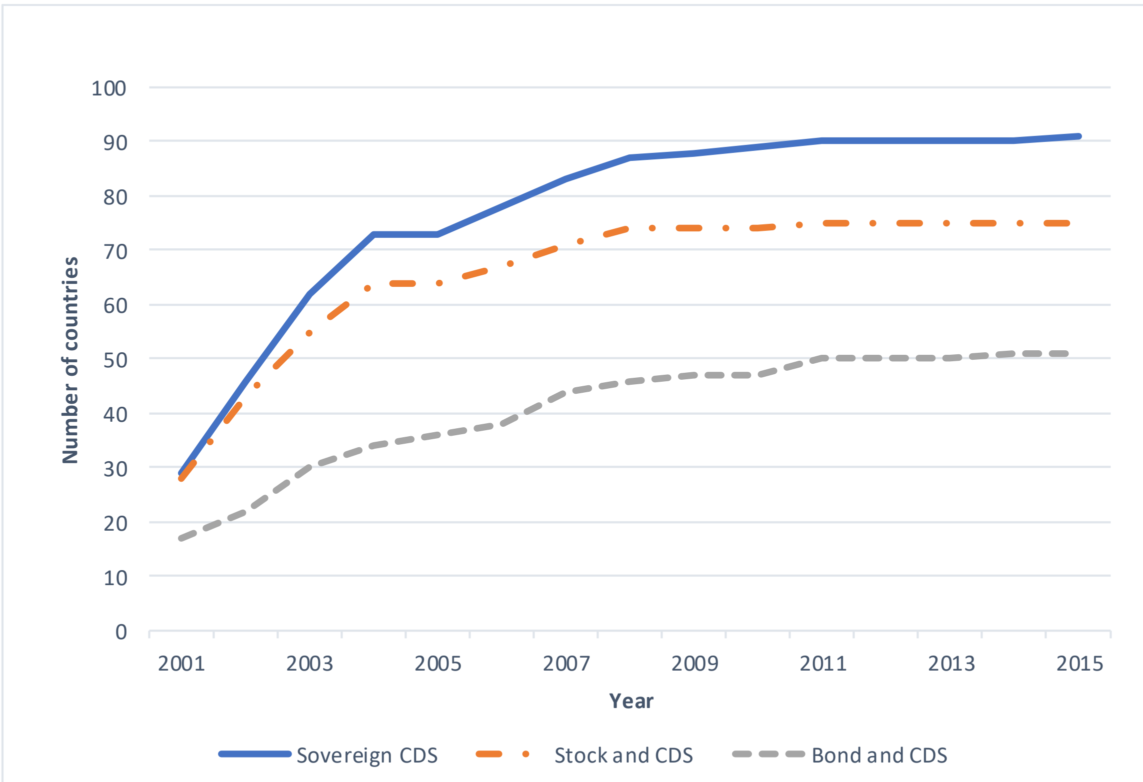

Figure 3. 2 Cumulative returns

Panel A plots the cumulative alphas of the long-short strategy in stock markets, after controlling for MKT_stock, MOM_stock, MKT_FX, HML_FX, and MOM_FX. Panel B plots the cumulative yield changes in sovereign bond markets, after controlling for MKT_bond and MOM_bond. All factors are described in Table 3. 2