Momentum and Flights from Stocks

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Abstract

This paper establishes a strong link between the profitability of the momentum strategy and market instability, as gauged by flight-to-quality episodes. Momentum gains are shown to be roughly ten times larger during flight episodes. Further, flights are significantly associated with larger momentum profits even after controlling for indicators of asset performance, volatility, illiquidity, market state, and monetary policy. This paper’s results also show that illiquidity shocks appear to diversely affect different types of flights, as predicted in Vayanos (2004). Finally, monetary policy announcements, past and contemporaneous, are shown to decrease the incidence of market instability.

1 Introduction

For a given asset class, say stocks, momentum is a simple trading strategy consisting of buying prior top performers while selling assets that have yielded the most discouraging returns. A key contribution of this study is to establish a link between the profitability of the momentum portfolio in the US stock market and the incidence of flight-to-quality episodes (henceforth

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flights), over the 1990-2014 period. Our results indicate that large momentum profits are strongly linked to an increase in the incidence of flights. Furthermore, while momentum gains are shown to be roughly one order of magnitude larger during months with versus without flight episodes. This profitability gap is amplified for the 2007-2009 financial crisis, a period during which very large momentum profits appeared to coincide with clusters of flight episodes. Lastly, the strong link between momentum showings and market instability is documented for flights from stocks to not only long-term Treasuries, but also to T-Bills and top-grade (Moody’s AAA) corporate bonds.

Behavioral pattern are often invoked to explain the profitability of momentum. Most contributions in this literature cite investors’ overreaction as the source of mispricing, as in the framework proposed by Daniel et al. (1998), while others discuss the effects of underreaction, as in Barberis et al. (1998), also coupled with gradual information dissemination (Hong and Stein (1999)). Johnson (2002) notes that the profitability of the momentum strategy is not at odds with agents’ rationality. Vayanos and Woolley (2013) propose an asset pricing model with rational agents that explains the profitability of the momentum anomaly by invoking agency considerations echoing those discussed in Shleifer and Vishny (1997) and Vayanos and Wang (2012). Other studies (e.g., Berk et al. (1999) and Belo (2010)), link the momentum effect to firm behavior.

The strong link between the incidence of flights and large momentum gains documented in this paper can be interpreted both in the risk and behavioral framework. Market instability, as measured by flights, appears to be affected by the same risk factors or behavioral patterns that cause the momentum effect. By establishing an unexplored link between momentum and market instability, this paper provides new perspective to the debate on the causes of the momentum effect, as it broadens the discussion to the task of identifying the roots of aggregate market instability.

Baele et al. (2014) consider a host of economic and financial describers, but not momentum, and evaluate their unconditional covariance with flight indicators. Our work complements their analysis of Baele et al. (2014) by focusing on the simultaneous effects of selected market forces on the incidence of market instability, as the impact of each considered potential drivers of market instability is evaluated controlling for the effect of a battery of other market forces. In particular, we show that the profitability of the momentum strategy remains strongly associated with the incidence of flights also after controlling for markets’
volatility, and stock market illiquidity, as well as for different measures of extraordinary performance of assets, for monetary policy activities, and, finally, for the market state.

The conditional analysis of market instability discussed in this paper confirms the result of the unconditional evaluation proposed in Baele et al. (2014) for the US market. Low stock market returns, and volatility, are associated with market instability. Superior performance of the bond markets invites more flights to safe haven, while, we add, volatility at the long end of the yield curve appears to be associated with turmoil in the market. Illiquidity in the stock market is positively associated with the incidence of flights to long-term Treasuries and top-rated corporate bonds, a result that we complement by documenting an opposite illiquidity effect for short-term Treasuries.

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 goal 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. To preview, this paper’s 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 safe haven securities with longer maturities. The frequency of flights is also shown to be nonlinearly 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 (inter alia, Campbell and Hentschel, 1992; Ghysels et al., 2013; Maheu et al., 2013; Jensen and Maheu, 2013) by examining how volatility affects sharp changes in the relative profitability of the asset classes.

This paper’s empirical analysis finds that monetary policy announcements of 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. However, the analysis of dynamic models of incidence of flights also indicates that expectations of future loose monetary stance are associated with an increased probability of future flight occurrence. This result could be interpreted as indicating
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; Gürkaynak et al., 2005; Bernanke and Kuttner, 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. 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 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’s 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 paper’s empirical analysis strongly supports the model predictions 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.

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 interdependencies (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 safer than stocks in different ways: short-term Treasuries 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 the authors’ knowledge, this is the first paper modelling flights to three fixed income categories.

The inclusion of T-Bills in the pool of safe 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 assets, while waiting for market uncertainty to be resolved. Indeed, we find evidence that omitting flights 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). In view of the results of these studies, including top-grade corporate bonds appears to be necessary to provide a more complete 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 showing a flight to corporate bonds component.

The remainder of the article is laid out as follows. The next section begins the empirical analysis by illustrating the methodology employed to identify flights. Section 2.1 describes the characteristics of the flight indicators employed to analyze market instability. The analysis includes an unconditional evaluation of the profitability of the momentum strategy in months with versus without flights. The following section explores models of flight incidence and on the conditional association of momentum and flights. This part of the empirical analysis includes static models of flight incidence, a discussion of the 2007-2014 subsample, the evaluation of market state effects, and a brief presentation of the results yielded by dynamic models of flight incidence. A concise statement of conclusions completes

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1We recognize that Treasuries and high-grade corporate bonds may fail to subsume all types of investments that are traditionally considered safe 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 investors’ quest for safety.
the paper. Robustness checks for the proposed flight indicators, the description of some variables, and a more detailed discussion of market state effects, and of the dynamic models are all relegated to the online appendix.

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. In the empirical literature, we encounter two main empirical methodologies to identify flights occurring during a given time period. The first examines order imbalances or order flows around crisis periods (e.g., Kasch et al., 2011; Beber et al., 2009). The second approach, also adopted in this paper, is to employ changes in the correlation between asset returns, so that flights are defined by significant correlation shocks, i.e., by changes in the relative performance of two asset groups.

Consistently 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. 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 1 clearly shows that for about half of our sample, from 1998 onwards, these two asset classes have been negatively correlated. 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.³

²The 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).

³Furthermore, 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-
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 few exogenously defined sub-samples. Rather, this paper’s 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.\footnote{Pesaran and Pick (2007) also discuss the perils of distinguishing pre-crisis from crisis periods a priori for the estimation of international contagion.}

In this paper’s the timing of flights is made endogenous by evaluating a static flight identification methodology within a rolling-sample framework.

Our approach also sports a real-time flavour, as rolling subsamples 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 characteristic of that period might artificially raise the bar for market instability episodes occurring in periods preceding the summer of 2007 to be acknowledged. This concerns is material to our analysis as we employ a sample of returns and yields spanning from January 1990 to December 2014.\footnote{The availability of the VIX index defines the span of our sample.}

For each time interval $I = [\tau_0, \tau_1]$, the incidence over $I$ 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:

\[ r_{b,t} = \alpha_b + \beta_b r_{s,t} + \gamma_b r_{s,t} D_{\tau_0} + \gamma_b^* r_{s,t} D_{\tau_0}^* + e_{b,t} \] (1)

\[ r_{f,t} = \alpha_f + \beta_f r_{s,t} + \gamma_f r_{s,t} D_{\tau_0} + \gamma_f^* r_{s,t} D_{\tau_0}^* + e_{f,t} \] (2)

\[ r_{c,t} = \alpha_c + \beta_c r_{s,t} + \gamma_c r_{s,t} D_{\tau_0} + \gamma_c^* r_{s,t} D_{\tau_0}^* + e_{c,t} \] (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 \( r_{b,t} \), \( r_{f,t} \), 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 \( r_{b,t} \), and \( r_{f,t} \), and \( r_{c,t} \) as returns in the following.\(^6\)

Equations (1), (2), and (3) are designed around two dichotomous variables, denoted by \( D_{\tau_0} \) and \( D_{\tau_0}^* \), which are defined on the basis of two adjacent time intervals of fixed width, namely the crisis and benchmark periods, where the benchmark period precedes the crisis window. The variable \( D_{\tau_0} \) is equal to 1 for all the observations over the interval \( I \), i.e., over the crisis period, and zero otherwise. The second variable, \( D_{\tau_0}^* \) is always 0 except for the observations falling in the crisis and benchmark periods. In short, during the benchmark period the variable \( D_{\tau_0} \) is zero while \( D_{\tau_0}^* \) equals 1, while both variables take the value 1 during the crisis window.\(^7\)

The coefficient on the crisis indicator \( D_{\tau_0} \) in Equations (1), (2), and (3), denoted by \( \gamma_i \), 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 correlation level between the returns of the safe asset and the stock index, during the crisis period. Asset performance during the crisis period is

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\(^6\)For example, the correlation between \( r_{b,t} \) and the return on the monthly rebalanced portfolio of 10-year maturities (variable TDRETAJ in CRSP database) is 0.95 over the sample 1990-2014. Bond yields are sourced from the Board of Governors of the Federal Reserve. In our sample we retain only days for which returns on all four classes of assets are available.

\(^7\)Equations (1), (2) and (3) are designed according to the approach proposed in Baur and Lucey (2009), where the authors estimate the long-term Treasuries equation alone (equation (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.
measured by the average of daily returns.

A flight is a market dynamic in which the change in correlation, the estimated coefficient $\gamma_t$, and the correlation level, the sum $\hat{\beta}_t + \hat{\gamma}_t + \hat{\gamma}_t^*$, are both negative, the coefficient $\hat{\gamma}_t$ 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 (1) provide evidence of a flight-to-quality from stocks to long-term Treasuries occurring during the crisis period starting in $t$ 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 stocks to corporate bonds and to short-term Treasuries are identified analogously.

Equations (1), (2), and (3), are 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 step between the start of two consecutive rolling subsamples counts one trading day. The contiguous benchmark and crisis periods count two and one month, respectively, where a month is approximated by 22 trading days. The sample is cut after the crisis window. For each subsample, the significance of the coefficient $\hat{\gamma}_t$, together with the remaining conditions noted above, determine whether a flight has occurred during the crisis period. In our 1990-2014 sample we have 6,236 rolling samples.

Consistently with the rolling sample approach adopted to obtain the flight variables, the resulting flight indicators are highly autocorrelated. This feature of flight indicators is both expected-as market instability is unlikely to be a one-day only events-and not unique to our study. For example visual inspection of the indicators proposed in Baele et al. (2014) clearly show strong persistency. Indeed one of their measures shows that a trading day over which

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8 We have tried alternative length of the rolling sample (e.g., five and two years). The resulting flight variables are virtually indistinguishable from those employed in this paper’s analysis. See also the robustness checks in the online appendix.

9 More precisely, each rolling sample counts 779 observations, of which 22 form 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 $D^*_b$ and $D^*_r$ in equations (1), (2), and (3) are nonzero for the last 66 and 22 days of the rolling sample, respectively. The benchmark period consists of 44 trading days. See also the robustness checks in the online appendix.

10 As in Section 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 start on January 2, 1990 and ends on Friday March 2, 1990, while the first crisis interval starts on Monday, March 5, 1990.
a flight takes place has 94.7% chances to be followed by another flight date.

The design of equations (1), (2), and (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, so that 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 future as it allows to evaluate the incidence and characteristics of market instability from the perspective of contemporaneous investors.

2.1 Incidence of Flights

This joint estimation of equations (1), (2), and (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 $ftqs_{b,t}$, $ftqs_{f,t}$, and $ftqs_{c,t}$, where each of the 6,236 observations of a flight variable summarizes the result of the assessment on the existence of a flight for 22-day crisis period starting with date $t$.

Column 1 of Table 1 reports the frequencies for the occurrence of flights for the full 1990-2014 sample. We also construct an aggregate flight indicator, 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.\textsuperscript{11}

The tetrachoric correlation between the variables counting flights to long-term corporate bonds and to long-term Treasuries score a hefty 0.94.\textsuperscript{12} 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. The conditional analysis discussed in the following section will reinforce this assessment.

\textsuperscript{11}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 (1), (2), and (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.

\textsuperscript{12}In this work, correlations between indicator variables are tetrachoric correlations.
An analysis of the coefficients $\gamma_i$ in equations (1), (2), and (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 indicates 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 corporate debt is not too surprising, as the long maturity side of the Treasury yield curve tends to drive the yields of corporate bond (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 longer term securities, while flights to top-rate corporate bonds and long-term Treasuries are closely related. The conditional analysis discussed in the following section will reinforce this assessment.

[Table 1 about here]

Given the severity of the financial crisis initiate 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 turmoil. To evaluate this possibility, we calculated the frequencies of the four types of flights for three sub-period which are carved out from the 1994-2014 sample around the breakpoints June 29, 2007 and June 30, 2009, where these date are chosen to roughly encapsulate the most disruptive phases of the financial crisis.\footnote{Using alternative breakpoints confirms the increase of all types of flights during the 2007-2009 crisis.} Flight
variables are assigned to each subsample on the basis of the first day of the crisis period. The calculated frequencies are reported in columns 2, 3, and 4 of Table 1.

The main message of the subsample analysis is that the incidence of all types of flights roughly doubled during the financial crisis (sample 2007-2009 in Table 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 interpreted as an indirect validation of our methodology to identify flights.

In the full sample, there are (unreported in Table 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 subsamples covering the years of the crisis, the analogous percentage reaches 4.37%, which reveals that simultaneous flights, though still rare, became more prevalent during the crisis.

A qualitative validation of this paper’s methodology to elicit the timing of flight episodes from the data is yielded by the ability of the resulting indicators of market instability to match major events. This analysis suggests that the flight indicators are able to 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 in 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, it may create the impression of market prescience in plots of flight variables.\(^{14}\) Hence, to eliminate this visual appearance of foreknowledge, an observation of $ftqs_t$ is mapped to the last day of the crisis period starting in date $t$. Figure 2 displays the plot of $ftqs_t$ with $t$ falling in the year 2008.

\(^{14}\)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.
Figure 2 clearly shows that flights tend to cluster, which is an expected feature 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 begins 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.\footnote{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 web site of the Federal Reserve Bank of St. Louis, last accessed on June 10, 2016. See also the timeline in Bartram and Bodnar (2009).}. Overall Figure 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 captures not only periods of prolonged market instability but also responds to large market swings occurring over short time intervals.

Figure 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 about here]

Figure 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 Brothers’ bankruptcy filing date.

2.2 Flights and Momentum Gains

Table 2 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 \(ftqs_t\).\(^{16}\) 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 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 \(ftqs_t\).\(^{17}\) 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 subsample 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 subsample we find that momentum yielded exceptionally strong gains, for a monthly return of 4.55%, 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 subsample. This finding suggests that periods of market instability may hide some silver lining for momentum traders. We note that a return gap of somewhat smaller size, with some notable exceptions, is discernible in the remaining sub-periods.\(^{18}\) In particular, we note that the profitability differential of momentum may be impressive, even if the average monthly return 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 without, flights.

\[\text{Table 2 about here}\]

Overall, the stratified averages reported in Table 2 appear to suggest that large momentum gains are associated with the type of market instability described by the flight indicators

\(^{16}\)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 momentum return over each rolling 22-day crisis period, and then stratify this series of rolling monthly returns by the flight indicators.

\(^{17}\)Crisis periods have been defined in Section 2.

\(^{18}\)For example, in the post-crisis period, flights to T-Bills are associated with momentum monthly return that is about 240% larger in months with versus without flights.
defined in Section 2. Some preliminary thoughts on why this may be the case are suggested by the risk-based explanation of momentum suggested in Asness et al. (2013) and by the behavioral finance literature.

Asness et al. (2013) find that momentum loads positively on measures of funding liquidity risk, and thus to broadly defined illiquidity measures.¹⁹ Funding illiquidity risk can be thought as the effect of binding borrowing constraints on financial intermediaries in the spirit of the asset pricing model proposed in Brunnermeier and Pedersen (2009).²⁰ Asness et al. (2013) suggest that funding shocks may force the liquidation of overcrowded momentum positions, which would explain why momentum is positively linked to funding illiquidity risk indicators.

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.²¹ 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 assets’ fundamental value.

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 asset groups, and that investors over-extrapolate past returns.²² This framework not only provides justification to the momentum effect, but also predicts a pattern of negative 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

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¹⁹Asness et al. (2013) document a robust and strong positive correlation of momentum with measures of funding risk like the TED spread (i.e., the spread between the LIBOR interest rate and the government rate), and the spread between the LIBOR and the same-maturity repurchase agreement rate.

²⁰The key feature of the model is that the financial middle-man, i.e., speculators, is subject to borrowing constraints that interact with margin requirements imposed by the agents (e.g., banks) financing their activities.

²¹As in Daniel and Moskowitz (2013), overconfidence is to be understood as agents’s excessive reliance on signals, not as an enhanced belief in market positive performance.

²²Barberis and Shleifer (2003) focuses on investment styles, rather than assets 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.
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 Daniel et al. (1998) and Barberis and Shleifer (2003) can be integrated to jointly yield the prediction that large momentum profits are consistent with higher flight incidence. The stratified averages in Table 2 appear to be consistent with these predictions.\footnote{An informal explanation of the link between market instability and momentum strong showings can be inferred also from the underreaction framework proposed by Hong and Stein (1999). Underreacting investors fail to fully adjust prices in response of shocks that affect negatively (positively) the stock market (safe haven assets), thus creating an opportunity for momentum traders (in the stock market) to gain abnormal profits. Flights are thus associated with large momentum gains when shocks are strong enough to cause severe reallocation in the aggregate portfolio, despite the muting effect of the underreaction bias.}

The large returns generated by the momentum portfolio during flight episodes, while suggestive, might be the by-product of comovements between the momentum strategy and market forces affecting market stability. For example, Daniel and Moskowitz (2013) show that poor showings of the momentum strategy appear to be associated with periods during which the stock market is expanding, tend to follow downturns, and are associated with periods of large market volatility, during bear markets. Extraordinarily asset performance, market state, and volatility may also be linked to the incidence of flights, as we shall discuss in the next section. Our analysis then proceeds with an exploration of the conditional association between large momentum showings and flights, when we consider other indicators of market conditions.

3 A Model of Flight Incidence

For the purpose of modeling flight incidence, we assume that flights are extreme manifestations of unobservable continuous, and time-varying, market instability variable. The flight indicators introduced in Section 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:

$$Prob(ftqs_t = 1|x_t) = \Phi (x'_t\beta)$$  (4)
where, $\Phi$ is the standard normal distribution function, and $\beta$ is a vector of coefficients and $x_t$ is a vector of explanatory variables.$^{24}$

The use of a nonlinear model is deliberate. Both theoretical models (e.g., Brunnermeier and Pedersen, 2009; Vayanos, 2004; Vayanos and Wang, 2012) and empirical applications (e.g., Adrian et al., 2015; Maheu et al., 2013; Jensen and Maheu, 2013) have suggested that linear relationships may be insufficient to describe the effects of illiquidity and volatility, as well as, one could argue, of other market forces, on the composition of the aggregate portfolio, during periods of market turmoil. The use of a nonlinear model provides some flexibility in the formalization of the link between flight incidence and market conditions.

The use of a limited dependent variable is also motivated on the basis of statistical considerations. Recent advancements in statistics suggest that the standard binary response models are particularly suitable to the inclusion of nonstationary variables.$^{25}$ Notably, unit-root variables are the natural outcomes of the recursive framework we employ to endogenize the timing of flight episodes.

To evaluate the potential role of the momentum effect in explaining the occurrence of flights, we include in equation (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. This variable identifies the crisis windows during which momentum gains are large. Consistently with this paper’s approach, this indicator sports a real-time flavour, as exceptionally large gains are defined relatively to a time-varying reference period.

The first set of control variables employed in equation (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

$^{24}$The use of a logistic regression yields identical conclusions, as it is often the case. We opt for the probit model, for ease of interpretation of the marginal effects.

$^{25}$Park and Phillips (2001) examine 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 $\chi^2$ limiting distributions. Put differently, their findings show that the usual battery of inference techniques is applicable to binary choice models with non-stationary covariates.
Treasuries, and $c$ for top-grade corporate bonds. To facilitate the discussion of our results, throughout the remainder of this paper the prefix "$c$" indicates contemporaneous variables.\footnote{Since the $car_{s,t}$ 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.}

Two types of additional return-based covariates are introduced in equation (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 indicator variable $cmax_{s,t}$ equals 1 when the best daily return on stocks over the 22-day crisis window better 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 by means of 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., Farmer et al., 2004; Mike and Farmer, 2008; Weber and Rosenow, 2006; Gillemot et al., 2006). 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 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’s model also predicts that pair-wise correlations might decrease in response to an illiquidity shock for assets groups sporting very diverse risk profiles in terms of 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 (2002) 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 online 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 3.1 we shall quickly discuss a model of flights that includes performance and volatility gauges for all the four asset classes considered in this paper. The model is in the online 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.\textsuperscript{27}

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. Consistently with these findings, the effects of illiquidity

\textsuperscript{27}Goyenko and Ukhov (2009) show that measures of stock and bond illiquidity are strongly and positively correlated, with the correlation at 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) reports smaller, and yet statistically significant, correlation levels between similarly defined illiquidity measures.
of Treasuries on market instability are subsumed by the joint inclusion in equation (4) of gauges of stock market illiquidity, bond and stock market volatility, and of monetary policy announcements.\textsuperscript{28}

Theoretical models as that 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 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., Kiyotaki and Moore, 2002; Brunnermeier and Pedersen, 2009) 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, this being the interest rate charged when brokers borrow from banks to cover clients’ security positions.\textsuperscript{29} In an unreported result, available upon request, we document neither the EFF rate nor the call rate play a significant role in explaining flights.\textsuperscript{30}

Filipović and Trolle (2013) note that most of the recent literature measures interbank (lending) risk by the Libor-OIS spread.\textsuperscript{31} 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 subsample, summarized in Section 3.1, and detailed in the online 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

\begin{itemize}
  \item \textsuperscript{28}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 similar for similar types of illiquidity measures, which suggests a similar relationship between both stock and bond market illiquidity with flights.
  \item \textsuperscript{29}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.
  \item \textsuperscript{30}The lack of explanatory power of the EFF rate is maintained when the rate is extended as suggested in Wu and Xia (2016).
  \item \textsuperscript{31}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 online appendix.
\end{itemize}
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 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 purchased. 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., Bernanke and Kuttner, 2005; Rangel, 2011; Rosa, 2011; Wright, 2012; Fiordelisi et al., 2014). To account for monetary policy activities, we include in the model displayed in equation (4) the variable $cFed_1$, which is defined as the number of monetary policy announcements issued during the crisis period starting in $t$, 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 $cFed_1$ are relegated to the online appendix.

To explore the possibility that flights are state dependent, we include in equation (4), a dichotomous variable that accounts for the state of the stock market before 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.32

Table 3 report the summary statistics for the continuous and binary variables described above, for the 1990-2014 full sample.

[Table 3 about here]

The results presented in this paper refer to model 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.

32A 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 $down_t$. 
3.1 Static Models

Equation (4) is estimated using the aggregate flight indicator ($ftqs_{it}$), and then, separately, for the indicator variable of flights to long-term Treasuries ($ftqsb_{it}$), to T-Bills ($ftqsf_{it}$), and to top-grade corporate bonds ($ftqsc_{it}$). Estimates are summarized in Panel A of Table 4. We report only the marginal effects, for brevity’s sake, relegating the table with the probit coefficients and t-statistics to the online appendix of this paper.

Covariates are appropriately scaled to facilitate the interpretation of the marginal effects, which are reported in Panel A of Table 4. One should interpret the marginal effects in Panel A as follows. In Column 1, an increase of 10% of the standard deviation of daily stock returns over the crisis window (variable $cstdev_{a,t}$) is associated with an increase of 0.1 percentage points (i.e., 10 basis points) of the probability of a flight. For the standard deviations $cstdev_{a,t}$, with $a$ in $\{s, b, f, c\}$, the 10% increment is calculated with respect to the standard deviation of the corresponding series of daily returns, 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 4, 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 $cFed_{1t}$ is for one additional monetary policy announcement during the crisis window.

In Panel B of Table 4 we report the McFadden Pseudo R-squared measures of prediction success. 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 probit

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33 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 value for each observation.

34 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.
probabilities.\textsuperscript{35} In view of the low frequency of flights in our sample, the models presented in Table 4 explain these rare events surprisingly 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.\textsuperscript{36}

The large and positive coefficients of the momentum dichotomous variable $cdmom_t$ in Table 4 corroborate the existence of a positive link between the mechanisms causing the profitability of the momentum strategy and market instability. The coefficient 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 less 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 consistency 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 estimates presented in Table 4 show that the coefficients on the average returns $car_{a,t}$ for $a$ in $\{s, b, f, c\}$ feature the expected signs.\textsuperscript{37} 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 very significant, which is not surprising as average returns

\textsuperscript{35}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 (4), but fail to modify any of this paper conclusions, and are therefore omitted.

\textsuperscript{36}The frequencies in Table 1 show that flights to individual classes of fixed income securities occur with rather low incidence. 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 4. Choice sampling techniques do not modify any of this paper’s finding.

\textsuperscript{37}This paper’s empirical approach to the identification of flights, which is described in Section 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.
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.

The coefficients in columns 2 and 3 of Table 4 show that a larger average return of 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 quasi-substitute long-term securities, falls as investors weigh foregone returns in their portfolio choices.

The coefficient 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 coefficients in columns 2, 3 and 4 of Table 4 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 to corporate bonds.

The difference in the effects of extremely negative daily returns on the three types of flights to fixed income securities suggests 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 to describe the behavior of in-
vestors 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 extreme short-term performance of the stock market have a differential effect on T-Bills and long-term bonds, the sign of the coefficient 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 4 suggest that a down market state triggers more flights to long-term Treasuries than flights to T-Bills and top-grade corporate bonds.

[Table 4 about here]

The estimated coefficient on $Fed1_t$ in column 1 of Table 4 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., Fama, 2013; Jarrow and Li, 2014). We note, however, that the Fed response is potentially endogenous with asset price variation, so the results in Table 4 should not be taken as evidence of the ability of the Fed to subdue market instability.

The negative sign of the coefficient 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’ model 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 estimates reported in columns 2, 3, and 4 of Table 4 suggest that illiquidity has indeed a differential effect on the probability of flights for different classes of safe haven investments. As predicted by Vayanos’ model, 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 coefficient on $c_{illq_t}$ in column 2 of Table 4 also shows that illiquidity tends to decrease the incidence of flights to long-term Treasuries. Taking Vayanos’ prediction backward, 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.\(^\text{38}\)

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 the by-product of omitting the volatility of the fixed income securities in the model reported upon in Table 4. The volatilities of the three safe haven securities are strongly correlated, and have the opposite effects of the volatility of the stock market on the incidence of flight.\(^\text{39}\) When the volatility of the safe haven assets are accounted for in equation (4) then the effect of stock market volatility is positive, as expected (see the online appendix).

The works of Cooper et al. (2004), Daniel and Moskowitz (2013), and Barroso and Santa-Clara (2015) suggest that momentum gains are state dependent. In view of 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 5, 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

\(^{38}\)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 2 enables the identification of cross-asset contagion episodes, in addition to flights. See the online appendix for details.

\(^{39}\)The correlations of the variable $c_{stdev_s}$ with $c_{stdev_h}$, $c_{stdev_f}$, and $c_{stdev_c}$, are 0.54, 0.35, and 0.56, respectively.
incidence of flights, following downturns. This state effect on the link between flights and large momentum gains is observed for all types of flights.

[Table 5 about here]

An online appendix presents an extension of the static model reported upon in Table 4 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 market turmoil of the 2007-2009 crisis has modified the role of momentum gains, asset performance, volatility, market illiquidity, market state, and monetary policy in determining flight incidence, we analyze the static models discussed in Section 3.1 for the 2007-2014 sample, with the first 22-day crisis window starting on June 29, 2007.

Asness et al. (2013) suggest 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. It is thus presumable that including the spread in the model explaining flights described in Section 3.1 could affect the degree of association between large momentum gains and market instability. To test this possibility, the 2007-2014 sub-period is sufficiently recent to include in the static model the Libor-OIS spread. The tabulation of the results of this subsample analysis is relegated to the online appendix. The analysis of the 2007-2014 sub-sample reveals a substantial robustness of the link between the momentum effect and flights.

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 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.

40 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).
Table 6 summarizes the subsample 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 4 where this model is evaluated for the subsamples 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 momentum large 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 6 about here].

3.2 Dynamic Models

Section 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 4 with covariates that are calculated using data from the 44 day benchmark period preceding the crisis window, where the crisis and benchmark periods have been defined in Section 2. In this section we briefly summarize the findings yielded by the dynamic models that add some new nuances to this paper’s conclusions. The detailed discussion of the dynamic approach is relegated to the variable description appendix. 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.

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 cmnin_s,t and cmnax_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 this paper’s
Table 7 reports the marginal effects, and fit measures, for the dynamic models. As the coefficients 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. In this section we briefly summarize the aspects of the dynamic approach that add some new nuances to our conclusions.

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.

Previous contributions on the effect of monetary policy on markets (e.g., Kuttner, 2001; Bernanke and Kuttner, 2005) have shown that price changes of federal funds futures can be used to gauge changes in expectations on policy activities. 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., Bernanke and Kuttner, 2005; Gürkaynak et al., 2007). 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 expectations of laxer monetary stances.

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 abun-
dance of credit, might galvanize the economy, thus making flights less likely. On the other hand, if market participants’ increased expectations 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 more flights. Our empirical evidence support the latter explanation, as heightened expectations of loose monetary policy appear to increases the probability of flights to long-term Treasuries.

The marginal effect of the lagged variable $lFed_{1t}$ indicates that past monetary policy announcements exert a downward pressure on flight occurrence.\textsuperscript{44} Periods following announcements are less likely to be characterized by flights than periods following a benchmark period during which no announcement is observed, perhaps owning to 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 strict exogeneity assumption for explanatory variables, used to obtain the Probit maximum likelihood estimates, cannot be used in a dynamic setting owing to the presence of the lagged dependent variable.\textsuperscript{45} To obviate to this limitation, this paper’s takes a different approach 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. 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 asset classes is characterized by negative average returns over the crisis period for both markets and 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.\textsuperscript{46} 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

\textsuperscript{44}The variable $lFed_{1t}$, counts the number of monetary announcements over the benchmark period.

\textsuperscript{45}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.

\textsuperscript{46}Care has been exercised not to include flights and contagion episodes occurring during the crisis window.
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 $lfqst$ suggests that such 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 includes also 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 $lavix_t$ in the four models reported in Table 7 suggest that increased expectations of future volatility prompt investors to rebalance their portfolio away from stocks, causing an appreciation of safer assets.\footnote{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 3.1). This comparison unfortunately cannot be performed due to a large correlation, at 0.91, between $lstdev_{s,t}$ and $lavix_{s,t}$.}

We considered augmenting the extended static model discussed in the online 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 7, 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.

\section{Conclusions}

An innovation of this paper’s approach to the study of flights is that we consider three classes of safe 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 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. In the 1994-2014 sample, 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.

We document that strong showings of the momentum strategy are associated with the incidence of market instability. In particular, momentum is disproportionately profitable during 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. The strong profitability of the momentum strategy during flight-to-quality episodes suggests that periods of market instability may hide some silver lining for momentum traders.

Flights can be informally integrated in the classical interpretative framework proposed by the overreaction behavioral models. For example, flights can be thought as originating from the behavior of overconfident investors, as these overreact to news triggering rebalancing in favour of fixed income securities. However, flights might be the result of the reallocation of the aggregate portfolio in response to rising systematic risk, as risk averse investors shed riskier positions.

The analysis of Asness et al. (2013) suggests that momentum might capture the effects of funding illiquidity risk, where this is thought as the nonlinear effect of binding borrowing constrains on financial intermediaries, in the spirit of the asset pricing model proposed in Brunnermeier and Pedersen (2009). From this perspective, the significant link between momentum gains and market instability, established in this paper, may be interpreted as evidence that funding illiquidity is strongly associated with market instability.

Funding illiquidity is of course hard to measure. Indeed, our empirical analysis suggests that familiar direct measures of funding costs, like the Effective Federal Fund rate and the Libor-OIS spread, fail to effectively diminish the degree of association between momentum profits and market instability. The inability of these familiar gauges of credit availability to eclipse momentum in explaining market instability suggests that these measures may fail to capture the full effect of funding illiquidity. In this sense, these gauges of investors’ borrowing costs may be suitable to capture only selected features of the dynamics of credit flows in the market.

This paper’s results 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. 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, 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 market participants’ increased expectations 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).

From a methodological perspective, our analysis sports a real-time flavour which is new to the literature on market instability, as flights are identified avoiding look-ahead biases. To avoid sample selection biases, our work also endogenizes the timing of flights, by exploiting a rolling sample technique.

References


Adrian, T., R. K. Crump, and E. Vogt (2015). Nonlinearity and flight to safety in the risk-


Snider, C. A. and T. Youle (2012). The fix is in: Detecting portfolio driven manipulation of the libor. *Available at SSRN 2189015*.


### Table 1: Frequencies of Flights

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Windows</td>
<td>n = 6,236</td>
<td>n = 4,367</td>
<td>n = 504</td>
<td>n = 1,365</td>
</tr>
<tr>
<td>$ftqs$</td>
<td>932</td>
<td>589</td>
<td>135</td>
<td>209</td>
</tr>
<tr>
<td>(14.94)</td>
<td>(13.49)</td>
<td>(26.78)</td>
<td>(15.31)</td>
<td></td>
</tr>
<tr>
<td>$ftqs_b$</td>
<td>604</td>
<td>369</td>
<td>97</td>
<td>139</td>
</tr>
<tr>
<td>(9.68)</td>
<td>(8.45)</td>
<td>(19.24)</td>
<td>(10.18)</td>
<td></td>
</tr>
<tr>
<td>$ftqs_f$</td>
<td>428</td>
<td>300</td>
<td>75</td>
<td>53</td>
</tr>
<tr>
<td>(6.86)</td>
<td>(6.90)</td>
<td>(14.88)</td>
<td>(3.88)</td>
<td></td>
</tr>
<tr>
<td>$ftqs_c$</td>
<td>527</td>
<td>317</td>
<td>68</td>
<td>143</td>
</tr>
<tr>
<td>(8.45)</td>
<td>(7.25)</td>
<td>(13.49)</td>
<td>(10.47)</td>
<td></td>
</tr>
</tbody>
</table>

**Note:** This table summarizes the frequency of incidence of flights from stocks to long-term Treasuries ($ftqs_b$), T-Bills ($ftqs_f$), and Moody’s AAA corporate bonds ($ftqs_c$). The aggregate flight indicator $ftqs$ is the point-wise maximum of $ftqs_b$, $ftqs_f$, and $ftqs_c$. The table lists the raw number of events and the percentage over the number (n) of rolling subsamples in each subsample. The 1990-2014 period is partitioned into three subsamples, with cut-off dates being June 29, 2007 and June 30, 2009.

### Table 2: Average Momentum Returns

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Unconditional</td>
<td>0.63</td>
<td>0.93</td>
<td>-0.56</td>
<td>0.13</td>
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<tr>
<td>$ftqs = 0$</td>
<td>0.28</td>
<td>0.61</td>
<td>-2.45</td>
<td>0.09</td>
</tr>
<tr>
<td>$ftqs = 1$</td>
<td>2.63</td>
<td>2.94</td>
<td>4.63</td>
<td>0.39</td>
</tr>
<tr>
<td>$ftqs_b = 0$</td>
<td>0.44</td>
<td>0.77</td>
<td>-1.77</td>
<td>0.10</td>
</tr>
<tr>
<td>$ftqs_b = 1$</td>
<td>2.47</td>
<td>2.67</td>
<td>4.55</td>
<td>0.42</td>
</tr>
<tr>
<td>$ftqs_f = 0$</td>
<td>0.48</td>
<td>0.77</td>
<td>-1.04</td>
<td>0.07</td>
</tr>
<tr>
<td>$ftqs_f = 1$</td>
<td>2.74</td>
<td>3.06</td>
<td>2.20</td>
<td>1.70</td>
</tr>
<tr>
<td>$ftqs_c = 0$</td>
<td>0.48</td>
<td>0.80</td>
<td>-1.52</td>
<td>0.12</td>
</tr>
<tr>
<td>$ftqs_c = 1$</td>
<td>2.36</td>
<td>2.55</td>
<td>5.63</td>
<td>0.26</td>
</tr>
</tbody>
</table>

**Note:** The table reports the unconditional and stratified averages of the variable $mom_{22_t}$, in terms of percentage monthly returns. The variable $mom_{22_t}$ 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 $mom_{22_t}$, multiplied by 22. Stratification is by indicators of flights from stocks to long-term Treasuries ($ftqs_b$), T-Bills ($ftqs_f$), and Moody’s AAA corporate bonds ($ftqs_c$), and the aggregate flight variable $ftqs$. The aggregate flight indicator $ftqs$ is the point-wise maximum of $ftqs_b$, $ftqs_f$, and $ftqs_c$. 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 subsamples, with the cut-off dates being June 29, 2007 and June 30, 2009.
Table 3: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>$cdmom_t$</th>
<th>$car_s$</th>
<th>$car_b$</th>
<th>$car_f$</th>
<th>$car_c$</th>
<th>$cFed_{t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.547</td>
<td>0.044</td>
<td>0.101</td>
<td>0.131</td>
<td>0.088</td>
<td>3.188</td>
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<tr>
<td>Std.dev</td>
<td>0.499</td>
<td>0.216</td>
<td>1.272</td>
<td>1.093</td>
<td>1.004</td>
<td>2.425</td>
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<tr>
<td>Min</td>
<td>0</td>
<td>-1.639</td>
<td>-4.318</td>
<td>-4.591</td>
<td>-4.500</td>
<td>0</td>
</tr>
<tr>
<td>Max</td>
<td>1</td>
<td>0.984</td>
<td>7.273</td>
<td>8.455</td>
<td>7.318</td>
<td>15</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>$cstdev_{s,t}$</th>
<th>$camin_{s,t}$</th>
<th>$cmin_{s}$</th>
<th>$cmax_{s,t}$</th>
<th>$down_{t}$</th>
<th>$cilliq$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.963</td>
<td>0.475</td>
<td>0.065</td>
<td>0.088</td>
<td>0.191</td>
<td>0.660</td>
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<tr>
<td>Std.dev</td>
<td>0.596</td>
<td>0.499</td>
<td>0.247</td>
<td>0.284</td>
<td>0.393</td>
<td>1.240</td>
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<tr>
<td>Min</td>
<td>0.271</td>
<td>0</td>
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<tr>
<td>Max</td>
<td>5.346</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>14.597</td>
<td>11.505</td>
</tr>
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</table>

Note: The table reports the mean, standard deviation, minimum and maximum values of the variables employed in the probit model displayed in equation (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 $cFed_{t}$ 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 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 4: Static Model

### Panel A Marginal Effects (in percentage)

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1)</th>
<th>(2)</th>
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<th>(4)</th>
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<tbody>
<tr>
<td>cdmom</td>
<td>2.9***</td>
<td>1.5**</td>
<td>1.5***</td>
<td>1.7***</td>
</tr>
<tr>
<td>car_s</td>
<td>-2.6***</td>
<td>-0.8***</td>
<td>-1.2***</td>
<td>-1.1***</td>
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<tr>
<td>car_b</td>
<td>31.1***</td>
<td>67.5***</td>
<td>20.9***</td>
<td>17.6***</td>
</tr>
<tr>
<td>car_f</td>
<td>26.7***</td>
<td>-1.8</td>
<td>33.9***</td>
<td>-3.0</td>
</tr>
<tr>
<td>car_c</td>
<td>25.7***</td>
<td>-16.7**</td>
<td>-17.9***</td>
<td>43.6***</td>
</tr>
<tr>
<td>camin_s</td>
<td>18.5***</td>
<td>15.1***</td>
<td>9.2***</td>
<td>13.1***</td>
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<td>cmin_s</td>
<td>-0.8</td>
<td>-3.4***</td>
<td>4.1***</td>
<td>-4.8***</td>
</tr>
<tr>
<td>cmax_s</td>
<td>0.6</td>
<td>2.1**</td>
<td>-1.8*</td>
<td>3.6***</td>
</tr>
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<td>cstdev_s</td>
<td>0.1</td>
<td>-0.04</td>
<td>-0.1</td>
<td>0.02</td>
</tr>
<tr>
<td>calliq</td>
<td>-0.1***</td>
<td>-0.3***</td>
<td>0.02*</td>
<td>-0.2***</td>
</tr>
<tr>
<td>cFed1</td>
<td>-0.9***</td>
<td>-0.4***</td>
<td>-0.9***</td>
<td>-0.5***</td>
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<tr>
<td>down</td>
<td>4.8***</td>
<td>3.4***</td>
<td>2.4***</td>
<td>2.4***</td>
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</table>

### Panel B Basic Diagnostics

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<tr>
<th>McFadden Pseudo R-squared</th>
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<th>(4)</th>
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<td>Prediction Success</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual 1s correctly predicted</td>
<td>45.6%</td>
<td>36.0%</td>
<td>34.7%</td>
<td>32.1%</td>
</tr>
<tr>
<td>Actual 0s correctly predicted</td>
<td>90.9%</td>
<td>93.4%</td>
<td>95.3%</td>
<td>94.0%</td>
</tr>
</tbody>
</table>

**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 (4), over the 1990-2014 sample. The dependent variables are the indicators of flights from stocks to long-term Treasuries ($ftqs$), T-Bills ($ftqsf$), and to Moody’s AAA corporate bonds ($ftqsc$). The aggregate flight indicator $ftqs$ is the point-wise maximum of $ftqs$, $ftqsf$, 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 online appendix.
Table 5: State Dependent Marginal Effects

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>$ftqs$</th>
<th>$ftqsb$</th>
<th>$ftqsf$</th>
<th>$ftqsc$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$cdmom$, $Down = 0$</td>
<td>2.88***</td>
<td>1.41***</td>
<td>1.38***</td>
<td>1.64***</td>
</tr>
<tr>
<td>$cdmom$, $Down = 1$</td>
<td>3.53***</td>
<td>1.78***</td>
<td>1.85***</td>
<td>2.04***</td>
</tr>
</tbody>
</table>

**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 $cdmom$ over the market state for the static model summarized in Table 4. 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 6: Subsamples Marginal Effects of $cdmom$ (in percentage)

<table>
<thead>
<tr>
<th>Sample Period</th>
<th>$ftqs$</th>
<th>$ftqsb$</th>
<th>$ftqsf$</th>
<th>$ftqsc$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample 1994-2014</td>
<td>2.9***</td>
<td>1.5**</td>
<td>1.5***</td>
<td>1.7***</td>
</tr>
<tr>
<td>Subsample 1990–2007</td>
<td>3.1***</td>
<td>0.59</td>
<td>1.74***</td>
<td>2.89</td>
</tr>
<tr>
<td>Subsample 2009-2014</td>
<td>5.32***</td>
<td>3.18***</td>
<td>2.97***</td>
<td>3.80**</td>
</tr>
</tbody>
</table>

**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 4 evaluated in the subsamples 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 $ftqsc$. 

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Table 7: Dynamic Model

<table>
<thead>
<tr>
<th>Panel A Marginal Effects (in percentage)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Dependent Variable</td>
</tr>
<tr>
<td>cdmom</td>
</tr>
<tr>
<td>ldmom</td>
</tr>
<tr>
<td>car_s</td>
</tr>
<tr>
<td>car_b</td>
</tr>
<tr>
<td>car_f</td>
</tr>
<tr>
<td>car_c</td>
</tr>
<tr>
<td>camin_s</td>
</tr>
<tr>
<td>cmin_s</td>
</tr>
<tr>
<td>cmax_s</td>
</tr>
<tr>
<td>cstdev_s</td>
</tr>
<tr>
<td>cFed1</td>
</tr>
<tr>
<td>lamin_s</td>
</tr>
<tr>
<td>lavix</td>
</tr>
<tr>
<td>lFed1</td>
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<tr>
<td>lFed2</td>
</tr>
<tr>
<td>lffqs1</td>
</tr>
<tr>
<td>lncns1</td>
</tr>
<tr>
<td>down</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B Basic Diagnostics</th>
</tr>
</thead>
<tbody>
<tr>
<td>McFadden Pseudo R-squared</td>
</tr>
<tr>
<td>Prediction Success</td>
</tr>
<tr>
<td>Actual 1s correctly predicted</td>
</tr>
<tr>
<td>Actual 0s correctly predicted</td>
</tr>
</tbody>
</table>

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 online appendix.
Figure 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 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: 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 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.