Three Essays in Financial Economics: the Interactions of Stocks and Fixed Income Securities

by

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Abstract

This dissertation consists of three essays in the field of financial economics, which examine the interactions of stocks and fixed income securities, at the individual bond level and aggregate market level. The first chapter provides a general introduction for the whole thesis.

The second chapter studies asynchronous and contemporaneous links between values of individual stocks and bonds issued by the same firm. These correlations offer indications on how firm-specific information streams between the stock and bond markets. We examine those links using a novel database which contains bonds issued by Canadian firms over three decades. The overall result provides strong evidence of information flows streaming from the stock market to the bond market, and suggests that significant bidirectional information flows were triggered by the 2007 financial crisis. Further, information regarding the mean of firm's value, rather than its volatility, prevails in driving contemporaneous variations in stocks and bonds.

The third chapter examines flights from stocks to three types of safe-haven assets: long-term Treasuries, T-Bills, and top-grade corporate bonds. We propose an innovative data-driven approach to identify flight-to-quality, and thus eliminate the exogenous identification of the crisis period. The chapter then examines the role of asset performance, volatility, illiquidity, and monetary policy activities on the flight-

to-quality episode. The results indicate that illiquidity shocks appear to diversely affect different types of flights. Monetary policy announcements, both past and contemporaneous, are shown to decrease the incidence of flight-to-quality. In addition, this chapter establishes a strong link between the profitability of the momentum strategy and flight-to-quality.

In Chapter 4, we check the robustness of the methodology to identify flight-to-quality proposed in Chapter 3. We find that flight indicators obtained by employing sub-samples, crisis periods or benchmark periods with different numbers of observations are highly correlated with each other. Our flight to long-term Treasuries indicators are robust to inclusion of the two other safe-haven assets. Results based on a series of data simulations with correlation changes of various possible sizes indicate that when a correlation change is about 5 times as large as the benchmark correlation level, our model can identify a flight in 90% of the data simulations.

The last chapter concludes.

Preface

I collaborated with my supervisor Professor Valentina Galvani, and Professor Stefano Gubellini from San Diego State University on some of the research in this thesis.

Chapter 2 was coauthored with Professors Valentina Galvani and Stefano Gubellini. A version of this chapter has been published as Cao, N., Galvani, V. and Gubellini, S., 2017. "Firm-specific stock and bond predictability: New evidence from Canada." *International Review of Economics* & *Finance*, Volume 51, 174-192. I was responsible for data collection and cleansing, research methodology development, empirical analysis and regressions, results interpretation and presentation, as well as manuscript composition. Professors Valentina Galvani and Stefano Gubellini were involved with motivation, research methodology development, results interpretation as well as manuscript composition and edit.

Chapter 3 was coauthored with Professor Valentina Galvani. I was responsible for motivation, data collection and cleansing, research methodology development, empirical analysis and regressions, results interpretation and presentation, as well as manuscript composition. Professor Valentina Galvani contributed to motivation, research methodology development, results interpretation as well as manuscript composition and edit.

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Finally, I leave my big "Thank You" to my lovely family, who always believe in me, give me endless courage, and accompany me throughout my Ph.D. journey. You are my strength to keep going and become better.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

This dissertation consists of three chapters reporting research in the field of financial economics. The first essay is titled "Firm-specific Stock and Bond Predictability: New Evidence from Canada," while the second and the third are titled "Flights from Stocks" and "A Robustness Study on Identification of Flights." The databases employed for the empirical analyses cover several asset classes, including stocks, corporate bonds, and federal bond markets. Data for both Canada and the United States are employed.

The second chapter examines the comovements of individual stocks and bonds issued in the Canadian market, and relies on bond and equity-level data. The third and fourth chapters evaluate one type of market instability, namely flight-to-quality, using data for the U.S. financial markets, at the aggregate level.

Chapter 2 answers questions such as: how is firm-level information incorporated into security price? Do informed traders systematically rely on the stock market, or on the bond market, to profit from their superior information? To address these questions, I, and my coauthors, examine the asynchronous and contemporaneous correlations between the returns on stocks and bonds, where stocks are matched to individual bonds by issuing firm. This work employs an extensive and original database of bonds issued by Canadian firms which covers the 1984-2010 period, and an extension of this dataset that updates the analysis to the year 2016.

Asynchronous and contemporaneous links between the values of individual stocks and bonds issued by the same firm offer indications on how firm-specific information streams between the stock and bond markets. The results provide strong evidence of information flows streaming from the stock market to the bond market. The analysis of the sub-sample starting in the summer of 2007 suggests that significant bidirectional information flows were triggered following the 2007-2009 financial crisis.

According to the classical model of corporate bond valuation proposed by Merton (1974), the sign of the contemporaneous correlation between the returns on stock and bonds issued by the same firm responds to the type of information resulting in a change in price. The empirical results show that news regarding the mean of the firm's value, rather than its volatility, drives price adjustments of stocks and bonds.

Chapter 3 examines the effects of asset performance, realized and expected volatility, illiquidity, and monetary policy on the incidence of flight-to-quality episodes for the U.S. market. In addition, this chapter establishes a strong link between the profitability of the momentum strategy and flight-to-quality. Our sample covers the period of 1990 to 2014, a sample that includes the 2007-2009 financial crisis. In a departure from the literature, which typically focuses on flights from stocks into long-term Treasuries only, this paper's analysis considers flight-to-quality from stocks into three classes of safe havens. These are long-term Treasury bonds, T-Bills, and top-grade corporate bonds. The inclusion of T-Bills in this paper's analysis is meant to model the behavior of investors who decide to "park" their wealth in liquid and short-term securities, while waiting for the uncertainty to be resolved. Existing research has also documented evidence of substantial flights into corporate bonds occurred during the 2007-2009 financial crisis. As our sample covers the months of that recent crisis, including into our discourse corporate bonds appears to be preferable, in the name of completeness. Our analysis shows that flights into T-Bills and corporate bonds represent a sizeable share of the total number of flights.

With respect to the extant literature, this paper proposes several technical innovations in the methodology employed to identify flights. Following the common approach in the literature on market instability, we identify flights by means of significant changes in the correlation between asset returns, during a given time interval. The time-period over which such correlation changes are evaluated is the (potential) crisis period.

Due to a lack of consensus on the defining moments of the 2007-2009 financial crisis, our approach is to eliminate the exogenous identification of potential crisis periods. The timing of flights is made endogenous by evaluating correlation changes for a series of rolling-samples of fixed width. Making the timing of the shocks endogenous enables to dispense with researchers' perception of the timing of events, and eliminates concerns of sample selection bias in the identification of flight episodes. We then analyze the indicators of flights obtained within the rolling sample framework using a probit regression, thus eschewing concerns about the lack of stationarity.

The estimation of a series of probit models allows us to analyze the effects of fundamental market forces on the incidence of flights. Our findings indicate that illiquidity has a differential effect on different types of flights, as predicted by the illiquidity model of Vayanos (2004). In addition, Federal Reserve's activities appear to have a benign effect on market stability, as monetary policy announcements, lagged or contemporaneous, decrease the probability of flights. We also document that strong performance of the momentum strategy is associated with the incidence of market instability. In particular, momentum is disproportionately profitable during periods in which there is evidence of flight incidence.

Chapter 4 provides a number of robustness checks for the methodology employed to identify flight-to-quality in Chapter 3. We estimate flight indicators by employing sub-samples with different numbers of observations, and various widths of the crisis and benchmark periods. The results show that the obtained flight indicators are highly correlated with the flight indicator employed in Chapter 3. We also compare flight indicators for long-term Treasuries estimated using a single equation, as it is the custom in the literature, with those obtained from a system of equations, designed to account for flight into T-Bills and top-grade corporate bonds, as done in Chapter 3. We find that the flight to long-term Treasuries indicator obtained using an individual equation is strongly correlated to the one obtained in the multiple equation setting. Other robustness checks include an examination of the assumptions about the error term variance-covariance matrix employed to evaluate the flight indicators. Finally, we conduct a more formal evaluation of the ability of the proposed flight indicator to capture large market changes, by simulating shocks of different magnitudes to asset correlation. This analysis allows us to qualify the types of correlation shocks that are detected by the methodology proposed in Chapter 3. Results based on these data simulations with correlation changes of various possible sizes indicate that when a correlation change is about 5 times as large as the benchmark correlation level, our model can identify a flight in 90% of the data simulations.

Chapter 2

Firm-specific Stock and Bond Predictability: New Evidence from Canada

2.1 Introduction

Starting in the 1980s, the comovements between stock and bond markets became the subject of several studies. A stream of this literature aims to integrate the price dynamics of stocks and bonds by showing that the same set of systematic risk factors explains cross-sectional excess returns and yields, as proposed in the seminal studies of Gebhardt et al. (2005), Elton et al. (2001), and Fama and French (1993). A concurrent body of research examines the lead-lag dynamics between stock and bond values. Studies in this line of inquiry evaluate whether bonds or stocks show any predictive ability for each other, where predictability is typically interpreted in the framework of the gradual information diffusion model proposed by Hong and Stein (1999), or it is explained by invoking liquidity arguments (Ronen and Zhou, 2013). A related stream of research examines whether stocks and bonds are contemporaneously correlated at the firm-level. If they are, the interest lies in identifying the nature of the information that dominates adjustments in equity and debt prices.

As we discuss in the subsequent literature review, conclusive evidence on the degree of predictability of stocks and bonds, as well as on cross-market correlations has not been provided. In this paper, we offer new evidence on the informational role of security prices in the Canadian market and thus add to the open debate stemming from U.S. related studies.

As the first step in our analysis, we examine the existence of significant information flows between the Canadian stock and bond markets. These flows are measured by the asynchronous relationships between stock returns and bond yield changes. If stock and bond prices adjust to information instantly and simultaneously, then asynchronous cross-correlations should be absent. We show that in the years preceding the Fall of 2007, information appears to stream from the stock market to the bond market without bouncing back. We also provide evidence of an information flow streaming from the bond to the stock market, as gauged by a significant link between current bond yield changes and leading stock returns in the post-2007 period. In summary, we find that when the years following the 2007 financial crisis are included in the sample, the information flow appears to stream both ways: from the stock market to the bond market, and vice versa. We interpret these bilateral flows as evidence of intensified information exchanges triggered by the recent financial crisis. In a designated sub-section of the paper, we discuss in depth the potential causes of this phenomenon. To preview, we ascribe the heightened predictive ability of bonds after 2007 to an increased relevance of monetary policy in determining asset prices, coupled with bonds being more responsive than equities to the activities of central banks (Brandt and Wang, 2003).

Several U.S related studies have highlighted the puzzling finding that the correlation between contemporaneous stock and bond returns at the firm level tends to be negligible. As pointed out by Collin-Dufresne et al. (2001), this insignificant cross-market correlation is surprising. Indeed institutional investors should be able to exploit informed trading on both markets, thus causing any information-driven arbitrage opportunity to vanish. Kapadia and Pu (2012) suggest that illiquidity and idiosyncratic risk in the U.S. equity or bond market may inhibit the execution of such information-based arbitrage trades, thus explaining the absence of significant cross-market correlations. Contrary to these findings, our analysis of Canadian data documents a significant degree of integration between contemporaneous prices of stocks and bonds that, as we discuss in a dedicated sub-section on market dynamics, is robust to the consideration of liquidity.

Elaborating on the extension of the Kyle (1985) model proposed by Back and Crotty (2015), evidence of a significant cross-market correlation may be also interpreted as a sign of asymmetric information in the Canadian financial market. Corroborating this conjecture is the notion that, in general, the regulatory stance to inside trading is more lenient in Canada than in the United States. Furthermore, prosecutions for illegal insider trading in Canada are unusual and, when occurring, yield outcomes that are less punitive than those observed in the United States (King, 2009; Jabbour et al., 2000).

Another contribution of this study is to shed light on the nature of the prevailing firm-specific information that drives security price adjustments in the Canadian market. According to the structural model of bond pricing by Merton (1974), the sign of the contemporaneous correlation between the value of a firm's equity and that of the bonds issued by the same firm indicates whether the informational shocks driving concurrent variation in stock and bond prices are mostly affecting the mean or the volatility of the firm's underlying assets. The model builds on the firm value being the only state variable that associates prices of alternative claims (e.g., stocks and bonds) to the same firm's assets. Merton's model suggests that the value of a bond is related to the price of a put option on the firm's assets. Due to the limited liability feature of equity, the price of a stock is instead defined by that of a call option on the firm's assets. The bondholder (shareholder) position is equivalent to selling (buying) a European put (call) option. Concurrently, the bondholder also offers a risk-free loan to the shareholder. [1] When the volatility of the firm's assets increases, options appreciate. In this case, the bondholder (short) position deteriorates (as the yield increases), while the shareholder (long) position appreciates (as the stock return increases). In contrast, when the mean of the firm's assets declines, the put appreciates and the call value depreciates. In this instance, both bondholder and shareholder positions worsen (yield increases and stock return declines). Within this theoretical framework, firm-specific information affecting the firm's asset volatility (mean) results in a positive (negative) contemporaneous correlation between

[1] The values of the shareholder and bondholder positions are reconciled using the put and call parity relationship.

stock returns and bond yield changes. The empirical correlations we obtain in our Canadian data indicate that the prevailing type of information affecting concurrent variation in stock and bond prices pertains to the expected value of the issuing firm's assets, rather than to their volatility.

This is the first paper employing Canadian firm-level data to analyze the informational efficiency of the stock and bond markets, as well as the nature of the information that triggers simultaneous price variations in these markets. This study also extends the existing literature on Canadian bonds, which is, unfortunately, sparse, mainly due to a paucity of readily available data.[2] Importantly, our analysis employs a novel database of bonds issued by publicly owned Canadian firms. We collect bond data from two publications: the Financial Post Bonds Canadian Prices and the Financial Post Bonds Corporate. Taken together, these two outlets provide comprehensive records for a large number of Canadian corporate bonds. For comparison, the entire Bloomberg database on Canadian Corporate bonds consistently covers about half of our bond database over the 1984-2010 period. Our sample consists of monthly stock and bond data which include prices for 1,065 bonds issued by 93 publicly traded Canadian firms. The considered time period of 27 years makes our sample the longest among those used in similarly aimed studies. Despite their comprehensive nature, the Financial Post publications were discontinued in December 2010. To corroborate our results suggesting the presence of a firm-specific information flow from the bond to the stock market in the post-2007 period we employ Bloomberg data. In this alternative setting, we favorably replicate our main results and extend their validity to the period ending in 2015.

As noted by Hong et al. (2012) most of the firm-level studies focusing on the serial correlation between stocks and bonds examine the U.S. market and rely on relatively

[2] Other papers which examine Canadian bonds include Batten et al. (2014), Landon (2009), Booth et al. (2007), Landon and Smith (2007), Peters (2007), Landon and Smith (2006), Ackert and Athanassakos (2005), and Hatch and White (1986).

short samples. Therefore, the use of our novel database of Canadian corporate bonds covering three decades of data not only assuages data mining concerns, but also evaluates the robustness of the conclusions yielded by the literature focusing on U.S. data to the examination of a sample covering several phases of the business cycle.

To establish a common ground with the extant literature on stock and bond co-movements, we first employ a standard model specification where we regress changes in monthly bond yields on asynchronous and contemporaneous stock returns. Next, we consider various model specifications, sub-samples, and inferential procedures to suppress potential confounding effects and better isolate the stock-bond relationship. To do so we include a battery of control variables for cross-country investing, time-variation, as well as individual bond fixed effects. In further analyses, we exclude the recent financial crisis, eliminate bonds issued by financial firms, and partition the sample according to firm size and credit rating. The alternative model specifications are then evaluated by pooled and bond-level regressions. In particular, we generate parameter estimates in the GMM framework of Hansen (1982) which abstracts away from distributional assumptions on the price variation dynamics of stocks and bonds.

The remainder of the paper is organized as follows. The next section discusses the literature and outlines our empirical approach. Section 2.3 presents the main characteristics of the databases we employ. Section 2.4 introduces the econometric framework. Section 2.5 discusses the results of the pooled and bond-level regression analyses. Section 2.6 concludes.

2.2 Motivation

2.2.1 Literature Review

Previous empirical studies suggest that returns and spreads on bonds issued by U.S. firms might exhibit limited co-variation with systematic risk factors after controlling for bond-related characteristics. Fama and French (1993) document common variation between bond and stock returns, and ascribe it to interest rate and default risk. From this perspective, the commonality in risk factors has the potential to generate the comovements between stocks and bonds. Additional studies investigate the ability of the Fama and French factors based on stock returns to account for corporate bond yields. Elton et al. (2001) examine yield spreads between corporate and government bonds, and find that stock market risk factors are of primary importance in explaining corporate spreads. Liu and Wu (2009), and Gebhardt et al. (2005) present evidence that partially support the conclusions of Elton et al. (2001). However, King and Khang (2005) show that, after controlling for firm and bond characteristics, equity risk factors have very limited explanatory power for corporate bond yield spreads. The conclusions in King and Khang (2005) are consistent with the predictions of structural models of bond pricing which posit that the price of a corporate bond depends solely on parameters specific to the bond and on the issuing firm's financial strength. Interestingly, these early empirical studies reach different conclusions on the explanatory power of market risk factors for corporate bonds despite relying on the same Lehman Brothers Fixed Income database, and focusing on time periods of similar breadth.[3]

A concurrent early literature (Campbell and Ammer, 1993; Campbell, 1987) investigates the correlation between U.S. stocks and bonds using returns on indexes rather than individual securities. Chan (1992) and Kawaller et al. (1987) employ a regression framework where current returns are regressed on lead-lag returns to ascertain the direction of the information flow among alternative asset classes.[4] The

[3]The time periods are as follows: 1987-1996 (Elton et al., 2001), 1973-1996 (Gebhardt et al., 2005), 1985-1998 (Liu and Wu, 2009), and 1987-1996 (King and Khang, 2005).

[4]Kawaller et al. (1987) analyze the intraday price relationship between S&P 500 Futures and the S&P 500 Index. Chan (1992) examines the inter-temporal correlation between the Major Market cash index and the Major Market Index Futures, as well as the S&P 500 Futures. Other early studies that employ lead-lag analyses to evaluate information flows include Stephan and Whaley

study of Kwan (1996) introduces the use of firm-level data to examine the correlation between U.S. stocks and corporate bonds. His analysis is based on the regression of bond yield changes on leading, lagging, and contemporaneous stock returns of the bond issuing firm. Using weekly data for the 1986-1990 period, Kwan documents that stocks lead bonds in reflecting firm-specific information. Campbell and Taksler (2003) regress the yield spread of corporate bonds on the lagged average and standard deviation of the return on the equity of the bond issuing firm, as well as of the return on the aggregate stock portfolio, over the 1995-1999 period. The authors conclude that changes in market volatility play a minor role in driving bond yields, as opposed to variations in the mean and volatility of the return of the equity of the bond issuing firm. Similarly to Kwan (1996), Campbell and Taksler (2003) document a significant lead-lag relationship between the values of U.S. stocks and bonds issued by the same firm, with stocks leading bonds. In contrast, Hotchkiss and Ronen (2002) employ Granger causality tests and find that lagged stock returns fail to predict current bond yields around earnings news.

The advent of the Trade Reporting and Compliance Engine (TRACE) in 2002 has increased the quality of corporate bond data for the U.S. market, leading to a spur of contributions examining the lead-lag relationship between stocks and bonds for high-frequency data. Using vector autoregression analysis, Downing et al. (2009) report evidence of a significant inter-temporal correlation between lagged stock returns and bond yields, but only for low-grade corporate bonds. Tsai (2014) employs Granger causality tests to evaluate the lead-lag relationship between U.S. stocks and corporate bonds over the 18 months following July 2005. Her findings indicate that the U.S. bond market reacts more slowly to earnings surprises than the stock market. Tsai also shows that stocks appear to lead bonds, but the results are sensitive to the consideration of large bond trades and of speculative bonds. Hong et al. (2012)

(1990) and Stoll and Whaley (1990).

find that bonds are predicted by lagged aggregate stocks returns, while the reverse direction of predictability is significant only after the 2007-2009 crisis is included in the sample. Bittlingmayer and Moser (2014) focus on the leading behavior of bonds and regress U.S. stock returns on lagged bond and stock returns over the 2002-2008 period. They show that, for high-yield bonds, past bond price changes anticipate stock price movements.

Studies on cross-serial correlations between stock and bond values have obtained contrasting results. These mixed findings could partially be explained by the fact that contributions to this literature use data sampled at different frequencies. Hotchkiss and Ronen (2002) uses both daily and hourly data, Hong et al. (2012) and Downing et al. (2009) employ daily data, while Tsai (2014) uses 5-minute spaced observations. Kwan (1996) relies on weekly price points, while Campbell and Taksler (2003), as well as Bittlingmayer and Moser (2014), employ data at a monthly frequency. It is plausible that the limited predictability documented with high-frequency data is due, at least in part, to the dissemination of firm-level information requiring a longer time interval than that separating the sampling points, in the spirit of the gradual information diffusion model proposed by Hong and Stein (1999). Therefore, as discussed in Bittlingmayer and Moser (2014), the monthly frequency may provide a better environment to isolate the stock-bond relationship in the long-run.

An additional controversy might arise from the consideration of alternative samples that, at times, are limited either from a cross-sectional or time-series standpoint and therefore may mask that specific dimension of variation. Taken together, the extant empirical literature has not clarified the relevance of firm-specific and economy-wide factors in assessing firm-level information flows between stock and bond markets. More importantly, these flows have been the subject of academic scrutiny but still lack conclusive evidence on the coexistence of the underlying lead-lag mechanics.

2.2.2 Empirical Approach

We adopt a regression approach that builds on previous studies (Kwan, 1996; Chan, 1992; among others). In our baseline specification, bond yield changes are regressed on asynchronous and contemporaneous stock returns of the bond-issuing firm, as well as on yield changes of a Government of Canada bond with matched maturity. We then add individual fixed effects to proxy for unobservable bond characteristics. The set of considered control variables also includes indicators of Canadian and U.S. stock and bond markets performance, to account for domestic market conditions as well as for cross-country investing between U.S. and Canada (Tinic et al., 1987)

While Kwan (1996)'s analysis of the U.S. market relies on weekly observations, we employ monthly stock returns and bond yields. We argue that the use of monthly returns, in addition to being dictated by data availability, provides some safeguard from detecting spurious lead-lag relations across Canadian stocks and bonds that are due to stale price quotes. As discussed in Chan (1992), the observed lead-lag relations between two markets might be due to infrequent trading. The staleness of some quotes can in fact cause assets with more responsive prices to exhibit a leading behavior. The Canadian corporate bond market is rather thin, especially in the first years of the sample which starts in 1984. Therefore, using daily, or even weekly data, could raise concerns on the availability of sufficient time for prices to adjust. Our choice of monthly data mitigates the potential of finding lead-lag relationships which are simply due to infrequent trading.

Even if the market is informationally efficient, nonsynchronous data recording might still generate a spurious lead-lag relationship. This could be a potential concern also for our study, as bond prices are collected at the end of the month, while stock prices are reported on the first trading day of the month. It is conceivable that informational shocks that simultaneously affect bond and stock prices occur after bond prices are collected, but before stock prices are recorded. As a result, stock returns might appear to lead bond yields. We find that, for each firm in our sample, the stock return series sampled at month-end and on the following trading day exhibit a correlation coefficient exceeding 0.99. Therefore, the lack of synchronicity in the official stock and bond data we employ is not likely to affect the results significantly.

The Canadian and American economies are closely linked. The early work of Hatch and White (1986) documents a significant correlation between broad indicators of the U.S. and Canadian security markets. Therefore, one could conjecture that the correlations between stocks and bonds in the Canadian market are common responses to shocks originating within the U.S. economy. Tinic et al. (1987) argue that, due to the significant trading activities of U.S. investors in Canadian stocks, indicators of the state of the U.S. economy might matter in determining returns on the Canadian market. The link between the two economies is reinforced by the considerable proportion of large public companies listed in the Canadian market owned by U.S. investors. As these investors manage their international holdings while responding to the domestic state of the economy, shocks to the U.S. economy are likely to propagate to the Canadian market. Indeed, Landon and Smith (2006) document that the yields on Canadian provincial bonds respond to the dynamics of yields on long-term U.S. Treasuries. Our analysis takes into account the potential effects of price fluctuations in the U.S. market on the firm-level relationship between Canadian stock and bond prices. Building on previous studies, we do so by augmenting our baseline model with the returns on a broad index of the U.S. stock market and the yield changes of 10 year U.S. Treasury bonds.

2.3 Data and Summary Statistics

Our sample of Canadian firms is culled from the intersection of firms in the bond data listing of the Financial Post and firms with stock data from the Datastream database (Thomson Reuters). Among the potential Canadian bond data sources, the Financial

Post provides the best alternative in terms of representativeness and reliability. We collect monthly data for stocks and bonds issued by 93 Canadian corporations over the 1984-2010 period. Appendix A provides details on the design of our dataset. Most of our empirical analyses employ the data over the 1994-2010 period where we identify 83 firms.[5] We then use the sample starting in 1984 to examine the stock-bond relationship in the early years of the Canadian corporate bond market. We are reluctant to base our main assessment of the information flows between stocks and bonds over the 1984-1993 period for two reasons. First, the market for Canadian corporate bonds is extremely thin during those years. As a result, price quotes in the first part of the full sample might carry a large liquidity premium which is difficult to gauge, in the absence of bid and ask prices. Second, Landon (2009) examines the effective tax rate implied by Government of Canada bonds and shows that following a wave of institutional amendments, the composition of the investor pool in Canada might have changed around the year 1993. These two aspects of the Canadian market suggest that the post-1993 sample provides a better environment in which to isolate the stock-bond relationship.

Due to the end of the Financial Post booklet publications our main sample ends in 2010. For completeness, we then employ Canadian corporate bond data from Bloomberg to extend our analyses to the period ending in 2015. We note that over the 1994-2010 period the Financial Post and Blomberg databases include 937 and 478 bonds, respectively. The Bloomberg database, therefore, contains about 50% of the bonds available in the Financial Post for the years preceding the disappearance of

[5] In the 1994-2010 period the average capitalization of the Canadian outstanding debt was 1,163 billions of dollars, 38% of which issued by corporations. The per capita corporate debt in Canada is about 1/3 of that in the U.S. market and equal to $14,000. Canadian bond market participants include a handful of independents (e.g., Blackmont, Merrill Lynch, Desjardins) and is dominated by the Big Six (RBC Dominion, TD Securities, CIBC World Markets, BMO Nesbitt Burns, Scotia Capital, and National Bank Financial). Retail investors generate a very small fraction of the observed trading volume. A description of the Canadian bond market structure can be found in Patel and Yang (2015) and Cunningham (2009).

its booklet series.[6] This substantial discrepancy motivates our focus on the Financial Post database.

We identify 83 Canadian publicly owned firms that have issued ordinary stocks and have reliable corporate bond data for the period from January 1994 to December 2010. The resulting dataset includes 937 corporate bonds. The number of bonds per company varies greatly, with a handful of firms issuing only one bond. Bell Canada Enterprises has the largest number of issues, with 76 bonds. The average number of bonds issued by each firm is about 11. We eliminate bonds with fewer than 12 consecutive observations. The longest bond-level time-series covers 20 years. On average, we obtain about 49 monthly observations per bond.

[Table 2.1 about here]

Table 2.1 reports our summary statistics for bond yields and stock returns over the 1994-2010 period. In Panel A, we note that the mean and median of the individual bond time-series averages are almost identical at 5.82 and 5.81% respectively, with a standard deviation of 1.06%. Bond maturities range between 1 and 41 years and exhibit an average of about 12 years (149 months). Panel B.1 reports similar statistics for bond yields subdivided into four maturity-based groups. The first three groups span maturities up to 20 years. We note that the average yield increases with maturity for all but the fourth group (above 20 years). The average yield on the longest maturity bonds is, in fact, equal to 6.96%, which is 31 basis points lower than in the third group (e.g., 10 to 20 years). Bonds in the highest maturity group tend to be long-term bonds (typically with a maturity of 10+ years) which are periodically renewed and are often issued by firms with high credit scores.

Panels B.2, B.3 and B.4 report additional summary statistics on bonds subdivi-

[6] The average bond yields in the Bloomberg and Financial Post databases over the 1994-2010 period are 5.1 and 5.82%, respectively. The average standard deviation of the yields in both databases is equal to 1.06. Bonds omitted in the Bloomberg database therefore carry a sizeable yield premium, suggesting that Bloomberg may not provide a fully representative sample of the Canadian corporate bond market over the two decades leading to the 2007 financial crisis.

ded according to volume at issue, market capitalization of the issuer (sampled at the beginning of the year of issuance), and financial vs. non-financial firms. In the absence of Canadian transaction data and of reliable bid-ask prices, the volume at issue gauges bond-specific illiquidity. Consistently, small volume bond issues tend to be penalized by larger yields and induce a yield spread across volume-related categories that is comparable to the maturity spread, which is 239 basis points. Financial firms appear to bear a smaller cost of borrowing (5.26% versus 6.13% for non-financial firms), possibly as they tend to issue bonds with shorter maturities. Yields exhibit a substantial homogeneity across market capitalization categories. Unreported summary statistics over the 1994-2007 and 2007-2010 sub-samples are qualitatively similar and fail to modify the broad description of the Canadian corporate bond market offered by Table 2.1.

Panel C of Table 2.1 reports summary statistics for annualized stock returns on our 83 firms. The mean return is 15.74 %, and the average standard deviation is 31.73%.[7] In subsequent analyses, we match corporate bonds with risk-free zero-coupon bonds of similar maturities. Panel D of Table 2.1 provides statistics for the zero-coupon yields, which are obtained from the Bank of Canada's constant maturity yield curve. Both the mean and median of the zero-coupon yields are about 4.50%, with a standard deviation of 0.84%. As expected, these risk-free rates are comparable to (but lower than) the yields on corporate bonds.[8]

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[7]The correspondent values of the S&P/TSX 60 index, which tracks large capitalization stocks, are 10.07%, and 16.36%, respectively.

[8]Details on the procedure to identify bonds with similar maturities are available upon request. The mean (and median) of zero-coupon yields refers only to sovereign bonds which are maturity matched to at least one of the corporate bonds in our sample. As maturities of corporate bonds are not uniformly distributed, the yield on a zero-coupon bond matching the average maturity of our corporate bonds does not need be equal to the reported mean of the yields of the matched zero coupon bonds.

2.4 The Econometric Framework

The estimation framework builds on a regression of bond yield changes over leading, lagging, and contemporaneous stock returns. The considered linear model is:

$$\Delta Yield_{jt} = \beta_0 + \beta_1 \Delta T_{jt} + \beta_2 R_{jt+1} + \beta_3 R_{jt} + \beta_4 R_{jt-1} + \gamma CONT_{jt} + \varepsilon_{jt} \qquad (2.1)$$

where $\Delta Yield_{jt}$ denotes the change in the monthly yield for bond j, defined as $Yield_{jt} - Yield_{jt-1}$. We employ stationary series of bond yield changes, rather than yield levels because, as already documented for U.S. corporate bonds (e.g., Campbell and Taksler, 2003), we find that most of the individual bond time-series of yields exhibit a unit root.

The variable ΔT_{jt} is the change in the interest rate on a risk-free (i.e., Government of Canada bond) zero-coupon bond which has a maturity similar to bond j. Under the assumption that the stock-bond relationship is homogenous along the entire yield curve, we implement a research design that relies on including bonds of different maturities in the sample. To control for the maturity effect, we include maturity-matched sovereign yield changes (i.e., the term ΔT_{jt}), in Equation (2.1). Consistently, the coefficient β_1 gauges the link between contemporaneous changes in corporate bond yields and risk-free interest rates. As bond yields tend to comove with risk-free rates, we expect this coefficient to be positive. The term R_{jt} in Equation (2.1) is the one-month net return from $t-1$ to t on the stock of the firm that issued bond j, while R_{jt+1} and R_{jt-1} are the correspondent leading and lagging stock net returns, respectively. Finally, $CONT_{jt}$ denotes a set of control variables which are shown in the tables reporting the regression results, while ε_{jt} is a zero-mean error term. When none of the variables in $CONT_{jt}$ are included, Equation (2.1) is equal to the model proposed by Kwan (1996).

If stocks and bonds adjust to information instantly and simultaneously, then asynchronous links between stock returns and bond yield changes should be absent. The coefficients β_2 and β_4 in Equation (2.1) gauge these cross-serial linkages. If β_4 is significantly different from zero, then lagged stock returns are correlated with current changes in bond yields. The significance of this coefficient indicates that price adjustments are triggered by firm-level information streaming from the stock to the bond market. This could be the case if informed traders choose first to inject their private information in the equity market. In this scenario, their portfolio decisions would produce a signal which is subsequently used by other agents to trade on the bond market, following a gradual information diffusion pattern similar to that theorized by Hong and Stein (1999). The significance of the coefficient on the leading stock returns can be interpreted similarly. If β_2 is significant, we can infer that firm-level news tends to stream from the bond to the stock market, suggesting that bond yield adjustments carry relevant information for future stock returns. Summarizing, significant estimates of both β_2 and β_4 would suggest the presence of bidirectional information flows between the stock and bond markets.

We note that the correlation between contemporaneous bond yield changes and leading stock returns can be spurious if bonds and stocks are contemporaneously correlated and stock returns are serially correlated. In the framework of Equation (2.1), the concern is that β_2 might be spuriously significant if β_3 is significant and stock returns are significantly autocorrelated. For each stock in our sample, we evaluate the time-series regression of returns on a constant and their lagged values for the 1994-2010 period. Panel A of Table 2.2 reports summary statistics for the estimated coefficients and significance levels of lagged stock returns. The average first-order autocorrelation for stock returns is nearly zero, and only 13.98% of the coefficient estimates are statistically significant. Panel B documents similar values for bond yield changes. In an unreported analysis, we evaluate the results reported in this study after excluding from the sample all the securities exhibiting a significant lag-1 autocorrelation, and obtain similar results. We, therefore, shelve concerns of detecting spurious relationships due to serial autocorrelation.

The coefficient β_3 gauges the contemporaneous correlation between bond yield changes and net returns on the equity of the bond issuing firm. The decomposition of the bond value into a position on a risk-free asset and a put option, as proposed in Merton (1974), suggests that the sign of the contemporaneous correlation between price changes for stocks and bonds issued by the same firm reveals which type of information affects the price adjustment. Stock and bond values move in opposite directions in response to information that affects the volatility of the issuing firm's assets. Thus, this type of information entails a positive correlation between bond yield changes and stock returns; i.e., a positive sign for β_3. However, prices will move in the same direction in response to information affecting the mean (i.e., the expected) value of the firm's assets. Therefore, a predominance of information concerning the mean of the firm's value translates into a negative sign for the coefficient β_3.

In this study, we estimate the alternative specifications included in Equation (2.1) using both pooled and bond-level regressions. Pooled estimates allow extracting a common, average coefficient across bonds. In contrast, to evaluate the results of the individual bond regressions, the inference is based on the empirical distribution of the obtained coefficients. Regressions are evaluated using an exactly identified two-step Generalized Method of Moments methodology (Hansen, 1982) that incorporates the Newey and West (1987) spectral matrix. As we employ pooled data, we allow the joint time-series and cross-sectional dimensions of our sample to determine the lag structure of the Newey-West corrections. Throughout the paper, the chosen number of lags is identified by the rule of thumb $n^{1/4}$, where n is the total number of observations in the sample under examination. The conclusions of this paper are robust to the consideration of different lags. Further, the errors associated with different bonds issued by the same firm have the potential to be correlated, due to the underlying commonalities induced by a shock affecting the issuing firm. In unreported results, we compute the month and firm clustered standard errors of Cameron et al. (2011) in all the time-series and cross-sectional samples discussed in the ensuing result section. Our results based on Newey-West standard errors are robust to this further test.

In this paper, we employ bond yield changes, rather than returns, in view of several considerations. While historical reasons may lie at the root of the use of yields rather than returns, an important caveat in using returns for Canadian data is that the methodology to calculate bond returns for coupon-bearing bonds is not well established, and, crucially, may be affected by data availability. For example, returns for Canadian bonds cannot be calculated using the familiar approach proposed in Gebhardt et al. (2005) due to the unavailability of accrued interest (as the date of the coupon payment is not available in our database). Using yield changes eliminates the potential for measurement errors stemming from the use of inappropriate return calculation techniques. Further, relying on yield changes facilitates the direct comparison with the results for the U.S. economy documented by Kwan (1996). From an empirical standpoint, we note that over the 1994-2010 period the correlation between the CRSP-calculated returns and the yield changes of the 10 year benchmark is equal to -0.94.[9] This extremely large correlation between yield changes and returns suggests that, in the absence of comprehensive data, using yield changes offers an acceptable approximation of bond returns.

However, we should also note the limitation of using yield change as a proxy for bond return. The same price change may have a different effect on yield to maturity for discount and premium bonds. For example, an increase or decrease in price

[9] In CRSP the 10-year index is obtained selecting the valid issue that best represents the 10 year maturity, at the end of each month. The issue is held through the next month.

will cause larger change in yield for discount bonds than that for premium bonds. However, for both types of bonds, their yield changes and returns are negatively correlated. Therefore, employing yield changes will not affect our main conclusions, but it may slightly affect the magnitudes of the coefficients for discount and premium bonds.

[Table 2.2 about here]

2.5 Empirical Results

2.5.1 Pooled Regressions

We begin our empirical evaluation of the models nested in Equation (2.1) by estimating a pooled regression for the 1994-2010 period.[10] Each bond is coupled with a risk-free zero-coupon rate of matching maturity as well as with the leading, contemporaneous, and lagging returns on the stock of the firm that issued the bond. We then build our pooled sample by stacking the time-series observations of the individual bonds. The total number of bond-month observations in our sample is equal to 52,992.[11]

The first column of Table 2.3 (i.e., Model 1) reports the coefficient estimates from the pooled regression estimation of Equation (2.1) without control variables. The remaining columns of Table 2.3 (i.e., Models 2 to 6) report the results of the pooled estimation for five variations of the base model which always include bond fixed effects. Our results are therefore potentially robust to the omission of bond-specific variables (i.e., issue size, coupon rate, and maturity provisions). To account for shocks in the Canadian economy, we employ the return on the S&P TSX Composite

[10] As we discuss in Appendix B, and show in Table 2.7, our findings over the period 1984-2010 are qualitatively similar to those we obtain over 1994-2010.

[11] Consistent with the highly concentrated structure of Canadian markets, subsequent analyses on firm size-related groups indicate that more than half of the bonds in our overall sample are issued by large capitalization firms.

from Standard and Poor's (hereafter TSX), obtained from Datastream (Thomson Reuter). The index tracks large capitalization stocks traded on the Toronto stock exchange. To control for shocks originating in international markets, we rely on the return on the U.S. stock market factor, as defined in Fama and French (1993), and the yield change for the 10 year U.S. Treasury benchmark, from the Federal Reserve Bank of St. Louis. These three control variables are added individually to the baseline specification in Models 3, 4, and 5, respectively. In the last column of Table 2.3, Model 6 refers to a specification which includes the three aggregate financial indicators simultaneously. These indicators have been identified in previous studies as potential drivers of Canadian bond yields and stock returns (Landon and Smith, 2006; Tinic et al., 1987; Hatch and White, 1986). Hence, this paper's results also contribute to this stream of literature by showing that these same financial indicators also affect the stock-bond relationship, at the firm-level.

A glance at the results in Table 2.3 reveals that all the coefficients of the issuing firm's stock returns are strongly significant, irrespective of the inclusion of the fixed effect terms, the TSX index and the U.S. financial indicators. The adjusted R^2 values across models, although relatively small, are in line with those reported in the extant literature. For example, Collin-Dufresne et al. (2001) analyze the U.S. market and find that in a regression of monthly changes in corporate bond spreads on stock returns, and other control variables, the adjusted R^2 ranges between 17% and 34%.

Given that we are analyzing a fairly long time period, overfitting concerns (e.g., Roodman, 2009), make us inclined to avoid including month-level dummies (as in Model 2) in favor of established economic indicators which proxy for domestic and cross-country investing. Further, multicollinearity measures suggest that Model 6 is more stable than Model 2.[12]

[12] We note that the variance inflation index, a multicollinearity measure, reaches a very large value (above 20, for both the 1994-2010 and 1994-2007 samples) when both month and bond fixed effects are considered. The same index suggests that Model 6, which includes aggregate financial

[Table 2.3 about here]

Due to a substantial stability of the estimates across different models, the ensuing discussion focuses on Model 6 which includes all three macroeconomic indicators.[13] The coefficient on the zero-coupon interest rate, β_1 is equal to 0.84. The coefficient shows that if the yield on a risk-free bond increases by one percentage point, a corporate bond yield with similar maturity will increase by about 84 basis points. The magnitude and t-statistic of β_1 are substantially larger than those of other coefficients. However, the average standard deviation (Panel D of Table 2.1) of zero-coupon yields is extremely small, at best negligible when compared to that of stock returns, indicating a potential attenuation of their relative explanatory power (for corporate bond yields). Hence, despite the large regression coefficient estimate, only a limited proportion of bond yield changes might be explained by yield curve movements.[14]

The coefficient estimates of contemporaneous and asynchronous stock returns are negative and rather small.[15] For example, when the contemporaneous return on a firm's equity increases by one percentage point, then the yield on the bond issued by the same firm will decrease by 0.04 basis points.[16] While this coefficient

indicators, does not raise multicollinearity concerns.

[13]In unreported results, we augment Model 6 with the VIX index. We also repeat our estimates in sub-samples of 598 and 504 bonds obtained in the period 1994-2010 excluding bonds with less than 36 observations, and then eliminating bonds issued by financial firms, respectively. Our findings are robust to these additional tests.

[14]Kwan (1996) also obtains an estimate of the zero-coupon coefficient which largely dominates those of the individual stock-based variables.

[15]An (unreported) F-test strongly rejects the hypothesis that the coefficients of the stock return variables are jointly insignificant. Small coefficients are expected when evaluating yield changes. For example, Collin-Dufresne et al. (2001) explore the contemporaneous relation between changes in credit spreads and firm equity returns. They report coefficients (Table V, page 2191) equal to -0.005 (or smaller) for BB- (or lower) rated bonds. For long-term bonds, spreads are typically one or two orders of magnitude larger than yield changes. Consistently, our contemporaneous correlation coefficients based on yield changes are about one order of magnitude smaller than those reported in Collin-Dufresne et al. (2001).

[16]Yield changes move in the opposite direction of returns. This negative relationship is consistent with the results documented in the extant literature (Bittlingmayer and Moser, 2014; Tsai, 2014;

is significant, its magnitude could suggest that the contemporaneous link between stock and bonds is economically negligible. However, we note that a yield change should not be directly compared to a return change, as yields are defined as interest when the asset is held to maturity. For example, a yield increase of 0.04 basis points entails a decrease of about 0.85% in the return on a 10 year zero-coupon bond carrying a yield of 5.82% (the average yield in our sample).[17] Both coefficients on leading and lagging stock returns (i.e., β_2 and β_4 in Equation (2.1)) are statistically significant. The respective values are 0.01 and 0.05 basis points. The results in Table 2.3 suggest that individual bond prices respond to past stock price changes, and also that variations in bond prices affect future stock returns. Hence, our findings indicate that individual stock returns have predictive power for the correspondent bond yields. At the same time, but to a smaller extent, bond yields show some predictive power for stock returns.

In unreported results, we re-examine all of our inferences using the month and firm clustered standard errors of Cameron et al. (2011). The alternative inferential framework, while corroborating the conclusions of this study, points to a weaker significance of the macroeconomic variable coefficients, thus confirming the fundamental role of firm-level information in characterizing the links between stocks and bonds (Merton, 1974).

In this study, we find evidence of a significant contemporaneous correlation between stock returns and yield changes. The result is novel for Canadian markets

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Ronen and Zhou, 2013; Hong et al., 2012; Schaefer and Strebulaev, 2008; Kwan, 1996). Bittlingmayer and Moser note that an increase in stock returns implies a subsequent appreciation of the corresponding bond, which is consistent with the gradual information spreading model proposed by Hong and Stein (1999). Positive news on a firm's outlook may spread from stock traders to bond traders gradually, thus first increasing stock returns and then depressing bond yields.

[17]Since we employ monthly observations, we calculate the 10 year zero-coupon bond prices at issue and one month later using the formulas $p_t = F(1+y_t)^{-10}$, and $p_{t+1} = F(1+y_{t+1})^{-(10-(1/12))}$, where F is the face value. We then obtain the raw bond return as the usual ratio of $(p_{t+1} - p_t)$ to p_t.

and contributes to the debate on cross-market correlations, which mostly focuses on U.S. data and has provided mixed evidence. Indeed, some of the U.S. based studies do not find (e.g., Kapadia and Pu, 2012; Collin-Dufresne et al., 2001), or do find (Schaefer and Strebulaev, 2008; Kwan, 1996) evidence of contemporaneous correlation between stocks and bonds. A significant contemporaneous correlation between stocks and bonds, of any sign, may be evidence of a significant degree of market integration across security classes. From this perspective, this paper's results suggest that the Canadian financial market may be fairly well integrated with respect to the larger U.S. market.

In interpreting the sign and significance of the stock-bond contemporaneous correlation, the literature typically refers to Merton's corporate bond pricing model, which capitalizes on the decomposition of the payoff of bonds and stocks into nonlinear components (e.g., see the discussion in Back and Crotty, 2015). In this study we find a β_3 estimate that is negative, and significant. The negative sign suggests that the prevailing type of information affecting the concurrent variation in stocks and bonds pertain to the present value of the firm's underlying assets rather than to the firm's risk.

An important caveat in interpreting the sign of the coefficient β_3 in Equation (2.1) is that the empirical correlation we estimated stems from a reduced form of Merton's model. As such, the negative sign of β_3 does not allow inferring a stronger sensitivity of stock and bond prices to information regarding the mean of the firm's value. It may be the case that prices of Canadian securities are also sensitive to changes in risk, but most new information mostly concerns firms' present value rather than volatility.[18] In the same spirit, a hypothetical lack of significant links between stock and bonds would be consistent with a negative mean effect in some months being

[18]Using order-flows for corporate bonds, Back and Crotty (2015) find that information is predominantly about asset mean rather than risk. They hypothesize that information about risk may be simply harder to come by than information on expected value.

offset by a positive volatility effect in others.

Our sample includes the recent financial crisis. To investigate whether our findings are driven by plummeting asset values at the height of the financial turmoil, we replicate the analysis reported in Table 2.3 using data from January 1994 to September 2007.[19] The results are reported in Table 2.4. We find that using the pre-crisis sample delivers the same qualitative results except for the leading stock return coefficient, β_2, which is now statistically insignificant. This additional result suggests that during the pre-crisis years, information used to flow from the stock to the bond market, without then bouncing back.[20]

Our results over the January 1994-2007 period are in line with those of Kwan (1996); i.e., only contemporaneous and lagging stock returns exhibit a significant link with corporate bond yields.

[Table 2.4 about here]

When the months following the 2007 financial crisis are included in the sample, the information flow appears to stream both ways: from the stock market to the bond market, and vice versa (i.e., both β_4 and β_2 are significant). In view of the results obtained in the pre-crisis sample, one could conjecture that the observed correlation between current yield changes and leading stock returns (i.e., β_2) over the 1994-2010 period might be due to stocks being significantly autocorrelated during the recent financial crisis. If this is the case, the bidirectional information flow

[19]The National Bureau of Economic Research sets the start of the 2007-2009 recession in December 2007. However, two major events potentially raised investor concerns on the quality of asset-backed commercial papers before year-end. First, the bankruptcies of two Bear Stearns' hedge funds with strong exposure to the sub-prime mortgage market in July 2007. Second, the decision of BNP Paribas to prevent withdrawals from three of its funds similarly exposed to the U.S. sub-prime credit market in August 2007. To capture these early phases of the crisis, we break the sample at the end of the third quarter of 2007.

[20]To increase the power of our estimates, we re-examine the potential effects of the recent financial crisis by augmenting the baseline model with a dummy variable (equal to unity in the post-2007 period) and its interaction terms with the other covariates. The implications of the financial crisis on the stock-bond relationship remain unchanged. Detailed results are available upon request.

that we observe over 1994-2010 might be partially explained by the presence of spurious relationships. In unreported results, we repeat the analysis of the stock return and bond yield changes autocorrelations for the October 2007-December 2010 period. The sub-sample results are extremely similar to those obtained in the 1994-2010 period (detailed in Table 2.2), suggesting that stock returns were not serially correlated during the recent financial turmoil.[21]

A related concern might arise from the autocorrelation structure of bond yields. In the analyses reported in Panel B of Table 2.2, we confirm the absence of this potential source of spurious relationships. Unreported results over the 1994-2007 and 2007-2010 periods yield similarly low autocorrelation levels. Hence, the significance of the leading return coefficient, β_2, when the years of the financial crisis are included needs not be spurious. We shall delve on the potential reasons for which bonds may, sometimes, lead stocks in sub-section 2.5.2.

The comparison of the significance of the leading stock return coefficient for 1994-2010 and 1994-2007 samples indicates that the predictability of stocks given bonds is driven by the 2007-2010 subsample. For completeness, we evaluate the pooled regression over the sub-sample from October 2007 to December 2010 (Table 2.8). The point estimates of the coefficient of leading and lagging stock returns are equal to -0.04 and -0.06 (0.002 and -0.03) basis points in the 2007-2010 (1994-2007) sample, which suggests a potential increase in firm-level informational flows over the crisis.

Pooled regression results can be summarized as follows. First, corporate bond yields strongly co-move with the yields on a riskless bond of similar maturity. Second, price-relevant information tends to flow from the stock to the bond market, with a weaker reverse flow originating from the bond market that might be the result of the recent, exceptional, market circumstances. Third, informational shocks

[21]As a further robustness tests we re-evaluate our pooled regression results over the periods 2007-2010 and 1994-2010 omitting the firms which exhibit significantly autocorrelated returns. The results are robust to this further restriction and are available upon request.

affecting the mean of the firm's value tend to dominate those concerning its volatility in driving simultaneous stock and bond price adjustments. Additionally, since we employ a longer sample than previous studies, our results seem also to suggest that the relationship between stocks and bonds has been rather stable over the past two decades, with perhaps the exception of the recent financial turmoil. All our results remain qualitatively unchanged when we include control variables pertaining to the U.S. economy. Therefore, an additional contribution of this paper is to show that while Canadian stock returns and bond yields might be affected by shocks to the U.S. economy, the relationship between bond and stock values observed at the firm-level is little affected.

In Appendix D we verify that the main conclusions of this paper are supported by the evaluation of Equation (2.1) after sorting the bonds in our sample by credit ratings. The ratings are issued by DBRS (Dominion Bond Rating Service), the major credit rating agency for the Canadian market, as well as the only agency that covers the entirety of our sample period.[22] We are however wary of relying too much on the results stemming from the evaluation of the pooled regression within individual rating groups. For instance, several rating categories simply contain too few bonds to yield reliable results. To provide an example, our database contains only 3 bonds in the AAA rating category, and a total of 21 bonds in the combined BB and B categories, for the 1994-2010 sample. Further, we also harbor concerns about the informational content of credit ratings for Canadian corporations. Wang and Zhang (2014) documented that credit ratings are imperfect measures of risk when defined benefit (DB) pension obligations represent a significant portion of the issuer's balance sheet. Their conclusion raises legitimate concerns about Canadian ratings' signaling power, given the large portion of DB retirement plans in Canada.

[22]DBRS does not provide credit ratings for individual bonds but only for issuers. Bond ratings are therefore identified each month in accordance with the issuer's rating.

2.5.2 Bloomberg Data: the 2010-2015

As previously discussed, our main sample is culled from Financial Post publications that were discontinued in 2010. To further investigate the robustness of our novel results in the period following the 2007-2009 financial crisis we employ the Bloomberg database over January 1994-October 2015. Bloomberg has less bonds issued by fewer firms. For example, for the period of 1994-September 2007, it contains 282 bonds issued by 59 firms, while the FP database consists of 787 bonds issued by 83 firms. The firms that are not included in the Bloomberg database cover different industries, such as mining, food, transportation, investment and etc. Despite its limited cross-sectional coverage of Canadian corporate bonds in the 1994-2010 period, Bloomberg provides a consistent sample that allows for an exhaustive analysis of the period following the financial crisis that started in 2007. Table 2.8 provides the results across several sub-periods. To establish a common ground we first replicate our main findings based on Financial Post data (i.e. Model 6 of Tables 2.3 and 2.4).

We note that Bloomberg-based estimates strongly confirm our main pre- and post-2007 results ending in 2010. Next, the consideration of Bloomberg data over the period ending in 2015 shows that the coefficient of leading stock returns is strongly significant in the 2007-2010, 2007-2015 and 2010-2015 sub-periods. These results suggest that the ability of bonds yields to predict stock returns does not appear to be confined to the 2007-2010 sub-period. However, the relative importance of the information flowing from the bond to the stock market appears to be decreasing. Indeed, the point estimates of the coefficient of leading and lagging stock returns are equal to -0.04 and -0.02 (-0.01 and -0.02) basis points over the 2007-2010 (2010-2015) period. When considering the overall 1994-2015 sample, the corresponding point estimates are -0.01 and -0.02. These changes suggest that the predictive power of the bond market over the stock market may have been weakening after 2010.

Summarizing, the consideration of alternative estimates, stemming from the analysis of an independent database, does not appear to alter our conclusions and yields results that are consistent with the presence of a significant information flow from the bond to the stock market when considering the post-2007 period.

2.5.3 Bond-level Regressions

We now evaluate the stock-bond relationship for each individual bond in our sample.[23] To this end, we first discard bonds for which we have less than three years of monthly data to foster inference robustness. Over the 1994-2010 period, there are 598 bonds that satisfy this filtering criterion.[24] Next, for each bond, we evaluate the specification of Equation (2.1) which includes the returns on the S&P TSX Composite, the U.S. stock market factor, and the 10 year U.S. Treasury yield changes. Panel A of Table 2.5 reports for each regression coefficient the mean, median and standard deviation of its empirical distribution obtained from the 598 bond-level regressions. The reported t-statistic evaluates the null hypothesis that the average coefficient estimate across bonds is zero using the robust standard errors of Newey and West (1987) with 5 lags.[25] The individual regression results over the period ending in December 2010 corroborate those obtained in the pooled regression framework.[26] Absolute and relative magnitudes of the average regression coefficients are

[23]We employ bond-level regressions to show that our pooled-regression results are not the product of aggregation, and that we obtain similar implications when we increase the granularity of the analysis. Further, both bond-level and pooled regressions are common in the literature investigating stock-bond relationships (Schaefer and Strebulaev, 2008).

[24]None of our conclusions changes when we employ 5 or 10 year filters.

[25]Each bond level regression generates a vector of beta estimates. For each beta, we then regress the coefficient estimates obtained across bonds on a vector of ones to estimate the average value. The joint implementation of these moment conditions within a GMM framework allows to obtain Newey and West (1987) standard errors that take into account the potential heteroskedasticity and autocorrelation occurring across different firms, and bonds issued by the same firm. The chosen number of lags is the smallest integer greater than $598^{\frac{1}{4}}$. The approach builds on the work of Cooper (1999) (page 907) and is consistent with the methodology we employ to draw inferences in our analyses based on pooled regressions.

[26]These results are robust to the consideration one-way (issuing firm) clustered standard errors (Cameron et al., 2011) when regressing individual beta coefficients over a vector of ones.

in fact similar to those obtained in Model 6 of Table 2.3.

[Table 2.5 about here]

When we repeat the bond-level regression analysis over the pre-crisis period from January 1994 to September 2007, the number of individual bond regressions drops to 477. Panel B of Table 2.5 reports the basic statistics for the obtained coefficients. Overall, the implications of Table 2.5 are in line with our previous findings. Similar to the results yielded by the pooled regression approach, for the January 1994-September 2007 sample, the average coefficient of the leading stock returns is statistically insignificant. However, the coefficient of the contemporaneous stock returns is negative and significant only at the 10% level, suggesting a weaker corroboration of the analogous result obtained in the pooled regression framework; i.e., the prevailing information flow affects the mean of the firm's value. When in unreported results we repeat individual bond regressions over the October 2007-December 2010 period, leading stock return coefficients are on average statistically significant (even if marginally), a finding that confirms the intensification of the information flow between stock and bonds documented in the pooled regression framework.

As an additional robustness test, we separate bonds into four groups on the basis of firm size. Each year we classify the issuing companies into quartiles on the basis of the firm annual average market value. Each bond is then assigned to a specific group matching the size quartile of the issuing firm at the year of bond issuance. As a result, bonds are included in one of the four size-related groups, which we denote by G1, G2, G3, and G4; where G1 refers to the lowest market capitalization quartile and G4 to the highest. Before sorting, we have 598 bonds over the 1994-2010 period. The resulting groups, from G1 to G4, contain 42, 67, 135, and 354 bonds, respectively. As quartiles are based on firm size, the number of bonds in each group need not be constant. In our sample, large market capitalization firms issue about 60% of the available corporate bonds.

[Table 2.6 about here]

Panels A to D of Table 2.6 provide summary statistics for bond-level regressions in each size-related group for the 1994-2010 sample. For each coefficient, we again report the mean, median, standard deviation, and t-statistic of the estimates obtained from the bond-level regressions. Both mean and median values of the regression coefficients are close to those obtained in the pooled framework. The reported t-statistics indicate that zero-coupon Government of Canada yields and lagging stock returns are significantly related to bond yields. The relationship is positive for zero-coupon rates, and negative for lagging stock returns. Again, the magnitude of β_1 (Government of Canada bonds) dominates those of the remaining coefficients. We note that, in all size-related groups, the sign of the point estimates reported in Table 2.6 for the stock return variables are consistent with those obtained in the pooled regression framework. However, inference on the coefficients of leading and contemporaneous stock returns fails to deliver consistent conclusions across market value groups. Unreported analyses using the pre-crisis sample ending in 2007 yield similar results. In particular, the lack of significance for contemporaneous stock return coefficients in the second and third groups could suggest that for mid-size firms, which issue a limited number of bonds, the effects of informational shocks regarding the mean and volatility of the issuing firm offset each other.[27]

As previously discussed, the empirical correlations we estimate in Equation (2.1) stem from a reduced form of the Merton (1974) model. In this framework, the negative sign of β_3 does not allow inferring a stronger time-series sensitivity of stock and bond prices to information regarding the mean or the volatility at the firm level. Also, the documented lack of a significant cross-sectional relationship between contemporaneous stock and bond prices for mid-size firms might be consistent with

[27]Pooled regressions for the same (G1 to G4) market capitalization groups confirm the insignificance of contemporaneous links in mid-size firms, and the substantial stability of the stock-bond relationship in larger capitalization firms.

a negative mean effect in some firms being offset by a positive volatility effect in others. This issue might arise especially when drawing inference on a limited subset of firms.

Indeed, a closer look at bond-level estimates of the contemporaneous stock-bond coefficient β_3 indicates that some of the few positive and significant values we obtain across our entire sample of bonds are concentrated in mid-capitalization firms. The ensuing cross-sectional inference, based on the mean parameter estimate and standard error obtained from a relatively limited number of bonds, leads to an insignificant beta across medium-capitalization firms. This insignificant estimate is consistent with the effects of shocks affecting the mean being balanced by those affecting the volatility of the firm's assets for mid-size issuers.

To the best of our knowledge, we cannot compare the findings reported in Table 2.6 directly with those from the extant literature. In fact, previous firm-level studies exploring the contemporaneous correlation between corporate bonds and stocks do not investigate sub-samples sorted by market capitalization. However, we note an intriguing consistency between the results from the early literature on idiosyncratic volatility and this paper's evidence. Duffee (1995) shows that the impact of firm-level volatility is hump-shaped across size quintiles, with medium-size firms being more sensitive to idiosyncratic volatility than small and large issuers. This non-linear relationship between size and the effects of idiosyncratic volatility on stock returns suggests that shocks to the present value of the firm are more likely to prevail in driving the prices of stocks (and potentially bonds) for small and large firms than for medium-size issuers. This conjecture is consistent with the overall evidence reported in this paper for size-related groups.[28]

[28] We note that our findings might also be driven by different pre- and post-2007 observation distributions across the different capitalization groups. In unreported results we verify that the relative cross-sectional dimensions of size-based groups are quite stable over the entire sample and are therefore unlikely to introduce a bias in our results.

2.5.4 Discussion of Market Dynamics and Robustness

The literature yields mixed conclusions with regard to the dynamics of the stock-bond relationship at the firm-level (Bittlingmayer and Moser, 2014; Downing et al., 2009; Hotchkiss and Ronen, 2002). Ronen and Zhou (2013) reconcile these contrasting findings by hypothesizing that the information content of bonds issued by the same firm may vary. The underlying rationale is that institutional investors focus on few bonds per firm (the "top bonds") to execute information-driven trades. Pooled regressions, which include all the available bonds for all firms (i.e., a bond-weighted framework), might cloud the assessment of the information exchange between the stock and bond markets, as non-informative and informative price movements are equally weighted by the estimator. On the contrary, restricting the evaluations of the stock and bond relationship to top bonds provides a firm-weighted approach (i.e. each firm is represented by only one bond, at each time) that can magnify the information transmission mechanism at firm-level.

Ronen and Zhou (2013) identify the top bond for each firm on the basis of transaction data from TRACE, with the top bonds being those on which large trades are concentrated. The assumption underlying this identification strategy is that institutional traders are more informed and place large orders.[29] Unfortunately, transaction-level data does not exist for the Canadian bond market. However, capitalizing on the results in the literature we propose a methodology that allows us to explore whether the top bond effect changes any of this paper's conclusions. The characterization of top bonds proposed in Ronen and Zhou shows that for U.S. firms issuing only investment grade bonds, the most recently issued is the top bond in a remarkable 94% of the instances (Ronen and Zhou; Table 2.6). In our 1994-2010

[29]That markets dominated by institutional investors may be more informationally efficient than markets in which retail investors play a more relevant role is also suggested by the results in Erdogan et al. (2013), where freight costs, which are determined in a highly institutionalized market, are shown to predict the Dow Jones Industrial Average (DJIA) index.

sample, more than 96% of bonds are issued by firms with credit ratings at or above the BBB threshold.[30] Building on the results of Ronen and Zhou, we thus identify the top bond of each Canadian firm in our sample with its most recently issued bond.

Table 2.10 reports the top bond results from the estimation of Model 6 (in Table 2.3) over multiple periods. The evaluation of regressions including only top bonds supports this paper's conclusions. In fact, the signs and significance of the lagged and contemporaneous stock return coefficients are very similar to those yielded by pooled regressions (Tables 2.3 and 2.4). The leading stock return coefficient is significant only at the 10% level for the 1994-2010 sample, but it is strongly significant in the 2007-2010 sub-sample.[31]

We note that over the 2007-2010 sample the leading stock return coefficient is similar to the lagged one for top bonds, whereas the pooled regression including multiple bonds per firm still shows an uneven relationship in favor of lagged stock returns (Table 2.8). The increase in the preeminence of the leading coefficient in the top bond approach suggests that pooling may introduce a bias, if any, against finding relative evidence of significant flows originating from the bond market over the post-2007 period. In line with the critique of Ronen and Zhou (2013), the top bond analysis shows that using the pooled regression methodology is more prone to failing to detect recent in-sample predictability rather than to yielding spurious evidence of a lead-lag relationship.

Ronen and Zhou (2013) suggest that bonds that attract the trades of institutional

[30] As bond-level credit ratings are unavailable, we postulate that straight bullet bonds are awarded a credit rating that is similar to that of the issuing firm, each month and for each firm.

[31] During the 2007-2010 period, Canadian firms took advantage of record low interest rates and issued a large number of corporate bonds, resulting in about 25% of the observations in the 1994-2010 sample being concentrated in the 2007-2010 period. Focusing on one (top) bond per firm decrease the influence of the 2007-2010 sub-period on the coefficient yielded by the pooled regression for the 1994-2010 sample. This reduced influence explains the weaker significance of the leading stock return coefficients in the 1994-2010 sample in Table 2.10, with respect to the analog coefficients in Table 2.3.

investors show some predictive ability for stocks. Tsai (2014) studies the informational efficiency of stocks and bonds by focusing on firms that issue bonds actively traded by institutional investors. She documents that focusing on top bonds increases the ability of speculative bonds to predict stocks, but slightly decreases the predictive content of the returns of investment grade bonds.

The Canadian market for corporate bonds is strongly dominated by institutional investors (Patel and Yang, 2015; Cunningham, 2009). Further, the vast majority of Canadian corporate bonds in our database are rated at or above investment grade. Hence, this study's evidence that bonds, as well as top bonds, may sometimes predict stocks complements the findings of Tsai (2014), and Ronen and Zhou (2013).

Stock predictability, given bonds, is also one of the results presented in Hong et al. (2012). As in this paper, the authors find that bonds are significantly predicted by lagged stocks returns, and predictability in the opposite direction emerges only when the 2007-2009 crisis is included in the sample. Hong et al. (2012) adopt a methodological approach that is very different from that used in this paper and rely on daily returns of U.S. stock and bond indexes. Despite these important differences, both studies conclude that bonds may have led stocks during the latest financial crisis. The remainder of this section discusses several possible explanations for this empirical result.

In the context of an open economy, Verdelhan (2010) evaluates the effect of aggregate shocks to the domestic economy on the risk-free cost of borrowing. His analysis suggests that accounting for exchange rates may be advisable when investigating bond markets in a small open economy like Canada. Since the U.S. and Canadian dollar exchange rate had been fluctuating substantially during the 2007-2010 period (as a result of the financial crisis), the inclusion of the exchange rate in the baseline regression (i.e., Model 6 of Tables 2.3 and 2.4) may conceivably help in explaining the predictability of stocks given bonds over the same period. Unreported results confirm that the USD/CAD exchange rate may be important to describe the Canadian economic environment, even beyond its role in influencing the yields of Canadian sovereign bonds. However, the consideration of the exchange rate does not appear to affect either the direction or the magnitude of the information flows between stock and bonds in the pre- and post-2007 periods.

As the 2007 crisis originated in the financial sector, one may conjecture that the concurrent predictive ability of bonds is concentrated in bonds issued by financial firms. We then partition the sample in financial and non-financial issuers and evaluate Model 6 (in Tables 2.3 and 2.4) separately for the two resulting groups of bonds. In unreported results we find that the leading stock return coefficient, which gauges the predictive ability of bonds, is significant (insignificant) for both types of issuers over the 2007-2010 (1994-2007) period. We, therefore, conclude that the post-2007 information flow streaming from bonds to stocks exhibits a pervasive nature across financial and non-financial bond issuers.

To investigate whether the predictive ability of bonds hinges on the specificity of the 2007 financial crisis or it is also associated with other severe fluctuations in the economic environment, we take a closer look at the burst of the dot.com bubble. In unreported results, we evaluate Model 6 of Table 2.3 for three sub-periods: January 1994-February 2000, March 2000-March 2003, and April 2003-September 2007. We find that bonds have significant predictive ability for stocks only over the 2000-2003 period. In contrast, the significant information flow streaming from stocks to bonds is not sensitive to the consideration of any sub-period, thus confirming the predictability of bonds given stocks. Again, we evaluate our baseline regression separately for financial and non-financial bonds over the 2000-2003 period, and find that the leading effect of bonds is concentrated in non-financial bonds. This result, coupled with the findings stemming from the analysis of the post-2007 sample, suggests that the forces driving bond predictability had a more pervasive impact during the 2007-2010 crisis than during the dot.com bubble.

The theoretical work by Brandt and Wang (2003) may provide additional guidance when interpreting this paper's evidence on the significant predictive ability of bonds during periods of severe market fluctuations. Brandt and Wang (2003) build on the Campbell and Cochrane (1999) framework and propose a model where the representative consumer exhibits a dynamic risk aversion that depends on the realizations of relative consumption growth and inflation. Among other results, they find that U.S. long-term bonds appear to respond more precisely than stocks to innovations in inflation dynamics. They argue that shocks to inflation expectations may affect bonds more promptly and deeply than stocks. In this framework, a significant coefficient for the leading stock returns in Equation (2.1) (i.e., bond leading stocks) may be associated with a shift in inflation expectations that manifests itself through bond yields rather than stock returns.

In the work of Brandt and Wang (2003), inflation shocks are modeled as exogenous, and as such, they may be interpreted as market's responses to monetary and fiscal policy activities. Hence, aggressive and highly correlated monetary and fiscal policy activities in Canada and the U.S. may lie at the root of the richer information content carried by bonds during financial crises. The literature examining the effects of monetary policy activities enacted by central banks during and following the 2007-2009 crisis is vast (e.g., see Martin and Milas, 2012, for an early review).[32] Many studies focusing on the 2007-2009 crisis found that in the U.S. bond yields responded to asset purchase programs. For example, D'Amico and King (2013) and Gagnon et al. (2011) document that the yields on securities purchased under the Federal Reserve Bank large asset purchase programs fell more than the yields on securities that were not purchased. Concurrently, Wright (2012) shows that monetary

[32]This line of research builds on an already developed body of knowledge analyzing the impact of monetary policy on asset pricing (Bernanke and Kuttner, 2005; Gürkaynak et al., 2005; Rigobon and Sack, 2004; Cochrane and Piazzesi, 2002; Kuttner, 2001; among others).

policy activities have affected not only Treasuries but also corporate bond spreads.

Most of the studies on the effects of monetary policy activities following the 2007 crisis focus on the programs enacted by the Federal Reserve and the U.S. Department of Treasury. The integration between the Canadian and U.S. markets, due to institutional investors operating in both environments, strongly suggest that monetary policy activities in the U.S. are very likely to affect those enacted in the Canadian economy (Fratzscher et al., 2012).[33] It is therefore not clear which monetary policy gauges should be used to control for the interaction of the monetary policy actions of the Bank of Canada and the Federal Reserve, as well as for other fiscal policies enacted by the U.S. and Canadian governments to counter the economic downturn. This challenge outlines a promising line of research which we leave for future investigations. At the current state of the analysis, and given the results of the literature on the price effects of monetary policy activities in the U.S. and international markets, we suggest that bonds have been leading stocks in the post-2007 because a) the role of monetary policy in determining asset prices raised of importance after 2007, and b) bonds are more responsive to the activities of central banks than equities.

2.6 Conclusion

We employ firm-level data to analyze the relative informational efficiency of stocks and bonds, as well as the nature of the information that drives their simultaneous price adjustments. Our investigation relies on a novel database that includes bonds issued by Canadian firms over three decades. The structural default models related to Merton (1974) suggest the presence of common variation between stocks and bonds due to their dependence on the value of the same firm's assets. In this framework,

[33]The influence of U.S. monetary policy on the cost of borrowing in Canada is evident from the correlation between the monthly U.S. Federal Fund Rate and the one month Government of Canada Treasury Bills, that is equal to 0.97 (0.85) over the 2007-2010 (1994-2010) period.

the sign of the contemporaneous correlation between the values of stocks and bonds issued by the same firm indicates whether the informational shocks driving concurrent variation in stock and bond prices are those affecting the mean or the volatility of the firm's assets. Our investigation on the nature of firm-specific information flows indicates that information regarding the mean of the firm's value, rather than its volatility, prevails in driving contemporaneous variation in stock and bond values.

Additionally, we examine the informational efficiency of the stock and bond markets by studying the asynchronous relationships between individual stock returns and yield changes of bonds issued by the same firm. We find that lagging stock returns and current bond yield changes are strongly related. Further, we show that the relationship between current bond yield changes and leading stock returns, while significant, might be weaker than the one with lagging stock returns. Taken together these two results suggest the existence of bidirectional information flows between the stock and bond markets, which weaken when originating from the bond side. Indeed, when we focus on the sub-sample ending in 2007, bond yield changes turn out being uncorrelated with leading stock returns. This finding suggests that in the pre-crisis years, most of the price-relevant information was flowing from the stock market to the bond market. The bidirectional patterns documented over the recent years seem to suggest that the information exchanges between the bond and stock markets have intensified in response to the financial crisis initiated in 2007. Overall, our results lend support to the conclusions of extant studies which advocate a leading role for the stock market in transmitting firm-specific information, but also suggest a secondary role for the bond market that is enhanced during market fluctuations.

Table 2.1: Summary statistics (January 1994 to December 2010)

	Mean	Median	Standard Deviation	Average Maturity	Number of Bonds
Panel A: Bond yields					
	5.82	5.81	1.06	149.60	937
Panel B.1: Bonds by maturity					
1st Maturity Band: 12-60	4.74	4.74	0.96	54.52	214
2nd Maturity Band: 61-120	5.59	5.63	1.13	104.83	351
3rd Maturity Band: 121-240	7.27	7.30	1.34	181.93	207
4th Maturity Band: >240	6.96	6.86	1.09	348.96	165
Panel B.2: Bonds by volume at issue					
1st 0-70	7.15	7.21	1.21	209.15	114
2nd 70-150	6.31	6.34	1.20	164.08	245
3rd 150-275	5.97	5.91	1.13	175.47	291
4th >275	4.76	4.73	0.91	105.27	287
Panel B.3: Bonds by market capitalization					
1st	6.02	6.03	1.01	167.87	62
2nd	5.85	5.83	1.04	133.65	93
3rd	5.73	5.72	1.05	160.51	196
4th	5.83	5.81	1.08	161.77	586
Panel B.4: Bonds by fin and non-fin					
Financial	5.26	5.27	0.92	184.97	337
Non-financial	6.13	6.11	1.14	173.87	600
Panel C: Stock returns					
	15.74	12.14	31.73		
Panel D: zero-coupon interest rates					
	4.55	4.57	0.84		

Note: The table reports summary statistics for annualized corporate bond yields, stock returns, and zero-coupon interest rates. Panel A reports the mean and the median of yield time-series averages for the 937 bonds in our sample. The next two columns report the average of bond yield standard deviations, the average bond maturity (in months), and the number of bonds. Similar statistics are reported in Panels B.1-B.4 (for bond yields classified according to maturity bands, market capitalization of the issuing firm (quartiles, in millions), volume and issue, and financial vs. non-financial issuers), in Panel C for annualized percentage returns on the 83 stocks of the bond issuing firms, and in Panel D for zero-coupon bonds of matching maturities with the corporate bonds.

Table 2.2: Autocorrelations of individual securities (January 1994 to December 2010)

	Mean	Median	Standard deviation	Percentage of Significant Coef.	5th percentile	95th percentile
Panel A: Stock returns						
Lag 1	0.0203	0.0204	0.0970	13.98	-0.1476	0.1696
Lag 2	-0.0164	-0.0078	0.0801	8.60	-0.1678	0.1022
Panel B: Bond yield changes						
Lag 1	0.0581	0.0667	0.1517	7.88	-0.2377	0.2980
Lag 2	0.0321	0.0178	0.1244	5.41	-0.1588	0.2657

Note: Panel A reports summary statistics for the autoregressive coefficients of the 1st and 2nd order obtained from individual regressions of bond yields on a constant and the correspondent lagged values. For each coefficient, the statistics include mean, median, standard deviation, percentage of significant coefficients at the 5% level or better, as well as the 5th and 95th percentile of the estimates' distribution across 937 bonds. Panel B reports similar statistics for changes in corporate bond yields.

Table 2.3: Pooled regressions - dependent variable: bond yield changes (January 1994 to December 2010)

Variable	1	2	3	4	5	6
ΔT_{jt}	0.8395**	0.6860**	0.8413**	0.8523**	0.9004**	0.9050**
	(97.17)	(43.86)	(99.52)	(100.56)	(102.53)	(102.03)
R_{jt+1}	-0.0002**	0.00008**	-0.0002**	-0.0001**	-0.0002**	-0.0001**
	(-7.82)	(3.29)	(-6.64)	(-6.14)	(-7.59)	(-5.65)
R_{jt}	-0.0005**	-0.0003**	-0.0004**	-0.0004**	-0.0005**	-0.0004**
	(-11.65)	(-5.60)	(-7.84)	(-7.95)	(-11.78)	(-7.67)
R_{jt-1}	-0.0005**	-0.0002**	-0.0005**	-0.0005**	-0.0005**	-0.0004**
	(-14.04)	(-6.94)	(-13.70)	(-13.80)	(-13.87)	(-13.43)
TSX			-0.0068**			-0.0020**
			(-22.83)			(-4.58)
USMKT				-0.0077**		-0.0058**
				(-24.57)		(-12.58)
$\Delta US10TB$					-0.1199**	-0.1113**
					(-13.48)	(-12.22)
Constant	0.0025					
	(-1.82)					
Bond fixed effects	No	Yes	Yes	Yes	Yes	Yes
Month fixed effects	No	Yes	No	No	No	No
Number of observations	52,992	52,992	52,992	52,992	52,992	52,992
Adjusted R^2	0.2673	0.3387	0.2660	0.2674	0.2636	0.2706

Note: The table reports pooled GMM regression coefficient estimates from the alternative model specifications nested in Equation (2.1). The overall set of explanatory variables includes the yield changes of Government of Canada bonds (ΔT_{jt}), the leading, contemporaneous and lagging stock returns of the bond issuing firm (R_{jt+1}, R_{jt} and R_{jt-1}), as well as the S&P TSX Composite returns (TSX), the U.S. stock market returns ($USMKT$), and the change in 10 year U.S. Treasury yields ($\Delta US10TB$). We include individual bond and month fixed effects by removing the constant and including one dummy variable for each of the 937 bonds, and one dummy variable for each month (except one) in the sample period. Underlying stock returns and yield changes are measured in percentage terms. The reported t-statistics (in parentheses) are based on the autocorrelation and heteroskedasticity robust standard errors of Newey-West (1987) with 15 lags (significant values, at the 5% and 1% level, are denoted by 1 and 2 asterisks).

Table 2.4: Pooled regressions - dependent variable: bond yield changes (January 1994 to September 2007)

Variable	1	2	3	4	5	6
ΔT_{jt}	0.9385**	0.6559**	0.9365**	0.9400**	0.9395**	0.9334**
	(103.6)	(35.86)	(106.9)	(106.8)	(93.33)	(92.85)
R_{jt+1}	0.000008	0.000052	0.000017	0.000022	0.000003	0.00002
	(0.31)	(1.79)	(0.67)	(0.87)	(0.11)	(0.87)
R_{jt}	-0.0004**	-0.0003**	-0.0003**	-0.0003**	-0.0004**	-0.0003**
	(-5.78)	(-4.32)	(-4.56)	(-4.78)	(-5.80)	(-4.48)
R_{jt-1}	-0.0003**	-0.0002**	-0.0003**	-0.0003**	-0.0003**	-0.0003**
	(-6.68)	(-4.60)	(-6.64)	(-6.82)	(-6.81)	(-6.73)
TSX			-0.0038**			-0.0016**
			(-13.97)			(-3.42)
USMKT				-0.0041**		-0.0029**
				(-13.76)		(-5.65)
$\Delta US10TB$					0.0008	0.0111
					(0.10)	(1.47)
Constant	-0.0012					
	(-0.74)					
Fixed bond effects	No	Yes	Yes	Yes	Yes	Yes
Fixed time effects	No	Yes	No	No	No	No
Number of observations	41,404	41,404	41,404	41,404	41,404	41,404
Adjusted R^2	0.3054	0.3215	0.2989	0.2991	0.2975	0.2992

Note: The table reports pooled regression coefficient estimates from the alternative model specifications nested in Equation (2.1). The overall set of explanatory variables includes the yield changes of Government of Canada bonds (ΔT_{jt}), the leading, contemporaneous and lagging stock returns of the bond issuing firm (R_{jt+1}, R_{jt} and R_{jt-1}), as well as the S&P TSX Composite returns (TSX), the U.S. stock market returns ($USMKT$), and the change in 10 year U.S. Treasury yields ($\Delta US10TB$). We include individual bond and month fixed effects by removing the constant and including one dummy variable for each of the 787 bonds, and one dummy variable for each month (except one) in the sample period. Underlying stock returns and yield changes are measured in percentage terms. The reported t-statistics (in parentheses) are based on the autocorrelation and heteroskedasticity robust standard errors of Newey-West (1987) with 14 lags (significant values, at the 5% and 1% level, are denoted by 1 and 2 asterisks).

Table 2.5: Bond - level regressions

Coefficient on:	Mean	Median	Std. Deviation	t-statistic
Panel A: January 1994 - December 2010				
ΔT_{jt}	0.9604**	0.9957	0.3366	71.76
R_{jt+1}	-0.0002**	-0.00004	0.0008	-3.19
R_{jt}	-0.0003**	-0.0002	0.0011	-4.49
R_{jt-1}	-0.0004**	-0.0002	0.0009	-8.24
TSX	-0.0020**	-0.0028	0.0153	-2.68
USMKT	-0.0065**	-0.0029	0.0196	-6.09
$\Delta US10TB$	-0.1235**	-0.0692	0.2465	-7.85
Avg. adjusted R^2	0.6394			
Panel B: January 1994 - September 2007				
ΔT_{jt}	0.9998**	1.0136	0.3305	66.41
R_{jt+1}	0.00004	0.00002	0.0006	1.14
R_{jt}	-0.0001	-0.0001	0.0011	-1.81
R_{jt-1}	-0.0002**	-0.0002	0.0008	-5.41
TSX	-0.0025**	-0.0026	0.0131	-3.67
USMKT	-0.0027**	-0.0021	0.0163	-2.79
$\Delta US10TB$	-0.0265**	-0.0263	0.1470	-3.10
Avg. adjusted R^2	0.7687			

Note: The table reports summary statistics for the empirical distribution of bond-level estimates. For each corporate bond, we first estimate the time-series model:

$$\Delta Yield_{jt} = \beta_0 + \beta_1 \Delta T_{jt} + \beta_2 R_{jt+1} + \beta_3 R_{jt} + \beta_4 R_{jt-1} + \beta_5 TSX + \beta_6 USMKT + \beta_7 \Delta US10TB + \zeta_{jt}$$

The correspondent explanatory variables are: yield changes of risk-free bonds, leading, contemporaneous, and lagging stock returns of the bond issuing firm, as well as the S&P TSX Composite returns, the U.S. stock market returns, and the change in 10 year U.S. Treasury yields. We then compute cross-sectional summary statistics for each of the resulting coefficient estimates. We exclude bonds with less than 3 years of data. Panel A report the results for 598 bonds for January 1994 to December 2010. Panel B reports the results for 477 bonds from January 1994 to September 2007. For each beta, the mean value estimate is obtained by regressing the correspondent coefficients from the first step individual bond regressions on a vector of ones of the same dimension. The moment conditions are implemented in the GMM framework of Hansen (1982). The reported t-statistics evaluate the null hypothesis that the average regression coefficient is zero using the robust standard errors of Newey-West (1987) with 5 lags (significant values, at the 5% and 1% level, are denoted by 1 and 2 asterisks).

Table 2.6: Bond-level regressions - bonds by firm market capitalization (January 1994 to December 2010)

Coefficient on:	Mean	Median	Std. Deviation	t-statistic
Panel A: G1				
ΔT_{jt}	0.8638**	0.9743	0.3467	22.18
R_{jt+1}	-0.0003*	-0.0002	0.0009	-2.13
R_{jt}	-0.0008**	-0.0002	0.0016	-2.63
R_{jt-1}	-0.0004*	-0.0001	0.0008	-2.23
TSX	-0.0024	-0.0030	0.0107	-1.33
USMKT	-0.0037*	-0.0011	0.0154	-2.09
$\Delta US10TB$	-0.1885**	-0.1108	0.3458	-2.64
Avg. adjusted R^2	0.5835			
Panel B: G2				
ΔT_{jt}	1.0294**	1.0368	0.2405	34.05
R_{jt+1}	-0.0002	0.00002	0.0015	-0.83
R_{jt}	-0.0001	-0.0001	0.0014	-0.75
R_{jt-1}	-0.0007**	-0.0003	0.0016	-3.70
TSX	0.0011	-0.0011	0.0187	0.48
USMKT	-0.0084**	-0.0065	0.0198	-3.43
$\Delta US10TB$	-0.2083**	-0.1210	0.3599	-3.38
Avg. adjusted R^2	0.6085			
Panel C: G3				
ΔT_{jt}	0.9583**	1.0090	0.2605	34.92
R_{jt+1}	-0.0002**	-0.0001	0.0006	-2.62
R_{jt}	-0.0001	-0.0001	0.0010	-0.55
R_{jt-1}	-0.0004**	-0.0002	0.0009	-3.55
TSX	-0.0035*	-0.0022	0.0191	-1.99
USMKT	-0.0098**	-0.0051	0.0261	-3.73
$\Delta US10TB$	-0.1575**	-0.0893	0.2731	-5.54
Avg. adjusted R^2	0.5898			
Panel D: G4				
ΔT_{jt}	0.9597**	0.9905	0.3729	44.05
R_{jt+1}	-0.0001*	-0.00002	0.0006	-2.46
R_{jt}	-0.0004**	-0.0002	0.0010	-4.44
R_{jt-1}	-0.0003**	-0.0002	0.0007	-6.96
TSX	-0.0020*	-0.0030	0.0132	-2.02

Continued on next page

Table 2.6: Bond-level regressions - Continued

Coefficient on:	Mean	Median	Std. Deviation	t-statistic
USMKT	-0.0051**	-0.0021	0.0168	-4.19
$\Delta US10TB$	-0.0867**	-0.0570	0.1807	-6.36
Avg. adjusted R^2	0.6709			

Note: The table reports summary statistics for the empirical distribution of bond-level estimates clustered according to the market capitalization of the issuing firm. Each year we classify companies into four quartiles on the basis of their annual average market capitalization. Each corporate bond is then assigned to one of four groups according to the size-based quartile of the issuing firm at the year of issue. For each bond, we first estimate the time-series model:

$$\Delta Yield_{jt} = \beta_0 + \beta_1 \Delta T_{jt} + \beta_2 R_{jt+1} + \beta_3 R_{jt} + \beta_4 R_{jt-1} + \beta_5 TSX + \beta_6 USMKT + \beta_7 \Delta US10TB + \zeta_{jt}$$

The correspondent explanatory variables are: yield changes of risk-free bonds, leading, contemporaneous, and lagging stock returns of the bond issuing firm, as well as the S&P TSX Composite returns, the U.S. stock market returns, and the change in 10 year U.S. Treasury yields. We then compute cross-sectional summary statistics within size-related bond groups for each of the resulting coefficient estimates. We exclude bonds with less than 3 years of data. Panels A to D report the results for the four size-based groups (G1 to G4) that include 42, 67, 135, and 354 bonds, respectively. G1 refers to the lowest market capitalization quartile, G4 to the highest. For each beta, the mean value estimate is obtained by regressing the correspondent coefficients from the first step individual bond regressions on a vector of ones of the same dimension. The moment conditions are implemented in the GMM framework of Hansen (1982). The reported t-statistics evaluate the null hypothesis that the average regression coefficient is zero using the robust standard errors of Newey-West (1987) with 5 lags (significant values, at the 5% and 1% level, are denoted by 1 and 2 asterisks).

2.7 Appendix

2.7.1 Corporate Bond Database

Our analysis employs three main data sources. Corporate bond data are from the Financial Post (FP) publications, Stock data are from Datastream (Thomson Reuters), and the zero-coupon rates are from the Bank of Canada yield curve.[34] For each bond, we collect the issuer's name, month-end closing price, coupon, yield to maturity, and the maturity date from the annual edition of Financial Post Bonds Canadian Prices (hereafter, FP Price Book).[35] The FP Price Book records start in 1984. All bond values are quoted in Canadian currency. For each bond, we collect the issue volume, the issuing date, and the coupon payment frequency. These characteristics are available in the annual edition of the FP Bonds Corporate.[36] For all years in our sample (1984 to 2010), we find that there are more bonds in the FP Bonds Corporate than in the FP Price Book. This implies that for some bonds we have the information on characteristics, while the monthly yield quotes are not available.[37] Since our study relies on yields (to maturity), we discard all bonds for which yield data are not available in the FP Price book. We identify each bond in the FP Price Book by its coupon and maturity dates (CUSIP numbers are not listed in the FP Price Book). Each bond is then matched with its characteristics as published in the FP Bonds Corporate.[38] Dealing with mergers, acquisitions, and firm name

[34]Bolder et al. (2004) explain the methodology for obtaining the Bank of Canada yield curve.

[35]The FP Price Book book is produced by the Financial Post DataGroup and published by the Financial Post DataGroup (2000-2003), CanWest Interactive Inc. (2004), CanWest Media Works Publications Inc. (2005, 2006), and Canwest Publishing Inc. (2007-2009).

[36]The FP Bonds Corporate is produced by the Financial Post DataGroup and published by the Financial Post DataGroup (2000-2004) and Canwest Publishing Inc (2005-2009).

[37]This may occur for bonds with low trading volumes, or for floating rate bonds which have prices but no yield data.

[38]For a few bonds, we could initially match only the coupon rate. We then look at the FP Bonds Corporate notes to verify the presence of a maturity extension (which is extremely common). Our database reports the new maturity dates.

changes represents an extremely laborious step in our data collection. Another data task relates to missing observations. In particular, when a few monthly observations are missing over a bond's life, we replace the missing values with the average of the yields in the previous and following months. In all other cases, bonds are discarded. Further details on the criteria used to handle these occurrences are available upon request from the authors. After matching bond yields and characteristics, and dealing with missing values, our dataset includes 1065 (937) corporate bonds issued by 93 (83) Canadian companies over Jan. 1984-Dec. 2010 (Jan. 1994-Dec. 2010).

2.7.2 The 1984-2010 Sample

The analysis of the 1984-2010 sample is relegated to this appendix for two reasons. First, the quality of the data, especially of price quotes, might be of variable nature at the beginning of the sample, mainly due to the lack of transparency in the Canadian bond market at its early stages. Second, Landon (2009) studies the market for Government of Canada bonds and finds a significant decrease in the tax rate borne by the price-setting agents around the year 1993. The documented variation in the implied-tax-rate regime seems to indicate that the institutional changes experienced by the Canadian financial sector in the early nineties had a profound impact on the market at that point. The fact that the same study does not identify any other tax-regime switches indicates that this new regime persists over the remainder of our sample. Hence, past changes in the Canadian market potentially raise concerns on including in the same sample pre- and post-1993 prices. We therefore repeat the pooled regression analyses over the 1984-2010 period. The results are reported in Table 2.7, which is similar in structure to Table 2.3. We find that signs, magnitude, and significance of the coefficients estimated over 1984-2010 are very close to those obtained in the 1994-2010 period. Our findings suggest that, despite pervasive changes in the Canadian market, the firm-level relation between stocks and bonds exhibits a substantial stability over time.

Table 2.7: Pooled Regressions - dependent variable: bond yield changes (January 1984 to December 2010)

Model	1	2	3	4	5	6
ΔT_{jt}	0.6938**	0.5109**	0.6901**	0.6962**	0.6491**	0.6477**
	(67.45)	(24.75)	(66.98)	(67.77)	(51.76)	(51.92)
R_{jt+1}	-0.0002**	0.0001**	-0.0002**	-0.0002**	-0.0002**	-0.0002**
	(-10.37)	(3.10)	(-9.02)	(-8.88)	(-10.37)	(-8.70)
R_{jt}	-0.0007**	-0.0003**	-0.0005**	-0.0005**	-0.0006**	-0.0004**
	(-16.14)	(-6.58)	(-10.77)	(-11.91)	(-15.71)	(-10.14)
R_{jt-1}	-0.0004**	-0.0002**	-0.0004**	-0.0004**	-0.0004**	-0.0004**
	(-14.11)	(-7.65)	(-13.33)	(-13.54)	(-14.55)	(-13.65)
TSX			-0.0083**			-0.0063**
			(-27.14)			(-14.24)
USMKT				-0.0075**		-0.0025**
				(-23.58)		(-5.55)
$\Delta US10TB$					0.1267**	0.1265**
					(10.63)	(10.75)
Constant	-0.0007					
	(-0.53)					
Fixed bond effects	No	Yes	Yes	Yes	Yes	Yes
Fixed time effects	No	Yes	No	No	No	No
Number of observations	68,553	68,553	68,553	68,553	68,553	68,553
Adjusted R^2	0.2755	0.4209	0.2761	0.2747	0.2733	0.2810

Note: The table reports pooled regression coefficient estimates from the alternative model specifications nested in Equation (2.1). The overall set of explanatory variables includes the yield changes of Government of Canada bonds (ΔT_{jt}), the leading, contemporaneous and lagging stock returns of the bond issuing firm (R_{jt+1}, R_{jt} and R_{jt-1}), as well as the S&P TSX Composite returns (TSX), the U.S. stock market returns ($USMKT$), and the change in 10 year U.S. Treasury yields ($\Delta US10TB$). We include individual bond and month fixed effects by removing the constant and including one dummy variable for each of the 1065 bonds, and one dummy variable for each month (except one) in the sample period. Underlying stock returns and yield changes are measured in percentage terms. The reported t-statistics (in parentheses) are based on the autocorrelation and heteroskedasticity robust standard errors of Newey-West (1987) with 16 lags (significant values, at the 5% and 1% level, are denoted by 1 and 2 asterisks).

2.7.3 Analyses with Bloomberg Data

Table 2.8: Pooled Regressions with Bloomberg data - dependent variable: bond yield changes

	Financial Post			Bloomberg					
Period	1994-2007	1994-2010	2007-2010	1994-2007	1994-2010	1994-2015	2007-2010	2007-2015	2010-2015
ΔT_{jt}	0.9347**	0.9050**	0.8676**	0.8906**	0.8361**	0.8664**	0.7871**	0.8785**	0.9442**
	(105.9)	(102.03)	(43.75)	(60.02)	(57.67)	(82.74)	(27.07)	(65.33)	(102.16)
R_{jt+1}	0.000019	-0.0001**	-0.0004**	-0.00002	-0.0002**	-0.0001**	-0.0004**	-0.0002**	-0.0001**
	(0.76)	(-5.65)	(-7.13)	(-0.52)	(-5.96)	(-6.14)	(-8.06)	(-7.85)	(-3.85)
R_{jt}	-0.0003**	-0.0004**	-0.0004**	-0.0002**	-0.0002**	-0.0002**	-0.0002*	-0.0002**	-0.0002**
	(-4.54)	(-7.67)	(-6.75)	(-2.82)	(-4.88)	(-5.71)	(-2.48)	(-4.71)	(-4.07)
R_{jt-1}	-0.0003**	-0.0004**	-0.0006**	-0.0002**	-0.0002**	-0.0002**	-0.0002**	-0.0003**	-0.0002**
	(-6.71)	(-13.43)	(-11.64)	(-2.91)	(-5.28)	(-7.51)	(-3.68)	(-8.77)	(-7.96)
TSX	-0.0020**	-0.0020**	-0.0051**	-0.0050**	-0.0060**	-0.0072**	-0.0066**	-0.0105**	-0.0087**
	(-4.22)	(-4.58)	(-5.59)	(-3.57)	(-5.39)	(-10.16)	(-3.75)	(-11.80)	(-15.70)
USMKT	-0.0023**	-0.0058**	-0.0084**	0.0010	-0.0032**	-0.0030**	-0.0069**	-0.0035**	-0.0046**
	(-4.27)	(-12.58)	(-8.23)	(0.53)	(-2.62)	(-4.14)	(-5.35)	(-5.06)	(-10.62)
$\Delta US10TB$	0.0182**	-0.1113**	-0.4093**	0.0872**	0.003	0.0042	-0.1259**	-0.0437**	-0.0016
	(10.50)	(-12.22)	(-20.21)	(3.74)	(0.15)	(0.34)	(-4.72)	(-3.49)	(-0.19)
Bond fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	41,404	52,992	10,751	10,971	16,750	32,691	6,393	22,334	18,022
Number of bonds	787	937	421	282	478	650	318	490	451
Adjusted R^2	0.3002	0.2706	0.2564	0.3321	0.2937	0.3484	0.2207	0.3956	0.5731

Note: The table reports pooled regression coefficient estimates from the most extended specification of Equation (2.1) which includes the yield changes of Government of Canada bonds (ΔT_{jt}), the leading, contemporaneous and lagging stock returns of the bond issuing firm (R_{jt+1}, R_{jt} and R_{jt-1}), as well as the S&P TSX Composite returns (TSX), the U.S. stock market returns ($USMKT$), and the change in 10 year U.S. Treasury yields ($\Delta US10TB$). We include bond fixed effects by removing the constant and including one dummy variable for each bond in the considered sample period. Underlying stock returns and yield changes are measured in percentage terms. For comparison, the first three columns (labeled "Financial Post") report the coefficient estimates based on Financial Post publications over the Jan.1994-Sept.2007, Jan.1994-Dec.2010 and Oct.2007-Dec.2010 periods. The reported t-statistics (in parentheses) are based on the autocorrelation and heteroskedasticity robust standard errors of Newey-West (1987) with lags that vary as a function of the considered period.

2.7.4 Credit Ratings and Top Bonds

To further investigate the Canadian stock-bond dynamics, we repeat our analyses according to bond ratings over the 1994-2007 period. We obtain six bond sets based on the AAA, AA, A, BBB, BB and B ratings, and a residual set which includes bonds not rated by DBRS (Dominion Bond Rating Service). Consistent with the features of the Canadian market, the extreme sets referring to AAA-, BB- and B-rated bonds are scarcely populated and do not allow for reliable comparisons with other bond sets. A summary of the ratings-based analysis is summarized in Table 2.9. Focusing on the 1994-2017 sample, we note that the estimation confirms the irrelevance of leading stock returns over the 1994-2007 period. We also find that the coefficient magnitudes of contemporaneous stock return increase from AA- to BBB-rated bonds, while those of lagging returns are relatively more stable across bond rating sets. In our sample, BBB-rated bonds do exhibit stronger relationships with contemporaneous stock returns but maintain a marked dependence on riskless bond yields. On the other hand, AA-, and A-rated bonds do not exhibit larger sensitivities than BBB-rated bonds to riskless yields. Therefore, classifying Canadian corporate bonds according to credit rating over the 1994-2007 period does not provide a separation in bond sets which clearly exhibit the features of fixed income or equity securities.

We then extend our credit rating analysis to the 1994-2010 period and find very similar results for contemporaneous and leading stock return coefficients. We also find that the significant informational flows from the bond to the stock market (i.e., significant β_2 estimates), are concentrated in the large portion of AA-rated Canadian bonds. These results suggest that the consideration of credit ratings may provide further guidance in the identification of significant information flows from the bond to the stock market.

Table 2.9: Pooled regressions - dependent variable: bond yield changes by credit ratings (January 1994 to December 2010)

Variable	AAA	AA	A	BBB	BB	B	Unavailable
ΔT_{jt}	0.5505	0.9128**	0.9255**	0.9457**	0.5852**	0.8581	0.1119
	(1.42)	(58.74)	(85.26)	(30.89)	(4.79)	(1.11)	(0.82)
R_{jt+1}	-0.0001	-0.0003**	-0.00003	-0.0001	0.0004**	-0.0001	0.0001
	(-0.70)	(-7.90)	(-0.94)	(-1.65)	(1.98)	(-0.08)	(0.41)
R_{jt}	-0.0007	-0.0003**	-0.0002**	-0.0007**	-0.0009**	-0.0002	-0.0014*
	(-1.25)	(-5.70)	(-3.05)	(-4.10)	(-3.98)	(-0.36)	(-2.27)
R_{jt-1}	0.0001	-0.0005**	-0.0003**	-0.0006**	-0.0001	-0.0007	-0.00004
	(0.44)	(-10.05)	(-6.28)	(-7.18)	(-0.60)	(-0.63)	(-0.14)
TSX	-0.0167	0.0011	-0.0029**	-0.0022	0.0079	-0.0798	-0.0159
	(-0.60)	(1.25)	(-5.47)	(-1.57)	(1.25)	(-0.70)	(-1.59)
USMKT	0.0618	-0.0095**	-0.0044**	-0.0099**	-0.0091	0.0729	-0.0034
	(1.35)	(-10.56)	(-7.83)	(-6.51)	(-1.23)	(0.48)	(-0.32)
$\Delta US10TB$	-0.4675*	-0.1862**	-0.053**	-0.2602**	0.0599	-0.4172	0.3125*
	(-2.00)	(-8.73)	(-5.43)	(-7.84)	(0.66)	(-0.34)	(2.06)
Constant							
Bond fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	36	10,473	33,555	8,351	293	22	262
Number of bonds	3	343	618	203	18	3	13
Adjusted R^2	0.2810	0.5165	0.2473	0.2235	0.2828	0.6446	0.1362

Note: The table reports pooled regression coefficient estimates from the alternative model specifications nested in Equation (2.1). The overall set of explanatory variables includes the yield changes of Government of Canada bonds (ΔT_{jt}), the leading, contemporaneous and lagging stock returns of the bond issuing firm (R_{jt+1}, R_{jt} and R_{jt-1}), as well as the S&P TSX Composite returns (TSX), the U.S. stock market returns ($USMKT$), and the change in 10 year U.S. Treasury yields ($\Delta US10TB$). We include individual bond fixed effects by removing the constant and including one dummy variable for each of the 937 bonds in the sample period. Underlying stock returns and yield changes are measured in percentage terms. DBRS does not provide credit ratings for individual bonds but only for issuers. Bond ratings are therefore identified each month in accordance with the issuer rating. Due to infrequent revisions, we obtain over time a sample of bond ratings that is only slightly larger than the total number of bonds. The reported t-statistics (in parentheses) are based on the autocorrelation and heteroskedasticity robust standard errors of Newey-West (1987) with 15 lags (significant values, at the 5% and 1% level, are denoted by 1 and 2 asterisks).

Table 2.10: Pooled regressions - dependent variable: bond yield changes of top bonds (January 1994 to December 2010)

Top Bonds				
Variable	1984-2010	1994-2007	1994-2010	2007-2010
ΔT_{jt}	0.5781**	0.8643**	0.8474**	0.5129**
	(16.51)	(30.19)	(33.23)	(5.52)
R_{jt+1}	-0.0002**	0.00003	-0.0001	-0.0006**
	(-3.25)	(0.58)	(-1.86)	(-4.16)
R_{jt}	-0.0006**	-0.0004**	-0.0004**	-0.0003
	(-5.77)	(-3.19)	(-3.92)	(-1.61)
R_{jt-1}	-0.0004**	-0.0003**	-0.0005**	-0.0006**
	(-7.58)	(-4.67)	(-7.72)	(-4.24)
TSX	-0.0075**	-0.0014	-0.0022	-0.0067
	(-5.38)	(-1.05)	(-1.49)	(-1.87)
USMKT	-0.003*	-0.0031*	-0.0068**	-0.0035
	(-1.97)	(-2.21)	(-4.85)	(-0.95)
$\Delta US10TB$	0.1152**	-0.0078	-0.1430**	-0.2397**
	(3.81)	(-0.40)	(-5.37)	(-3.89)
Constant				
Bond fixed effects	Yes	Yes	Yes	Yes
Number of observations	10,015	5,901	7,551	1,508
Number of bonds	568	367	466	141
Adjusted R^2	0.2761	0.3944	0.3066	0.0925

Note: The table reports pooled regression coefficient estimates from the alternative model specifications nested in Equation (2.1). The overall set of explanatory variables includes the yield changes of Government of Canada bonds (ΔT_{jt}), the leading, contemporaneous and lagging stock returns of the bond issuing firm (R_{jt+1}, R_{jt} and R_{jt-1}), as well as the S&P TSX Composite returns (TSX), the U.S. stock market returns ($USMKT$), and the change in 10 year U.S. Treasury yields ($\Delta US10TB$). We include individual bond fixed effects by removing the constant and including one dummy variable for each of the 937 bonds in the sample period. Underlying stock returns and yield changes are measured in percentage terms. Building on the results of Ronen and Zhou (2013), the top bond of each firm is identified in each month with the most recently issued bond. The reported t-statistics (in parentheses) are based on the autocorrelation and heteroskedasticity robust standard errors of Newey-West (1987) with 15 lags (significant values, at the 5% and 1% level, are denoted by 1 and 2 asterisks).

Chapter 3

Flights from Stocks

3.1 Introduction

From the standpoint of asset pricing analysis, flight-to-quality episodes (henceforth flights) are extreme representations of the mechanisms governing how the aggregate portfolio responds to shocks to expected economic growth. One of the goals of this study is to ascertain the relative importance of monetary policy activities, volatility, stock illiquidity, and asset performance in explaining flights from stocks to long- and short-term Treasuries, and to top-grade (Moody's AAA) corporate bonds. In addition, this paper also proposes an original link between the momentum literature and studies of market instability.

Flights are extreme and rare market dynamics that are generally understood as deviations from a normal regime of interdependence between two markets. In this paper, as in related works (inter alia, Baur and Lucey, 2009; Pesaran and Pick, 2007; Forbes and Rigobon, 2002), a flight involves a significant decrease, within the negative range, of the pair-wise correlation between the returns on two representative indexes. In particular, a flight-to-quality is a flight for which the average returns of the indexes bear opposite signs, with the index yielding a positive average return being that representing assets carrying a lower risk of loss of the principal.

Other recent papers that study flights include Bekaert and Hoerova (2016), Baele et al. (2014), and Mueller et al. (2012). Mueller et al. (2012) proposes a Treasury Implied Volativity measure, TIV, similar to the VIX index for the equities, using futures on 30 year Treasuries. They further build a measure of flight-to-quality using the spread between the VIX and TIV indices, and find that this spread triples during the crises of October 1987, LTCM in August 1998 and Lehman bankruptcy in September 2008. Baele et al. (2014) build a flight-to-safety indicator that allows for an endogenous timing of flight episodes. They construct four dichotomous variables to evaluate flights, each calculated by means of a different methodology. The measures they consider to define flights include filters on market volatility, signs and magnitudes of asset returns and the correlation between two market returns. They then aggregate these variables into a final flight-to-safety indicator. Bekaert and Hoerova (2016) builds a risk aversion measure and an uncertainty measure for the US and Germany, respectively. They calculate the correlations between these two measures with Mueller et al. (2012)'s flight-to-quality indicator and Baele et al. (2014)'s flight-to-safety indicator. Their results show that risk aversion measure is highly correlated with flights in the US market.

To preview, our results show that dismal monthly average stock returns are strongly associated with flight occurrence. In contrast, indicators of exceptionally depressed, or euphoric, trading days have mixed effects on market instability, with extreme negative returns triggering flights to short-term T-Bills rather than to haven securities with longer maturities. The frequency of flights is also shown to be associated with large stock market realized volatility, and to be increasing in the expectations of future stock market volatility. These results add to the literature on the interplay between returns and volatility (e.g., Sarwar, 2017; Ghysels et al., 2013; Jensen and Maheu, 2013; Maheu et al., 2013; Campbell and Hentschel, 1992, among others) by examining how volatility affects sharp changes in the relative profitability of the asset classes.

Monetary policy announcements by the U.S. Federal Reserve (Fed) significantly decrease the probability of flight incidence. Furthermore, the effect of monetary policy press releases is rather similar across the types of flights considered, a feature that speaks of a pervasive, and benign, influence of the Federal Reserve's activities on market stability, over the 1990-2014 period. However, the analysis of dynamic models of incidence of flights also indicates that expectations of a future loose monetary stance are associated with an increased probability of future flight occurrence. This result is consistent with the hypothesis that, when markets brace for the worst, expectations for monetary easing increase. Our work thus contributes to the well-rooted literature on the influence of monetary policy activities on aggregate returns (e.g., Fiordelisi et al., 2014; Gagnon et al., 2011; Bernanke and Kuttner, 2005; Gürkaynak et al., 2005; Krueger and Kuttner, 1996), by documenting that significant deviations in relative asset profitability are influenced by monetary policy activities.

This study also contributes to the extensive literature on (stock market) illiquidity by documenting that illiquidity bouts affect the probability of flights (Bethke et al. (2017), Rösch and Kaserer (2014)). The link between illiquidity and market instability is interpreted in light of the asset pricing framework described in Vayanos (2004) which links agency concerns with flight incidence and a time-varying market illiquidity premium. The model in Vayanos predicts that as long as assets are similar in sensitivity to volatility and liquidity, then illiquidity shocks are likely to increase pair-wise correlations of asset returns, an effect that would decrease the probability of flights (and increase the probability of cross-asset contagion). However, Vayanos model also predicts that pair-wise correlations may even decrease in response to an illiquidity shock for assets groups sporting very diverse risk profiles. Such a decline in correlation, if significant, may cause flights. Pairs of asset classes featuring radically different risk profiles are easy to come by, an obvious example being stocks and short-term T-Bills. Asset classes like AAA-corporate bonds and stocks instead display more similarities in terms of risk exposure. Our empirical analysis strongly supports the predictions of Vayanos by showing that illiquidity bouts depress the probability of flights to corporate bonds, and even to long-term Treasuries, but that illiquidity has a much weaker, or even opposite, effect on flights to T-Bills.

Finally, this paper proposes an original link between the momentum literature (Bijlsma and Vermeulen, 2016; Daniel and Moskowitz, 2013; Cooper et al., 2004; Jegadeesh and Titman, 1993) and studies of market instability (Baele et al., 2014; Baur and Lucey, 2009). Our results show that large momentum profits are strongly linked to an increase in the occurrence of flights. This finding holds for all the specifications of the empirical model of flight incidence employed in this paper, and for all types of flights considered. Building on the insight stemming from the classical behavioral models proposed in Daniel et al. (1998) and Barberis and Shleifer (2003), we propose a simple link between the profitability of the momentum strategy on the stock market and flight incidence.

Studies like ours contribute to the vast literature on market comovements (e.g., Adrian et al., 2015; Büyükşahin and Robe, 2014; Brownlees and Engle, 2012; Cappiello et al., 2006; Scruggs and Glabadanidis, 2003) and deviations from usual trend of market inter-dependences (e.g., Baele et al., 2014; Baur and Lucey, 2009; Forbes and Rigobon, 2002). An important innovation of this paper with respect to this literature is that we model flights from stocks to three types of fixed income securities: top-grade corporate bonds, as well as short and long-term Treasuries. In contrast, the vast majority of contributions in the extant literature on flights focus on comovements between stocks and long-term sovereign bonds.

The rationale for including top-grade corporate bonds and T-Bills in an analysis of flights is that investors might flee from stocks to acquire positions in assets that are less risky than stocks in different ways. Historically, long-term Treasuries have been considered the most natural refuge during periods of uncertainty and low inflation (e.g., Baele et al., 2014). Short-term Treasuries, however, offer unbeatable liquidity during turbulent times (e.g., Engle et al., 2012), while top-grade corporate bonds allow investors to decrease their risk profile without completely renouncing to equity market potential gains. To our knowledge, this is the first paper modeling flights to three fixed income categories.

The inclusion of T-Bills in the pool of haven assets used to define flight-to-safety episodes is meant to account for the behavior of those investors who decide to "park" their wealth in liquid and short-term risk-free securities, while waiting for market uncertainty to be resolved. Indeed, we find evidence that omitting flights to T-Bills results in severely underestimating the incidence of market instability. For the 1990-2014 sample, about 24% of flights correspond to flights from stocks to T-Bills *only*, i.e., of flights to T-Bills not occurring simultaneously with flights to long-term Treasuries, or top-grade corporate bonds.

Krishnamurthy and Vissing-Jorgensen (2012) find that AAA-rated corporate bonds share some of the safety attributes of Treasuries, a result that further motivates the inclusion of these securities in the safe haven asset pool used to analyze flights. Furthermore, previous research has produced evidence of flights to top-grade corporate bonds during the financial crisis initiated in 2007 (Dick-Nielsen et al., 2012). Given the results of these studies, including top-grade corporate bonds in the set of safe haven assets appears to be for a more nuanced description of aggregate market instability. Our empirical analysis confirms that flights to AAA-rated corporate bonds represent a sizeable share of the total number of flights, with a hefty 56.21% of flights involving a flight to corporate bonds component.[1]

The remainder of the paper is laid out as follows. The next section begins the empirical analysis by illustrating the methodology employed to identify flights and the characteristics of the flight indicators. Section 3.3 explores models of flight incidence. This part of the empirical analysis includes static models of flight incidence, a discussion of the 2007-2014 sub-sample, the evaluation of market state effects, and a brief presentation of the results from dynamic models of flight incidence. A concise statement of conclusions completes the paper.[2]

[1] We recognize that Treasuries and high-grade corporate bonds may fail to subsume all types of investments that are traditionally considered havens in time of crisis, as, for example, real estate, some types of commercial paper, or selected commodities (e.g., Taylor and Williams, 2009). However, many of these investments have been shown to carry more risk than expected in recent years, thus making it difficult to characterize flights into these asset categories as responses to investor quests for safety.

[2] Robustness checks for the proposed flight indicators, some variable descriptions, and a more detailed discussion of market state effects and of the dynamic models are all relegated to the

3.2 Identification of Flight Episodes

Flights are extreme and rare market dynamics that are generally understood as deviations from a normal regime of interdependence between two markets.[3] In the empirical literature, we encounter two main empirical methodologies to identify flights occurring during a given period. The first examines order imbalances or order flows around crisis periods (e.g., Kaul and Kayacetin, 2017; Kasch et al., 2011; Beber et al., 2009). The second approach, adopted in this paper, is to employ changes in the correlation between asset returns. In this case flights are defined by significant shocks to the correlation between two return series, i.e., by changes in the relative performance of two asset groups.

Consistent with the approach proposed by previous studies (among others, Baur and Lucey, 2009; Pesaran and Pick, 2007; Forbes and Rigobon, 2002), we characterize a flight episode by a significant drop, within the negative range, of the pair-wise correlation between two return series. The emphasis here is on the significance of the correlation change: we identify as flights only return dynamics that represent significant deviations from the status quo of the relative profitability of assets. In particular, a negative value of the correlation between two asset classes does not suffice to identify a flight episode. We motivate this deviation from methodologies that identify flights using negative correlation levels by noting that the correlation between asset classes is very persistent in sign. For example, the Dynamic Conditional Correlation (DCC) of US stock returns and yield changes (changed of sign) on long-term Treasuries depicted in Figure 3.1 clearly shows that for about half of our sample, from 1998 onwards, these two asset classes have been negatively correlated.

appendix.

[3]The literature on international market contagion has long recognized the distinction between market interdependence (e.g., Büyükşahin and Robe, 2014; Brownlees and Engle, 2012; Cappiello et al., 2006) and deviations from the status quo relationship between two markets (e.g., Forbes and Rigobon, 2002).

If flights were to be identified by a negative value of return correlation, then we should conclude that flights have been pervasive events over the 1998-2014 interval.[4]

[Figure 3.1 about here]

Much of the previous literature on market instability has focused on episodes of market turmoil that were clearly linked to specific events or dates (e.g., the Thailand Crisis in July 1997, the Hong Kong Crisis in October 1997, the Russian Crisis in August 1998, the 9-11 in 2001, the bankruptcy of Enron in December 2001 and the bankruptcy of WorldCom in July 2002). The challenge posed by the financial crisis initiated in 2007 is that this period is characterized by a sequence of diverse market shock which are spread over about two years. The results of any empirical analysis aiming to identify flight episodes by examining only a selection of sub-samples of this eventful period is bound to be liable to sample selection bias. Put differently, as there is no consensus on which events are at the root of market instability for a substantial part of our sample, our analysis does not focus on a few exogenously defined sub-samples. Rather, this study adopts a data-driven approach and thus strongly mitigates concerns of sample selection biases associated with the researcher's perception on the causes of financial instability.[5] In this work the timing of flights is made endogenous by evaluating a static flight identification methodology within a rolling-sample framework.

This empirical approach also sports a real-time flavor, as each rolling sub-sample is truncated at the end of the time window for which the evaluation of the existence of flights is performed, i.e., at the end of the (potential) crisis period. Excluding the observations following the crisis period serves the purpose of eliminating concerns of a look-ahead bias. We deem this precaution particularly important for any study

[4]Furthermore, we should also conclude that flights are not necessarily linked to episodes of market instability, unless we are willing to assume that the market has been continuously unstable over the 1998-2014 period.

[5]Pesaran and Pick (2007) also discuss the perils of distinguishing pre-crisis from crisis periods a priori for the estimation of international contagion.

of market instability that analyzes asset comovements over a sample including the 2007-2009 financial crisis, as the large market swings characteristic of that period might artificially raise the bar for any market instability episode occurring in periods preceding the summer of 2007 to be detected. This concern is material to our analysis as we employ a sample of returns and yields spanning from January 1990 to December 2014.[6]

For each time interval $I_t = [\tau_{0t}, \tau_{1t}]$, the incidence over I_t of flight episodes from stocks to long-term Treasuries, to T-Bills, and to top-rated corporate bonds, are simultaneously evaluated by jointly estimating the following system of linear equations:

$$r_{b,t} = \alpha_b + \beta_b r_{s,t} + \gamma_b r_{s,t} D_t + \gamma_b^* r_{s,t} D_t^* + e_{b,t} \tag{3.1}$$

$$r_{f,t} = \alpha_f + \beta_f r_{s,t} + \gamma_f r_{s,t} D_t + \gamma_f^* r_{s,t} D_t^* + e_{f,t} \tag{3.2}$$

$$r_{c,t} = \alpha_c + \beta_c r_{s,t} + \gamma_c r_{s,t} D_t + \gamma_c^* r_{s,t} D_t^* + e_{c,t} \tag{3.3}$$

where the variable $r_{s,t}$, stand for the daily returns on the US value-weighted market portfolio from the Centre for Research in Security Prices, CRSP. The variables $r_{b,t}$, and $r_{f,t}$, and $r_{c,t}$ represent the negative of the daily yield changes for the 10-year Treasury bond index, the three-month T-Bill, and the Moody's AAA long-term corporate bond index, respectively. Due to known approximations, daily yield changes, with the signs reversed, can be loosely interpreted as returns on a rolling portfolio, so that we shall refer to $r_{b,t}$, and $r_{f,t}$, and $r_{c,t}$ as returns in the following.[7]

Equations (3.1), (3.2), and (3.3) are designed around two dichotomous variables, denoted by D_t and D_t^*, which are defined on the basis of two adjacent time intervals of

[6] As in Section 3.3.2 we shall employ the average of the implied volatility index, the VIX index, the availability of the VIX index defines the span of our sample.

[7] Empirically, the correlation between $r_{b,t}$ and the return on the monthly rebalanced portfolio of 10-year maturities (variable TDRETADJ in CRSP) is 0.95 over the sample 1990-2014. Bond yields are sourced from the data library of the Federal Reserve Board of Governors. In our sample, we retain only trading days for which returns on all four classes of assets are available.

fixed width, namely the crisis and benchmark periods, where the benchmark period precedes the crisis window. The variable D_t is equal to 1 for all the observations over the interval I, i.e., over the crisis period, and zero otherwise. The second variable, D_t^* is always 0 except for the observations falling in the crisis and benchmark periods. In short, during the benchmark period the variable D_t is zero while D_t^* equals 1, while both variables take the value 1 during the crisis window.[8]

The coefficient on the crisis indicator D_t in Equations (3.1), (3.2), and (3.3), denoted by γ_i, for i in $\{b, f, c\}$, measures the change in the correlation between the stock returns and the considered fixed income security, when moving from the benchmark to the crisis period. The sum of the coefficients $\beta_i + \gamma_i + \gamma_i^*$ is the a gauge of correlation level between the returns of the safe asset and the stock index, during the crisis period.[9] Asset performance during the crisis period is measured by the average of daily returns.

A flight is a market dynamic in which the change in correlation, the estimated coefficient $\hat{\gamma}_i$, and the correlation level, the sum $\hat{\beta}_i + \hat{\gamma}_i + \hat{\gamma}_i^*$, are both negative, the coefficient $\hat{\gamma}_i$ is significant, and, finally, the average return of the safe (risky) asset during the crisis window is positive (negative). For example, the estimates of equation (3.1) provide evidence of a flight-to-quality from stocks to long-term Treasuries occurring during the crisis period starting on day t when $\hat{\gamma}_b$ is negative and significant, the expression $\hat{\beta}_b+\hat{\gamma}_b+\hat{\gamma}_b^*$ is negative, and the average return over the crisis period on long-term Treasuries (on stocks) is positive (negative). Flights from

[8]Equations (3.1), (3.2) and (3.3) are designed according to the approach proposed in Baur and Lucey (2009), where the authors estimate the long-term Treasuries equation alone (equation (3.1)). In turn, the linear model proposed by Baur and Lucey (2009) generalizes that described in Forbes and Rigobon (2002) by including the pre-crisis indicator variable.

[9]In this dissertation, we use the estimated coefficient to gauge the correlation between two asset series. However, strictyly speaking, the estimated coefficient does not equal the correlation level. Rather, it is the correlation rescaled by the standard errors of the two series. In the later text, the term "correlation" and "correlation change" are used when discussing $\hat{\beta}_i + \hat{\gamma}_i + \hat{\gamma}_i^*$ and $\hat{\gamma}_i$ for convenience.

stocks to corporate bonds and to short-term Treasuries are identified analogously.

Equations (3.1), (3.2), and (3.3), are estimated for rolling samples of fixed width. More specifically, the equations are evaluated for a sequence of overlapping rolling sub-samples, each of three years and one month in length.[10] The step between the start of two consecutive rolling sub-samples counts one trading day. The contiguous benchmark and crisis periods count two and one months, respectively, where a month is approximated by 22 trading days. The sample is cut after the crisis window. More precisely, each rolling sample counts 779 observations, of which 22 define the crisis window and 757 represent the three years preceding the start of the crisis period, with 22 and 252 trading days approximating a calendar month and a calendar year respectively. Hence, for each subsample, the benchmark and crisis indicator variables D_t^* and D_t in equations (3.1), (3.2), and (3.3) are nonzero for the last 66 and 22 days of the rolling sample, respectively. The benchmark period consists of 44 trading days.[11] For each sub-sample, the significance of the coefficient $\hat{\gamma}_i$, together with the remaining conditions noted above, determine whether a flight has occurred during the crisis period.[12] In our 1990-2014 sample we have 6,236 rolling samples. Baur and Lucey (2009) rely on benchmark and crisis windows of 50 and 20 trading day in estimating equation (3.1) for a set of exogenously identified crisis periods. As in the 1990-2014 sample the average number of trading days is 21.7, we prefer to approximate the month with 22 daily observations rather than 20.

Consistent with the rolling sample approach adopted to obtain the flight variables, the resulting flight indicators are highly autocorrelated. This feature of flight

[10]We have tried alternative lengths of the rolling sample. The resulting flight variables are virtually indistinguishable from those employed in the analysis presented. See also the robustness checks in Chapter 4 of this dissertation.

[11]See also the robustness checks in the fourth chapter of this dissertation.

[12]As in Section 3.3.2 we shall employ the average of the implied volatility index, the VIX index, over the benchmark window, our first sub-sample starts from 44 days after the first available observation of the VIX. Hence, the first benchmark period starts on January 2, 1990 and ends on Friday, March 2, 1990, while the first crisis interval starts on Monday, March 5, 1990.

indicators is both expected, as market instability is unlikely to be a one-day only event, and not unique to our study. For example, visual inspection of the indicators proposed in Baele et al. (2014) clearly shows strong persistence. Indeed one of their measures shows that a trading day over which a flight takes place has a 94.7% chance to be followed by another flight date.

The design of equations (3.1), (3.2), and (3.3) implies that flights are identified by deviations from the *status quo* emerging during the benchmark period. The use of rolling benchmark periods captures the evolution of the information set employed by market participants. Hence, flights are defined with respect to recent market activities, rather than to some ideal period of "normal" markets. In fact, the benchmark period itself may include episodes of market instability, which is a desirable feature as it allows us to evaluate the incidence and characteristics of market instability from the perspective of contemporaneous investors.

3.2.1 Incidence of Flights

This joint estimation of equations (3.1), (3.2), and (3.3) yields three time-varying dichotomous variables, collectively called the flight variables. These indicators record the occurrence of flight episodes from stocks to each group of fixed income securities. We denote flights to long-term Treasuries, T-Bills, and top-grade corporate bonds by $ftqsb_t$, $ftqsf_t$, and $ftqsc_t$, where each of the 6,236 observations of a flight variable summarizes the result of the assessment on the existence of flight for a 22-day crisis period starting with date t.

Column 1 of Table 3.1 reports the frequencies of the occurrence of flights for the full 1990-2014 sample. We also construct an aggregate flight indicator, $ftqs_t$, which is defined as the cross-sectional point-wise maximum of the individual flight variables. The use of the point-wise maximum, instead of the simple summation of the flight variables, aims to avoid double counting flights that simultaneously involve several categories of fixed income securities.[13]

The tetrachoric correlation between the variables counting flights to long-term corporate bonds and long-term Treasuries score a hefty 0.94.[14] In contrast, the correlations between the indicators of flights to T-Bills and flights to top-grade corporate bonds and long-term Treasuries are 0.45 and 0.61, respectively. These relatively low correlation values suggest that flights to T-Bills may be inherently different from flights to longer term securities.

An analysis of the coefficients $\hat{\gamma}_i$ in equations (3.1), (3.2), and (3.3) for i in $\{b, f, c\}$, the details of which are not reported, indicates that episodes likely to cause extreme market uncertainty and illiquidity (e.g., the collapse of Lehman Brothers) are signaled by massive flights to T-Bills, rather than to long-term Treasuries or top-rated corporate bonds. This link between dramatic market events and flights to T-Bills suggests that not including short-term Treasuries in the pool of safe haven investments would result in an understatement of the relevance of flights as a type of market instability.

To quantify this intuition, we further report that for the 1990-2014 sample about 24% of the flights (i.e., 223 of 932) measured by the aggregate flight variable $ftqs_t$ correspond to flights from stocks to T-Bills *only*, i.e., to flights to T-Bills not occurring concurrently with flights to long-term Treasuries, or top-grade corporate bonds. Furthermore, our estimates indicate that flights involving T-Bills are pervasive, as fully 46% of flights identified by the indicator $ftqs_t$ involve a flight to short-term securities.

The high degree of correlation between flights to Treasuries and top-grade corpo-

[13]For the estimated flight variables, and thus also for $ftqs_t$, observation t refers to the first date of the 22-day crisis window that is identified by the variable D_t in equations (3.1), (3.2), and (3.3). So, for example, the zero value of $ftqs_1$ signals that no flight took place over the 22-day window spanning from March, 5 to April 3, 1990.

[14]In this work, all correlations between indicator variables are calculated as tetrachoric correlations.

rate debt is not too surprising, as the long maturity side of the Treasury yield curve tends to drive the yield of corporate bonds (e.g., Campbell and Taksler, 2003; Kwan, 1996). Corroborating the important role played by Treasuries in determining price dynamics for corporate bonds documented in the literature, in our sample we find that flights to Treasuries and to corporate bonds manifest some degree of synchronicity, as 69.6% of flights to Treasuries occur simultaneously with flights to top-grade corporate bonds.

All in all, the unconditional analysis of the frequency of flights suggests that flights to T-Bills may be different from flights to long-term securities, while flights to top-rate corporate bonds and long-term Treasuries are closely related. The conditional analysis discussed in the following section reinforces this assessment.

[Table 3.1 about here]

Given the severity of the financial crisis initiated in the summer of 2007, a plausible conjecture is that the incidence of the different types of flights has dramatically changed during, or following, the ensuing turmoil. To evaluate this possibility, we calculate the frequencies of the four types of flights for three sub-periods which are carved out from the 1994-2014 sample around the breakpoints June 29, 2007 and June 30, 2009, where these dates are chosen to roughly encapsulate the most disruptive phases of the financial crisis.[15] Flight variables are assigned to each sub-sample on the basis of the first day of the crisis period. The calculated frequencies are reported in columns 2, 3, and 4 of Table 3.1.

The sub-sample analysis reveals that the incidence of all types of flights roughly doubled during the financial crisis (sample 2007-2009 in Table 3.1). Given that the crisis was indeed a time of market instability, as large shocks hit financial markets, this sharp increase of flight incidence over the 2007-2009 sample can be loosely in-

[15] Bear Stearns liquidated two hedge funds exposed to the subprime mortgage sector in July 2007. The NBER recession indicator identifies the end of the downturn in June 2009. Using alternative breakpoints confirms the increase of all types of flights during the 2007-2009 crisis.

terpreted as an indirect validation of our methodology to identify flights.

In the full sample, there are (unreported in Table 3.1) only 106 simultaneous flights from stocks to all the three categories of fixed income securities, over the considered $6,236$ rolling samples. Simultaneous flights feature similarly low frequencies, about 1%, before and after the 2007-2009 crisis. For the sub-samples covering the years of the crisis, the analogous percentage reaches about 4%, which reveals that simultaneous flights, though still rare, became more prevalent during the crisis.

The ability of the flight indicators of market instability to match major events is a qualitative validation of the effectiveness of this methodology to elicit the timing of flight episodes from the data. The analysis suggests that the flight indicators capture dramatic market events, a point that we illustrate by discussing the performance of the aggregate flight indicator $ftqs_t$ over the year 2008.

Flight indicators have been defined, early on in this section, so that the time t observation summarizes the assessment of flight occurrence for the 22-day crisis window starting on date t. This mapping is somewhat artificial, as the flight variables gauge the correlation shift associated with the entire crisis period. While this choice of notation is convenient for the presentation of the statistical model presented in Section 3.3, it may create the impression of market prescience in plots of flight variables.[16] Hence, to eliminate this visual appearance of foreknowledge, an observation of $ftqs_t$ is mapped to the last day of the crisis period starting on date t. Figure 3.2 displays the plot of $ftqs_t$ with t falling in the year 2008.

[Figure 3.2 about here]

Figure 3.2 clearly shows that flights tend to cluster, which is an expected feature

[16]For example, we find evidence of a flurry of flights for rolling windows starting on August 14, 2008. These flights correspond to the rolling samples including the day of the collapse of Lehman Brothers (September 15, 2008), with August 14 being the first day of the first 22-day crisis window including the bankruptcy filing. Mapping the values of the flight indicator $ftqs_t$ into the first day of the crisis periods would result in the visual appearance of market foreknowledge, as the plot would show a cluster of flights starting about one month before Lehman Brothers' collapse.

for a variable estimated using rolling samples. The cluster in February and early March corresponds to the week preceding the rescue of Bear Stearns. Concerns about the financial standing of the Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac) are mirrored by the flurry of flights starting in mid-July. The following cluster is associated with the collapse of Lehman Brothers in September. The last recognizable cluster of flights starts in mid-November and stretches to the end of the year, a time interval that does not appear to be linked to a specific event, but rather to a sequence of market shocks.[17]. Overall Figure 3.2 suggests that the flight indicator is able to capture prolonged period of pervasive market instability.

The analysis of two dramatic events of 2008, namely the rescue of Bear Stearns on March 14, and the demise of Lehman Brothers on September 15, reveals that the flight indicator to captures not only periods of prolonged market instability but also responds to large market swings occurring over short time intervals.

Figure 3.3 plots the flight indicator $ftqs_t$ from the beginning of February to the end of April 2008. The non-zero values of the flight indicator cluster in the month of March. Overall, the qualitative analysis of the $ftqs_t$ indicator around the collapse of Bear Stearns tells a story of pronounced market instability, with flights distributed evenly around the climax.

[Figure 3.3 about here]

Figure 3.4 plots the aggregate flight indicator $ftqs_t$ from the beginning of September to the end of October 2008. This dichotomous variable equals 1 in about 50% of the crisis periods with an ending date falling either in September or October. We find evidence of flights for 19 of the 22 crisis windows that include the Lehman

[17]The timeline of events proposed by the Federal Reserve identifies no less than 26 press releases during the months of November and December in 2008. Consistently, we find evidence of flights in about 40% of the crisis periods with ending date falling in these two months. The timeline is available on the website of the Federal Reserve Bank of St. Louis, last accessed on June 10, 2016. See also the timeline in Bartram and Bodnar (2009).

Brothers' bankruptcy filing date.

[Figure 3.4 about here]

3.3 A Model of Flight Incidence

For the purpose of modeling flight incidence, we assume that flights are extreme manifestations of an unobservable continuous, and time-varying, market instability variable. The flight indicators introduced in Section 3.2 are thus viewed as proxies for this latent variable, as they capture the extreme realizations of the unobservable market instability variable. Consistently, we formalize the link between the probability of incidence of instability and market characteristics with a limited dependent variable model. Hence, the realizations of the flight indicator $ftqs_t$ are modeled by the following probit model:

$$Prob(ftqs_t = 1|x_t) = \Phi\left(x_t'\beta\right) \tag{3.4}$$

where, Φ is the standard normal cumulative distribution function, β is a vector of coefficients and x_t is a vector of explanatory variables.[18] The flight indicators of flights to long-term Treasuries ($ftqsb_t$), T-Bills ($ftqsf_t$), and top-grade corporate bonds, ($ftqsc_t$), are substituted to the aggregate flight indicator $ftqs_t$, in equation (3.4) to add some nuances to the empirical analysis of the determinant of flights.

The first set of control variables employed in equation (3.4) includes the average returns of the return series $r_{s,t}$, $r_{b,t}$, $r_{f,t}$ and $r_{c,t}$, over the 22-day crisis window initiating with observation t. These averages are denoted by $car_{a,t}$ where the subscript a takes value in the set $\{s, b, f, c\}$, i.e., where a equals s for stocks, b for long-term Treasuries, f for short-term Treasuries, and c for top-grade corporate bonds. To

[18] The use of a logistic regression yields identical conclusions, as it is often the case. We opt for the probit model, for ease of calculation of the marginal effects.

facilitate the discussion of our results, throughout the remainder of this paper the prefix "c" indicates contemporaneous variables.[19]

Two types of additional return-based covariates are introduced in equation (3.4) to capture different dimensions of asset performance, with one responding to month-long slumps, and the other signaling the occurrence of extreme daily returns. The variable $camin_{s,t}$ is a dichotomous variable that takes on a value of 1 when the average stock market return $car_{s,t}$ is below the average of the daily stock market returns over the year preceding date t. The indicator variable $cmin_{s,t}$ equals 1 when the worst daily return on stocks over the 22-day crisis window is worse than the worst daily return in the previous year. Analogously the indicator variable $cmax_{s,t}$ equals 1 when the best daily return on stocks over the 22-day crisis window betters all the daily returns obtained over the year preceding t.

The variable $cstdev_{s,t}$ measures realized contemporaneous stock market volatility by the standard deviation of the stock market index daily returns, over the 22-day crisis window starting with. In a later specification, we shall measure market expectations for future volatility using the implied volatility index VIX.

The notion that illiquidity commands a return premium has been discussed in the financial literature for a long time (e.g., Amihud and Mendelson, 1986). Studies of order-flows have shown that liquidity is a determinant of volatility, at least for short time intervals (e.g., Mike and Farmer, 2008; Gillemot et al., 2006; Weber and Rosenow, 2006; Farmer et al., 2004). Others have shown that volatility and illiquidity are related sources of risk for longer investment horizons. For example, Chordia and Shivakumar (2002) find cross-sectional relationships between stock returns and illiquidity, with illiquidity being measured by volume and turnover. Importantly, they

[19]Since the $car_{a,t}$ variable is an average over a 22-day rolling window, the lag-1 autocorrelation of any of these series is close to 1. Lack of stationarity would pose obvious concerns of spurious results within the regression framework. However, as mentioned earlier in this section, Park and Phillips (2001) find that the usual battery of inference techniques applies to binary choice models with non-stationary covariates.

find that the effect of illiquidity is robust to the inclusion of volatility, which suggests that volatility and illiquidity might measure separate, although linked, dimensions of risk.

Cues on how illiquidity may affect flight incidence can be elicited from several asset pricing models with liquidity. We focus on the multi-asset illiquidity model proposed in Vayanos (2004) which features agency considerations and offers nuanced predictions for flights. The model predicts that as long as assets are similar in sensitivity to volatility and liquidity, then illiquidity shocks are likely to increase pair-wise correlations of asset returns, a price dynamic that would decrease the probability of flights (and increase the probability of cross-asset contagion). This could be the case, for example, for stocks and corporate bonds, given that stock market volatility is one of the main drivers of corporate bond yields (e.g., Campbell and Taksler, 2003). Vayanos model also predicts that pair-wise correlations might decrease in response to an illiquidity shock for assets groups sporting very diverse risk profiles regarding their responsiveness to illiquidity and volatility changes. Such a decline in correlation, if significant, may cause flights. Pairs of asset classes featuring radically different risk profiles are easy to come by, an obvious example being stocks and short-term T-Bills. Our empirical analysis tests these model predictions using a familiar gauge of stock market illiquidity, namely the Amihud (2002) $ILLIQ$ measure. To align the design of the Amihud measure with this paper's empirical framework, we evaluate this aggregate illiquidity measure using firm-level return and volume for the 22 days of the crisis period. The resulting variable, which is denoted as $cilliq_t$, measures illiquidity in the stock market over the crisis period. Details on this variable design are provided in the appendix.

The unconditional analysis of Baele et al. (2014) and Engle et al. (2012) suggests that illiquidity in the long-term government bond market is associated with flights. In Section 3.3.1 we shall quickly discuss a model of flights that includes performance and volatility gauges for all the four asset classes considered in this paper. Details of the model are in the appendix. The evaluation of this extended model suggests that adding measures of the characteristics of the four asset classes, like asset-specific illiquidity gauges, would severely undermine the statistical soundness of the resulting model, due to multicollinearity concerns.[20]

The analysis of the relationship between illiquidity for stocks and Treasuries in Goyenko and Ukhov (2009) documents that these two variable are strongly associated, with illiquidity in the stock market typically leading that of Treasuries. An opposite lead-lag relationship can be observed in response to monetary policy activities, as the level of liquidity for Treasuries strongly responds to rate adjustments, then followed by stock illiquidity. Chordia et al. (2005) show that illiquidity gauges for bonds and stocks are significantly correlated to the volatility measures of these asset classes. Consistent with these findings, the effects of illiquidity of Treasuries on market instability are subsumed by the joint inclusion in equation (3.4) of gauges of stock market illiquidity, bond and stock market volatility, and of monetary policy announcements.[21]

Theoretical models as those of Vayanos (2004) or Acharya and Pedersen (2005) suggest that illiquidity, measured as asset group specific trading costs, plays a role in asset pricing. Yet another dimension of illiquidity that has surged to preeminence during the most disruptive phases of the financial crisis initiated in the summer of

[20]Goyenko and Ukhov (2009) show that measures of stock and bond illiquidity are strongly and positively correlated, with a correlation of 0.61. Furthermore, short term and long term Treasuries illiquidity measures are correlated at an even larger level, with the correlation being 0.72. Chordia et al. (2005) report smaller, and yet statistically significant, correlation levels between similarly defined illiquidity measures.

[21]Some of the findings in the extant literature on the relationship between stock market illiquidity and other market forces further comfort us in the choice not to include illiquidity measures for long-term Treasuries, T-Bills, and AAA-corporate bonds in models of flight incidence. Baele et al. (2014) employ three illiquidity measures for stocks and for long-term government bonds, as they regress each individual illiquidity measures on the flight indicator. The obtained coefficients are comparable for similar types of illiquidity measures, which suggests a consistent relationship between both stock and bond market illiquidity with flights.

2007 is linked to the easiness, or difficulty, experienced by large financial institutions to obtain credit. The centrality of the borrowing constraints affecting speculators in other asset pricing with illiquidity model (e.g., Brunnermeier and Pedersen, 2009; Kiyotaki and Moore, 2002) suggests that aggregate liquidity could be measured by variables summarizing credit easiness for market makers, or large financial institutions.

Measures of easiness of credit for financial investors that come to mind are the Effective Federal Funds (EFF) rate and the broker's call rate, the latter being the interest rate charged when brokers borrow from banks to cover clients' security positions.[22] In an unreported result, available upon request, we document neither the EFF rate nor the call rate plays a significant role in explaining flights.[23]

Filipović and Trolle (2013) note that most of the recent literature measures interbank (lending) risk by the Libor-OIS spread.[24] As data for the overnight indexed swaps are first available in 2001, the most pressing drawback of using the Libor-OIS spread is that it would limit our sample. The analysis of the 2007-2014 sub-sample, summarized in Section 3.3.1, and detailed in the appendix, reveals that the effects of the Libor-OIS spread on flight incidence are hard to disentangle from those of monetary policy activities. The inclusion of the spread does not modify any of this paper's conclusions.

Studies on the effectiveness of the response of the Fed to the 2007-2009 crisis have argued that monetary policy activities had a pervasive impact on financial

[22]The broker's call rate, as sourced from Bloomberg, is the rate on an unsecured line of credit extended to brokers from banks to cover client security positions. The loan is callable on notice of 24 hours.

[23]The EFF rate went flat and stayed at near zero level during January 2009 to December 2013. The lack of explanatory power of the EFF rate is maintained when the rate is extended using implied shadow rate proposed by Wu and Xia (2016).

[24]In the literature there is some debate on whether the Libor-OIS spread is a good measure of illiquidity. We shall briefly elaborate on the concerns associated with using the Libor-OIS spread rate in the appendix.

markets during the crisis. For example, the works of D'Amico and King (2013) and Gagnon et al. (2011) document that yields on securities purchased in the Fed's large asset purchase programs (initiated in the last months of 2008) fell more than yields on securities that were not acquired. Wright (2012) shows that monetary policy activities have affected corporate bond yields as well. Furthermore, responses to monetary policy announcements have been investigated with respect to stock prices and volatility in several papers (e.g., Fiordelisi et al., 2014; Wright, 2012; Rangel, 2011; Rosa, 2011; Bernanke and Kuttner, 2005). To account for monetary policy activities, we include, in the model displayed in equation (3.4) the variable $cFed1_t$ which is defined as the number of monetary policy announcements issued during the crisis period starting at date t, where announcements are identified following the classification employed by the Fed. We opt for the use of announcements because these are silent on the expected direction of the effect of monetary policy (Gürkaynak et al. (2005)). More details on the design of the variable $cFed1_t$ are relegated to the appendix.

To evaluate the potential role of the momentum effect in explaining the occurrence of flights, we include in equation (3.4) a dichotomous variable based on the daily profits of the momentum strategy, henceforth denoted by $cdmom_t$. This variable equals 1 when the average return of the daily momentum strategy over the 22 day crisis period is larger than the average return of the momentum portfolio over the year preceding the crisis period. Hence $cdmom_t$ identifies the crisis windows during which momentum gains are substantial, with respect to the recent past. The return of the momentum strategy is the momentum factor provided by the Kenneth R. French Data Library, calculated as the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios.[25] Consistently with

[25]The momentum series of daily returns for US stocks is sourced by Kenneth French website. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The detailed description of the composition of the momentum portfolio can be found in Fama this paper's approach, this indicator sports a real-time flavor, as exceptionally large gains are defined relative to a time-varying reference period.

To explore the possibility that flights are state dependent, we include in equation (3.4), a dichotomous variable that accounts for the state of the stock market in the period preceding the crisis period. Following the approach suggested in previous contributions (e.g., Cooper et al., 2004) a market is defined to be down, or up, on the basis of its annual average. We thus define the $down_t$ variable as taking the value of 1 when the average of the stock market daily returns, over the past year (i.e., the year ending on date t), is negative.[26]

The use of a limited dependent variable is motivated by statistical considerations. Recent advancements in statistics suggest that the standard binary response models are particularly suitable to the inclusion of nonstationary variables.[27] Notably, unit-root variables are the natural outcomes of the recursive framework we employ to endogenize the timing of flight episodes.

Table 3.2 reports the summary statistics for the continuous and binary variables described above, over the $6,236$ rolling sub-samples during 1990-2014. The mean of average daily stock return in the 22-day rolling period, car_s, is 0.044%, which corresponds to a monthly return of 0.97%. The mean of standard deviation for stock return during the rolling period, $cstdev_s$, is 0.963%. The mean of average yield changes in the 22-day rolling period for long-term Treasuries, short-term T-Bills and AAA corporate bonds (car_a, for a in $\{b, f, c\}$) are 0.101, 0.131 and 0.088

and French (2012).

[26]A state variable defined analogously to $down_t$ but for the year ending at the end of the crisis window has been considered, but it is virtually collinear with $down_t$.

[27]Park and Phillips (2001) examine familiar binary choice models in which covariates are a mixed bag of stationary and non-stationary variables and find that the maximum likelihood estimates are consistent. They also show that the limit distribution of the estimates is a mixed normal distribution, which implies that the standard Wald tests of restrictions on the estimates still have χ^2 limiting distributions. Put differently, their findings show that the usual battery of inference techniques applies to binary choice models with non-stationary covariates.

basis points respectively. With regard to the monetary activities, we note that in the 1990-2014 sample, the Federal Reserve made 3 announcements on average each month (22 trading days), and in some months as many as 15. In total, there are 908 announcements in our sample for 300 calendar months. The average illiquidity measure during the 22-day rolling period, *cilliq*, is 0.66.[28]

Variables *cdmom*, $camin_s$, $cmin_s$, $cmax_s$ and *down* are binary variables, therefore their values are between 0 and 1. $cdmom_t$ has a mean of 0.547, indicating that for 54.7% (45.3%) of the rolling sub-samples, the average return of the daily momentum strategy over the crisis period is larger (smaller) than the corresponding average daily return over the previous year. The mean of $camin_s$ equals 0.475, indicating that in 47.5% of the rolling sub-samples the average return in the crisis period (car_s) is below the average return over the previous year. Similarly, the worst (best) daily return on stocks over the crisis window is worse (better) than the worst (best) return in the previous year in 6.5% (8.8%) of all rolling windows, as shown by $cmin_s$ and $cmax_s$.

[Table 3.2 about here]

3.3.1 Static Models

Equation (3.4) is estimated using the aggregate flight indicator ($ftqs_t$), and then, separately, for the indicator variable of flights to long-term Treasuries ($ftqsb_t$), to T-Bills ($ftqsf_t$), and to top-grade corporate bonds ($ftqsc_t$). Estimates are summarized in Panel A of Table 3.3. We report only the marginal effects, for brevity's sake, relegating the table with the probit coefficients and t-statistics to the appendix. Basic model diagnostics are reported in Panel B.

Covariates are appropriately scaled to facilitate the interpretation of the marginal

[28] In line with what is documented in Amihud (2002), *cilliq* is obtained by multiplying 10^6.

effects.[29] Given these scalings, one should interpret the marginal effects in Panel A as follows.[30] In Column 1, an increase of 10% of the liquidity measure of stock market (variable *cilliq*) is associated with a decrease of 0.1 percentage points (i.e., 10 basis points) of the probability of a flight. The 10% increment is calculated with respect to the average of the liquidity measure, over the 1990-2014 sample. The return variables $car_{a,t}$ are scaled so that the marginal effects are for an increase of 10 basis points over the full sample average of the corresponding return series. The marginal effect of a dichotomous variable is measured as the change in the expected probability of incidence of a flight when switching from state 0 to state 1. For example, in column 1 of Panel A in Table 3.3, the probability of a flight occurring over the 22-day crisis window is found to be 4.8 percentage points larger when the market is in a down state than when it is in an up state. The marginal effect of the variable $cFed1_t$ is for one additional monetary policy announcement during the crisis window.

In Panel B of Table 3.3 we report the McFadden Pseudo R-squared measures of prediction success.[31] Previous literature (e.g., King and Zeng, 2001) has shown that explaining events occurring with very low frequencies poses concerns of a possible downward bias for the probabilities in a binary variable model.[32] In view of the

[29]The marginal effect of a continuous variable x_t is the sample average of the partial effects of x_t for each observation. For a dichotomous variable y_t, the marginal effect is the sample average of the difference between the predicted probability when $y_t = 1$ versus $y_t = 0$, while the other covariates are at their sample values for each observation.

[30]All the return variables are measured in 10 basis points. Other explanatory variables are rescaled such that one unit change measures a change of 10% of the mean value of that variable.

[31]The McFadden pseudo R-squared cannot be interpreted exactly as a standard R-squared in regression analysis. For instance, this measure of model fit tends to be lower, so that values between 0.2 and 0.4 are usually considered evidence of excellent model fit (McFadden, 1979). We have considered other measures of model fit for the probit regression (e.g., Estrella, 1998) but they are very similar to the McFadden pseudo R-squared values, and are thus not reported.

[32]The bias is intuitively plausible: if the dichotomous variable assumes the value 1 for about 5% of the observations, a naive model predicting zero for all observations would appear to fit the data very well, predicting 100% of the 0 occurrences and mislabelling fewer than 5% of the events. Choice based sampling techniques improve the goodness of the fit for equation (3.4), but fail to modify any of this paper conclusions, and are therefore omitted.

low frequency of flights in our sample, the models presented in Table 3.3 explain these rare events rather well. For example, the static model successfully predicts about 45% of the flights for $ftqs_t$, while 91% of the non-events windows are correctly identified.[33]

The marginal effects presented in Table 3.3 reflect the fact that the coefficients on the average returns $car_{a,t}$ for a in $\{s, b, f, c\}$ feature the expected signs.[34] An increase in stock market performance is associated with a lower incidence of flights from stocks. Furthermore, flights to a fixed income security group become more likely with an increase in its performance. We note that the coefficients of these covariates are highly significant, which is not surprising as average returns over the crisis period enter the very definition of the dependent variable. Nevertheless, that the indicators of performance of fixed income securities, variables $car_{a,t}$ for a in $\{b, f, c\}$, display the expected sign for their estimated impact in the vast majority of the models, is not fully a by-product of the definition of flight. The average return on long-term Treasuries, for example, is not employed to define flights to T-Bills. As such, it is *per se* an interesting result that a higher performance of long-term Treasuries is associated with a larger probability of flights to T-Bills, but the performance of T-Bills has no bearing on the incidence of flights to long-term Treasuries. This asymmetry is another piece of evidence revealing an intrinsic difference between flights to long and short-term Treasuries, on which we shall comment further later on in this section.

[33]The frequencies in Table 3.1 show that flights to individual classes of fixed income securities occur with a rather low incidence rate. The paucity of ones in the flight variables $ftqsb_t$, $ftqsf_t$, and $ftqsc_t$, explains the slight drop in the fit measures reported in columns 2, 3 and 4 of Table 3.3. Choice sampling techniques do not modify any of this paper's finding.

[34]The empirical approach to the identification of flights, which is described in Section 3.2, jointly employs correlation changes and average levels of returns over the crisis window. The levels of the average returns on the four asset classes, the variables $car_{a,t}$ for a in $\{s, b, f, c\}$, are therefore included in all models used to explain flights, lest we bias our results by omitting variables that, by construction, constitute an integral part of the definition of flights.

The results in columns 2 and 3 of Table 3.3 show that a larger average return on corporate bonds (variable $car_{c,t}$) is associated with a lower incidence of flights to Treasuries. One way to interpret this result is that when the corporate bond market is doing well, the probability of a flight from stocks to low-yielding liquid assets (T-Bills) and to close substitute long-term securities, falls as investors weigh foregone returns in their portfolio choices.

The marginal effect on the variable $camin_{s,t}$ confirms the expectation that flights are more common when the average stock market return during the current month is exceptionally unfavorable, i.e., below its annual average. This effect is strong for all four types of flight indicators considered. In contrast, a day-long extremely bad (favorable) return, as gauged by the variables $cmin_{s,t}$ ($cmax_{s,t}$) is not significantly associated with the incidence of flights, when considering the merged flight indicator $ftqs_t$. This insignificance is, however, the product of aggregation across the types of flights. The results in columns 2, 3 and 4 of Table 3.3 show that extremely bad (good) days on the stock market increase (decrease) the probability of flights to T-Bills but they have the opposite effect on flights to Treasuries and corporate bonds.

The differences in the effects of extremely negative daily returns on the three types of flights to fixed income securities suggest that short-term Treasuries are the only real safe haven assets. In a complementary finding, extremely favorable returns, as identified by $cmax_{s,t}$, appear to bring buoyancy to long-term investments while causing cash-like assets to look less appealing.

Including T-Bills in the pool of safe haven assets allows describing the behavior of investors who decide to maintain liquid portfolios while waiting for extreme market uncertainty to resolve. This hypothesized behavior predicts diverse effects of major short-term shocks on the incidence of flights to cash-like holdings versus long-term fixed income securities. This prediction is supported by the differential effects of the indicators $cmin_{s,t}$ and $cmax_{s,t}$ on the incidence of flights to T-Bills and to top-quality long-term bonds.

While measures of extreme performance of the stock market, over the short term, appear affect differently flights to T-Bills and long-term bonds, the sign of the marginal effect of the market-state variable $down_t$ indicates that prolonged market downturns make all types of flights more likely. Specifically, the marginal effects reported in Panel A of Table 3.3 suggest that a down market state triggers more flights to long-term Treasuries than flights to T-Bills and top-grade corporate bonds.

[Table 3.3 about here]

The estimated marginal effect on $Fed1_t$ in column 1 of Table 3.3 indicates that an additional announcement of the Fed significantly decreases the probability of flight occurrence, with an impact per one additional announcement of about a 1% decrease in the flight probability. We note that the marginal effect of an additional Fed announcement yields a twice as strong effect on flights to short-term Treasuries than on flights to longer term bonds. This difference is not completely unexpected, as monetary policy activities tend to influence short-term interest rates, rather than long-term yields (e.g., Jarrow and Li, 2014; Fama, 2013). We note, however, that the Fed response is potentially endogenous with asset price variation, so the results in Table 3.3 should not be taken as evidence of the ability of the Fed to subdue market instability.

The negative sign of the marginal effect on the market illiquidity measure $cilliq_t$ in column 1 suggests that illiquidity bouts tend to decrease the probability of a flight, although by only a small margin. The theoretical model in Vayanos (2004) predicts that the effect of illiquidity bouts should vary across asset classes. Vayanos predicts that pair-wise correlations might decrease (as it happens in flights) in response to an illiquidity shock only for assets with very different sensitivities to volatility and illiquidity. Pairs of asset classes bearing different trading costs (the proxy for illiquidity in Vayanos model) and sporting diverse sensitivities to volatility shocks are easy to come by, an obvious example being stocks and T-Bills. Hence Vayanos' model predicts that illiquidity should increase the probability of flights from stocks to T-Bills. Furthermore, the model predicts that, as long as assets are similar in sensitivity to volatility and bear similar transaction costs, then a shock to illiquidity is likely to increase pair-wise correlations of asset returns, a dynamic that would decrease the probability of flights. Corporate bonds and stocks fit the mold of asset classes sharing similar sensitiveness to volatility and illiquidity, so that flight to corporate bonds should decrease in response to illiquidity.

The marginal effects reported in columns 2, 3, and 4 of Table 3.3 suggest that illiquidity has indeed a differential effect on the probability of flights for different classes of safe haven investments. As predicted by Vayanos (2004), illiquidity bouts on the stock market increase the probability of flights to T-Bills, but depresses the probability of flights to top-grade corporate bonds. The negative marginal effect on $cilliq_t$ in column 2 of Table 3.3 also shows that illiquidity tends to decrease the incidence of flights to long-term Treasuries. Taking Vayanos' prediction backwards, the empirical analysis thus suggests that long-term Treasuries are more similar to top-grade corporate bonds than to T-Bills, at least in terms of responsiveness to illiquidity and volatility shocks.[35]

Contemporaneous market volatility, summarized by the standard deviation of stock returns over the crisis period, is insignificant for the incidence of flights. However, this insignificance is a by-product of omitting the volatility of the fixed income securities in the model reported upon in Table 3.3. The volatilities of the three safe have securities are strongly correlated, and have the opposite effects of the volatility of the stock market on the incidence of flight.[36] When the volatility of the haven

[35]Rather, in an unreported analysis we find that illiquidity increases the probability of negative contagion between Treasuries and stocks, and between corporate bonds and stocks. The econometric framework proposed in Section 3.2 enables the identification of cross-asset contagion episodes, in addition to flights. See the appendix for details.

[36]The correlations of the variable $cstdev_s$ with $cstdev_b$, $cstdev_f$, and $cstdev_c$, are 0.54, 0.35, and

assets are accounted for, in equation (3.4), then the effect of stock market volatility is positive, as expected (see the appendix).

The large and positive marginal effect of the momentum dichotomous variable $cdmom_t$ in Table 3.3 corroborate the existence of a positive link between the mechanisms causing the profitability of the momentum strategy and market instability. The marginal effect shows that if the momentum strategy is yielding very large returns then flights are about three times more likely to be observed. To compare, the effect is about equivalent to three fewer announcements from the Federal Reserve, but it is only about a half of the marginal effect of one year of downturn, as measured by the $down_t$ variable.

The marginal effect of the momentum variable is positive and significant for all types of flights, a result that suggests that the forces causing the link between momentum gains and market instability affect multiple asset classes. This pervasiveness is consistent with previous studies documenting that the momentum effect is present across a large range of asset classes, as summarized in, among others, Asness et al. (2013), Durham (2013), and Jostova et al. (2013).

The works of Barroso and Santa-Clara (2015), Daniel and Moskowitz (2013), and Cooper et al. (2004) produce evidence that momentum gains are state dependent. Given these results, we evaluate the effect of the market state on the strength of the association between large momentum profits and market instability. The analysis of marginal effects in the up and down markets, reported in Table 3.4, reveals that the role of large momentum profits in explaining market instability is significantly different in up and down markets, as there appears to be a stronger (about 20%) association between large momentum profits and the incidence of flights, following downturns. This state effect on the link between flights and large momentum gains is observed for all types of flights.

0.56, respectively.

[Table 3.4 about here]

The appendix presents an extension of the static model reported upon in Table 3.3 that accounts for the performance of Treasuries and top-grade corporate bonds. The extended model also controls for volatility measures, to isolate the effect of performance from that of risk taking. The conclusions of this paper remain unchallenged from the results of this extended model.

To assess whether the validity of this article's findings is affected by the market turmoil of the 2007-2009 crisis, we analyze the static models discussed in Section 3.3.1 for the 2007-2014 sub-sample, with the first 22-day crisis window starting on June 29, 2007. Full tabulation of the results for this sub-sample analysis is relegated to the appendix. The analysis of the 2007-2014 sub-sample reveals a substantial robustness of the link between the momentum effect and flights.

With regard to the role of the momentum effect, we note that Asness et al. (2013) has suggested that momentum abnormal returns might be the compensation for the exposure to funding illiquidity risk, where this type of illiquidity should be understood in the spirit of the model in Brunnermeier and Pedersen (2009). As noted by Filipović and Trolle (2013), most of the recent literature measures interbank (lending) risk by the Libor-OIS spread.[37] It thus can be presumed that including the spread in the model explaining flights described in Section 3.3.1 could affect the degree of association between large momentum gains and market instability. To test this possibility, we include the spread in the static model for the 2007-2014 sub-period.

The weak influence of the Libor-OIS spread, and of other measures of aggregate funding liquidity as the EFF rate, on the role played by momentum in explaining

[37] In line with the literature that analyzes liquidity during the financial crisis (e.g., Taylor and Williams, 2009; Sarkar, 2009), we focus on the three-month maturity Libor-OIS spread, which we source from Bloomberg. Obvious concerns with using the Libor rate to gauge illiquidity arise also in view of the alleged manipulations of the rates during time periods that are included in our sample (e.g., Snider and Youle, 2012; Kuo et al., 2012).

flights does not necessarily imply that the effect of funding illiquidity risk on market instability is unrelated to the momentum effect. Rather, a possible interpretation is that these measures fail to capture the full effect of illiquidity funding risk.

Table 3.5 summarizes the sub-sample analysis of the link between large momentum gains and the incidence of flights. The table reports the marginal effects of the indicator variable of large momentum gains, namely of $cdmom_t$, for the static model described in Table 3.3 where this model is evaluated for the sub-samples carved around the breakpoints June 29, 2007, and June 30, 2009. The analysis reveals a substantial stability of the link between large momentum profits and market instability for the aggregate flight indicator. However, over time, momentum gains appear to be linked with different types of flights in different time periods. Flights to long and short-term Treasuries are associated with large momentum gains mostly after the end of the acute phase of the financial crisis, while flights to top-rated corporate bonds are associated with flights also over the 2007-2009 period.

[Table 3.5 about here]

3.3.2 Dynamic Models

Section 3.3.1 analyzes the contemporaneous correlation of market instability episodes with a range of financial and economic indicators. In this section, we explore whether this contemporaneous relationship is affected by past market conditions. To this end, we augment the static model presented in Table 3.3 with covariates that are calculated using data from the 44 day benchmark period preceding the crisis window, where the crisis and benchmark periods are as defined in Section 3.2. Hereafter we briefly summarize the findings yielded by the dynamic models that add some new nuances to our conclusions. A detailed discussion of the dynamic approach is relegated to the variable description appendix. The notation is adjusted by substituting the prefix "*c*" for contemporaneous with "*l*", for lagged. So, for example, the lagged version of the performance indicator $camin_{s,t}$, is the variable $lamin_{s,t}$ which equals 1 when the average of the daily stock market returns over the benchmark period is below the average of the daily stock market returns over the year preceding the benchmark period.[38]

[Table 3.6 about here]

Table 3.6 reports the marginal effects, and fit measures, for the dynamic models. As the marginal effects on the contemporaneous variables are left substantially unchanged by the dynamic component, we conclude that dynamic analysis corroborates the conclusions yielded by the static approach.

Previous studies on the effect of monetary policy on markets (e.g., Bernanke and Kuttner, 2005; Kuttner, 2001) have shown that price changes of federal funds futures can be used to gauge changes in expectations on policy activities.[39] To explore the effect of this traditional measure of monetary policy expectations on flights, we introduce a continuous variable, denoted by $lFed2_t$, that is designed along the lines of the measure for market expectations on monetary policy activities devised in Kuttner (2001) and subsequently revisited by other researchers (e.g., Gürkaynak et al., 2007; Bernanke and Kuttner, 2005). This variable captures changes in market expectations of the value of the EFF rate to emerge during the crisis window. These changes are measured using the values of the futures on the rate at the beginning and the end of the benchmark period. The variable $lFed2_t$ is constructed to be increasing with the

[38]Due to an excessively large correlation, we cannot include both the contemporaneous and lagged Amihud (2002) measures in the dynamic model. This section's results are obtained using the lagged illiquidity variable $lilliq_t$, but none of our the stated conclusions changes when we rely on the contemporaneous variable $cilliq_t$. Furthermore, we do not include the indicators of extreme daily returns for the benchmark period, that is the lagged version of the variables $cmin_{s,t}$ and $cmax_{s,t}$. The reason for this exclusion is that the substantial length of the benchmark period makes these indicators very weak signals of extreme market events. In an unreported result, we confirm however that the inclusion of these two variables does not modify our conclusions.

[39]The Federal Funds futures are cash settled against the average daily EFF rate for the delivery (calendar) month.

expectations of laxer monetary stances.[40]

Increasing expectations of monetary policy activity might affect flight incidence in two contrasting ways. On one hand an expected decline of the EFF rate, and the related abundance of credit, might galvanize the economy, thus making flights less likely. On the other hand, if increased expectations by market participants of a laxer monetary policy are linked to expectations of incoming economic fragility, then increasing expectation of a looser monetary stance might be associated with increased risk aversion and thus with an increased frequency of flights. Our empirical evidence supports the latter explanation, as heightened expectations of loose monetary policy appear to raise the probability of flights to long-term Treasuries.

The marginal effect of the lagged variable $lFed1_t$ indicates that past monetary policy announcements exert a downward pressure on flight occurrence.[41] Periods following announcements are less likely to be characterized by flights than periods following a benchmark period during which no announcement is observed, perhaps in connection with market's expectations of future monetary policy activities aiming to support the economy. Interestingly, the effect of past announcements is not subsumed by current monetary policy activities.

When analyzing market instability in the context of a dynamic model, it is tempting to include among the explanatory variables the lagged dependent variable. However, the Probit maximum likelihood estimates cannot be used in this type of a dynamic setting.[42] To obviate this limitation, this paper takes a different appro-

[40]An alternative measure of short-term expectations of monetary policy activities, used in Rigobon and Sack (2004) and Cochrane and Piazzesi (2002), is the rate on 1-month Eurodollar deposits. The Eurodollar deposit rate displays a very large correlation with the EFF rate, at 0.98. From this perspective, therefore, including the EFF rate among the set of covariates in equation (3.4) may be interpreted as controlling for market expectations for monetary activities.

[41]The variable $lFed1_t$, counts the number of monetary announcements over the benchmark period.

[42]To the authors' knowledge, the analysis of Park and Phillips (2001) has not been extended to consider the case of probit models with lagged dependent variables.

ach to examine the role of past market instability in explaining flights. Namely, we include in the dynamic model an indicator of flight-*from*-quality and negative contagion episodes, which are defined as in Baur and Lucey (2009). A flight-*from*-quality is a flight-to-quality in reverse, that is a market dynamic in which the correlation between, say stocks and T-Bills drops significantly, but stocks are performing well and T-Bills yield negative returns. A negative contagion episode between two assets is characterized by negative average returns over the crisis period for both assets coupled with a significant increase, in the positive range, of the return correlation. The dichotomous variable $lffqs_t$ (variable $lncns_t$) takes the value of 1 whenever there is a flight-*from*-quality (a negative contagion episode) during the benchmark period.[43] Further details on the calculation of $lffqs_t$ and $lncns_t$ are provided in the appendix.

The marginal effects of the indicators of past market instability suggests that the market state associated with either of these extreme price dynamics are unlikely to be reversed moving from the benchmark to the crisis period. For example, a flight-*from*-quality implies market participants' enthusiasm for riskier assets, to the expense of safer, but low-yielding securities. The negative and significant marginal effect of $lffqs_t$ suggests that such a buoyant mood is unlikely to swing to its opposite, i.e. turn into flight-to-quality events, over a month. Similarly, cross-asset negative contagion episodes contribute to set the stage for flights from stocks to safe haven assets.

To ascertain whether expectations of future volatility influence future market instability, the dynamic model also includes a measure of expected volatility. This forward-looking measure is the average value of the VIX index over the benchmark period and is denoted by $lavix_t$. The availability of the VIX index defines the span of our sample. The positive and strongly significant coefficients of the variable $lavix_t$

[43]Care has been exercised not to include flights and contagion episodes occurring during the crisis window.

in the four models reported in Table 3.6 suggest that increased expectations of future volatility prompt investors to rebalance their portfolio away from stocks, causing an appreciation of safer assets.[44]

The dynamic model includes a dichotomous variable, denoted by $ldmom_t$, which captures large momentum gains during the benchmark period. The variable equals 1 when the average return of the daily momentum strategy over the benchmark period is larger than the corresponding average return over the year preceding the crisis period. As the coefficient of this variable is insignificant, lagged large momentum gains appear to have no effect on the incidence of flights, which suggests that contemporaneous momentum captures all the information carried by the momentum strategy that is relevant to market instability.

The results presented in this paper refer to models for which the VIF is never above 6, while usually being much lower. The robustness of our results to alternative model specification suggests that our results are not undermined by excessive collinearity (e.g., O'Brien, 2007). A tabulation of the VIF for all models estimated in this paper is available upon request.

We considered augmenting the extended static model discussed in the appendix with lagged measures of performance and volatility for all asset classes. While the results of the augmented dynamic model do not alter the general conclusions yielded by the results summarized in Table 3.6, the model features a VIF index that is close to the threshold of 10, and it is therefore not reported. The table of results for the dynamic model for the 2007-2014 sample is available upon request.

In Table 3.7, we provide a description for all the explanatory variables employed in the regressions of this section.

[44] A comparison with the effect of realized, instead of expected, stock market volatility could in principle be performed by introducing, alongside $lavix_{s,t}$, the realized standard deviation of stocks into the dynamic model (denoted by $lstdev_{s,t}$ in the notation of Section 3.3.1). This comparison unfortunately cannot be performed due to a large correlation, at 0.91, between $lstdev_{s,t}$ and $lavix_{s,t}$.

[Table 3.7 about here]

3.3.3 Flights and Momentum Gains

Table 3.8 reports the average monthly return of the momentum strategy, stratified respectively by the flight indicators of flights to long-term Treasuries ($ftqsb_t$), T-Bills ($ftqsf_t$), and top-grade corporate bonds ($ftqsc_t$), as well as by the aggregate flight indicator $ftqs_t$.[45] For the 1990-2014 sample, momentum profits are found to be exceedingly large during periods of market instability, with the gap being of one full order of magnitude between months with, versus those without, flights. Momentum yields a monthly return of 2.63% over 22-day crisis windows with flights, where flight incidence is identified by the aggregate indicator $ftqs_t$.[46] In contrast, the momentum strategy gains a paltry average return of 0.28% over crisis periods with no flight episode. Momentum gains of similar size can be obtained after stratifying monthly momentum returns by the indicators of flights to individual safe haven groups.

The unconditional monthly return of the momentum portfolio has been negative, at -0.56% over the 2007-2009 sub-sample defined by the breakpoints June 29, 2007 and June 30, 2009. This negative performance would suggest that the momentum strategy is not well-suited to periods of marked market instability. In fact, in the 2007-2009 sub-sample, we find that momentum yielded exceptionally strong gains, for a monthly return of 4.63%, over the months with flights. This excellent performance should be compared with the negative return (-2.45%) over the months for which we do not find evidence of flights, in the same sub-sample. This finding suggests that periods of market instability may hide a silver lining for momentum traders. We note that a return gap of somewhat smaller size, with some notable exceptions, is

[45] The flight indicators respond to market instability during rolling crisis periods of 22 day. To match the nature of these dichotomous variables, we calculate the average of the daily momentum return over each rolling 22-day crisis period, and then stratify this series of rolling monthly returns by the flight indicators.

[46] Crisis periods have been defined in Section 3.2.

discernible in the remaining sub-periods. In particular, we note that the profitability differential of momentum may be impressive, even if the average monthly returns of the momentum portfolio are not large. For example, while during the post-crisis period momentum gained a mere 0.13% monthly return, we note that flights to T-Bills are associated with a momentum monthly return that is about 240% larger in months with, versus those without, flights.

[Table 3.8 about here]

Overall, the stratified averages reported in Table 3.8 appear to suggest that large momentum gains are associated with the type of market instability described by the flight indicators defined in Section 3.2. Some preliminary thoughts on why this may be the case are suggested by the behavioral finance literature.

An intuitive inference from classical behavioral models helps to integrate market instability and behavioral patterns in investing. For example, one can consider the classical behavioral model proposed in Daniel et al. (1998) which posits that investors are overconfident about their private information and overreact to it, thus causing momentum gains.[47] Within this framework, flights may be interpreted as episodes driven by overconfident traders who overreact to signals by modifying the composition of their allocation of safe and risky assets away from the proportions suggested by their fundamental values.

The model proposed in Barberis and Shleifer (2003) proposes an explanation of short-term return continuation based on the assumptions that agents trade on the basis of the *relative*, rather than absolute, performance of two competing asset groups, and that investors over-extrapolate past returns.[48] This framework not only provides justification to the momentum effect but also predicts a pattern of negative

[47] As in Daniel and Moskowitz (2013), overconfidence is to be understood as the excessive reliance by agents on signals, not as an enhanced belief in market positive performance.

[48] Barberis and Shleifer (2003) focuses on investment styles, rather than asset classes. However, as in the first part of their analysis investors are not allowed to change their style classification, the model applies to competing asset classes.

return correlation across asset classes that is consistent with flights.

As noted in Lunn (2013), the effects of the extrapolation bias invoked in Barberis and Shleifer (2003) are hard to disentangle from those due to the overreaction bias, where this latter drives the profitability of the momentum strategy in Daniel et al. (1998). Hence, the insights provided by Barberis and Shleifer (2003) and Daniel et al. (1998) can be integrated to jointly yield the prediction that large momentum profits are consistent with higher flight incidence. The stratified averages in Table 3.8 appear to be consistent with these predictions.

3.4 Conclusion

An innovation of the approach used in this paper to study flights is that we consider three classes of haven securities, namely long and short-term Treasuries, and Moody's AAA corporate bonds. The inclusion of several types of safe assets allows for a more nuanced and comprehensive description of the elusive concept of market instability. Indeed, our empirical analysis shows that market instability is not always well-summarized by flights to long-term Treasuries alone. Over the 1994-2014 period, for example, we find plenty of flights from stocks to T-Bills that are not matched by flights to long-term Treasuries or top-rated corporate bonds. This study also suggests that flights to T-Bills are different in many aspects from flights to long-term safe bonds. Our study provides some implications for investment diversification. Asset classes like AAA-corporate bonds and stocks display more similarities in terms of risk exposure. Long-term Treasuries are more similar to top-grade corporate bonds than T-Bills in terms of responsiveness to illiquidity. Illiquidity bouts depress the probability of flights to corporate bonds and long-term Treasuries, but increase flights to T-Bills. This indicates investors may choose to diversify their portfolios to assets with shorter maturity, such as T-Bills when facing high liquidity shocks.

The results of this study show that asset performance, monetary policy, market state, volatility, illiquidity, and past market instability are all important determinants of the occurrence of flights, albeit to different extents. Rather unsurprisingly, we find that dismal month-long average stock returns are strongly associated with flight occurrence, rather unsurprisingly. In contrast, indicators of exceptionally depressed, or euphoric, daily stock returns have mixed effects on market instability, with extreme negative returns triggering flights to short-term T-Bills, but not to longer term quality securities.

Activities of the Federal Reserve, both past and contemporaneous, appear to have a benign effect on market stability, as monetary policy announcements decrease the probability of flights, significantly, for all types of flight considered. The analysis of dynamic models of flight incidence indicates that increased expectations of lax monetary policy increase the risk of flights. We explain this positive association by arguing that increased expectations by market participants of a more accommodating monetary policy stance are linked to expectations of future economic fragility. Furthermore, flights are shown to be associated with stock market realized volatility, and to respond in the expected fashion to expectations of future stock market volatility.

This paper documents that stock market illiquidity appears to have differential effects on different types of extreme market movements. The frequency of flights appears to increase with illiquidity for pairs of asset groups sporting very diverse sensitivity to illiquidity and volatility, e.g., T-Bills and stocks. Conversely, illiquidity appears to trigger cross-asset contagion, rather than flights, between assets with more similar risk profiles, as, for example, stock and corporate bonds. These empirical results confirm the predictions of the asset pricing model with illiquidity proposed in Vayanos (2004).

We also document that strong showings of the momentum strategy are associated with the incidence of market instability. In particular, momentum is disproportionately profitable during periods in which there is evidence of flight incidence. Furthermore, our results clearly show that the strong link between momentum profits and market instability is not explained away by taking in account the performance of stocks, Treasuries and AAA-rate corporate bonds, volatility indicators, market illiquidity, monetary policy activities, and the market state.

From a methodological perspective, our analysis sports a real-time flavor which is new to the literature on market instability, as flights are identified using a methodology that avoids look-ahead biases. To avoid sample selection biases, our work also endogenizes the timing of flights, by exploiting a rolling sample technique. Our methodology to identify flight-to-quality can also be applied to detect other types of market instability indicators, for example flight-from-quality and contagion. A promising direction of further research would be to investigate whether or how the set of economic and financial variables considered in this study would be associated with those market instability indicators.

Table 3.1: Frequencies of Flights

	Incidence of Flights			
Sample Period	1990–2014	1990–2007	2007–2009	2009–2014
Number of Windows	$n = 6,236$	$n = 4,367$	$n = 504$	$n = 1,365$
$ftqs$	932	589	135	209
	(14.94)	(13.49)	(26.78)	(15.31)
$ftqsb$	604	369	97	139
	(9.68)	(8.45)	(19.24)	(10.18)
$ftqsf$	428	300	75	53
	(6.86)	(6.90)	(14.88)	(3.88)
$ftqsc$	527	317	68	143
	(8.45)	(7.25)	(13.49)	(10.47)

Note: This table summarizes the frequency of incidence of flights from stocks to long-term Treasuries ($ftqsb$) T-Bills ($ftqsf$) and Moody's AAA corporate bonds, ($ftqsc$). The aggregate flight indicator $ftqs$ is the point-wise maximum of $ftqsb$, $ftqsf$, and $ftqsc$. The table lists the raw number of events and, in parentheses, the percentage over the number (n) of rolling-samples for the full sample and in each sub-period. The 1990-2014 period is partitioned into three sub-samples, with cut-off dates being June 29, 2007, and June 30, 2009.

Table 3.2: Descriptive Statistics

Variable	$cdmom$	car_s	car_b	car_f	car_c	$cFed1$
Mean	0.547	0.044	0.101	0.131	0.088	3.188
Std.dev	0.499	0.216	1.272	1.093	1.004	2.425
Min	0	−1.639	−4.318	−4.591	−4.500	0
Max	1	0.984	7.273	8.455	7.318	15
Variable	$cstdev_s$	$camin_s$	$cmin_s$	$cmax_s$	$down$	$cilliq$
Mean	0.963	0.475	0.065	0.088	0.191	0.660
Std.dev	0.596	0.499	0.247	0.284	0.393	1.240
Min	0.271	0	0	0	0	0.005
Max	5.346	1	1	1	1	11.505

Note: The table reports the mean, standard deviation, minimum and maximum values of the variables employed in the probit model displayed in equation (3.4), for the 1990-2014 sample. The variable $cdmom_t$, equals 1 when the average return of the daily momentum strategy over the 22-day crisis period starting in t is larger than the corresponding average daily return over the previous year. The variables $car_{a,t}$ for a in $\{s, b, f, c\}$ are the average of the daily returns on the CRSP value weighted stock market index, the 10-year Treasury bond, the 3-month T-Bill, and the Moody's AAA corporate bond index. These averages are taken over the rolling crisis window starting with date t, which contains 22 trading days. Stock returns are in percentage terms, while the yield difference (changed of sign) of the 10-year Treasury bond, the 3-month T-Bill, and of the Moody's AAA corporate bond index are in basis points. The variable $cstdev_{s,t}$ is the standard deviation of the stock index daily returns over the 22-day rolling window starting with t. The value $cFed1_t$ is the number of monetary policy press releases from the Federal Reserve over the crisis window starting in t. The variable $cilliq_t$, is the Amihud (2002) stock market illiquidity measure, again calculated over the 22-day rolling window starting in t. The variable $camin_{s,t}$ equals 1 when the average returns $car_{s,t}$ is below the average of the daily returns over the year preceding date t. The variable $cmin_{s,t}$ ($cmax_{s,t}$) equals 1 when the worst (best) daily return on stocks over the 22-day window beginning with observation t is worse (better) than the worst (best) return obtained in the year preceding t. The variable $down_t$ equals 1 when the average of the stock market daily returns over the year preceding observation t is negative.

Table 3.3: Static Model

Panel A Marginal Effects (in Percentage Points)				
	(1)	(2)	(3)	(4)
Dependent Variable	$ftqs$	$ftqsb$	$ftqsf$	$ftqsc$
car_s	-2.6***	-0.8***	-1.2***	-1.1***
car_b	31.1***	67.5***	20.9***	17.6***
car_f	26.7***	-1.8	33.9***	-3.0
car_c	25.7***	-16.7**	-17.9***	43.6***
$camin_s$	18.5***	15.1***	9.2***	13.1***
$cmin_s$	-0.8	-3.4***	4.1***	-4.8***
$cmax_s$	0.6	2.1**	-1.8*	3.6***
$cstdev_s$	0.1	-0.04	-0.1	0.02
$cilliq$	-0.1***	-0.3***	0.02*	-0.2***
$cFed1$	-0.9***	-0.4***	-0.9***	-0.5***
$down$	4.8***	3.4***	2.4***	2.4***
$cdmom$	2.9***	1.5**	1.5***	1.7***
Panel B Basic Diagnostics				
Log-likelihood_c	-1555.0	-1203.5	-945.8	-1144.3
Log-likelihood_null	-2614.5	-1968.3	-1555.5	-1787.7
McFadden Pseudo R-squared	0.41	0.39	0.39	0.36
Prediction Success				
Actual 1s correctly predicted	45.6%	36.0%	34.7%	32.1%
Actual 0s correctly predicted	90.9%	93.4%	95.3%	94.0%

Note: Significance levels are denoted by, * for $\alpha = 0.10$, ** for $\alpha = 0.05$, and *** for $\alpha = 0.01$. This table reports the results from the estimation of the probit mode displayed in equation (3.4), over the 1990-2014 sample. The dependent variables are the indicators of flights from stocks to long-term Treasuries ($ftqsb$), T-Bills ($ftqsf$), and to Moody's AAA corporate bonds ($ftqsc$). The aggregate flight indicator $ftqs$ is the point-wise maximum of $ftqsb$, $ftqsf$, and $ftqsc$. Panel A reports the marginal effects, in percentage points. Panel B presents basic model diagnostics. Log-likelihood_c denotes the log-likelihood value from the current model, while Log-likelihood_null is the corresponding value for the model with no covariates but a constant. The probit coefficients and t-statistic values can be found in the appendix.

Table 3.4: State Dependent Marginal Effects

Dependent Variable	$ftqs$	$ftqsb$	$ftqsf$	$ftqsc$
$cdmom, Down = 0$	2.88***	1.41***	1.38***	1.64***
$cdmom, Down = 1$	3.53***	1.78***	1.85***	2.04***

Note: Significance levels are denoted by, * for $\alpha = 0.10$, ** for $\alpha = 0.05$, and *** for $\alpha = 0.01$. This table reports the stratified marginal effects of the momentum variable $cdmom_t$ over the market state for the static model summarized in Table 3.3. The marginal effects are in percentage terms and are evaluated for the full sample. The state-dependent marginal effects are calculated as the average marginal effect over the observations in which the market is in an up (i.e., when $Down = 0$) or down state (i.e., when $Down = 1$). The dependent variables are the indicators of flights from stocks to long-term Treasuries ($ftqsb$), T-Bills ($ftqsf$), and to Moody's AAA corporate bonds ($ftqsc$). The aggregate flight indicator $ftqs$ is the point-wise maximum of $ftqsb$, $ftqsf$, and $ftqsc$.

Table 3.5: Marginal Effects of cdmom by Sub-sample (in Percentage Points)

	Dependent Variable			
Sample Period	$ftqs$	$ftqsb$	$ftqsf$	$ftqsc$
Sample 1994-2014	2.9***	1.5**	1.5***	1.7***
Sub-sample 1990–2007	3.1***	0.59	1.74***	2.89
Sub-sample 2007-2009	6.67*	6.76*	-3.64	10.39***
Sub-sample 2009-2014	5.32***	3.18***	2.97***	3.80**

Note: Significance levels are denoted by, * for $\alpha = 0.10$, ** for $\alpha = 0.05$, and *** for $\alpha = 0.01$. This table reports the marginal effects of the variable *cdmom* in the probit model described in Table 3.3 evaluated in the sub-samples defined by the dates June 29, 2007 and June 30, 2009. The first row of results reports the full sample marginal effects, for ease of comparison. The dependent variables are the indicators of flights from stocks to long-term Treasuries ($ftqsb$), T-Bills ($ftqsf$), and to Moody's AAA corporate bonds ($ftqsc$). The aggregate flight indicator $ftqs$ is the point-wise maximum of $ftqsb$, $ftqsf$, and $ftqsc$.

Table 3.6: Dynamic Model

Panel A Marginal Effects (in Percentage Points)				
	(1)	(2)	(3)	(4)
Dependent Variable	$ftqs$	$ftqsb$	$ftqsf$	$ftqsc$
car_s	-2.7***	-0.8***	-1.3***	-1.1***
car_b	33.8***	69.7***	19.5***	20.4***
car_f	26.1***	-2.9	33.2***	-3.3
car_c	21.9***	-20.6***	-17.4***	41.7***
$camin_s$	18.4***	15.0***	8.9***	13.4***
$cmin_s$	1.3	-1.3	4.7***	-3.0**
$cmax_s$	0.8	1.7**	-1.4	3.5***
$cstdev_s$	-0.1	-0.2**	-0.2**	-0.1
$cFed1$	-0.5**	0.2	-0.8***	-0.1
$cdmom$	2.9***	1.1*	1.3**	1.8***
$lamin_s$	0.5	0.02	0.9	1.1*
$lavix$	0.6***	0.3**	0.2*	0.5***
$lFed1$	-0.5***	-0.7***	-0.1	-0.4***
$lilliq$	-0.1***	-0.5***	0.01	-0.2***
$lFed2$	0.2	0.5***	-0.002	0.1
$lffqs$	-0.9	-1.4**	-2.1***	0.4
$lncns$	3.4***	4.7***	-0.3	2.9***
$ldmom$	-0.3	-0.2	0.4	-0.9
$down$	3.3***	2.9***	1.9**	1.5
Panel B Basic Diagnostics				
Log-likelihood_c	-1537.7	-1155.9	-938.6	-1130.3
Log-likelihood_null	-2614.5	-1968.3	-1555.5	-1787.7
McFadden Pseudo R-squared	0.41	0.41	0.40	0.37
Prediction Success				
Actual 1s correctly predicted	46.4%	38.5%	35.4%	33.3%
Actual 0s correctly predicted	91.0%	93.6%	95.4%	94.1%

Note: Significance levels are denoted by, * for $\alpha = 0.10$, ** for $\alpha = 0.05$, and *** for $\alpha = 0.01$. This table reports the results of the estimation of the dynamic model for four categories of flights, for the full sample. The dependent variables are the indicators of flights from stocks to long-term Treasuries ($ftqsb$), T-Bills ($ftqsf$), and to Moody's AAA corporate bonds ($ftqsc$). The aggregate flight indicator $ftqs$ is the point-wise maximum of $ftqsb$, $ftqsf$, and $ftqsc$. Panel A reports the marginal effects, in percentage terms. Panel B presents basic model diagnostics. The probit coefficients and t-statistic values can be found in the appendix.

Table 3.7: Variable Description

Measure	Variable	Description
Asset	car_a	Average returns over the "crisis" window, where a is in $\{s, b, f, c\}$
Performance	$camin_a$	Dummy var: when the avg. daily return of asset a during the "crisis" window is less than the avg. daily return for the previous year
	$lamin_s$	Lagged version of $camin_s$, indicating a dismal stock market in the benchmark period
	$cmin_s$	Dummy var: when the worst daily return on stocks over the "crisis" window is smaller than all the daily returns for the previous year
	$cmax_s$	Dummy var: when the best daily return on stocks over the "crisis" window is larger than all the daily returns for the previous year
Volatility	$cstdev_a$	Standard deviation of the daily returns over the "crisis" window, where a is in $\{s, b, f, c\}$
	$lavix$	The avg. value of the VIX index over the benchmark period
Illiquidity	$cilliq$	Amihud illiquidity measure over the "crisis" window
	$lilliq$	Amihud illiquidity measure over the benchmark period
Market State	$down$	Dummy var: when the avg. daily stock market return in the past year is negative
Fed Activities	$cFed1$	Number of Fed monetary policy announcements during the "crisis" window
	$lFed1$	Number of Fed monetary policy announcements during the benchmark period
	$lFed2$	Expectations of monetary policy activity
Credit Easiness	$cLiOIS$	Libor-OIS spread
Momentum	$cdmom$	Dummy var: when the avg. return of the momentum strategy over the "crisis" window is larger than the corresponding avg. return over the previous year
	$ldmom$	Similar as *cdmom* but captures large momentum gains during the benchmark period
Instability	$lffqs$	Dummy var: when there is a flight-from-quality during the benchmark period
Indicator	$lncns$	Dummy var: when there is a negative contagion during the benchmark period

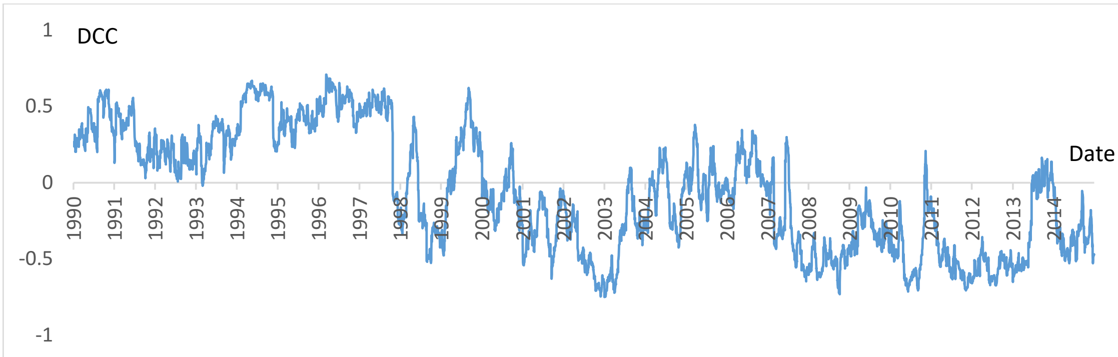
Note: Prefix "c" denotes contemporaneous variables using information during the "crisis" period, while "l" denotes the lagged version of the contemporaneous variables, using information during the benchmark period.

Table 3.8: Average Momentum Returns

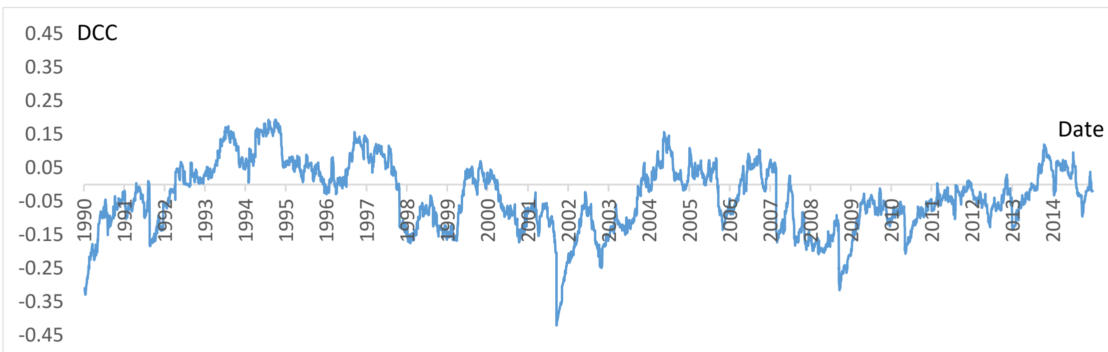
	Stratified Momentum Average Monthly Return (%)			
Sample Period	1990–2014	1990–2007	2007–2009	2009–2014
Unconditional	0.63	0.93	-0.56	0.13
$ftqs = 0$	0.28	0.61	-2.45	0.09
$ftqs = 1$	2.63	2.94	4.63	0.39
$ftqsb = 0$	0.44	0.77	-1.77	0.10
$ftqsb = 1$	2.47	2.67	4.55	0.42
$ftqsf = 0$	0.48	0.77	-1.04	0.07
$ftqsf = 1$	2.74	3.06	2.20	1.70
$ftqsc = 0$	0.48	0.80	-1.52	0.12
$ftqsc = 1$	2.36	2.55	5.63	0.26

Note: The table reports the unconditional and stratified averages of the variable $mom22_t$, in terms of percentage monthly returns. The variable $mom22_t$ is the average (over the 22-day crisis period starting in observation t) of the daily returns of the momentum strategy. The first row refers to the unconditional average of the variable $mom22_t$, multiplied by 22. Stratification is by indicators of flights from stocks to long-term Treasuries ($ftqsb_t$), T-Bills ($ftqsf_t$), and Moody's AAA corporate bonds ($ftqsc_t$), and the aggregate flight variable $ftqs_t$. The aggregate flight indicator $ftqs_t$ is the point-wise maximum of $ftqsb_t$, $ftqsf_t$, and $ftqsc_t$. Monthly average returns are obtained by multiplying the corresponding daily averages times 22, the length of the crisis period. The 1990-2014 sample is partitioned into three sub-samples, with the cut-off dates being June 29, 2007 and June 30, 2009.

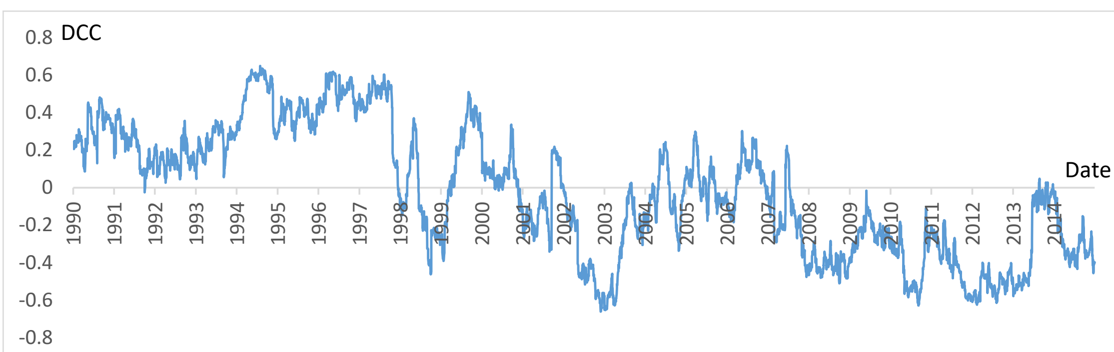
Figure 3.1: Dynamic Conditional Correlation (DCC)



(a) DCC between Daily Returns of Stocks and Long-term Treasuries



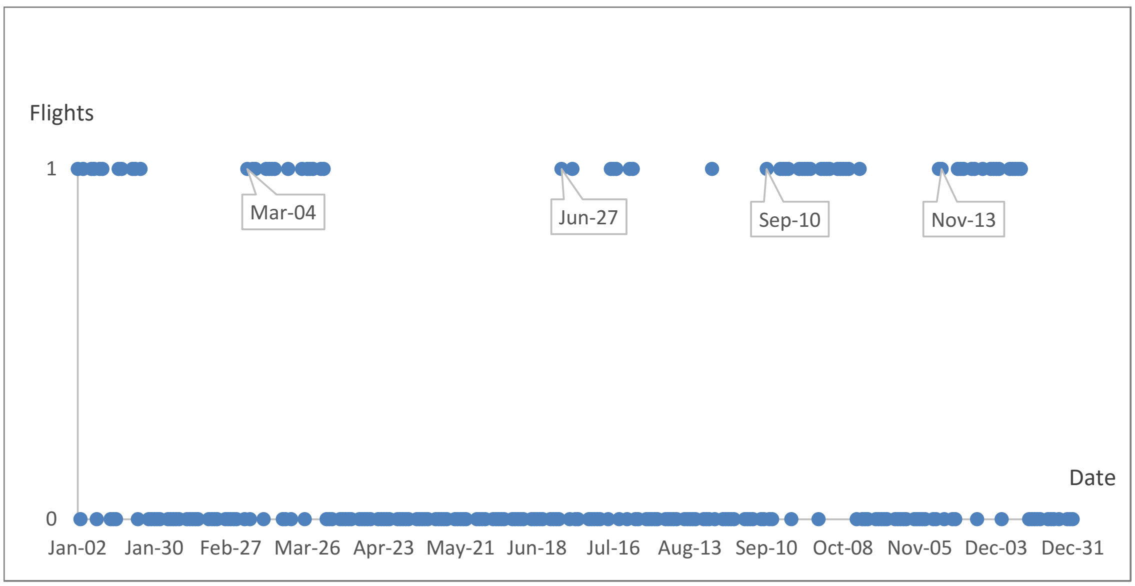
(b) DCC between Daily Returns of Stocks and T-Bills



(c) DCC between Daily Returns of Stocks and Long-term Moody's AAA Corporate Bonds

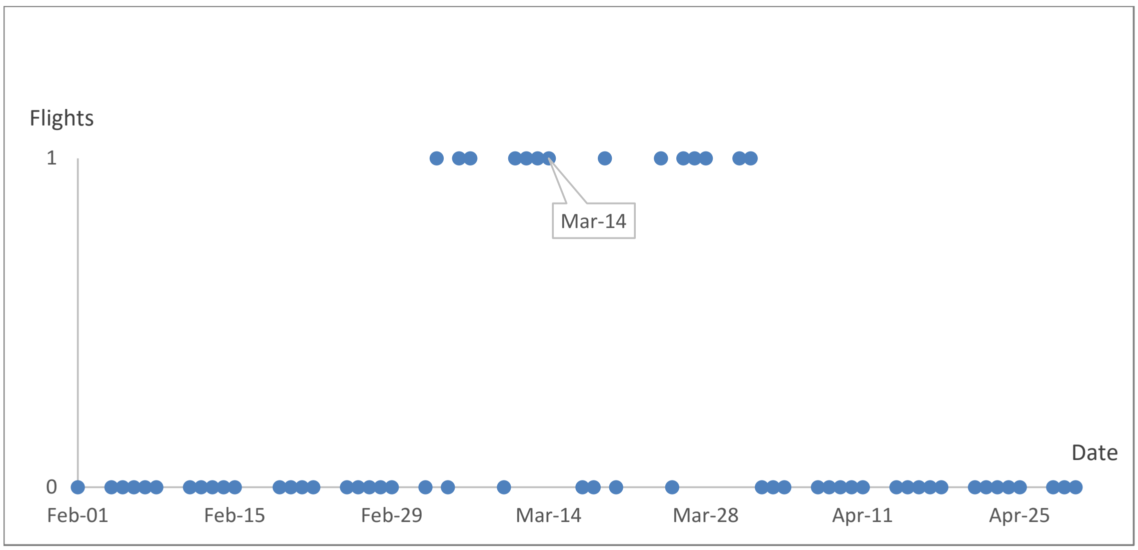
Note: Panel A depicts the Dynamic Conditional Correlation (DCC) between daily stock returns and the returns of long-term Treasuries. Panel B and Panel C show the DCC of daily stock returns with returns of T-Bills and long-term Moody's AAA corporate bonds, respectively. The sample considered is from January 1990 to December 2014.

Figure 3.2: Flights in 2008



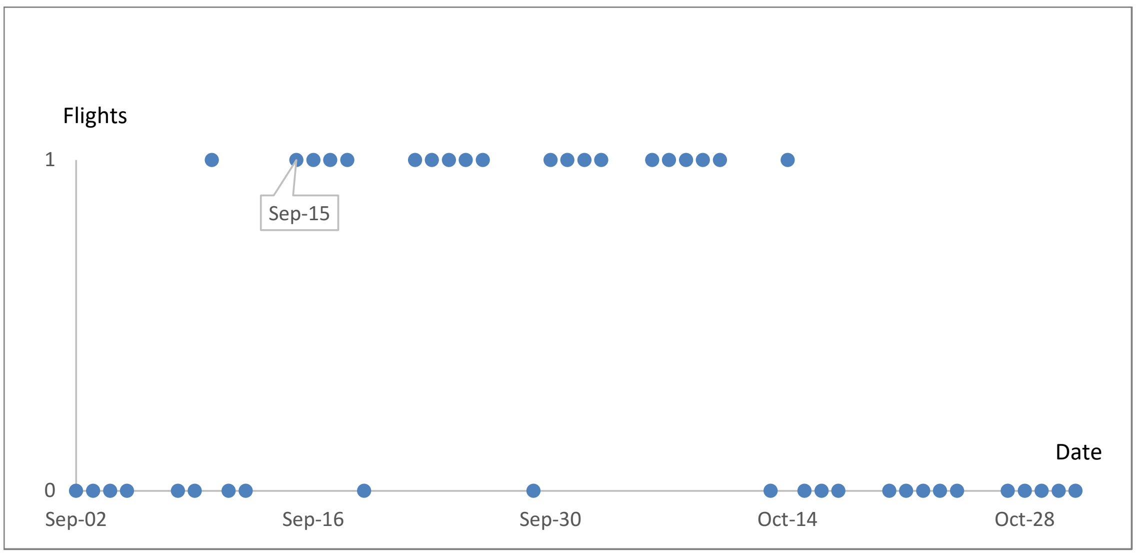
Note: This figure plots the variable $ftqs_t$ with t falling in the year 2008. Values of $ftqs_t$ refer to the last day of the 22-day crisis period.

Figure 3.3: Flights from February to April, 2008



Note: This figure plots the variable $ftqs_t$ with t falling between the beginning of February to the end of April 2008. Values of $ftqs_t$ refer to the last day of the 22-day crisis period.

Figure 3.4: Flights in September and October, 2008



Note: This figure plots the variable $ftqs_t$ with t falling between the beginning of September to the end of October 2008. Values of $ftqs_t$ refer to the last day of the 22-day crisis period.

3.5 Appendix

This appendix contains the coefficients of the probit models estimated as well as the analysis of the extended static model. The appendix also reports the results for the 2007-2014 sub-sample analysis. Variable descriptions are at the end of this document.

3.5.1 Probit Model Coefficients

Let us consider the probit model discussed in Section 3.3, namely equation (3.4), reproduced below:

$$P(ftqs_t = 1|x_t) = \Phi\left(x_t'\beta\right), \tag{3.5}$$

where Φ is the standard normal cumulative distribution function, and β is a vector of coefficients and x_t is a vector of explanatory variables. The (average) marginal effect $Av\left[\frac{\partial P}{\partial x_{it}}\right]$ corresponding to a continuous explanatory variable x_i is the quantity:

$$Av\left[\frac{\partial P}{\partial x_{it}}\right] = \frac{1}{T}\sum_{t=1}^{T}\phi\left(x_t'\widehat{\beta}\right)\widehat{\beta}_i, \tag{3.6}$$

where ϕ is the density of a standard normal and $\widehat{\beta}$ and $\widehat{\beta}_i$ are the estimated full vector of probit coefficients and the coefficient on x_i respectively. For a dichotomous explanatory variable x_j, the marginal effect on the predicted probabilities is the sample average of the difference:

$$P(ftqs_t = 1|x_{t(x_{jt})}, x_{jt} = 1) - P(ftqs_t = 1|x_{t(x_{jt})}, x_{jt} = 0), \tag{3.7}$$

which in turn equals the sample average of the difference:

$$\Phi\left(x_t'\widehat{\beta}|x_{t(x_{jt})}, x_{jt} = 1\right) - \Phi\left(x_t'\widehat{\beta}|x_{t(x_{jt})}, x_{jt} = 0\right). \tag{3.8}$$

where $x_{t(x_{jt})}$ denotes all other variables in x except for x_j, at time t. The standard errors of the marginal effects are computed using the delta method.

In calculating these average marginal effects, marginal effects are calculated observation by observation, a feature employed to evaluate the state-dependent marginal effects reported in Table 3.5. The estimates of the coefficients of the probit models used for Tables 3.3 and 3.6 are reported in Tables 3.9 and 3.10.

[Tables 3.9 and 3.10 about here]

3.5.2 The Extended Static Model

The cross-market correlation pattern predicted by the asset pricing model proposed by Barberis and Shleifer (2003) poses a question about the role played by safe haven returns in determining the frequency of flights. On the face of it, appreciated (depreciated) long-term fixed income securities should increase (decrease) the probability of flights, as these assets become more (less) attractive investment vehicles. The opposite prediction however is suggested by the widespread use of Treasuries as collateral for short sales of stocks.

To illustrate, recall that, in the context of a security market model with borrowing constraints, as that in Kiyotaki and Moore (2002), negative shocks to the values of a security transmit easily to other assets, if the former is commonly used as a collateral (Longstaff, 2010). Changes in the value of the collateral influence holdings of other assets, as covered positions may become more, or less, costly to maintain. Through this mechanism, information may spread from the collateral, which typically are liquid assets, to asset classes with slower price discovery processes.[49] While this paper's analysis does not focus on securities that trade upon the posting of a collateral (e.g., futures or repo agreements), we note that shorting stocks typically requires the posting of some form of collateral, commonly Treasuries. As such, spikes

[49] For example, when the quality of mortgage pools backing Mortgage Backed Securities came in doubt, yields for repurchase aggreements using these derivatives as collateral were greatly affected (e.g., Fleming et al., 2010; Longstaff, 2010). The cost of the collateral can also play a role in the spillover trading model proposed in Fleming et al. (1998).

in Treasury prices might make executing short sales more expensive. The resulting friction may exacerbate mispricing as arbitrage traders become less ready to deliver downward price corrections, much as the literature on limited arbitrage suggests (e.g., Stambaugh et al., 2012; Mitchell et al., 2002). An increase in the value of Treasuries thus might make less probable a decline in stock values, and thus may depress the probability of flight occurrence. Symmetrically, depressed Treasury returns could increase flight incidence by facilitating short selling of stocks.

The static model reported upon in Table 3.3 is expanded to account for the performance of Treasuries and corporate bonds. The model also controls for volatility measures, to isolate the effect of performance from that of risk taking. Table 3.11 reports the descriptive statistics for the continuous and binary covariates employed to estimate the extended model that have not already been described in Table 3.2 of the paper.

[Table 3.11 about here]

The estimates yielded from the extended static model are reported in Table 3.12, Panels A, B, and C.

[Table 3.12 about here]

While the analysis of the extended model do not modify the conclusions yielded by the analysis of the static model, the inclusion of performance and volatility measures for the safe haven asset classes offer a mixture of expected and unexpected results.[50] It is expected that flights to safe assets are less likely when these securities yield dismal average returns, a finding that is confirmed by the coefficients on the performance variables $camin_{a,t}$ for a in $\{b, f, c\}$ in Table 3.12. Less expected is the finding that flights to each group of fixed income securities respond to periods of

[50]Unreported Wald test indicate that the inclusion of performance and volatility indicators for the fixed income asset groups significantly increases the model fit with respect to the static models discussed in Section 3.1, a result that is also apparent by the improved prediction success, and by the increased McFadden Pseudo R-squared.

exceptional performance of their own representative indices, but are unaffected by unfavorable showings of other safe haven asset categories. So, for example, flights to T-Bills respond to poor performance of short-term Treasuries, but not to those of long-term Treasuries and top-grade long-term corporate bonds.[51]

That the frequencies of flights to long-term Treasuries and to T-Bills fail to respond to measures of each other's dismal performance suggests that market participants consider these two categories of sovereign debt as different types of safe haven assets. As the indexes employed to represent the short and long ends of the yield curve are both linked to the valuations of extremely liquid assets, the main difference between flights to T-Bills and to long-term Treasuries appears to be the investment horizon, i.e., the maturity. From this perspective, flights to T-Bills could be thought of as market dynamics according to which agents invest in cash-like assets to hedge risk over the short run. Conversely, flights to long-term Treasuries may respond to risk management needs for the long-run.

The volatility of short-term Treasuries appears to be an insignificant determinant across types of flights. Its significance in column 1 of Table 3.12, though carrying the expected sign, is the by-product of flight aggregation. That T-Bill rate volatility does not matter for the incidence of flights to T-Bills might be interpreted as suggesting that the safe haven status of these short-term Treasuries always outweighs the risk of fluctuations in its value.

The realized volatilities of stocks and corporate bonds exert an opposite pressure on the likelihood of flights, as expected. However, the positive and significant coefficients of the variable $cstdev_{b,t}$ in all columns of Table 3.12 indicate that volatility in long-term Treasury rates increases the incidence of all types of flights. Such consistency suggests that volatility at the long end of the yield curves is an omen of

[51]Corporate bonds are an exception to this rule, in the sense that they also respond to dismal performance of long-term Treasuries, a finding that is consistent with the strong influence of long-term Treasuries on the valuation of long-term corporate debt.

pervasive market instability: shocks to the long-term side of the yield curve may be more linked to variations in macroeconomic uncertainty than to fluctuations of the benchmark interest rate for the short-term (e.g., Gürkaynak et al., 2005).

We have evaluated, for the 2007-2014 sample, the extended static model. The obtained results yield conclusions that are consistent with those of the analysis of the 1994-2014 sample. The VIF index of these models, exceeding the threshold of 6 for all four flight indicators, suggests that these results should be interpreted with caution. The large VIF index appears to be associated with a large correlation between the standard deviations of the returns in the sub-sample.[52] The table of results for the extended static model for the 2007-2014 sample is available upon request.

3.5.3 The 2007-2014 Sub-sample

We analyze the static models discussed in Section 3.3.1 of the paper for the 2007-2014 sample, with the first 22-day crisis window starting on June 29, 2007. This sub-sample analysis aims to assess whether the market turmoil of the 2007-2009 crisis has modified the role of asset performance, volatility, market illiquidity, market state, momentum gains, and monetary policy in determining flight incidence. Furthermore, the sub-period is sufficiently recent to include in the analysis a familiar measure of interbank (lending) risk by the Libor-OIS spread Filipović and Trolle (2013).[53] Tables 3.13 and 3.14 report the summary statistics for the continuous and binary covariates in the sub-sample.

[Tables 3.13 and 3.14 about here]

[52] Over the 2007-2014 time period, the correlation between $cstdev_b$ and $cstdev_c$ is 0.89 and between $cstdev_s$ and $cstdev_c$ is 0.76.

[53] In line with the approach employed in studies that analyze liquidity during the financial crisis (e.g., Sarkar, 2009; Taylor and Williams, 2009), we focus on the three-month maturity Libor-OIS spread, which we source from Bloomberg. Obvious concerns with using the Libor rate to gauge illiquidity arise also in view of the alleged manipulations of the rates during time periods that are included in our sample (e.g., Kuo et al., 2012; Snider and Youle, 2012).

Presently, we estimate the static model reported in Table 3.3 augmented with the average of the Libor-OIS spread over the 22-day crisis window, denoted by $cLiOIS_t$, for the 2007-2014 sub-sample.[54] The estimated results are reported in Table 3.15.

[Table 3.15 about here]

The coefficient on Libor-OIS takes the sign of the monetary policy variable $cFed1_t$. That is, the estimates of the coefficient on the spread are negative and significant, for all types of flights except for flights to long-term Treasuries. Our conclusion is that the effects of the spread on the incidence on flights cannot be easily disentangled, in the empirical framework proposed in this paper, from those of monetary policy activities. With regard to the other variables, we note that the conclusions of this study are upheld by the analysis of the 2007-2014 sample. The effects of the monetary policy activities on the Libor-OIS spread are not uncontested in the literature.[55] While we do not enter into the debate of the main drivers of the Libor-OIS spread during the crisis, in our sample we find that $cLiOIS_t$ is highly correlated, at 0.61, with our indicator of monetary policy activities, i.e., the variable $cFed1_t$, where this discrete variable counts Fed's monetary policy announcements during the 22-day crisis window. This large correlation suggests that monetary policy activities and banks' borrowing costs are closely related.

3.5.4 Description of Selected Variables

To align the design of the Amihud (2002) measure with the empirical framework employed in this paper, we calculate our Amihud measure over the crisis period to

[54] We have also estimated the static model reported in Table 3.3 for the 2007-2014 sample, thus omitting the average of the Libor-OIS spread. The comparison of the marginal effects for this static model, available upon request, and those reported in Table 3.15, indicate that the $cFed1_t$ variable loses explanatory power to the benefit of the Libor-OIS spread indicator.

[55] Refer, for example, to the debate between the contrasting view of Sarkar (2009), Taylor and Williams (2009), and McAndrews et al. (2008) for the Term Auction Facility (TAF) program. Sarkar uses the auction announcement dates rather than the date of the actual auctions to measure the effectiveness of the program.

obtain variable $cilliq_t$. For for each stock i and each t, the value of $cilliq_{i,t}$ is defined by on the basis of the expression displayed in equation (3.9):

$$cilliq_{i,t} = \frac{1}{D_{i,\tau}} \sum_{\tau=t}^{t+21} \frac{|r_{i,\tau}|}{vol_{i,\tau}} \tag{3.9}$$

where $D_{i,t}$ is the number of days for which data are available over the 22 days of the crisis period, $r_{i,\tau}$ is the net return on stock i on day τ, and $vol_{i,\tau}$ is the corresponding trading volume. For each t the aggregate quantity $cilliq_t$ is the cross sectional average of $cilliq_{i,t}$, i.e., the average taken over the stocks for which $cilliq_{i,t}$ can be calculated. As done in Amihud (2002) we multiply the resulting quantity by 10^6.

To account for monetary policy activities in equation (3.4) we include the variable $cFed1_t$ which is the number of monetary policy announcements issued by the Fed during the crisis period starting with date t. This variable gauges the intensity of monetary policy activities during the crisis window. We note that before 1994, market participants would find out about the decisions of the Federal Open Market Committee (FOMC) by observing the Fed open market operations on the day following the meeting. Thus in constructing $cFed1_t$, the effects of the pre-1994 FOMC meetings are attributed to the trading day following the meeting. Two exceptions, namely the meetings of December 1990 and October 1998, are handled as suggested in Kuttner (2001).

Monetary policy announcements included in $cFed1_t$ are identified following the Fed's classification.[56] These announcements include the release of the post-meeting statements and minutes, and include the press releases of the special programs initiated during the summer of 2007. Gürkaynak et al. (2005) note that markets appear to react both to Fed actions and statements, as the latter are read by Fed observers as cueing market expectations for future policy moves.[57]

[56]Monetary policy announcements that occurred before 1996 are obtained from the archives of the FOMC transcripts from the Fed website.

[57]Gürkaynak et al. (2005) bring the example of a Fed statement commenting the outcome of

We opt for the use of announcements because these are silent on the expected direction of the effect of monetary policy.[58] Gürkaynak et al. (2005) points out that even for traditional monetary policy actions (e.g., an increase of the target federal funds rate) the monetary surprise need not be in the same direction as the monetary action.[59] Gürkaynak et al. note that asset price responses to monetary policy activities occur within minutes of the policy announcement. As such, monetary shocks could be considered imbued into end-of-the-day bond and stock prices. As the empirical analysis in this paper employs end-day prices, or yields, monetary shock indicators should be redundant in explaining the frequency of flights, once asset returns are take into account. However, as observed by Gürkaynak et al. (2005), if monetary shocks affect observers' expectations for the long-term cost of capital, then monetary surprises might influence asset prices far beyond the daily horizon.[60]

The works of Kuttner and collaborators (e.g., Bernanke and Kuttner, 2005; Kuttner, 2001; Krueger and Kuttner, 1996), and the empirical analysis of Gürkaynak et al. (2007) have shown that market based indicators, and in particular price quotes of futures on the effective federal funds rate, perform better than a host of macroeconomic

the FOMC meeting of January 18, 2004 that resulted in an unchanged target Federal fund rate. Markets reacted with large price adjustments, despite the lack of change in the target rate, because of a change in language in the FOMC press statement.

[58]In his study of the effects of monetary policy announcements on bond yields, Wright (2012) employs monetary announcements to measure monetary policy activity. Wright, however, does not include the release of FOMC meeting minutes in the stock of relevant monetary announcements, but includes testimonies to Congress, which we do not include in our measure. The timing of the releases of the minutes and Congressional testimonies being highly predictable, these differences are unlikely to differentiate the two measures of monetary policy activities. We include the release dates of FOMC meetings minutes because the language employed during the time of the Fed statements has shown to affect markets (Blinder et al., 2008).

[59]As an illustrative example, Gürkaynak et al. (2005) refer to the FOMC meeting of June 25, 2003, that resulted in a decrease of 0.25% of the target Federal funds rate. Gürkaynak and his coauthors note that the change was perceived as monetary tightening, and resulted in an increase in yields for Treasuries, because the market had expected a stronger adjustment.

[60]Furthermore, the analysis of the impulse response functions in Bernanke and Kuttner (2005) well illustrate that a monetary shock might cause long lasting deviations from equilibrium prices.

indicators in forecasting monetary policy shocks.[61] Using this measure of monetary surprise, Kuttner (2001) documents that Treasury yields increase significantly following monetary tightening, with the effect being larger for longer maturities, while Bernanke and Kuttner (2005) show that an unexpected increase in the target federal fund rate appears to significantly depress stock market returns.

This paper employs a measure of expectations of monetary policy activity, denoted by $lFed2_t$ in Section 3.3.2 of the paper, that is calculated using price quotes for futures written on the monthly average of the EFF rate. The variable is defined along the lines of the gauge of monetary policy surprises described in Kuttner (2001) and measures how expectations, of the prevailing average EFF rate during the crisis period are changing between the start and the end of the benchmark period. Futures on the EFF rate are settled, at the end of each (calendar) month, on the basis of the (calendar) monthly average of the prevailing daily EFF rates. The crisis period being 22 trading days, at most two futures price series have to be considered, for each crisis window.

Denote by t the first day of the crisis period. Assume that the crisis period straddles two calendar months, say month 1 and month 2, with $\tau_{1,t}$ and $\tau_{2,t}$ being the number of trading days of that crisis window falling into each month. Then the measure of expectations of monetary policy actions, denoted by $lFed2_t$, is defined by the following expression:

$$lFed2_t = \frac{\tau_{1,t}}{\tau_{1,t}+\tau_{2,t}}\left(ff_{1,t-1} - ff_{1,t-44}\right) + \frac{\tau_{2,t}}{\tau_{1,t}+\tau_{2,t}}\left(ff_{2,t-1} - ff_{2,t-44}\right), \qquad (3.10)$$

[61] A competing approach for evaluating the effects of monetary policy on asset returns is to model interest rates using vector autoregressions (VAR). An early application of the VAR methodology is Campbell and Ammer (1993). The VAR approach typically relies on the estimation of a reduced form model linking asset values to macroeconomic indicators summarizing market expectations. The resulting predictive models require careful handling of the timing of the shocks affecting the variables driving asset value response, i.e., of the orthogonalization process for the VAR system (e.g., Evans and Kuttner, 1998).

where $ff_{i,t}$ for $i = 1, 2$ is the time-t price of the futures on the EFF rate with settlement date at the end of month i. If the 22 crisis window is entirely contained in the portion of the calendar month, say $\tau_{1,t}$, for which we have price quotes for the associated futures contract, then the above equation is modified by setting $\tau_{2,t}$ equal to 0. As futures on the EFF rate are quoted as the difference between 100 and the rate, then an increase in $lFed2_t$ signifies that market expectations of monetary loosening have increased.

We conclude this appendix by illustrating the definition of the flight-from-quality and negative contagion variables employed to obtain the results in Table 3.6. A flight-from-quality is a flight-to-quality in reverse, that is a market dynamic in which the correlation between, say stocks and T-Bills drops significantly, but stocks are performing well and T-Bills yield negative returns. Referring to the econometric framework described in Section 3.2 of this chapter, a flight-from-quality is a market dynamic in which the change in correlation, the coefficient $\hat{\gamma}_i$, and the level of correlation, the sum $\hat{\beta}_i + \hat{\gamma}_i + \hat{\gamma}_i^*$, are both negative, while $\hat{\gamma}_i$ is significant, and, finally, the average performance of the safer asset during the crisis window is negative, while it is positive for the riskier asset. For example, estimates of equation (3.1) provide evidence of a flight-from-quality from long-term Treasuries into stocks occurring during the crisis period, when $\hat{\gamma}_1$ is negative and significant, the expression $\hat{\beta}_1 + \hat{\gamma}_1 + \hat{\gamma}_1^*$ is negative, and the average return over the crisis period on stocks (long-term Treasuries) is positive (negative). Flights into stocks from corporate bonds and from short-term Treasuries are identified analogously.

A negative contagion episode between two asset classes is characterized by negative average returns over the crisis period, and a significant increase in the return correlation. Using the terminology employed in Section 3.2 of the paper, we observe negative contagion when the change in correlation, the coefficient $\hat{\gamma}_i$, and the level of correlation, the sum $\hat{\beta}_i + \hat{\gamma}_i + \hat{\gamma}_i^*$, are both positive, with $\hat{\gamma}_i$ being significant, and, the average returns of the two asset classes are negative over the crisis period.

The variable $lffqs_t$ employed in Table 3.6 is dichotomous and takes the value of 1 whenever there is a flight in the 22 days preceding the crisis window starting with date t, i.e., in the 22-day time interval closest to time t that is entirely contained in the benchmark period. The variable $lncns_t$ is designed analogously and responds to the occurrence of negative contagion.

Table 3.9: Static Model - Coefficients

Static Model Probit Coefficients				
	(1)	(2)	(3)	(4)
Dependent Variable	$ftqs$	$ftqsb$	$ftqsf$	$ftqsc$
car_s	-0.192***	-0.080***	-0.149***	-0.112***
	(-10.43)	(-4.10)	(-6.52)	(-5.54)
car_b	2.271***	6.446***	2.570***	1.768***
	(4.88)	(10.55)	(4.42)	(3.18)
car_f	1.947***	-0.169	4.163***	-0.305
	(7.54)	(-0.61)	(13.66)	(-1.02)
car_c	1.877***	-1.597**	-2.198***	4.389***
	(3.50)	(-2.52)	(-3.16)	(7.03)
$camin_s$	1.353***	1.444***	1.128***	1.319***
	(14.62)	(13.24)	(8.86)	(12.22)
$cmin_s$	-0.058	-0.327***	0.509***	-0.486***
	(-0.64)	(-3.17)	(5.12)	(-4.29)
$cmax_s$	0.044	0.203**	-0.223**	0.367***
	(0.48)	(2.03)	(-1.96)	(3.56)
$cstdev_s$	0.005	-0.004	-0.010	0.002
	(0.80)	(-0.66)	(-1.37)	(0.39)
$cilliq$	-0.006***	-0.031***	0.003*	-0.017***
	(-3.83)	(-7.75)	(1.85)	(-6.09)
$cFed1$	-0.066***	-0.040***	-0.114***	-0.049***
	(-5.28)	(-2.94)	(-7.15)	(-3.46)
$down$	0.349***	0.322***	0.289***	0.245***
	(4.53)	(3.80)	(3.20)	(2.83)
$cdmom$	0.214***	0.140**	0.180***	0.174***
	(4.04)	(2.30)	(2.63)	(2.79)
$Intercept$	-2.277***	-2.488***	-2.505***	-2.568***
	(-21.21)	(-19.55)	(-16.89)	(-20.72)

Note: t-statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the results from the estimation of the static model for four categories of flights, for the full sample. The second, third and fourth columns pertain to flights into long-term Treasuries, T-Bills, and long-term Moody's AAA corporate bonds. The first column reports on the model explaining the aggregate flight variable, i.e., flights into any of the three categories of fixed income securities.

Table 3.10: Dynamic Model - Coefficients

Dynamic Model Probit Coefficients				
	(1)	(2)	(3)	(4)
Dependent Variable	$ftqs$	$ftqsb$	$ftqsf$	$ftqsc$
car_s	-0.202***	-0.081***	-0.163***	-0.116***
	(-10.68)	(-3.98)	(-6.98)	(-5.58)
car_b	2.495***	6.910***	2.407***	2.067***
	(5.20)	(10.69)	(4.05)	(3.60)
car_f	1.930***	-0.286	4.103***	-0.331
	(7.21)	(-0.97)	(12.81)	(-1.07)
car_c	1.619***	-2.041***	-2.153***	4.229***
	(2.91)	(-3.03)	(-3.00)	(6.51)
$camin_s$	1.357***	1.486***	1.105***	1.355***
	(14.47)	(13.24)	(8.61)	(12.32)
$cmin_s$	0.098	-0.132	0.587***	-0.304**
	(1.01)	(-1.17)	(5.34)	(-2.54)
$cmax_s$	0.059	0.173*	-0.171	0.351***
	(0.61)	(1.65)	(-1.45)	(3.32)
$cstdev_s$	-0.010	-0.018**	-0.023**	-0.013
	(-1.33)	(-2.09)	(-2.33)	(-1.50)
$cFed1$	-0.035**	0.020	-0.093***	-0.008
	(-2.31)	(1.21)	(-4.74)	(-0.47)
$cdmom$	0.217***	0.107*	0.167**	0.185***
	(3.95)	(1.69)	(2.36)	(2.89)
$lamin_s$	0.038	0.002	0.109	0.109*
	(0.69)	(0.03)	(1.59)	(1.68)
$lavix$	0.042***	0.035**	0.030*	0.048***
	(3.52)	(2.48)	(1.84)	(3.48)
$lFed1$	-0.030***	-0.068***	-0.016	-0.037***
	(-3.30)	(-6.36)	(-1.35)	(-3.47)
$lilliq$	-0.008***	-0.054***	0.002	-0.016***
	(-4.70)	(-8.66)	(0.86)	(-6.03)
$lFed2$	0.012	0.048***	-0.002	0.006
	(0.87)	(2.83)	(-0.09)	(0.38)
$lffqs$	-0.068	-0.137*	-0.255***	0.045
	(-1.00)	(-1.72)	(-2.69)	(0.57)
$lncns$	0.250***	0.464***	-0.043	0.290***
	(2.85)	(4.72)	(-0.38)	(3.02)

Continued on next page

Table 3.10: Dynamic Model - Coefficients - Continued

Dynamic Model Probit Coefficients				
	(1)	(2)	(3)	(4)
Dependent Variable	$ftqs$	$ftqsb$	$ftqsf$	$ftqsc$
$ldmom$	-0.025	-0.019	0.050	-0.088
	(-0.44)	(-0.29)	(0.70)	(-1.32)
$down$	0.243***	0.290***	0.240**	0.149
	(2.90)	(3.07)	(2.43)	(1.57)
$Intercept$	-2.467***	-2.439***	-2.635***	-2.874***
	(-17.92)	(-14.38)	(-13.75)	(-17.81)

Note: Significance levels are denoted by, * for $\alpha = 0.10$, ** for $\alpha = 0.05$, and *** for $\alpha = 0.01$. This table reports the results of the estimation of the dynamic model for four categories of flights, for the full sample. The dependent variables are the indicators of flights from stocks to long-term Treasuries ($ftqsb$), T-Bills ($ftqsf$), and to Moody's AAA corporate bonds ($ftqsc$). The aggregate flight indicator $ftqs$ is the point-wise maximum of $ftqsb$, $ftqsf$, and $ftqsc$.

Table 3.11: Summary Statistics - Continuous Variables

Variable	$cstdev_s$	$cstdev_b$	$cstdev_f$	$cstdev_c$
Mean	0.963	5.683	3.684	4.706
Std.dev	0.596	1.873	3.688	1.971
Min	0.271	1.956	0.375	1.098
Max	5.346	14.597	32.888	14.214
Variable	$camin_s$	$camin_b$	$camin_f$	$camin_c$
Mean	0.475	0.479	0.555	0.484
Std.dev	0.499	0.500	0.497	0.500
Min	0	0	0	0
Max	1	1	1	1

Note: The table reports the mean, standard deviation, minimum and maximum values of the continuous variables employed in the extended probit model, for the 1990-2014 sample that are not already described in Table 3.2 of the paper. The variables $cstdev_{a,t}$ for a in $\{b, f, c\}$ are the standard deviation of the fixed income securities daily yield changes (changed of sign) over the 22-day rolling window starting with t. The variable $camin_{a,t}$, for a in $\{b, f, c\}$, equals 1 when the the average returns $car_{a,t}$ is below the corresponding average of daily returns over the year preceding date t. The variable $cmin_{s,t}$ ($cmax_{s,t}$) equals 1 when the worst (best) daily return on stocks over the 22-day window beginning with observation t is worse (better) than the worst (best) return obtained in the year preceding t. The variable $down_t$ equals 1 when the average of the stock market daily returns over the year preceding observation t is negative.

Table 3.12: Extended Static Model

Panel A Probit Coefficients				
	(1)	(2)	(3)	(4)
Dependent Variable	$ftqs$	$ftqsb$	$ftqsf$	$ftqsc$
car_s	-0.196***	-0.087***	-0.156***	-0.114***
	(-10.52)	(-4.31)	(-6.72)	(-5.37)
car_b	0.272	3.151***	2.522***	-0.543
	(0.48)	(4.45)	(3.59)	(-0.78)
car_f	2.101***	-0.129	3.172***	0.029
	(6.21)	(-0.35)	(7.66)	(0.07)
car_c	1.757***	-0.825	-2.439***	2.852***
	(2.80)	(-1.11)	(-3.03)	(3.82)
$camin_s$	1.327***	1.437***	1.163***	1.290***
	(14.21)	(12.99)	(9.00)	(11.88)
$camin_b$	-0.482***	-1.039***	0.018	-0.460***
	(-5.14)	(-8.36)	(0.15)	(-3.69)
$camin_f$	-0.116*	0.028	-0.428***	0.008
	(-1.80)	(0.37)	(-5.05)	(0.10)
$camin_c$	-0.150*	-0.099	-0.020	-1.047***
	(-1.73)	(-0.96)	(-0.19)	(-8.38)
$cstdev_s$	0.024***	0.018**	0.004	0.026***
	(3.60)	(2.49)	(0.51)	(3.50)
$cstdev_b$	0.026*	0.082***	0.068***	0.026
	(1.65)	(4.27)	(3.62)	(1.31)
$cstdev_f$	-0.009***	0.002	-0.006	-0.003
	(-2.69)	(0.71)	(-1.44)	(-0.65)
$cstdev_c$	-0.047***	-0.082***	-0.095***	-0.029*
	(-3.55)	(-5.00)	(-5.76)	(-1.78)
$cmin_s$	-0.129	-0.381***	0.440***	-0.564***
	(-1.40)	(-3.57)	(4.34)	(-4.78)
$cmax_s$	0.074	0.078	-0.251**	0.239**
	(0.77)	(0.74)	(-2.07)	(2.17)
$cilliq$	-0.008***	-0.039***	-0.003	-0.018***
	(-4.67)	(-8.26)	(-1.43)	(-5.53)
$cFed1$	-0.040***	-0.024	-0.061***	-0.037**
	(-2.87)	(-1.52)	(-3.35)	(-2.29)
$down$	0.277***	0.094	0.256***	0.149
	(3.32)	(0.93)	(2.58)	(1.45)

Continued on next page

Table 3.12: Extended Static Model - Continued

	(1)	(2)	(3)	(4)
Dependent Variable	$ftqs$	$ftqsb$	$ftqsf$	$ftqsc$
$cdmom$	0.207***	0.135**	0.197***	0.143**
	(3.82)	(2.11)	(2.82)	(2.16)
$Intercept$	-1.839***	-2.263***	-2.258***	-2.177***
	(-13.50)	(-14.43)	(-11.92)	(-13.96)
Panel B Marginal Effects (in Percentage Points)				
car_s	-2.6***	-0.9***	-1.2***	-1.1***
car_b	3.6	31.5***	20.0***	-5.1
car_f	28.1***	-1.3	25.2***	0.3
car_c	23.5***	-8.2	-19.4***	26.7***
$camin_s$	17.8***	14.4***	9.2***	12.1***
$camin_b$	-6.5***	-10.4***	0.1	-4.3***
$camin_f$	-1.6*	0.3	-3.4***	0.01
$camin_c$	-2.0	-1.0	-0.2	-9.8***
$cstdev_s$	0.3***	0.2***	0.03	0.2***
$cstdev_b$	0.3*	0.8***	0.5***	0.2
$cstdev_f$	-0.1**	0.02	-0.05	-0.02
$cstdev_c$	-0.6***	-0.8***	-0.8***	-0.3*
$cmin_s$	-1.7	-3.8***	3.5***	-5.3***
$cmax_s$	1.0	0.8	-2.0**	2.2**
$cilliq$	-0.1***	-0.4***	-0.02	-0.2***
$cFed1$	-0.5***	-0.2	-0.5***	-0.3**
$down$	3.7***	0.9	2.0**	1.4
$cdmom$	2.8***	1.4**	1.6***	1.3**
Panel C Basic Diagnostics				
Log-likelihood_c	-1519.0	-1134.5	-918.4	-1064.5
Log-likelihood_null	-2614.5	-1968.3	-1555.5	-1787.7
McFadden Pseudo R-squared	0.42	0.42	0.41	0.40
Prediction Success				
Actual 1s correctly predicted	47.0%	38.8%	36.5%	35.4%
Actual 0s correctly predicted	91.2%	93.6%	95.4%	94.2%

Note: t-statistics are reported in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the results of the estimation of the extended static model for four categories of flights, for the full sample. The second, third, and fourth columns pertain to flights into long-term Treasuries, T-Bills, and long-term Moody's AAA corporate bonds. The first column reports on the model explaining the aggregate flight variable, i.e., flights into any of the three categories of fixed income securities. Panel A reports the probit regression coefficients while Panel B reports the marginal effects in percentage terms. Panel C presents basic diagnostics.

Table 3.13: Summary Statistics-Continuous Variables for the 2007-2014 Sample

Variable	car_s	car_b	car_f	car_c	$cFed1$	$cLiOIS$
Mean	0.037	0.082	0.054	0.082	4.229	0.268
Std.dev	0.230	1.278	1.023	1.078	2.791	0.357
Min	−1.639	−4.318	−4.591	−4.500	0.000	0.058
Max	0.984	7.273	8.455	7.318	15.000	2.965
Variable	$cstdev_s$	$cstdev_b$	$cstdev_f$	$cstdev_c$	$cilliq$	
Mean	1.062	5.741	2.889	5.352	0.080	
Std.dev	0.702	2.106	4.371	2.053	0.073	
Min	0.318	1.956	0.375	1.798	0.005	
Max	5.346	14.597	32.888	14.214	0.353	

Note: This table reports the mean, standard deviation, minimum and maximum values for the continuous covariates employed in Section 3.5.3 of this appendix, for the 2007-2014 sample. The variables $car_{a,t}$ for a in $\{s, b, f, c\}$ are the average, over the 22 (trading) day rolling window, of the daily returns on the CRSP value weighted stock market index, the 10-year Treasury bond, the 3-month T-Bills, and the Moody's AAA corporate bonds. For example, the first observation of $car_{s,t}$ is the average stock return from March 5 to April 3, 1990. The variables $cstdev_{a,t}$ for a in $\{s, b, f, c\}$ are defined as the standard deviation of returns over the 22-day rolling window. For example, the first observation of $cstdev_{s,t}$ is the standard deviation of stock returns from March 5 to April 3, 1990. The variable $cFed1_t$ counts the number of monetary policy press releases from the Federal Reserve over the 22-day rolling window. The variable $cilliq_t$, is the Amihud (2002) stock market illiquidity measure, calculated over the 22-day rolling window. The variable $cLiOIS$ is the average, over the 22-day rolling window of the Libor-OIS spread. All stock returns are in percentage terms. The returns of 10-year Treasury bond, the 3-month T-Bills, and the Moody's AAA corporate bonds are in basis points.

Table 3.14: Summary Statistics-Dichotomous Variables for the 2007-2014 Sample

Variable	$camin_s$	$camin_b$	$camin_f$	$camin_c$
Frequency	0.466	0.478	0.590	0.488
Std.dev	0.499	0.500	0.492	0.500
Variable	$cmin_s$	$cmax_s$	$down$	$cdmom$
Frequency	0.067	0.078	0.227	0.557
Std.dev	0.250	0.268	0.419	0.497

Note: This table reports frequency and standard deviation for the dichotomous covariates employed in Section 3.5.3 of this appendix, for the 2007-2014 sample. The variable $camin_{a,t}$ for a in $\{s, b, f, c\}$ equals 1 when the the average returns $car_{a,t}$ is below the average of daily returns over the year preceding date t, rounded to 255 trading days. The variable $cmin_{s,t}$ ($cmax_{s,t}$) equals 1 when the worst (best) daily return on stocks over the 22-day window beginning with observation t is worse (better) than the worst (best) return obtained in the year preceding t. The variable $down_t$ equals 1 when the average stock market return over the year preceding observation t is negative. The variable $cdmom_t$, equals 1 when the average return of the daily momentum strategy over the 22 day crisis period is larger than the corresponding average return of the strategy over the previous year.

Table 3.15: Static Model for the 2007-2014 Sample

Panel A Probit Coefficients				
	(1)	(2)	(3)	(4)
Dependent Variable	$ftqs$	$ftqsb$	$ftqsf$	$ftqsc$
car_s	-0.181***	-0.154***	-0.110***	-0.186***
	(-6.10)	(-4.54)	(-2.73)	(-5.19)
car_b	3.485***	5.670***	4.030***	1.339
	(3.99)	(5.33)	(3.55)	(1.35)
car_f	1.549***	0.924**	2.555***	-0.049
	(3.62)	(2.00)	(4.97)	(-0.09)
car_c	-0.122	-1.932**	-3.986***	3.905***
	(-0.14)	(-1.99)	(-3.73)	(3.89)
$camin_s$	1.430***	1.320***	1.257***	1.340***
	(7.81)	(5.80)	(4.49)	(5.82)
$cmin_s$	-0.787***	-2.194***	0.310	-2.303***
	(-3.89)	(-7.50)	(1.41)	(-6.60)
$cmax_s$	-0.092	0.301	0.135	0.161
	(-0.49)	(1.52)	(0.63)	(0.69)
$cstdev_s$	0.016	0.035**	-0.037**	0.063***
	(1.32)	(2.51)	(-2.24)	(4.33)
$cilliq$	0.019	-0.010	0.291*	-0.530***
	(0.15)	(-0.06)	(1.68)	(-2.75)
$cFed1$	-0.029	-0.036	-0.064**	0.014
	(-1.22)	(-1.35)	(-1.99)	(0.52)
$down$	0.505**	0.157	0.279	0.273
	(2.55)	(0.70)	(1.06)	(1.12)
$cdmom$	0.212**	0.236**	0.123	0.465***
	(2.20)	(2.17)	(0.99)	(3.98)
$cLiOIS_t$	-0.787***	-0.780***	-0.498	-0.763***
	(-3.59)	(-2.98)	(-1.63)	(-2.76)
$Intercept$	-2.251***	-2.695***	-2.278***	-3.175***
	(-9.70)	(-9.55)	(-6.98)	(-10.77)
Panel B Marginal Effects (in Percentage Points)				
car_s	-2.8***	-1.9***	-1.0***	-2.1***
car_b	54.2***	69.5***	35.4***	15.2
car_f	24.1***	11.3**	22.4***	-0.6
car_c	-1.9	-23.7**	-35.0***	44.4***

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Table 3.15: Static Model for the 2007-2014 Sample - Continued

	(1)	(2)	(3)	(4)
Dependent Variable	$ftqs$	$ftqsb$	$ftqsf$	$ftqsc$
$camin_s$	22.3***	16.2***	11.0***	15.2***
$cmin_s$	-12.3***	-26.9***	2.7	-26.2***
$cmax_s$	-1.4	3.7	1.2	1.8
$cstdev_s$	0.2	0.4**	-0.3**	0.7***
$cilliq$	0.3	-0.1	2.6*	-6.0***
$cFed1$	-0.4	-0.4	-0.6**	0.2
$down$	7.9**	1.9	2.4	3.1
$cdmom$	3.3**	2.9**	1.1	5.3***
$cLiOIS_t$	-12.3***	-9.6***	-4.4	-8.7***
Panel C Basic Diagnostics				
Log-likelihood_c	-516.9	-406.7	-299.1	-378.8
Log-likelihood_null	-877.9	-694.5	-462.7	-642.0
McFadden Pseudo R-squared	0.41	0.41	0.35	0.41
Prediction Success				
Actual 1s correctly predicted	49.0%	43.5%	30.7%	41.2%
Actual 0s correctly predicted	89.0%	92.0%	94.9%	92.8%

Note: Significance levels are denoted by, * for $\alpha = 0.10$, ** for $\alpha = 0.05$, and *** for $\alpha = 0.01$. This table reports the results from the estimation of the probit mode displayed in equation (3.4), for the 2007-2014 sample. The dependent variables are the indicators of flights from stocks to long-term Treasuries ($ftqsb$), T-Bills ($ftqsf$), and to Moody's AAA corporate bonds ($ftqsc$). The aggregate flight indicator $ftqs$ is the point-wise maximum of $ftqsb$, $ftqsf$, and $ftqsc$. Panel A reports the probit coefficients. Panel B presents basic model diagnostics.

Chapter 4

A Robustness Study on Identification of Flights

4.1 Introduction

During periods of market stress, volatility and illiquidity risk are heightened, and investors may choose to rebalance their portfolio and reduce the risk profile of their investments. A significant rebalancing of the aggregate portfolio from riskier to safer assets is commonly referred to as a flight-to-quality (henceforth flights). Flights are associated with strong and inverse price movements in assets bearing different levels of risk. Flights between stocks and long-term Treasuries are the most studied type of market instability.

In the empirical literature, we encounter two main methodologies used to identify flight occurrence during a given time period. The first approach examines order imbalances or order flows around crisis periods (e.g., Kaul and Kayacetin, 2017; Kasch et al., 2011; Beber et al., 2009). As for many asset classes micro-level transaction data are not available or are available only for short time periods, alternative approaches to identify flights rely on asset returns. For example, Baur and Lucey (2009) examine flights and contagion between stocks and long-term government bonds for eight countries over six crisis periods. They define flights and contagion by a significant change of return correlation while controlling for the correlation and return levels of the two assets. They find evidence of flights and negative contagion for some of the crises during the 1994-2006 sample period. The work of Baur and Lucey (2009) inspired the methodology examined in this paper.

Consistent with the approach proposed by previous studies (inter alia, Baur and Lucey, 2009; Pesaran and Pick, 2007; Forbes and Rigobon, 2002), we characterize a flight episode by a significant drop, within the negative range, of the pair-wise correlation between two return series. The emphasis here is on the significance of the correlation change, so that we identify as flights only return dynamics that represent significant deviations from the status quo of assets' relative profitability.

In particular, a negative value of the correlation between two asset classes does not suffice to identify a flight episode.

The existing literature on market instability has focused on episodes of market turmoil that were clearly linked to specific events or dates (e.g., the Thailand Crisis in July 1997, the Hong Kong Crisis in October 1997, the Russian Crisis in August 1998, the 9-11 in 2001, the Enron's bankruptcy in December 2001 and the bankruptcy of WorldCom in July 2002). The challenge posed by the financial crisis initiated in 2007 is that this period is characterized by a sequence of diverse market shocks which are spread over about two years. The results of any empirical analysis aiming to identify flight episodes by examining only a selection of sub-samples of this event-filled period is bound to be susceptible to sample selection bias. Put differently, as there is no consensus on which events are at the root of market instability for a substantial part of our sample, our analysis does not focus on a few exogenously defined sub-samples to then check for flights. Rather, our methodology detects months over which a flight has occurred. The timing of flights is made endogenous by employing a static flight identification methodology within a rolling-sample framework.

Our approach also sports a real-time flavor, as rolling sub-samples are truncated at the end of the time window for which the evaluation of the existence of flights is performed, i.e., the (potential) crisis period. Excluding the observations following the crisis period serves the purpose of eliminating concerns of a look-ahead bias. We deem this precaution particularly important for any study of market instability that analyzes asset comovements over a sample including the 2007-2009 financial crisis, as the large market swings of that period might artificially raise the bar for market instability episodes occurring in periods preceding the summer of 2007 to be acknowledged.

This paper explores the characteristics of the flight indicators obtained by applying our methodology to detect flight episodes with endogenous timing of the event. The discussion of the ability of the proposed methodology to capture market instability focuses on the evaluation of the incidence of flights from stocks to long-term Treasuries, in the US market, over the 1990-2014 period. This empirical application is chosen because it allows a qualitative validation of our flight indicator for a well-explored market over a significant period of market instability. The 1990-2014 time period includes the 2007-2009 crisis, a period of prolonged market instability as well as large shocks concentrated over short time periods. An ideal indicator of flights would be able to capture the market instability associated with both types of market conditions, and using the time period from 1990 to 2014 allows us to evaluate whether our estimator detects major shocks to the US asset market.

A more formal evaluation of the ability of the proposed flight indicator to capture large market changes is obtained by simulations of shocks to assets correlation of different magnitudes. This analysis allows qualifying the types of correlation shocks that are detected by our methodology.

The remainder of this chapter is laid out as follows. The next section introduces the baseline methodology to identify flights. Section 4.3 discusses the empirical application of our methodology. Section 4.4 compares the results for various lengths of crisis periods, benchmark periods, and rolling sub-samples. This section is followed by discussions on the effects of different regression methodologies on flight identification. In section 4.6 we perform a data simulation, and provide an evaluation of our flight model. A brief statement of conclusions completes the exposition.

4.2 Methodology

Our methodology to identify flights is inspired by three intuitive concepts: 1) that the timing of a flight must be deduced from the data; 2) that future events should not be considered when examining the incidence of flights within a given time frame, and 3) that flights are not defined in absolute terms as large deviations from an abstract "natural" relative profitability of two asset classes, but rather by deviations from the status quo (the benchmark) which has emerged over recent time.

We illustrate the methodology employed to identify flights in terms of flights between two unidentified asset classes, indexed by 1 and 2, yielding returns $r_{1,t}$ and $r_{2,t}$ respectively. For the sake of the exposition, it is assumed that asset class 2 are of higher quality than class 1, where the definition of quality is here left unspecified and it is employed only for ease of illustration. In the empirical part of this paper, we will identify the safer asset class with long-term US Treasuries, while the US stock market index will play the role of the riskier asset class. In this case, the "quality" of Treasuries should be considered the result of the guaranteed cash-flow yielded by sovereign bonds when the issuing government's default is so unlikely that it fails to affect asset valuation.

Following the approach of Baur and Lucey (2009), the incidence of a flight episode between the asset classes 1 and 2 is assessed on the basis of the coefficients appearing in the linear equation:

$$r_{2,t} = \alpha_2 + \beta_2 r_{1,t} + \gamma_2 r_{1,t} D_t + \gamma_2^* r_{1,t} D_t^* + e_{2,t}, \tag{4.1}$$

where the returns of the asset class 2 are regressed over the returns of asset class 1, a pair of interaction terms, and a column of ones. The term $e_{2,t}$ is a zero-mean error term. The linear model displayed in (4.1) is designed around two dichotomous variables, denoted by D_t and D_t^*, which are defined on the basis of two adjacent time intervals of fixed widths, namely the crisis and benchmark periods, where the benchmark period precedes the crisis window. The crisis period is the interval I_t starting from date τ_{0t} and ending with τ_{1t}. The variable D_t is equal to 1 for all the observations over the crisis window, and zero otherwise. The second variable, D_t^* is always 0 except for the observations falling in the crisis or benchmark periods. In short, during the benchmark period the variable D_t is zero and D_t^* equals 1, while both variables take the value 1 during the crisis window.[1] The mechanics of these indicator variables entail that the coefficient γ_2 on the crisis indicator D_t in equation (4.1) measures the change in the correlation between the returns of class 1 and 2 when transitioning from the benchmark to the crisis period. The sum of the coefficients $\beta_2 + \gamma_2 + \gamma_2^*$ is a gauge of the correlation level between the returns of assets 1 and 2 during the crisis period. The model in (4.1) has no causal implications, i.e., it is not meant to explain the returns of the asset class 2.

A flight-to-quality is a market dynamic in which the change in correlation, the estimated coefficient $\hat{\gamma}_2$, and the correlation level, the sum $\hat{\beta}_2 + \hat{\gamma}_2 + \hat{\gamma}_2^*$, are both negative, the coefficient $\hat{\gamma}_2$ is significant, and, finally, the performance of the safe (risky) asset during the crisis window is positive (negative). Performance is measured by the average of daily returns. For an illustrative example, if $r_{1,t}$ are daily returns on the US stock market index and $r_{2,t}$ are a measure of daily returns on long-term Treasuries, then the estimates of Equation (4.1) provide evidence of a flight-to-quality from stocks to long-term Treasuries occurring during the crisis period when 1) $\hat{\gamma}_2$ is negative and significant; 2) the expression $\hat{\beta}_2 + \hat{\gamma}_2 + \hat{\gamma}_2^*$ is negative; and 3) the average of $r_{2,t}$ on long-term Treasuries is positive, and the average of $r_{1,t}$ on stocks is negative.

In Chapter 3 and later in this paper's empirical part, equation (4.1) is estimated for rolling samples of fixed width. Each sample is truncated at the end of the crisis window, i.e., on date τ_{1t}, to mitigate concerns of forward-looking bias. In the empirical example introduced in the following section, the linear model is evaluated for a sequence of overlapping rolling sub-samples, each of three years and one month in length. The step between the start of two consecutive rolling sub-samples counts one trading day. The contiguous benchmark and crisis periods count two and

[1]Equation (4.1) is as in Baur and Lucey (2009). In turn, the linear model proposed by Baur and Lucey (2009) generalizes that described in Forbes and Rigobon (2002) by including the pre-crisis indicator variable.

one months, respectively, where a month is approximated by 22 trading days. For each sub-sample, the significance of the coefficient $\hat{\gamma}_2$, together with the remaining conditions noted above, determine whether a flight has occurred during the crisis period. Variations in the widths of the crisis and benchmark windows, as well as of the rolling sample length, are the subject of our discussion of the robustness of our methodology in Section 4.4.

The design of equation (4.1) implies that flights are identified by deviations from the *status quo* emerging during the benchmark period. The use of rolling benchmark periods captures the evolution of the information set employed by market participants. Hence flights are defined with respect to recent market activities, rather than to some ideal period of "normal" markets. In fact, the benchmark period itself may include episodes of market instability, which is a desirable feature as it allows the researcher to evaluate the incidence and characteristics of market instability from the perspective of contemporaneous investors.

Another paper that allows for an endogenous timing of flight episodes is Baele et al. (2014). We want to conclude this section by discussing their approach. Baele et al. (2014) construct four dichotomous variables, each calculated by means of a different methodology, to evaluate flights. They then aggregate these variables into a final flight indicator. The first variable signals a flight when bond (stock) returns are above (below) zero by a specified number of standard deviations. The second variable is constructed on the basis of a set of 6 market conditions: the difference between short and long term averages of stock and bond returns, volatility, and return correlation, together with short term equity market volatility, and the stock-bond spread relative to its long-term average. This variable indicates a flight when all of these listed measures have the sign that, from the authors' perspective, is associated with distress.

To build the third flight variable Baele et al. (2014) model the spread between returns for stocks and bonds by a univariate regime switching equations, where one of the three volatility regimes in the model corresponds to flights. The flight regime is characterized by larger spreads than in the other regimes. The resulting indicator for flights equals 1 when the smoothed probability of being in regime 3 is larger than 0.5.[2] The final type of the four variables is derived from a bivariate regime switching model where a latent variable is a flight to safety dummy. Again, as in the univariate case, the smoothed probabilities are employed to define a dummy variable for flights.

Baele et al. then combine their four dichotomous variables to obtain a unique flight to safety indicator. While not all these variable are extremely highly correlated, the aggregation follows the reasonable criteria that if 3 measures out of 4 indicate the occurrence of a flight, then in all probability a flight indeed occurred over the assigned date.[3]

The methodology proposed in this paper to evaluate flight episodes is a viable, and easier to implement, alternative to the multivariate procedure proposed in Baele et al. (2014). Our approach features two distinctive advantages. The first is the methodology relies only on the use of return time series, and thus can be applied to many types of market or asset class indexes. In particular, this paper's approach does not require the selection of market-specific indicators, the interpretation of which are always subject to uncertainty. The second valuable feature of our methodology is that relatively short samples can be used to produce reliable estimates. In contrast, regime-switching models may require a large number of observations to be adequately calibrated.

We note that some of the indicator variables defined in Baele et al. (2014) can answer the question of whether a flight-to-quality occurred *on a given day.* With our

[2]The smoothed probability relies on information from the full sample (e.g. Hamilton and Susmel, 1994; Kim, 1994).

[3]Technically, the aggregation is made under the assumption that the variables are drawn from a multivariate Poisson distribution.

methodology, "correlation" changes are evaluated over the set of trading days of the crisis window, rather than daily. Hence, our methodology should only be employed to determine whether a flight may have occurred within a given time frame.

4.3 Empirical Application

The focus of this paper is to provide a discussion of the strengths and weaknesses of the methodology employed in the third chapter of this dissertation to evaluate the incidence of flight-to-quality. To foster the consistency between the analysis here and the framework of the second chapter of this dissertation, we analyze flights from stocks to long-term Treasuries while allowing for two additional types of flight-to-safety, namely flights to short-term T-Bills, and to top-grade corporate bonds. Investors may choose to acquire positions in assets that are safer than stocks in different ways: short-term Treasuries offer unbeatable liquidity during turbulent times, while top-grade corporate bonds allow investors to decrease their risk profiles without completely renouncing to equity market potential gains. Investors may also flee from stocks to several types of safe-haven assets simultaneously. Therefore, flights to different categories of safe-haven products may be affected by similar shocks, and thus may be correlated.

We simultaneously estimate flights from stocks to long- and short-term Treasuries, as well as to top-grade corporate bonds, using a system of three linear equations. Each equation in the system has the form of the flight equation displayed in (4.1) where class 2 is substituted by returns of long-term Treasuries, short-term T-Bills, and top-grade corporate bonds, which are indexed by b, f and c, respectively. Class 1 is represented by the stock market aggregate portfolio, and it is indexed by s. The resulting linear system of equations, analogous to that considered in the third chapter of this dissertation, is displayed below:

$$
\begin{aligned}
r_{b,t} &= \alpha_b + \beta_b r_{s,t} + \gamma_b r_{s,t} D_t + \gamma_b^* r_{s,t} D_t^* + e_{b,t} && (4.2)\\
r_{f,t} &= \alpha_f + \beta_f r_{s,t} + \gamma_f r_{s,t} D_t + \gamma_f^* r_{s,t} D_t^* + e_{f,t} && (4.3)\\
r_{c,t} &= \alpha_c + \beta_c r_{s,t} + \gamma_c r_{s,t} D_t + \gamma_c^* r_{s,t} D_t^* + e_{c,t} && (4.4)
\end{aligned}
$$

We employ a sample of returns and yields spanning from January 1990 to December 2014. The variable $r_{s,t}$ stand for the daily returns on the US value weighted market portfolio from the Centre for Research in Security Prices, CRSP. The variables $r_{b,t}$, $r_{f,t}$, and $r_{c,t}$ represent the negative of the daily yield changes for the nominal 10-year Treasury bond index, the nominal three-month T-Bill, and the nominal Moody's AAA long-term corporate bond index, respectively. Due to known approximations, daily yield changes, with the signs reversed, can be loosely interpreted as returns on a rolling portfolio, so that we shall refer to $r_{b,t}$, $r_{f,t}$, and $r_{c,t}$ as returns in the following.

Equations (4.2), (4.3) and (4.4) are estimated jointly, to allow for correlation across the shocks hitting the three groups of safe haven assets. Error terms are assumed to cluster across equations and over the days of the crisis and benchmark periods, where the cluster robust variance estimator is obtained as in Cameron et al. (2011). Furthermore, time t error terms are potentially correlated with time $t-1$ error terms, where this autocorrelation pattern holds across the three equations.[4]

The system of equations is estimated for rolling samples of fixed width. More specifically, the equations are evaluated for a sequence of overlapping rolling subsamples, each of three years and one month in length. The contiguous benchmark and

[4] Thus, an error term $e_{i,t}$ with t falling neither into the crisis nor into the benchmark period is potentially correlated with the lagged error term $e_{i,t-1}$ of the same equation, and with the contemporaneous and lagged error terms $e_{j,t}$ and $e_{j,t-1}$, where $i, j \in \{b, c, f\}$, of the other equations. Furthermore, we assume that an error term $e_{i,t}$ falling into the union of the benchmark and crisis periods is potentially correlated with the error terms falling within the same time-frame, for all three equations. Put differently, $e_{i,t}$ is potentially correlated with $e_{j,\tau}$ where t and τ refer to observations for which D^* is not zero and i, j are in $\{b, c, f\}$.

crisis periods count two and one month, respectively, where a month is approximated by 22 trading days.

Each rolling sub-sample counts 779 observations, of which the last 22 form the crisis window I_t starting from date τ_{0t} and the remaining 757 represent the three years preceding the start of the crisis period, with 22 and 252 trading days approximating a calender month and a calendar year respectively. The initial 757 observations include the 44-day benchmark period, which precedes the crisis window. Hence, for each sub-sample, the benchmark and crisis indicator variables D_t^* and D_t are nonzero for the last 66 and 22 days of the rolling sample, respectively.

The step between the starts of two consecutive rolling sub-samples counts one trading day. For the 1990-2014 sample employed in this study, we have 6,280 rolling samples. The estimation of the system of equations yields three time-varying dichotomous variables with 6,280 observations, each of which summarizes the results for a 22-day crisis period starting with t. The three flight variables, denoted by $ftqsb_t$, $ftqsf_t$, and $ftqsc_t$, record the occurrence of flight-to-quality from stocks into long-term Treasuries, short-term T-Bills, and high-grade corporate bonds respectively.

Table 4.1 reports the frequency of the occurrence of flight-to-quality from stocks to U.S. long-term Treasuries as identified by the dichotomous variable $ftqsb_t$ for the full 1990-2014 sample as well as three other sub-periods.

In view of the dramatic events occurring over the 2007-2009 period, one may suspect that the incidence of flights may have changed dramatically during, or following, the crisis. To evaluate this possibility, we calculate the frequency of $ftqsb_t$ for three sub-periods carved out from the 1990-2014 sample around two dates that roughly enclose the main events of the financial crisis of 2007-2009, June 29, 2007 and June 30, 2009.[5] The values of $ftqsb_t$ are assigned to each sub-sample on the basis of the

[5]Bear Stearns liquidated two hedge funds exposed to the subprime mortgage sector in July 2007. The NBER recession indicator identifies the end of the downturn in June 2009.

Table 4.1: Frequency of Flight-to-quality from Stocks to Long-term Treasuries

Sample Period	**1990–2014**	**1990–2007**	**2007–2009**	**2009–2014**
No. of Sub-samples (n)	$6,280$	$4,411$	504	$1,365$
No. of Events	598	369	94	135
Percentage	9.5%	8.4%	18.7%	9.9%

Note: This table reports the frequency associated with the dichotomous variable for flight-to-quality from stocks to long-term Treasuries, $ftqsb_t$. It lists the number of flights both in raw terms and in percentage terms, with respect to the number (n) of rolling sub-samples employed in the estimation. The 1990-2014 flight variable is partitioned into three sub-samples, with cut-off dates being June 29, 2007 and June 30, 2009. The results are obtained from the estimation of the system of equations displayed in equations (4.2), (4.3) and (4.4), where the crisis period is of 22 days and benchmark period of 44 days. Error terms are allowed to cluster, and the level of significance is set at 5%.

first day of the crisis period, and the calculated frequencies are reported in columns 2, 3, and 4. The main message from this sub-sample analysis is that the incidence of $ftqsb_t$ roughly doubled during the the financial crisis of 2007-2009 (sample 2007-2009 in Table 4.1). Given that there was indeed a time of market instability, as large shocks hit financial markets, this sharp increase of flight incidence over the 2007-2009 sample may be interpreted as an indirect validation of our measure of market instability.

4.4 Sensitivity Analysis: Crisis Period, Benchmark Period, and Rolling Sub-sample Length

In the baseline regression described in the previous section, the contiguous benchmark and crisis periods count two and one months, respectively, of 44 and 22 trading days. The equation employed to estimate flights is estimated over a rolling sub-sample. Each rolling sub-sample consists of three years preceding the crisis period plus the crisis period, i.e. three years and one month. In this section, we check whether the identification of flight episodes is sensitive to the lengths of these periods and sub-samples. We present and compare the results obtained using different lengths of the crisis, benchmark periods, as well as the rolling sub-samples.

4.4.1 Crisis Period Length

The choice of the length of the crisis period, 22 days, in Chapter 3 of this dissertation, reflects a difficult balance between the desire to obtain precise estimates, and the recognition that market shifts may occur swiftly. Choosing crisis periods longer than one month, 22 trading days, may risk lumping different crises together. Choosing shorter crisis periods allows a consideration of incidence of flights within short time frames, with a cost of estimating the key coefficient, γ_2, in equation (4.1) with lower precision.

In this section we investigate the possibility that the characteristic of the flight indicators defined by the system of equations displayed in equations (4.2), (4.3) and (4.4) are strongly dependent on the length selected for the crisis period. To check whether the length of the potential crisis period affects the identification of flight episodes significantly, we consider crisis periods of 30 and 15 trading days. Table 4.2 presents a comparison of $ftqsb_t$ results generated with longer and shorter crisis periods, with those obtained for the baseline case of 22-day crisis period. We focus on the indicator of flight-to-long-term-Treasuries because this type of flights is most often examined in the literature.

The frequencies and correlations reported in Table 4.2 show that the three flight indicators obtained from the different crisis period lengths are fairly similar in terms of number of events and frequency. Furthermore they exhibit a relatively strong tetrachoric correlation, 0.68 or higher.[6]

One interesting point we notice is that flight incidence $ftqsb_t$ does not necessarily decrease with the lengths of the crisis period we choose. For example, the flight

[6]See Appendix 4.8.1 for more details about tetrachoric correlation.

Table 4.2: Summary Statistics for Flights with Different Lengths of Crisis Periods

Panel A	**Crisis Period Length**		
	22 days	**30 days**	**15 days**
No. of Events	598	576	565
Frequency	9.5%	9.2%	9.1%
Panel B	**Pairwise Correlation**		
	22-30	**22-15**	**30-15**
Simple Correlation	0.57	0.53	0.38
Tetrachoric Correlation	0.84	0.82	0.68

Note: This table reports summary statistics and correlations for indicators of flights from stocks to long-term Treasuries obtained using crisis periods of 22, 30, and 15 trading days. The first panel reports the number of events and frequencies, in percentage terms. The second panel presents the correlation and tetrachoric correlation for different pairing of these flights indicators. The flight indicators are obtained using a benchmark period of 44 trading days. Error terms are allowed to cluster and the level of significance is set at 5%.

incidence increases when we lengthen the crisis period from 15 days to 22 days, but decreases when we lengthen crisis period from 22 days to 30 days. The baseline 22-day crisis period aligns closely with those used in Baur and Lucey (2009), where crisis periods of 20 observations are considered along with benchmark windows of 50 trading days.[7] As in the 1990-2014 sample the average number of trading days is 21.7, we prefer to approximate the month with 22 daily observations rather than 20. In addition, we believe the use of a 22-day crisis period in the baseline regression allows us to capture deviations from the *status quo* of the correlation across asset classes that are associated with both sudden sharp price changes and more diffused short-run price trends.

4.4.2 Benchmark Period Length

In Chapter 3 of this dissertation the benchmark period, representing the status quo preceding the crisis period, consists of 44 trading days. In this section we discuss

[7]Baur and Lucey estimate equation (4.2) for a set of exogenously identified crisis periods.

Table 4.3: Summary Statistics for Flights with Different Lengths of Benchmark Periods

Panel A	**Benchmark Period Length**		
	22 days	**44 days**	**66 days**
No. of Events	569	598	615
Frequency	9.1%	9.5%	9.8%
Panel B	**Pairwise Correlation**		
	22-44	**44-66**	**22-66**
Simple Correlation	0.79	0.84	0.72
Tetrachoric Correlation	0.96	0.98	0.94

Note: This table reports summary statistics and correlations for indicators of flights from stocks to long-term Treasuries obtained using benchmark periods of 22, 44 and 66 days. The first panel reports the number of events and frequencies, in percentage terms. The second panel presents the simple correlation and tetrachoric correlation across these flight indicators. The flight indicators are obtained using a crisis period of 22 trading days. Error terms are allowed to cluster and the level of significance is set at 5%.

whether the use of different lengths for the benchmark periods would have yielded substantially different flight variables. To this end, we consider two alternative benchmark periods: one shorter (22 trading days) and one longer (66 trading days). For the purpose of this comparison we maintain the crisis period at 22 trading days. The comparison of the flight indicators with different widths of the benchmark periods are reported in Table 4.3. Once more we focus on the indicator of flight-to-long-term-Treasuries, as this type of flight is most often examined in the literature. The three versions of this flight indicator are highly correlated, with the tetrachoric correlations being higher than 0.90. The table shows a trend of increasing flight incidence as we lengthen the benchmark period from 22 days to 44 days, and again as we lengthen from 44 days to 66 days.[8]

[8] This is not surprising since as we lengthen the benchmark period, the market volatility tends to be smoothed out. Thus comparing a 22-day crisis period to a longer and smoother benchmark period may make it easier to identify a smaller correlation change as a flight.

4.4.3 Rolling Sub-sample Length

As mentioned in Section 4.3, our baseline regression is conducted for a sequence of overlapping rolling sub-samples. Each sub-sample consists of three years and one month of data, with the last month being the crisis window. To check whether the length selected for the rolling sub-sample affects the flight indicator, we examine two shorter durations for the sub-samples, these being of two years (plus one month), and one year (plus one month). The resulting flight variables, reported in Table 4.4, are virtually indistinguishable from those used in the analysis found in Chapter 3. The associated dichotomous variables are highly correlated with $ftqsb_t$ (greater than 0.95). We conclude that the size of the rolling sub-samples has no significant effect on our flight indicator characteristics.[9]

[9]Since we define flights by comparing the correlation levels during the 44-day benchmark period and 22-day crisis period, the length of rolling sub-sample should have little impact on the detection of flights. In fact, we also try to use the longest sub-sample available, i.e. use the full sample for each estimation window. We detect a flight in 10.4% of the windows, which is similar to our baseline results.

Table 4.4: Summary Statistics for Flights with Different Lengths of Rolling Sub-samples

Panel A	Length of Rolling Sub-sample (minus one month)		
	3 years	2 years	1 year
N. Events	598	589	576
Frequency	9.5%	9.4%	9.2%
Panel B	Pairwise Correlation		
	3 years-2 years	3 years-1 year	1 year-2 years
Simple Correlation	0.98	0.96	0.98
Tetrachoric Correlation	1	1	1

Note: This table reports summary statistics and correlations for indicators of flights from stocks to long-term Treasuries obtained using rolling sub-samples of different lengths: three years and one month, two years and one month, and one year and one month. The first panel reports the number of events and frequencies, in percentage terms. The second panel presents the simple correlation and tetrachoric correlation across these flight indicators. The flight indicators are obtained using crisis and benchmark periods of 22 and 44 trading days respectively. Error terms are allowed to cluster and the level of significance is set at 5%.

4.5 Choice of Regression Methods

In this section, we expand the discussion on the robustness of the flight-to-quality indicators employed in Chapter 3. We first check whether flight from stocks to long-term Treasuries are crucially affected by being jointly estimated with flights to short-term T-Bills and to top-grade corporate bonds. To this end we compare the flight indicators obtained by only estimating the first equation in the system, instead of joint estimation of the system of three equations. As a second check of the robustness of the flight indicator employed in the third chapter of this dissertation, we estimate the system of equations allowing for different assumptions regarding the error term variance-covariance matrix. In particular we compare the results obtained using cluster robust and the Newey-West standard errors. Finally, we compare the flight indicators obtained based on applying different levels of significance in the evaluation of the coefficients of the system equations.

4.5.1 Single Equation vs Simultaneous Equation Estimation

The flight indicator employed in Section 4.3, $ftqsb_t$, is obtained by jointly estimating equations (4.2), (4.3) and (4.4). The rationale for choosing a joint estimation strategy for the flight indicators (flights from stocks to long-term Treasuries, short-term T-Bills, and top-grade corporate bonds) resides in the observation that these markets may be affected by similar and correlated shocks. In this section, we evaluate the indicators of flights to one of the three categories of safe assets under the assumption that the market dynamics that affect the three types of shocks are independent. Once more the discussion focuses on the indicator of flight to long-term Treasuries (equation (4.2)), as this type of flight is most often examined in the literature.[10]

As reported in Table 4.5, the new flight-to-long-term-Treasuries indicator from estimation of equation (4.2) and $ftqsb_t$ obtained from joint estimation (used in Section 4.3) have a correlation of 1. The large correlation coefficient suggests that the indicator of flight to long-term Treasuries employed in Chapter 3 is very similar to the one obtained excluding flights to the other two safe-haven assets from the estimation.

4.5.2 Cluster Robust vs Newey-West Standard Errors

When estimating the system of equations in Section 4.3, we allow error terms to correlate across equations and over the crisis and benchmark periods. Furthermore, error terms at time t are allowed to be correlated with time $t-1$ error terms, with this autocorrelation pattern holding across the three equations. The cluster robust variance estimator was obtained as in Cameron et al. (2011).

As a point of comparison, we consider the Newey-West estimator and compare the associated indicator for flights to quality from stocks to long-term Treasuries

[10]In estimating the single equation, we still apply the clustered standand errors, i.e. error terms are assumed to cluster over the days of the crisis and benckmark periods, and time t error terms are potentially correlatied with time $t-1$ error terms.

Table 4.5: Summary Statistics for Flight-to-quality to Long-term Treasuries with Different Numbers of Equations

Panel A	**Equations included in the Estimation**	
	3 eqs ($ftqsb_t$, $ftqsf_t$ & $ftqsc_t$)	**1 eq** ($ftqsb_t$ only)
No. of Events	598	618
Frequency	9.5%	9.8%
Panel B	**Pairwise Correlation**	
	3 eq-1 eq	
Simple Correlation	1	
Tetrachoric Correlation	1	

Note: Panel A reports the number of flights to long-term Treasuries, together with the associated frequency, yielded by the estimation of the first equation of system equations (4.2), (4.3) and (4.4) and by the joint estimation of the three equations constituting the same system. The second panel reports the simple and tetrachoric correlation between the obtained indicators. The flight indicators are obtained using crisis and benchmark periods of 22 and 44 trading days respectively. Error terms are allowed to cluster and the level of significance is set at 5%.

with the indicator obtained relying on the cluster robust standard errors.[11] Table 4.6 summarizes the results of this comparison. When allowing for error terms to be correlated within clusters, we identify two times more flights than employing Newey-West standard errors. Although cluster robust inference generates 300 more flight occurrences than Newey-West estimation, the tetrachoric correlation between the two flight indicators is as high as 0.93. This is possibly due to the fact that applying clustering enables us to identify almost all flights identified using the Newey-West approach. However, Newey-West estimator is less preferable since it assumes error terms follow a simple correlation pattern, i.e. the correlation between error terms decreases as the time difference between error terms increases. On the other hand, the cluster robust standard errors that we employ can take into account more specifications of error terms' correlation, for example, correlation over the crisis and benchmark periods, and only on dates that are close.

[11]We choose the number of lags at $^{1}/_{3}\sqrt[3]{T}$, where T is the number of observations in each rolling sub-sample, which equals 779.

Table 4.6: Summary Statistics for Flights with Cluster or Newey-West Standard Errors

Panel A	**Standard Errors**		
	Our Cluster	**Newey-West**	**GOW Cluster**
No. of Events	598	207	654
Frequency	9.5%	3.3%	10.4%
Panel B	**Pairwise Correlation**		
	Cluster-NW	**NW-GOW**	**Cluster-GOW**
Simple Correlation	0.54	0.54	0.95
Tetrachoric Correlation	0.93	0.99	1.00

Note: This table summarizes the comparison of the indicators of flights from stocks to long-term Treasuries obtained using different types of standard errors correction. The first column is associated with cluster robust variance employed in chapter 3. The second column employs the Newey-West standard errors while the third refers to the clustering methodology proposed in Gow et al. (2010). The first panel reports the number of events and frequencies, in percentage terms. The second panel presents the simple correlation and tetrachoric correlation across these flight indicators. The flight indicators are obtained using crisis and benchmark periods of 22 and 44 trading days respectively. The level of significance is set at 5%.

As a further robustness check, we also evaluate the flight indicator for flights from stocks to long-term Treasuries using the clustering approach proposed in Gow et al. (2010) (henceforth, GOW)[12]. In the application of the clustering proposed in GOW we assume that an error term $e_{i,t}$ falling in the union of the benchmark and crisis periods is potentially correlated with the error terms falling within the same time-frame, for all three equations. The resulting flight indicator and $ftqsb_t$ employed in Chapter 3 are highly correlated, as shown in Table 4.6. A further comparison shows that employing the GOW clustering code picks up 56 more flights than the clustering correction employed in Chapter 3. In this sense, our method is more conservative than the GOW clustering approach.

[12]Gow et al. (2010) provided a Matlab routine called "clusterreg", which is built on the working paper version of Cameron et al. (2011). The code is available at: http://acct.wharton.upenn.edu/˜dtayl/code.htm.

4.5.3 Level of Significance

In this sub-section we examine whether our flight identification strategy is very sensitive to the chosen level of tolerance for Type I errors, i.e. to the choice of the level of significance, denoted by α. α is employed to determine the significance of the key coefficient $\hat{\gamma}_2$, in the generic equation (4.1) and in the system equations (4.2), (4.3) and (4.4).

Choosing a lower level of significance makes it more difficult to reject the null hypothesis that there is no flight, and thus it would yield fewer flights. On the other hand, a higher level of significance enable us to identify more flights, but also bears higher risk of getting a false positive, i.e. identifying a flight when none occurred. In our analysis, we focus on three popularly employed levels of significance, these being $\alpha = 1\%$, $\alpha = 5\%$, and $\alpha = 10\%$. Table 4.7 summarizes the results of this comparison for the indicator of flights to long-term Treasuries. The extremely large correlation levels, and the similar incidence of flights, reveal that the the flight indicators employed in Chapter 3 are very robust to the choice of the levels of significance.

4.5.4 Inclusion of Other Conditions in Flight Identification

In this subsection we examine some additional conditions that might be considered in defining flights, including filters on the correlation level during the crisis period, on the magnitudes of returns, and on the trading volume of stocks. In our baseline regression, when defining a flight, the estimated correlation between the two assets needs to be negative ($\hat{\beta}_b + \hat{\gamma}_b + \hat{\gamma}_b^* < 0$). In this analysis, we further check whether the estimated correlation is statistically significant, during the crisis period with $ftqsb = 1$. We add a filter on the correlation level during the crisis period, such that the new flight variable satisfies all the original conditions that define $ftqsb$, as well as the estimated correlation being significant during the crisis period. The correlation level during the crisis period is measured by the expression $\hat{\beta}_b + \hat{\gamma}_b + \hat{\gamma}_b^*$, and thus the

Table 4.7: Summary Statistics for Flights Estimated at Different Levels of Significance

Panel A	**Level of Significance**		
	$\boldsymbol{\alpha = 0.01}$	$\boldsymbol{\alpha = 0.05}$	$\boldsymbol{\alpha = 0.1}$
No. of Events	582	598	604
Frequency	9.3%	9.5%	9.6%
Panel B	**Pairwise Correlation**		
	$\mathbf{0.01 - 0.05}$	$\mathbf{0.05 - 0.1}$	$\mathbf{0.01 - 0.1}$
Simple Correlation	0.99	0.99	0.98
Tetrachoric Correlation	1	1	1

Note: This table reports summary statistics and correlations for indicators of flights from stocks to long-term Treasuries obtained at three different levels of significance: $\alpha = 1\%$, $\alpha = 5\%$, and $\alpha = 10\%$. The first panel reports the number of events and frequencies, in percentage terms. The second panel presents the simple correlation and tetrachoric correlation across these flight indicators. The flight indicators are obtained using crisis and benchmark periods of 22 and 44 trading days respectively. Error terms are allowed to cluster as described in Section 4.3.

sum of the three estimated coefficients ought to be significant. In Table 4.8 we report the comparison of this new flight variable with $ftqsb$. The new flight variable has the value of one in 499 rolling crisis windows, indicating that in all of the 598 windows that we find $ftqsb$ originally, 83% of them exhibit significant estimated correlations during the crisis period. A calculation of the correlation coefficient between the two time series shows that the two flight indicators are highly correlated, with correlation at 1.

In the second exercise, we include some constraints on the magnitudes of returns. In our baseline regression, we have set conditions that the two assets are negatively correlated, and their correlation should become more negative during the crisis period. One may also want to know whether the return of stock (bond) during the crisis period is much lower (higher) than that during the benchmark period. Therefore, we conduct a comparison of the two asset returns during the two periods. In particular, for each rolling sub-sample, we calculate the mean and standard deviation of the returns on stocks and bonds during the benchmark period, and add two other conditions to identify flights: (1) average bond return during the crisis period should be larger than average bond return during the benchmark period, by at least 10% of the standard deviation of the bond returns during the benchmark period, and (2) average stock return during the crisis period should be smaller than average stock return during the benchmark period, by at least 10% of the standard deviation of the stock returns during the benchmark period.[13] The estimated flight variable is reported in Table 4.8. We can see that employing the two extra conditions on the magnitudes of returns enables us to identify 327 flights, which takes about 55% of the original 598 $ftqsb$. The two flight indicators are highly correlated, with correlation at 0.99.

Last, we consider some conditions on the trading volume of stocks. As indicated in previous sections, we define flights relying on the correlation between two assets, rather than their trading volumes. In this subsection, we include information on the change of stock volume from the benchmark period to the crisis period.[14] We examine all the crisis periods with significant $ftqsb$, and find that in 377 (63%) crisis windows, the stock trading volume is higher than that in the benchmark period. As shown in Table 4.8 the obtained flight indicator and the original $ftqsb$ are highly correlated, with correlation at 1. However, since flight involves two types of assets, in order to perform a complete analysis, we also need to obtain the trading volume of long-term Treasuries. We will leave this for our future work.

[13]For the 44-day benchmark period, which is a relatively short period, it's expected that the two asset returns could be very volatile. We find that for both assets, the magnitude of the standard deviation is much higher than the magnitude of the mean. For example, the average stock (bond) return during the benchmark period is 0.04 (0.09), while its standard deviation is much higher at 0.98 (5.75). Therefore, our condition with a change of 10% of the standard deviation is quite large compared to the benchmark return level.

[14]We obtain the trading volume data from NYSE, since the volume data for CRSP at index level is not readily available. Therefore, we should keep in mind that the volume data and return data from different sources may not match perfectly.

Table 4.8: Summary Statistics for Flights Obtained Using Various Conditions

Panel A	**Conditions to Define Flight**		
	SignificantCorrelation	**ReturnMagnitude**	**StockTradingVolume**
No. of Events	499	327	377
Frequency	7.9%	5.2%	6.0%
Panel B	**Correlation with $ftqsb$**		
	SignificantCorrelation	**ReturnMagnitude**	**StockTradingVolume**
Simple Correlation	0.91	0.72	0.78
Tetrachoric Correlation	1	0.99	1

4.6 Importance of the Magnitudes of Correlation Shocks: Simulation Results

The methodology employed in Section 4.3 identified a flight-to-quality over the crisis period when a) there is a significant correlation change between the benchmark period and the crisis period, where this change is measured by the coefficient γ_2 in equation (4.1); b) the level of the correlation during the crisis window is negative; c) the two assets yield average returns of opposite signs, with the safer asset outperforming the riskier security class. Conditions b) and c) are verifiable using point estimates of the coefficients in equation (4.1), and can be given a precise economic interpretation. In contrast, it is harder to provide an economic intuition for the significance of the coefficient γ_2 in condition a).

In this section we provide some insights on the magnitude of the correlation shock yielding a significant difference between the correlations during the benchmark and during the crisis period. In the first step, we evaluate the magnitudes of the correlation shocks over the 1990-2014 sample period. The second step is to simulate data characterized by correlation shocks of reasonable sizes to ascertain the frequency with which the shocks are considered significant in the simulated environment. The analysis of the magnitudes of the correlation changes that our methodology classifies as flights, should the complementary economic conditions (condition b) and c)) be satisfied as well, sheds some light on the types of correlation shocks generating this type of market instability. In short, the intuition underlying this section's simulation exercise is to ascertain how large the correlation shock should be for a flight episode to be detected.

4.6.1 In-Sample Magnitudes of Correlation Shocks

The purpose of this section is to ascertain the size of correlation shocks that, together with other conditions, are identified as flight-to-quality episodes by the methodology employed in the third chapter of this dissertation. In this sub-section we wish to analyze the efficacy of the methodology to identify flights with respect to the correlation shocks only. Hence, we do not examine whether the two asset returns move in the same direction or in the opposite directions, or whether the correlation of the two return series increases or decreases. What we consider is whether the methodology identifies a significant change in the correlation level moving from the benchmark to the crisis period. Note that a flight corresponds to a significant change in the correlation and a resulting negative correlation level over the crisis period, while a contagion episode involves a significant correlation shock coupled with a positive correlation level in the crisis window. This distinction entails that in the data simulation, we only specify the change of correlation without imposing any constraint on the sign of the after-shock correlation, or on the signs of the average returns, which are simulated for the crisis period.

Presently, we define a new variable, called $corrjump_t$, which equals one whenever there is a significant change in the correlation between the returns of stocks and long-term Treasuries, regardless of the sign of the resulting correlation. With respect to equation (4.1), the variable $corrjump_t$ equals 1 when the coefficient $\hat{\gamma}_2$ is significant, where t is the first observation of the crisis period.

To investigate how large in the data are the shocks to correlation that, together with other conditions, identify flights, we evaluate $corrjump_t$ for each of the rolling sub-samples that have been used to define the flight variables in Section 4.3. For simplicity, we focus on the equation (4.1), that is employed to determine the flight to quality variable $ftqsb_t$, which gauges the flight from stocks to long-term Treasuries.

For each rolling sub-sample, we obtain the value of $corrjump_t$, with one indicating a significant change of correlation from the 44-day benchmark to the 22-day crisis period, and zero indicating no significant correlation change. We also obtain the estimate for the coefficient $\hat{\gamma}_2$ from each estimation, where this coefficient gauges the change in correlation moving from the benchmark to the crisis period. Panel A of Table 4.9 reports the summary statistics of the correlation changes for the 6,280 rolling sub-samples, stratified by the two values of $corrjump_t$ (1 and 0).[15] We note that the indicator $corrjump_t$ takes the value of one in 1,054 out of 6,280 windows, i.e., in about 16.8% of all the sub-samples. This percentage is naturally larger than the frequency (9.5%) associated with the flight variable $ftqsb_t$, as reported in Table 4.1. This is because when calculating $corrjump_t$ we do not apply the filters on asset performance and sign of the correlation that instead characterize the flight variable $ftqsb_t$.

The size of the absolute value of $\hat{\gamma}_2$, the estimated correlation shock, varies depending on whether the correlation change is significant or not. The average $|\hat{\gamma}_2|$ in all the sub-samples with $corrjump_t = 1$ is 3.89, more than twice as large as the analogous value (1.28) when the correlation jump is not significant. Panel B of Table 4.9 offers further details on the distribution of correlation changes in the 6,280 sub-samples. We report the number of sub-samples for different bands of correlation changes, stratified by the two values of $corrjump_t$. As expected, the larger the

[15] In this dissertation, we use $\hat{\gamma}_2$ to gauge the correlation change from the benchmark to the crisis period. However, strictly speaking, $\hat{\gamma}_2$ does not equal the change of correlation between the stock and long-term Treasury time series. Rather, it is the correlation change rescaled by the standard errors of the two series. Therefore, in Table 4.9, we may see correlation changes in larger scale than usual.

Table 4.9: Summary Statistics of Correlation Changes (1990-2014)

Panel A. Summary of Correlation Changes $\lvert\hat{\gamma}_2\rvert$							
	Average Change				No. of Samples		Percentage
$corrjump_t = 1$	3.89				1054		16.8%
$corrjump_t = 0$	1.28				5226		83.2%
Panel B. Distribution of Correlation Changes $\lvert\hat{\gamma}_2\rvert$							
Correlation Change Band	0-1	1-2	2-3	3-4	4-5	5-9	Total
No. of Samples When $corrjump_t = 1$	12	113	229	190	258	252	1054
No. of Samples When $corrjump_t = 0$	2585	1530	691	310	88	22	5226
Percentage of $corrjump_t = 1$	0.5%	6.9%	24.9%	38.0%	74.6%	92.0%	16.8%

Note: In this table we report the summary statistics and the distribution of $|\hat{\gamma}_2|$ for stocks and long term Treasury returns in the 1990-2014 sample. In Panel A, for each value of $corrjump_t$ (1 and 0), we report the average correlation changes, the number of samples and the percentage. In Panel B, we tabulate the distribution of correlation changes by different bands. For each band of correlation change, we report the number of samples for each value of $corrjump_t$ (1 and 0). We also calculate the percentage of samples when $corrjump_t$ equals one, by dividing the number of samples when $corrjump_t = 1$ by the total sample number in this correlation change band.

change of correlation, the higher the proportion of sub-samples with significant correlation changes. For example, when $|\hat{\gamma}_2|$ is between 0 and 1, the sub-samples with $corrjump_t$ equal to 1 take 0.5% of the total sub-samples. When $|\hat{\gamma}_2|$ lies between 3 and 4, the percentage of sub-samples with significant correlation changes increases to 38%. When $|\hat{\gamma}_2|$ is larger than 5, $corrjump_t = 1$ takes 92% of all the sub-samples.

Table 4.10 focuses on the sub-samples with significant changes in correlation, sorted by sign. We note that in all the sub-samples with significant correlation changes ($corrjump_t = 1$), positive and negative correlation changes occur with similar percentages, and the average absolute changes associated with them have similar magnitudes.

In Table 4.11, we report the relative magnitudes of shocks by dividing the correlation changes by the correlation level over the benchmark period. As discussed earlier regarding equation (4.1), $\hat{\gamma}_2$ measures the change of correlation from the benchmark to the crisis period, and the benchmark correlation level is represented by

Table 4.10: Summary Statistics of Correlation Changes by Sign (1990-2014)

corrjump$_t$= 1	**Average Corr. Change**	**No. of Samples**	**Percentage**
Positive Change	3.96	541	51.3%
Negative Change	-3.82	513	48.7%

Note: In this table we report the summary statistics of correlation changes by sign for the sub-samples in which the correlation change is significant, i.e., for the sub-samples in which $corrjump_t$ equals 1. The percentages reported are with respect to the number of sub-samples in which $corrjump_t$ equals 1.

Table 4.11: Summary Statistics of Relative Correlation Changes (1990-2014)

Relative Magnitudes of Shocks $\left\lvert\frac{\hat{\gamma}_2}{\hat{\beta}_2+\hat{\gamma}_2^*}\right\rvert$			
	Mean	Median	Percentage
$corrjump_t = 1$	5.99	1.64	16.7%
$corrjump_t = 0$	2.38	0.45	83.2%

Note: In this table we report the summary statistics of relative correlation changes for each value of $corrjump_t$ (1 and 0). The relative correlation shock is calculated by dividing the correlation change ($\hat{\gamma}_2$) by the correlation level during the benchmark period ($\hat{\beta}_2 + \hat{\gamma}_2^*$). We report the mean, median and percentages of $\left\lvert\frac{\hat{\gamma}_2}{\hat{\beta}_2+\hat{\gamma}_2^*}\right\rvert$ for sub-samples in which $corrjump_t$ equals 1 and 0.

$\hat{\beta}_2+\hat{\gamma}_2^*$. Therefore, the absolute value of $\frac{\hat{\gamma}_2}{\hat{\beta}_2+\hat{\gamma}_2^*}$ gives us an idea on how large the correlation change is relative to the benchmark correlation level. We can see that in relative level, when the $corrjump_t$ equals 1, the correlation change is 5.99 times of the benchmark correlation level, compared to 2.38 when the correlation jump is not significant ($corrjump_t = 0$).

4.6.2 Simulated Data

In this section, we simulate two time series to mimic the returns of stocks and long-term Treasuries employed for the evaluation of flights in Section 4.3. We generate a matrix X, consisting of two random vectors X_b and X_s, where $X = \begin{bmatrix} X_b & X_s \end{bmatrix}$, for the returns of long-term Treasuries and stocks respectively. Recall that each rolling sub-sample evaluated in Section 4.3 contains 779 observations, of which the last 22 cover the crisis period, and the 44 observations preceding the crisis window constitute the benchmark period. The remaining 713 observations cover the periods preceding benchmark period. The simulated X matrix mimics the structure of the sub-sample employed to estimate the flight indicators discussed in the third chapter of this dissertation, as well as in Section 4.3 of this chapter. The data employed as a baseline for the simulation exercise are stored in the 779×2 matrix X. The matrix X is obtained by concatenating three independent data generating processes. These processes generate the observations for the crisis period, the benchmark period, and the period preceding the benchmark, which are denoted by X_{crisis}, $X_{benchmark}$, and X_{other}, respectively. The values generated for these simulated data series are extracted from a bivariate normal distribution with mean vector μ_i and variance-covariance matrix $\Sigma_i = \begin{bmatrix} \sigma_{si}^2 & \sigma_{si}\sigma_{bi} \\ \sigma_{si}\sigma_{bi} & \sigma_{bi}^2 \end{bmatrix}$. In particular, X_{crisis} consists of two columns, $X_{b,crisis}$ and $X_{s,crisis}$, where the number of rows in X_{crisis}, denoted by n_{crisis}, is 22. With regard to the matrices $X_{benchmark}$ and X_{other}, these respectively contain 44 and 713 rows and two columns.

The overall baseline data matrix X is obtained by concatenating those three sub-matrices, as illustrated below:

$$X = \begin{bmatrix} X_{other} \\ X_{benchmark} \\ X_{crisis} \end{bmatrix} = \begin{bmatrix} X_{b,other} & X_{s,other} \\ X_{b,benchmark} & X_{s,benchmark} \\ X_{b,crisis} & X_{s,crisis} \end{bmatrix} = \begin{bmatrix} X_b & X_s \end{bmatrix},$$

where the matrices $X_{b,other}$ and $X_{s,other}$ as well as $X_{b,benchmark}$ and $X_{s,benchmark}$ are the two columns of X_{other} and $X_{benchmark}$ respectively.

For simplicity, we assume returns of stocks and long-term Treasuries in both the benchmark period and the 713 days prior are distributed similarly. In other words, $X_{benchmark}$ and X_{other} are drawn from similar distributions. The means, variances and covariances for the generated matrices are calibrated to the actual data in 1990-

2014.[16]

In Panel A of Table 4.12, we report the summary statistics for returns of stocks and long-term Treasuries for the entire 1990-2014 sample. The mean and variance of returns of long-term Treasuries are much higher than those of stock returns (for example, 0.07 versus 0.04, and 37.84 versus 1.28). The underlying reason is that the returns of long-term Treasuries are measured in basis points while the stock returns are measured in percentage terms in our sample. The difference in magnitude is thus due to the use of different units of measurement. The correlation between stocks and long-term Treasuries is relatively large, at -0.85.

For each simulated sample, we generate 713 observations included in the matrix X_{other} before the benchmark period by extracting from a bivariate normal distribution $N(\mu_o, \Sigma_o)$, where

$$\mu_o = (0, 0) \text{ and } \Sigma_o = \begin{bmatrix} 37 & -1 \\ -1 & 1 \end{bmatrix}.$$

The 44 observations of the benchmark period are generated from a similar distribution, $N(\mu_b, \Sigma_b)$, where

$$\mu_b = (0, 0), \text{ and } \Sigma_b = \begin{bmatrix} 37 & -1 \\ -1 & 1 \end{bmatrix}.$$

The aim of the simulation is to study how large the change in covariance between the benchmark and the crisis period should be for the methodology to identify a flight. We thus generate the simulated data for the crisis period, which are summarized in the matrix X_{crisis}, by extracting from a bivariate normal distribution $N(\mu_c, \Sigma_c)$ where

$$\mu_c = (0, 0), \text{ and } \Sigma_c = \begin{bmatrix} 37 & -1+\delta \\ -1+\delta & 1 \end{bmatrix}.$$

[16]We note that the level of the mean and of the variance of the distribution generating the simulated data of the sub-periods before the benchmark period (i.e., observation 1 to 713) and of the benchmark period (i.e., observation 714 and 758) are theoretically immaterial to the result of the simulation exercise. We verified this statement by generating returns for these two sub-periods using distributions with different mean and variance.

Table 4.12: Parameters for Real and Simulated Data

Panel A. Actuals	1990-2014		Panel B. Simulated Data				
	Full Sample			**Benchmark Period**		**Crisis Period**	
	r_b	r_s		$X_{b,benchmark}$	$X_{s,benchmark}$	$X_{b,crisis}$	$X_{s,crisis}$
Mean	0.07	0.04	Mean	0	0	0	0
Variance	37.84	1.28	Variance	37	1	37	1
Covariance	-0.85	-0.85	Covariance	-1	-1	$-1+\delta$	$-1+\delta$

Note: Panel A reports the mean, variance and covariance of the daily returns of long-term Treasuries (r_b) and stocks (r_s) for the 1990-2014 sample. Panel B reports the values of parameters we choose for the benchmark period and crisis period in the data simulation. Parameter δ measures the change of covariance, moving from the benchmark period to the crisis period.

The parameter δ measures the change of covariance moving from the benchmark to the crisis period. The covariance shocks obtained from the analysis of the 1994-2014 sample, which are reported in Table 4.9, provide a rough guidance to the range of reasonable values for the parameter δ. Therefore, we consider the values of δ over the range of -5 to 7.[17] For clarity of exposition, the values of parameters obtained from the 1990-2014 sample, and those used in our data simulation are summarized in Panel A and B of Table 4.12.

4.6.3 Simulation Results

For each value of δ in the range of -5 to 7 we generate the X matrix as described in Section 4.6.2. The significance of the correlation jump for the simulated sample summarized in the matrix X is evaluated by estimating equation (4.1). When the coefficient $\hat{\gamma}_2$ is significant in this linear model, the methodology employed in chapter 3 would identify a flight for the generated sample X, provided that the complementary economic conditions b) and c) are satisfied as well. We employ standard OLS estimates of the standard errors, as data are generated by independent draws.

[17] The lower bound -5 and upper bound 7 are chosen to ensure the variance-covariance matrix Σ is a symmetric positive semi-definite matrix.

Table 4.13: Summary Statistics of Correlation Changes for Simulated Sample

Magnitude of Shocks δ	0	-1	-2	-3	-4	-5	
Percentage of $corrjump_t = 1$	4.0%	8.9%	23.7%	46.4%	75.0%	95.8%	
Magnitude of Shocks δ	1	2	3	4	5	6	7
Percentage of $corrjump_t = 1$	9.7%	21.4%	44.0%	74.3%	89.9%	98.8%	100.0%

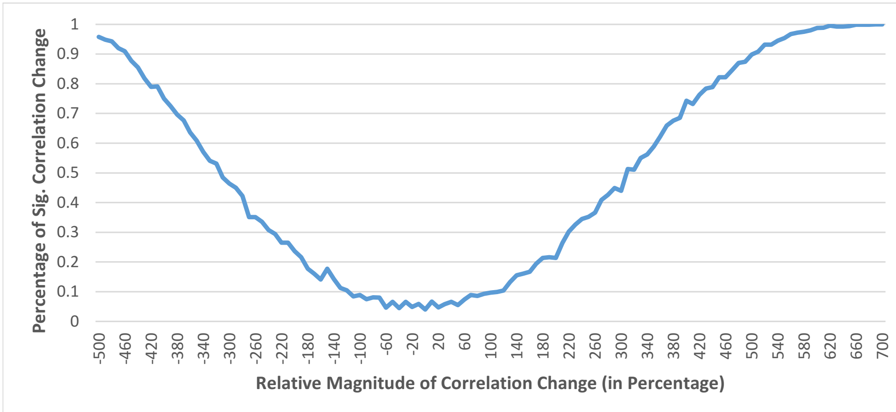
Note: In this table we summarize the results for the estimation of simulated data, for a list of representative values of δ. Parameter δ measures the change of covariance, which is also the change of correlation relative to the benchmark correlation level, moving from the benchmark period to the crisis period. The percentage of sub-samples for each band is calculated with respect to the total number of iterations (1000). The level of significance is set at 5%.

The values of the parameter δ are separated by a step size of 0.1, which is 10% of the covariance level in the benchmark period. This covariance is -1 in the benchmark period, by the design of the simulated data. Since we assume the variance parameters are the same for the benchmark and crisis period, the absolute value of our covariance change parameter δ essentially measures the change of correlation from the benchmark to the crisis period, relative to the benchmark correlation level.[18] For each value of δ we simulate the X matrix 1000 times, and evaluate whether the change in correlation is significant ($corrjump_t = 1$) in each of the 1000 estimations. Table 4.13 reports the percentage of generated sub-samples for which the changes in correlation are significant, for some representative values of δ. Figure 4.1 plots the analogous percentages for the full range of δ considered.

The power function in Figure 4.1 has an inverted bell shape, as expected. We

[18] In the simulated data, we have two assets s and b, and two periods: benchmark period (denoted by 0) and crisis period (denoted by 1). The change of covariance from the benchmark to the crisis period is measured by δ. The correlation levels during the benchmark period and in the crisis period are $\rho_0 = \frac{cov_0}{\sigma_{s0}\sigma_{b0}}$ and $\rho_1 = \frac{cov_1}{\sigma_{s1}\sigma_{b1}}$ respectively. Since we assume variances of the two assets do not change from the benchmark to the crisis period, we have $\sigma_{s0} = \sigma_{s1}$ and $\sigma_{b0} = \sigma_{b1}$. Change of correlation from the benchmark to the crisis period is measured by $\Delta\rho = \rho_1 - \rho_0 = \frac{cov_1}{\sigma_{s1}\sigma_{b1}} - \frac{cov_0}{\sigma_{s0}\sigma_{b0}} = \frac{(cov_1 - cov_0)}{\sigma_{s0}\sigma_{b0}} = \frac{\delta}{\sigma_{s0}\sigma_{b0}}$. The relative change of correlation w.r.t the benchmark correlation level is $\frac{\Delta\rho}{\rho_0} = \frac{\frac{\delta}{\sigma_{s0}\sigma_{b0}}}{\frac{cov_0}{\sigma_{s0}\sigma_{b0}}} = \frac{\delta}{cov_0} = -\delta$. Therefore, $|\delta|$ measures the size of the relative correlation change.

Figure 4.1: Power Function



Note: This figure plots the power function for our modified flight model that tests whether there is a significant change of correlation between the crisis and benchmark periods. The horizontal axis indicates the change of correlation in percentage with respect to the correlation level in the benchmark period. The vertical axis is the power of the test, which equals the percentage of samples when $corrjump_t$ equals one.

observe that as the covariance change parameter δ increases in size, we are able to detect more significant correlation jumps. When $\delta = 0$, we obtain a power of test around 4%, which is similar to the level of significance (5%) chosen when building the power function. When $|\delta|$ is very high, the power of the test approaches one. More specifically, in relative levels, when the correlation change is around 100% or 200% of the benchmark correlation level, we observe 100 or 200 flights in a 1000-time simulation, respectively. That is about 10% or 20% of all the simulation iterations. When the correlation change considered is much larger, say, at about 500% of the benchmark correlation level, the flight incidence increases to 90%, indicating that over 1000-time simulations, we will find a significant coefficient $\hat{\gamma}_2$ for 900 simulated samples. These magnitudes are basically in line with what we observed for the 1994-2014 real sample.

4.7 Conclusion

This paper considers several robustness checks on the methodology employed to identify flight-to-quality in Chapter 3. We consider different lengths of the benchmark and crisis periods and examine the effects of varying the sizes of rolling sub-samples. In all cases, we obtain flight indicators that are very strongly correlated to those used in Chapter 3, which suggests a substantial stability of the methodology proposed in this dissertation to gauge flights.

We also examine the effect of estimating flight incidence to the safe asset classes equation-by-equation or jointly, by comparing the flight indicators obtained estimating the asset-class specific equation by itself versus the joint estimation of different types of flights. We find that our methodology appears to be robust to the inclusion/exclusion of alternative categories of safe haven assets. However, different assumptions regarding the error term variance-covariance matrix, such as Cluster robust and Newey-West standard error corrections, do affect the characteristics of obtained flight indicators. Flight indicators obtained using different levels of significance are also highly correlated.

Finally, we use simulations and in-sample data to expand our understanding on magnitudes of the shocks that cause significant flights. A plot of the power of function shows that as correlation change increases in size, we are able to observe higher flight incidence. When the change of correlation is about 5 times as large as the benchmark correlation level, our model can identify a flight in 90% of the simulated samples.

In future research, instead of using the yield changes as proxies for the returns, we could also try the Treasury returns calculated by CRSP. In addition, in defining potential crisis period, we could use each calendar month instead of the 22-day rolling window, and compare the results.

4.8 Appendix

4.8.1 Tetrachoric Correlation

In this chapter, we mainly employ tetrachoric correlations to compare the dichotomous flight indicators obtained from different specifications of equation (4.1). Hereafter I briefly discuss the measurement of the tetrachoric correlation.[19]

When calculating the correlation between two dichotomous variables, the familiar Pearson product-moment correlation coefficient is inappropriate. Instead, a tetrachoric correlation can be calculated using a bivariate probit model. Suppose we have two dichotomous variables, y_1 and y_2, and they are normally distributed around fixed means with variance equal to one.

$$y_1 = 1(y_1^* > 0)|y_1^* \sim N[0,1] \tag{4.5}$$
$$y_2 = 1(y_2^* > 0)|y_2^* \sim N[0,1] \tag{4.6}$$

We can estimate the following bivariate probit model, in which the independent variables are constant terms.

$$y_1^* = \mu + \varepsilon_1,\ y_1 = 1(y_1^* > 0) \tag{4.7}$$
$$y_2^* = \mu + \varepsilon_2,\ y_2 = 1(y_2^* > 0) \tag{4.8}$$
$$(\varepsilon_1, \varepsilon_2) \sim N_2[(0,0),(1,1,\rho)]$$

Employing maximum likelihood estimation, we obtain the estimate of the correlation coefficient ρ. The tetrachoric correlation between y_1 and y_2 is the correlation coefficient ρ.

[19]See LIMDEP 10 Econometric Modeling Guide for more details.

Chapter 5

Concluding Remarks

The three chapters of my dissertation apply financial economic theory to investigate the interactions of stocks and fixed income securities in Canadian and the U.S. markets. Utilizing data at both the firm and aggregate level, we empirically analyze the relative informational efficiency of individual stocks and bonds, as well as the nature of the information that drives their simultaneous price adjustments. We also examine an extreme representation of asset comovement changes, flight-to-quality, and the fundamental market forces that may affect flight-to-quality.

The analysis conducted in the second chapter discusses the nature of the information that drives the contemporaneous variation in Canadian stock and bond values, which appears to be dominated by news regarding the mean of the firm's value, rather than its volatility. An examination of the informational efficiency of the two markets suggests that, before the 2007 financial crisis, most of the price-relevant information was flowing from the stock market to the bond market. After 2007, we observe a bi-directional pattern, suggesting that the information exchanges between the bond and stock markets have intensified in response to the financial crisis initiated in 2007. Overall, our results using Canadian data lend support to the conclusions of extant studies which advocate a leading role for the stock market in transmitting firm-specific information, but also suggest a secondary role for the bond market that is enhanced during market fluctuations.

The third chapter proposes an innovative approach to identifying flight-to-quality by considering three classes of safe haven assets: long-term Treasury bonds, T-Bills, and top-grade corporate bonds. Our results show that stock market illiquidity appears to have differential effects on different types of extreme market movements, confirming the predictions of the asset pricing model with illiquidity proposed in Vayanos (2004). The frequency of flights tends to increase with illiquidity for pairs of asset groups with very diverse sensitivity to illiquidity and volatility (e.g. T-Bills and stocks), and decrease for assets with more similar risk profiles (e.g. stock and corporate bonds). In addition, we also establish a strong link between the profitability of the momentum strategy and flight-to-quality.

The fourth chapter further examines the methodology employed to identify flight-to-quality in Chapter 3 and considers several robustness checks. Our results suggest a substantial stability of the methodology proposed in this dissertation to gauge flights. We further conduct simulations of data characterized by correlation shocks of reasonable sizes to ascertain the frequency with which the shocks are considered significant. Our results show that when the change of correlation is about 5 times as large as the benchmark correlation level, our model can identify a flight in 90% of the simulated samples.

The methodology to identify flight-to-quality proposed in this dissertation can also be applied to detect other types of market instability indicators, for example, flight-from-quality and contagion. A promising direction for further research would be to determine the incidence of flight-from-quality, and positive and negative contagion. A goal would be to investigate whether or how the set of economic and financial variables considered in this dissertation are associated with those alternative types of market instability. In addition, instead of using the yield changes as proxies for the returns, we could try the Treasury returns calculated by CRSP to evaluate whether different approaches of return calculation may yield different conclusions in terms of market instability indicators.

Another and a separate line of inquiry is offered by the use of a richer set of gauges of monetary policy activities, along with the lines of those employed in Baekert et al. (2013). The authors focus on several measures of monetary surprises that, while similar in spirit to those utilized in Kuttner (2001) and Bernanke and Kuttner (2005), are regressed on surprises of business cycle indicators. These unexpected indicators are obtained as the difference between the median of professional forecasting and the actual realizations of the variables.

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