Momentum and Seasonality in Corporate Bonds

by

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Abstract

This thesis explores the market efficiency in the US and Canadian corporate bond markets through examining the profitability and time variations of two widely studied asset pricing anomalies, i.e., the momentum effect and the return seasonality. The momentum effect refers to the abnormal gains from holding portfolios formed by taking long positions on past winners and short positions on past losers, where winners and losers are identified by ranking assets on the basis of their historical performance. The return seasonality, and more specifically the calendar effect, arises when mean returns on certain assets appear to be abnormally high/low in a given calendar period (e.g., in January).

Using transaction-based bond-level data from 2002 to 2014, Chapter 1 of this thesis documents that momentum profits for corporate bonds depend on the state of the market (UP/DOWN). Momentum gains exclusively follow UP periods. In contrast, DOWN markets herald momentum losses. Importantly, this study links momentum gains to underpricing, as measured by low stock market sentiment. In particular, the UP-market momentum gains are generated exclusively by momentum portfolios formed in periods of low sentiment. The DOWN-market reversal returns in low sentiment are even larger than the UP-market momentum gains. We also introduce a novel top-volume bond momentum strategy and show that it yields large and persistent unconditional profits.

The second chapter extends the analysis of the momentum effect in corporate bonds to the Canadian market. This chapter contributes to the sparse scholarly literature on the Canadian financial sector and provides an out-of-the-sample validation of the

empirical results obtained from the US market. Using bond-level data for a sample ranging from 1987 to 2016, this chapter documents that the momentum effect is significant in the Canadian market for corporate bonds. The strategy yields momentum gains that are comparable to those observed for US corporate bonds. Conditioning on the market state (UP/ DOWN) doubles the returns on the momentum portfolio for holding periods ranging from one month up to two years. Further, momentum gains are exclusive to the UP market state. Importantly, the conditional analysis reveals that the state of the market brings about sizeable momentum returns also for investment grade bonds, especially in the most recent years of the sample.

The third chapter studies monthly seasonal variations in Canadian corporate bond returns. I find that the seasonal patterns switched around the 2007-09 financial crisis, from a negative March effect to significant gains in January and July. The January and July effects can be attributed to the reinvestment of coupon payments, a majority of which are paid in December and June. The surging demand for bonds in the months following intensive coupon payments (i.e., in January and July) resulted in higher monthly realized returns. The long period of decreasing expected long-term interest rates in the post-crisis period made reinvestments into bonds more appealing, thus making the January and July effects much more pronounced in the post-crisis period. Further, I show that the negative March effect stems from seasonal variations in the US long-run borrowing cost, prior to the financial crisis.

Preface

Some of the research conducted for this thesis is collaborated with my supervisor, Dr. Valentina Galvani. Chapter One of this thesis has been published as Li, L. and Galvani, V., 2018. "Market states, sentiment, and momentum in the corporate bond market," *Journal of Banking & Finance*, 89, 249-265. I was responsible for the data collection and analysis. Dr. Galvani was the supervisory author, and we shared the work in concept formation and manuscript composition. Chapter Two of this thesis is a co-authored work with Dr. Galvani. I was responsible for the data collection and analysis. Dr. Galvani was the supervisory author, and we shared the work in concept formation and manuscript composition. Chapter Three of this thesis is my original work.

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Introduction

The corporate bond market is becoming increasingly important for firms to raise capital. Further, corporate bonds comprise of a sizeable portion of both institutional and retail investors, where small investors' participation is typically through bond market indexes. According to reports from the Securities Industry and Financial Markets Association (SIFMA), the new issuance of corporate bonds by US companies in 2017 was $1.7 trillion, contributing to the $9 trillion outstanding amount at the end of 2017.[1] While the number of listed US companies fell by 46.4% in 2017, relatively to the peak of 8,090 companies in 1996, the issuance of corporate bonds more than quadrupled during the same period. Meanwhile, the Canadian corporate bond market is much smaller, at 1.13 trillion in 2016, being about one-seventh of the US market. However, the relative size of the Canadian corporate bond market is larger than that of the stock market, which is one-tenth of the US market cap.[2]

However, the corporate bond market has not gained much attention from financial economists. Therefore, with respect to the scholarly literature on equities, that on corporate bonds is relatively limited. Particularly, the literature on the Canadian corporate bond market is extremely sparse, despite the substantial (relative) size of the market, a situation most likely due to the paucity of the available data. This thesis focuses on studying the market efficiency in both the US and Canadian corporate bond markets, and as such contribute to the development of the scholarly literature.

The classic theory of efficient market hypothesis (EMH) proposed by Fama (1991) states that the asset market is at least weakly efficient if historical price patterns have

[1] As a comparison, the US stock market capitalization was 32 trillion at the end of 2017.
[2] Canadian data are obtained from the Bloomberg database.

no predictability on future prices and returns. The literature has documented numerous asset pricing anomalies for stocks that weaken the EMH as, to name a few, the January effect (e.g., Wachtel, 1942; Rozeff and Kinney, 1976; Keim, 1983; Lakonishok and Smidt, 1984; Tinic and West, 1984), the momentum and reversal effects (first documented in Bondt and Thaler, 1985; Jegadeesh and Titman, 1993, respectively), as well as the cross-sectional seasonality documented in Heston and Sadka (2008).

Within the thin literature on corporate bond market efficiency, there is limited evidence supporting the prevalence of asset pricing anomalies, those first discovered for stocks, also in the corporate bond market. For instance, Gebhardt et al. (2005) document that the momentum effect fails to thrive in investment-grade bonds. Consistently, Jostova et al. (2013) find that the momentum effect is only profitable for high-yield speculative bonds. Further, studies have shown that the January effect is significant only for low quality corporate bond indexes (e.g., Smirlock, 1985; Chang and Huang, 1990; Fama and French, 1993; Al-Khazali, 2001).

As noted in Lin et al. (2017), the share of speculative bonds in the US market is small, at about 8%, in value terms. Further, the Canadian corporate bond market has been shown to be characterized by an even higher share of investment-grade to high-yield bonds than the US market (Patel and Yang, 2015). Therefore, the findings that both the momentum and seasonal gains are negligible for investment-grade bonds, as documented in the literature, indicate that asset pricing anomalies stemming from the stock market may be irrelevant for corporate bonds. However, more detailed analysis are required before reaching a firm conclusion on this conjecture. Therefore, the research question in this thesis is to ask whether the persistent stock market anomalies, i.e., the momentum effect and the seasonal calendar effect, lost their momentum in the corporate bond market.

Recently, as the development of the behavioral finance literature, studies on market efficiency have taken the approach of examining how the interaction between changes of market states and investors' behavior influences the time variations of asset pricing anomalies. For instance, it has been established that once the academic literature identifies an abnormally profitable strategy, its gains enter a descending trajectory, as more traders crowd the profitable positions (e.g., Chordia et al., 2014; McLean and Pontiff, 2016; Jones and Pomorski, 2017), a result that is consistent with the Adaptive Markets Hypothesis (AMH) proposed in Lo (2004). The AMH states that any anomaly can be more profitable in certain market environments, and less so in others. As the market condition changes, e.g., as a new anomaly is discovered, other profitable portfolios may be created, while existing profit opportunities may disappear. The AMH broadens the application of the EMH by viewing the various anomalies from the behavioral perspective as temporary adaptation and adjustment of investors to a changing environment.

Therefore, it is reasonable to argue that, in the corporate bond market, the overall poor performance of strategies exploiting the two anomalies might be the result of aggregations of significant gains and losses over different sub-periods. This hypothesis motivates the research question further to ask whether the profitability of the two anomalies are dependent on changes in the market environment.

Specifically, the first two chapters of this thesis study the profitability of the momentum effect and its time variations, in the US and Canadian corporate bond markets, respectively. The two chapters document that the profitability of momentum strategies is strongly dependent on the overall state of the bond market. Further, low levels of investors' sentiment magnify the market state effect on the performance of momentum strategies for the US corporate bonds. The third chapter focuses on market inefficiencies associated with seasonal patterns in the returns of Canadian corporate bonds. The results indicate the existence of strong seasonal effects, which, however, appear to have changed after the 2007-09 financial crisis.

Chapter 1

Market states, sentiment, and momentum in the corporate bond market

1.1 Introduction

The momentum strategy (Jegadeesh and Titman, 1993) exploits the persistence of the cross-sectional return spread between past winners and losers, where these groups are identified by ranking assets on the basis of their historical performance. Returns on the momentum strategy have been shown to be time-varying (e.g., Daniel and Moskowitz, 2016; Barroso and Santa-Clara, 2015), and also state dependent (Cooper et al., 2004) in the equity market. Less is know on the time variations of the momentum effect in the corporate bond market. This study aims to fill this gap by identifying indicators that serve to predict *ex-ante* the time variations of the momentum portfolio returns in the US corporate bond market. Our main contribution is to show that the momentum effect is markedly state-dependent with its conditional profitability originating from underpricing of the US corporate bonds.

Our empirical evidence indicates that momentum gains are obtained exclusively in UP markets, whereas significant momentum losses are detected only for the DOWN market state.[1] In UP markets, the six-month formation and holding period momentum strategy generates a significant monthly return of 58 bps. In DOWN markets, significant momentum losses, i.e., reversal profits, reach 38 bps and 49 bps per month over the 18 and 24-month horizons, respectively. Interestingly, these reversal returns are not preceded by any momentum profits in the short run, which suggests that momentum and reversal need not be temporally linked for corporate bonds, as already argued for the equity market (e.g., Cooper et al., 2004; Conrad and Yavuz, 2017). Further, the return spread for the momentum strategy in the UP and DOWN market states is statistically significant, with the state effect being observed for holding period horizons ranging from one month up to two years.

A comparison of the conditional momentum returns documented for equities and their analog for corporate bonds reveals strong similarities between the market state effect in the two markets. Momentum gains can be obtained only in UP markets. Moreover, momentum portfolios in DOWN states yield insignificant losses over the short run, but entail significant negative returns (i.e., reversal gains) for holding periods longer than one year. The UP-market momentum gains, as well as the losses observed for DOWN markets, are about a third weaker for corporate bonds than for equities.

We further document that conditioning on the market state brings about significant momentum profits also for investment-grade bonds, a result that is novel to the literature.[2] Meanwhile, the conditional analysis identifies a profitable investment opportunity for agents holding investment-grade bonds. There is evidence of a strong reversal effect in DOWN markets, especially for long holding periods, which yields an annual return of -5.5% over the two-year horizon. These results complement the conclusions of the extant literature on the profitability of the momentum strategy for investment-grade corporate bonds, which indicate that momentum gains are limited to speculative-grade bonds (e.g., Gebhardt et al., 2005; Jostova et al., 2013).

[1] Momentum returns are classified as stemming from UP or DOWN markets ex-ante, that is on the basis of the lagged one-year market return preceding portfolio formation.

[2] For instance, the two-year holding period cumulative returns reach 4% in the UP markets for strategies formed with investment-grade bonds.

The strong predictive power of the market state is consistent with the extended version of the behavioral theory developed by Daniel et al. (1998), as the market state influences investors' overconfidence (e.g., Gervais and Odean, 2001), which originates the momentum effect. However, the literature has proposed other aggregate measures of overconfidence (e.g., the BW sentiment index in Baker and Wurgler, 2006). For instance, Stambaugh et al. (2012) link the momentum effect in the equity market to investors sentiment. They document that the profitability of the momentum strategy is exclusive to periods marked by high levels of the BW sentiment index, which measures aggregate overpricing caused by market-wide sentiment in the stock market. In particular, they argue that, if frictions in selling assets short hamper agents' ability to counter overpricing (Miller, 1977), momentum gains should stem from past losers being more overpriced than past winners. The relationship between investors sentiment and the momentum effect for US corporate bonds remains mixed in the literature.[3] Our empirical study, therefore, also contributes to the scholarly discussion on the role of sentiment in determining asset mispricing.

Presently, we find that sentiment has a weaker predictive power than the market state for future momentum returns in the corporate bond market. Still, conditioning on sentiment magnifies the short-term momentum gains for speculative-grade bonds. Interestingly, however, the market state interacts with sentiment to yield strong predictability on the momentum returns. In particular, the momentum gains associated with UP markets originate exclusively from periods following low sentiment. To illustrate, conditioning on the UP state and low sentiment yields a 90 bps monthly return, over the six-month horizon, which is about 55% larger than the analogous return obtained conditioning on UP markets alone. Likewise, the negative momentum returns obtained in DOWN markets are exacerbated in periods following low sentiment months. The momentum returns on the two-year horizon observed in DOWN markets more than double when conditioning on both the DOWN market state and low

[3] For example, Lin et al. (2017) document that momentum gains are marginally stronger when sentiment is low than when sentiment is high. While evidence in Avramov et al. (2017) appears to suggest that high sentiment may be linked to large momentum gains in the corporate bond market.

sentiment, yielding a reversal profit of 1% per month.

Our empirical evidence reveals a significantly negative relationship between sentiment and momentum gains, with significant momentum profits being associated exclusively with periods of low sentiment.[4] Two possible mutually exclusive explanations offer themselves for the negative relationship. The first upholds the link between short-selling and the effect of overpricing proposed in Stambaugh et al. (2012), by assuming that high sentiment gauges stock market overpricing but bond market underpricing. The second explanation abandons the notion that overpricing is linked to strong momentum gains, and proposes that the momentum effect in the bond market is instead due to underpricing in low sentiment periods. Potentially, the causes of the persistence of underpricing do not depend on limitations on executing short sales. Both explanations yield testable predictions on the profitability of the short and long side of the momentum portfolio in periods of high or low sentiment. We examine these potential explanations in a dedicated section.

Our analysis concludes that sentiment gauges overpricing in both the stock and bond markets. Further, we find strong evidence indicating that the profitability of the momentum strategy is due to past winners being more underpriced than past losers. Hence, this study's conclusion on the role of sentiment supports the view that underpricing, rather than overpricing, is driving the profitability of the momentum strategy in the corporate bond market. This conclusion is unique to the bond market and offers a novel perspective on the role of mispricing in the corporate bond market. It suggests that underpricing cannot be counterbalanced by rational agents investing in corporate bonds as easily as done for equities. Conversely, the extent to which overpricing may be originating the momentum effect in the bond market appears to be limited. The literature documenting underpricing of US corporate bond issues is large (e.g., Cai et al., 2007; Brugler et al., 2016). However, this paper is the first to document that corporate bonds are also underpriced in the secondary market.

Stambaugh et al. (2012) attribute the effect of overpricing in the equity market to

[4]These empirical results are not inconsistent with the extant literature (e.g., Lin et al., 2017).

short-selling frictions, in that rational agents are unable or unwilling to exert downward pressure on inflated stock prices due to reasons such as arbitrage risk and behavioral biases of traders. Güntay and Hackbarth (2010), nevertheless, document that short-sale constraints have limited impact on corporate bond prices. Their conclusion implies that the link between short selling frictions and the profitability of trading strategies based on mispricing may be absent in the bond market. This argument is corroborated by our evidence of insignificant momentum gains following high sentiment. The results of this study, therefore, suggest the need for an alternative limited arbitrage argument for mispricing-based corporate bond momentum gains. A potential explanation of an underpricing-based risk premium is that agents may not be able to assume long positions on underpriced assets, due to low liquidity.

Sentiment is not the only market indicator featuring a weak predictive power for the profitability of the momentum strategy in corporate bonds. Indeed, we show that conditioning on the market state dominates a host of other market indicators in terms of their ability to discriminate momentum gains versus losses. As it is the case for sentiment, the interaction of these conditioning variables with the market state generally increases the state dependence of momentum returns, especially for holding period horizons exceeding the one-year mark. However, the ability of these indicators to amplify the market state effect is weaker than the one yielded by sentiment. These results are discussed in an appendix for the risk aversion and uncertainty indicators proposed in Bekaert et al. (2013) and Bekaert and Hoerova (2016), and the implied volatility index for Treasuries used by Mueller et al. (2012).

Our analysis relies on bond returns that are calculated using transaction-level data, as found in the Trade Reporting and Compliance Engine (TRACE). Besides minimizing measurement errors in bond returns, the granularity of the data offered by TRACE allows us to exploit an additional possibility to improve the unconditional returns on the momentum strategy. We construct a novel type of momentum portfolio which capitalizes on the heterogeneity in the information content of bond prices, at the issuer level.[5]

The proposed trading strategy relies only on bonds with the highest end-of-the-month trading volume per issuer per month. Hence, the top-volume bond momentum strategy is firm-based, as it is the case for the momentum strategy in the equity market. We document that the returns of the top-volume strategy are significantly larger, as well as more persistent, than those yielded by the momentum portfolios based on the entire cross-section of bonds.

The rest of the paper is organized as follows. The next section offers basic summary statistics of the bonds in our sample and describes the methodology employed to calculate holding period monthly returns, as well as cumulative rates of return. Section 1.3 offers an unconditional assessment of the profitability of the momentum effect in the corporate bond market, including the analysis of the momentum strategy based on top-volume bonds. The examination of the market state effect can be found in Section 1.4. Next, we analyze the predictive power of sentiment in Section 1.5, followed by the conclusion.

1.2 Data and Returns

Our empirical analysis relies on data from TRACE Enhanced for the period spanning from July 2002 to December 2014.[6] We include in our sample only publicly traded bonds.[7] Following the cleaning procedure in Dick-Nielsen (2014), we minimize data reporting errors by removing all transactions that are marked as cancellation, correction, and reversals, as well as their matched original trades. Agency transactions that may raise concerns of double-counting are also deleted.

To further filter the bonds based on their characteristics, we match bonds in TRACE

[5] The research of Ronen and Zhou (2013) and then Tsai (2014) documents a substantial heterogeneity in the information content of bond prices, at the firm level.

[6] Enhanced TRACE excludes the most recent 18 months of data that are available from standard TRACE. While the Enhanced TRACE contains fewer transactions than that included in the standard TRACE sample, more detailed transaction-level information (e.g., actual trade volume for larger transactions) are available only from Enhanced TRACE. The total number of intra-day transaction data recorded in TRACE Enhanced is 145,720,692 for the time-period considered.

[7] Hence, all transactions that are labeled as 144A are omitted from the sample.

with the Mergent FISD database using the 9-digit CUSIP. Among the matched bonds, we select those that are US-dollar denominated and pay a fixed-coupon (or zero-coupon). Further, we include in the sample only bonds issued by corporations, and that are not part of unit deals. We exclude bonds with warrants and special contingencies (i.e. preferred shares, puttable, convertible, exchangeable, asset-backed, etc.). The final sample contains 591,544 monthly transaction-based price observations for 12,017 bonds issued by 2,349 firms.[8] We use the TRACE Masterfile to classify bonds into the speculative and investment grade categories. Information on credit grade is available for about 61% of the bond-month observations in the final sample.

We calculate trade-size weighted daily prices from the intra-day transactions contained in the cleaned sample. The month-end prices that are required to calculate returns are obtained as the last available daily price of each bond in each month. Individual bond returns are calculated on the basis of these month-end prices for each bond in the sample. More precisely, the monthly return $r_{i,t+1}$ of bond i over the holding period from month t to $t+1$ is defined as follows:

$$r_{i,t+1} = \frac{(P_{i,t+1} + AI_{i,t+1} + C_{i,t+1}) - (P_{i,t} + AI_{i,t})}{P_{i,t} + AI_{i,t}} \tag{1.1}$$

where, $P_{i,t+1}$ is the price of bond i in month $t+1$, $C_{i,t+1}$ is the amount of coupon payment yielded by the bond between time t and $t+1$ (if any), which is calculated as the ratio of the annual coupon rate of bond i to its coupon frequency.[9] The accrued interest $AI_{i,t+1}$ is defined as follows:

$$AI_{i,t+1} = C_{i,t+1}\left(\frac{d_{t+1}}{D_{t+1}}\right),$$

where d_{t+1} is the number of days between time $t+1$ and the last coupon payment date, and D_{t+1} is the number of days between the two consecutive coupon payment

[8] The total number of monthly observation before filtering is 2,119,012 for 109,089 bonds.

[9] Information on coupon size and frequency as well as the first coupon-payment date that are required to calculate the returns are obtained through matching the bonds in our sample with the Bloomberg database using CUSIP numbers.

dates leading to, and following, the price $P_{i,t+1}$.[10] Table 1.1 tabulates basic descriptive statistics for our sample.

We form the momentum portfolio of bonds as already done in Gebhardt et al. (2005) and Jostova et al. (2013). Presently, the momentum portfolio formed in month t is obtained after sorting bonds into deciles on the basis of their historical cumulative returns over the formation period. An equally weighted portfolio of the bonds in the top (bottom) decile identifies the long (short) leg of the momentum anomaly. The holding period monthly return of the momentum strategy is defined following Jegadeesh and Titman (1993) as the average of the cross-section monthly returns of the overlapping decile portfolios. We also consider the sum of the monthly returns of the momentum portfolio over the holding period, to obtain the holding period *cumulative* return. We focus on momentum portfolios with a six-month formation period, as in Gebhardt et al. (2005) and Jostova et al. (2013).[11] For all strategies, we skip a month between the formation and holding periods. This month is henceforth called the formation month. We consider holding period horizons spanning from one month up to two years.

The series of momentum gains associated with six-month formation period and n-month holding period monthly returns and n-month holding period cumulative returns are denoted by $\mathrm{R}_{n,t}$ and $\mathrm{CR}_{n,t}$, respectively. Following Jegadeesh and Titman (1993), for each holding period n, the holding period return $\mathrm{R}_{n,t}$ is the cross-sectional average at time t of the returns on n overlapping momentum portfolios. Each of this overlapping strategies is formed in one of the n months preceding time t. The cumulative return $\mathrm{CR}_{n,t}$ is the sum of the n monthly returns of the momentum portfolio formed in month $t - n$.

Later on in this study we shall perform a conditional analysis of the return on the momentum strategy using cumulative rather than monthly holding period returns. Holding periods monthly returns are cross-sectional averages of overlapping momen-

[10] When dealing with the calculation of accrued interests, as well as determining whether coupons are paid in-between months, we apply the actual day count convention given information on the coupon frequency and the first coupon-payment date.

[11] In an unreported robustness check we have verified this study's conclusions using the symmetric momentum strategies proposed in De Bondt and Thaler (1987), where the formation and holding periods are of the same length. The results are available upon request.

tum portfolios which are formed in different months. Because the formation months are staggered, it is unclear the degree to which the returns on the overlapping portfolios are influenced by any given realization of a conditioning variable. In contrast, cumulative returns are calculated for momentum portfolios that are formed in a unique month, which then can be linked to a unique realization of the conditioning variable under consideration. This key difference between cumulative and monthly holding period returns make the latter less suitable than the former to perform a conditional analysis of the predictive type. Consistently, this study's conditional analysis of the performance of the momentum strategy focuses on cumulative returns. This approach is consistent with that relied upon in Cooper et al. (2004) to analyze the market state effect for momentum, in the equity market.[12]

The impact of rebalancing on portfolio performance may be particularly relevant in the corporate bond market, due to high transaction costs (e.g., Edwards et al., 2007). The buy-and-hold portfolios generating cumulative returns are thus potentially more cost efficient than the monthly rebalanced portfolios yielding the holding period monthly returns. From this perspective, an additional advantage of considering cumulative rather than holding period monthly returns is that the estimated profits are less susceptible to be wiped away by transaction costs.

1.3 Unconditional Momentum Returns

Panel A.1 in Table 1.2 documents that the momentum strategy yields holding period monthly returns that are significant up to the six-month horizon. In Panel A.2 and A.3 of the same table we document that for the one and three-month holding periods the significant gains appear to stem from portfolios of speculative-grade bonds, whereas pooling all the bonds in the sample, with the inclusion of those that are not categorized as speculative or investment grade, generates significant momentum gains over

[12] Recent literature has examined the conditional profitability of the momentum strategy for the one-month holding period (e.g., Lin et al., 2017), an approach that does not require the use of overlapping portfolios. However, using cumulative returns allows evaluating conditional profitability for holding period horizons longer than one month.

the six-month horizon.[13] Panel B.1 of the same table documents lower cumulative returns on the momentum portfolios for long holding period horizons. Getting ahead of ourselves, the conditional analysis will reveal that these low cumulative returns are the result of the aggregation of significantly different levels of momentum profitability across the market states.

A comparison of the returns on the six-month formation period strategy employed in Jostova et al. (2013) and in this study, reveals lower momentum profits for the recent years. Weaker momentum average returns may be attributed to many causes. For instance, the momentum effect in the corporate bond market may be vanishing in recent years because of its exposure to the scholarly debate. Indeed, McLean and Pontiff (2016) have suggested that once the academic literature identifies an abnormally profitable strategy, its gains enter a descending trajectory, as more traders crowd the profitable positions.[14] Further, the momentum strategy is prone to suffer several severe crashes, at least in the equity market (e.g., Daniel and Moskowitz, 2016), which potentially impair its average profitability.

1.3.1 Top-Volume Bonds

The momentum strategies for corporate bonds examined in the literature exploit the cross-sectional return spread between past winners and losers, where these groups are identified by ranking, on the basis of their historical performance, all the bonds in the cross-section. Hence, the momentum strategy is, by design, attributing the same informational content to the price movements of all the bonds included in the firm-level cross-section.

Using TRACE data Ronen and Zhou (2013), and then Tsai (2014), conclude that investors inject information into bond prices using a handful of bonds per firm, namely the top bonds, which are identified by a high concentration of large trades. We ar-

[13]Using a comprehensive dataset of US corporate bonds spanning the period from 1973 to 2011, Jostova et al. (2013) show that most of the momentum profits stem from portfolios of speculative-grade bonds.

[14]The first paper to discuss momentum gains in the corporate bond market dates back to 2005 Gebhardt et al. (2005).

gue that a substantial heterogeneity across bonds at the issuer level, in terms of the information content of prices, may imply a downward bias in the estimation of the returns on the momentum portfolios that are designed on the basis of all the bonds in the cross-section. For instance, should the momentum effect be linked to agents' overreaction (as in Daniel et al., 1998) or to underreaction (e.g., Hong and Stein, 1999) to firm-level news, the momentum effect would be detectable only for momentum portfolios including those bonds that investors choose to inject their information, or beliefs, into the market.

In the spirit of the top-bond argument proposed by Ronen and Zhou (2013), in this study we propose a momentum strategy based on top-volume bonds. These bonds are extracted from the monthly cross-section on the basis of end-of-the-month trading volume.[15] In particular, the top-volume bond for a given issuer, in a given month, has the highest end-of-the-month trading volume among the bonds issued by the same firm.[16] There is a unique top-volume bond per firm and per month.

To form the top-volume momentum strategy, past winners and losers are identified ranking into deciles firms on the basis of the cumulative returns of their top-volume bonds, over the six months preceding the formation month. Hence, the strategy identifies a set of firms, rather than a set of bonds, as past winners and past losers. In this sense, the top-volume bond momentum strategy is firm-based, as it is the case for the momentum strategy in the equity market.

The use of top-volume bonds is meant to capitalize on the heterogeneity of the information content of bond prices, at the firm-level. Recently, Avramov et al. (2017) aggregate bond returns at the issuer level, for publicly owned firms, by considering the return on the Equally Weighted (EW) portfolio of all bonds, for each firm. The use of top-volume bonds and of the EW portfolio are equivalent if the information content of

[15] For each month, and each bond, the monthly end-of-the-month trading volume is identified by the sum of volume of all the trades that support the end-of-the-month price. In turn, this price is a volume weighted average of the prices linked to individual end-of-the-month (i.e., last available) transactions.

[16] Ronen and Zhou (2013) focuses on large transactions to place emphasis on the activities of institutional traders, and thus to isolate information-rich bond prices. A distinction between the bond-level volume generated by large versus small trades would be useful to ascertain whether momentum traders are more prevalent among retail or institutional investors, a topic we leave for future research.

bond prices is uniformly distributed, at the firm level, across bonds. Also Chordia et al. (2017) employ the EW portfolio of the bonds in the firm cross-section. However, they additionally consider extracting from the issuer cross-section one randomly chosen bond, the bond with the shortest maturity, and the most recently issued bond. They motivate these alternative approaches invoking the findings of Bao et al. (2011) who show that bonds with the shortest maturity and the on-the-run issue are the most liquid bonds in the firm cross-section. From this perspective, the use of top-volume bonds is a way to capitalize on the availability of transaction-level data by identifying the most liquid bonds in the firm cross-section directly by the trading volume of the transactions supporting the prices used to calculate asset returns.

The empirical evidence presented in Panel A.4 of Table 1.2 for the momentum strategy in top-volume bonds is strongly consistent with the intuition that evaluating the momentum effect using the full cross-section causes a downward bias on momentum returns. Focusing on bonds that attract the highest level of trading volume yields unconditional momentum returns that are more persistent than those observed for momentum portfolios that are formed on the basis of the entire cross-section. The momentum effect for top-volume returns are significant for holding period horizons ranging from one month to two years, whereas momentum gains from the standard momentum portfolios are significant only up to six months from portfolio formation, as shown in Panel A.1 of Table 1.2. The top-volume returns are also stronger. For instance, the holding period monthly return on the momentum strategy in top-volume bonds is 83% larger than that stemming from the momentum strategy based on the entire cross-section, at the one-year holding period horizon. The analog figure for the one-month holding period is 39%.

Chordia et al. (2017) examine the relationship between the past six-month cumulative return on individual bonds, and their one-month holding period return, with a month skipped before the holding period. They find similar results when using the full cross-section of bonds and the single-bond per firm return approach. However, our results indicate that the use of top-volume bonds does improve the profitability of the momentum strategy.

In the following sections, as we examine the conditional profitability of the momentum strategy, we shall focus on cumulative returns, rather than on the monthly holding period returns. In particular, we examine cumulative returns for holding periods ranging from one month to two years. However, we won't be discussing cumulative returns for the top-volume bond momentum strategy beyond the one-month horizon. This limitation is driven by the very nature of the strategy, as the top-volume momentum portfolio maintains holdings of the top-volume bonds issued by the winner and loser firms throughout the holding period. The portfolio requires rebalancing in each month of the holding period, as the top-volume bonds representing winner and loser firms change over time.

Cumulative returns are typically designed to gauge the performance on buy-and-hold portfolios.[17] From this perspective, the cumulative return on the top-volume winner-minus-loser trade is a poor performance measure of this momentum strategy, as the portfolio is rebalanced every month of the holding period. Consistently, in this study we analyze the conditional performance of the top-volume strategy only using one-month cumulative returns.

In Panel B.4 of Table 1.2, the one-month cumulative return for the top-volume bond momentum portfolio is significant and higher than the one-month cumulative return yielded by the momentum strategy obtained employing the full bond cross-section. Its magnitude makes it comparable to the corresponding return for the speculative grade momentum portfolio.

1.4 State Dependent Momentum

Previous literature on the momentum strategy clearly illustrates that the strength of the momentum effect is time-varying (e.g., Daniel and Moskowitz, 2016; Barroso and

[17] For example, the cumulative returns on the six-month momentum portfolios summarized in Panel B.1 of Table 1.2 are yielded by a buy-and-hold strategy of the bonds that have been identified as past winners and losers in the formation month.

Santa-Clara, 2015). Substantial time variation in the profitability of the momentum strategy is also suggested by the visual appearance of the moving average of the returns yielded by the six-month formation and holding periods momentum portfolio, in Figure 1.1. Hereafter, we argue that the unconditional cumulative returns reported in Table 1.2 are the result of the aggregation over periods of low and high momentum profitability.

Previous literature has shown that the momentum effect is not only time-varying, but also state dependent, at least in the equity market. Cooper et al. (2004) find that the profitability of the momentum strategy in the US stock market is exclusive to holding periods following aggregate stock market gains. In this section, we document that the profitability of the momentum strategy is strongly state-dependent also in the corporate bond market. Further, the market state is shown to have significant predictive power for the profitability of the momentum strategy over a range of holding period horizons, spanning from one month up to two years.

To evaluate the predictive ability of the market state, and, later on, of other market indicators, we focus on the cumulative returns on the six-month formation period momentum portfolio. Conditional momentum gains are gauged by the cumulative returns on the buy-and-hold momentum portfolio that is formed in the month following the realization of the state of the market.

We define a month t as being in the UP (DOWN) market state if the overall market performance over the year *preceding* month t is above or equal (below) the sample average of the Equally Weighted (EW) market portfolio monthly returns.[18] The holding period cumulative returns generated by a momentum portfolio formed in date t are categorized as originated in the UP or DOWN market state on the basis of the market state emerging in month t.[19] Further details and a discussion on the definition of

[18]More precisely, at time t the market is in the UP (DOWN) state if the 12-month average of the monthly returns on the EW market portfolio of the bonds in our sample from $t-12$ to $t-1$ is above (below) the sample average of the return on the same EW index. Using the sample median of the returns on the EW index as the threshold to defined the market state yields similar results.

[19]Hence, the time-t cumulative return $\text{CR}_{n,t}$ of the momentum strategy with six-month formation period and n-month holding period is in the UP (DOWN) state if the market is in UP (DOWN) state in the formation month (i.e., at $t-n$).

the market states are relegated to Appendix A.1. The discussion includes the use of alternative cutoffs in defining the market states. In particular, this study's conclusions are robust to the use of return thresholds depending solely on information available before portfolio formation.

Panel A of Figure 1.2 plots the conditional and unconditional momentum cumulative returns for the bonds in our sample, where conditioning is on the market state during the portfolio formation month.[20] The plot clearly suggests that the mild unconditional momentum gains documented in Table 1.2 are the result of the aggregation of a very state-dependent return series across the market states. The most striking feature of the conditional momentum returns in UP and DOWN markets is their diverging paths. The average returns stemming from UP-state-formed portfolios are always positive. In contrast, for strategies formed in DOWN markets, the average cumulative returns are always negative. Further, the conditional performance of the momentum effect shows a marked monotonic pattern with gains (losses) steadily compounding in UP (DOWN) markets.

The visual evidence, as shown in Panel A of Figure 1.2, is corroborated by the statistical analysis. Presently, to ascertain whether momentum gains are zero in UP or DOWN markets, we evaluate a linear model of the cumulative returns as a function of the dichotomous variables identifying the market states, which are denoted by D_t^{UP} and D_t^{D}. Formally, the model is:

$$CR_{n,t} = \beta_{UP} D_{t-n}^{UP} + \beta_{DOWN} D_{t-n}^{D} + \varepsilon_t, \tag{1.2}$$

where $CR_{n,t}$ is the cumulative return series of the six-month formation and n month holding period momentum portfolio formed at time $t-n$, the variable D_t^{UP} is one if at t the market is UP and zero otherwise, the variable D_t^{D} is one if at t the market is DOWN and zero otherwise, and ε_t are zero-mean disturbances. To evaluate whether momentum gains are different conditionally on the market state, we evaluate a second

[20]The table of the cumulative returns plotted in Figure 1.2 are available from the authors upon request.

linear model in which the momentum series of $CR_{n,t}$ is a function of a constant and the UP market indicator for the formation month. Formally, the model is:

$$CR_{n,t} = \alpha + \gamma_{UP} D_{t-n}^{UP} + \nu_t, \tag{1.3}$$

where, once more, $t - n$ is the formation month, and ν_t are zero-mean error terms. Since the $\mathrm{CR}_{n,t}$ series use overlapping returns, we employ a heteroskedasticity-and-autocorrelation consistent (HAC) estimator for the variance of the coefficients in Equations 1.2 and 1.3 (e.g., Gallant, 1987; Cooper et al., 2004). For each strategy, the number of lags is set equal to the number of overlapping months in the holding period (e.g., 11 lags for the six-month formation and 12-month holding period return series $\mathrm{CR}_{12,t}$). The regression approach preserves the time-series structure of the data and yields standard errors that are robust for autocorrelation. Analogous regressions are evaluated for the cumulative returns on the winner and loser portfolios that generate the cumulative momentum return series $CR_{n,t}$.

Panel A in Table 1.3 reports the estimated coefficients β_{UP}, and β_{DOWN}, of Equation 1.2 for the entire sample. These coefficients, which are associated with the dichotomous variables UP and $DOWN$, are the stratified averages, over the market state, of the $CR_{n,t}$ series. For each holding period, the table also reports the t-statistic value for the coefficient γ_{UP} from Equation 1.3, which tests whether momentum gains are the same across market states. The table also reports the analogous coefficients and t-statistics for the cumulative returns on the portfolios of past winners and losers that define the momentum portfolio.

The estimates reported in Panel A of Table 1.3 indicate that momentum profits associated with the $\mathrm{CR}_{n,t}$ series are sizeable and significant only in the UP market state. Momentum gains stemming from strategies formed in the UP state reach 7.24% (i.e., 3.62% in annualized terms) over two years from portfolio formation, following an almost perfectly monotonic trend as the holding period increases.[21] For the DOWN markets, significant losses appear to be concentrated over the one-year mark, reaching -6.89% and -11.70% for the 18 and 24-month horizons (i.e., -4.6 and -5.85 in annualized percentage terms). In the short-run, momentum portfolios formed in DOWN markets appear to yield insignificant losses. The state dependence of the momentum effect becomes apparent over time. The spread between the cumulative returns on portfolios formed in UP vs. DOWN markets increases with the holding period horizon, reaching 18.94% at the two-year mark (i.e., 9.47% in annualized terms).[22]

Taken together, the empirical evidence presented in Panel A of Table 1.3 indicates that momentum gains, which can be substantial, are concentrated in periods following buoyant market conditions. DOWN markets are linked to reversal profits that are not preceded by momentum gains. Both conclusion are consistent with the results presented by Cooper et al. (2004) for the US equity market. A comparison of the cumulative returns documented for stocks in Cooper et al. and those reported in Panel A of Table 1.3 illustrates that the magnitude of momentum gains in the bond market, in the UP state, are about a third smaller than those observed for equities. Symmetrically, the magnitude of the significant long-run momentum losses in the DOWN state is about a third smaller than those documented for equities.

Evidence of a market state effect on momentum can be viewed as being consistent with both the extended versions of the behavioral theory developed by Daniel et al. (1998) as well as of the limited rationality argument proposed in Hong and Stein (1999). The market state influences investors' overconfidence (e.g., Gervais and Odean, 2001), which originates the momentum effect in Daniel et al. (1998). Hong and Stein (1999) argue that a decrease in risk aversion of momentum traders entails

[21]To obtain annualized rates from n-month cumulative returns we multiply it by $12/n$. We choose to report the stratified average of the cumulative returns, rather than the corresponding annualized rates, for consistency with Equations 1.2 and 1.3. Alternative tables in monthly or annualized terms are available from the authors upon request.

[22]Relying on the results of Edwards et al. (2007) and Feldhütter (2011), we calculate that the average transaction cost for bonds included in the momentum portfolios is at most half of the costs that would be required to mute the significant momentum gains in UP markets and the corresponding losses in DOWN markets. It is, therefore, safe to conclude that transaction costs are unlikely to be driving the market state effect.

stronger momentum gains, as well as more marked reversal returns in the long-run. The effect of the market state on agents' risk aversion can be linked to wealth fluctuations in the habit formation framework by Campbell and Cochrane (1999).

The theoretical frameworks proposed by Daniel et al. (1998) and Hong and Stein (1999) imply that momentum gains are followed by reversal profits. Lee and Swaminathan (2000) and Jegadeesh and Titman (1993), Chan et al. (1996) examine the unconditional mean profits of the six-month formation period momentum portfolio over a five-year holding period horizon, in the equity market. They find that the returns of this momentum portfolio change of sign around the end of the first year, from positive to negative. Their result suggests that it takes about one year for the equity market to correct momentum mispricing.

This study's empirical evidence shows robust momentum profits up to the two-year mark, in the UP market state. On one hand, this finding may be interpreted as suggesting that in the bond market the correction to momentum mispricing just takes longer than in the equity market. On the other hand, the absence of reversal over time horizons as long as two years may indicate that in UP markets momentum short-run profits are not followed by price correction. This interpretation would suggest that the underreaction/overreaction theoretical frameworks may be insufficiently comprehensive to explain the momentum effect. That momentum profits need not be followed by reversal gains is indeed clearly highlighted by the performance of the momentum portfolios formed in DOWN markets, for which there are no momentum gains and only reversal profits, over all the holding period horizons considered.[23]

Summarizing, the analysis of the conditional cumulative returns presented in Table 1.3 suggest that the temporal link between short-term momentum and long-term reversal may be an optical illusion generated by the aggregation of long-term reversals in DOWN markets with short and medium-run momentum gains in UP markets. From this perspective, this study's results suggest that the momentum and reversal

[23] Also Cooper et al. (2004) find that DOWN equity markets are linked to reversal profits that are not preceded by momentum gains.

effects are distinct phenomena that need to be separately explained.[24]

To conclude, we note that our empirical analysis documents that the momentum effect yields economically and statistically significant momentum gains only in the UP market state also for the momentum strategy in top-volume bonds, as shown in Panel D of Table 1.3. The one-month holding period return of the top-volume bond momentum strategy in UP markets is about the same of that yielded by the analogous momentum strategy that relies on the full cross-section of bonds.

1.4.1 Investment and Speculative Grade Bonds

The finding that there are substantial momentum gains following buoyant market periods is corroborated by evidence of significant momentum profits in UP markets for both speculative and investment-grade bonds.[25] Panel B and C of Figure 1.2 visually illustrates the dynamics of the momentum cumulative returns for investment and speculative-grade corporate bonds, respectively, both unconditionally and conditional on the market state. The plots outline a strong state dependence for securities falling in both credit risk categories. The implication is that the momentum profits observed in the unconditional case may be driven by aggregation across the market states. The spread between momentum returns in UP vs. DOWN markets appears to be increasing over the length of the holding period, in both the credit rating subsamples. The difference between momentum returns in UP and DOWN markets is particularly large for speculative bonds, especially over short-term holding period horizons.

The statistical analysis reveals that both for investment and speculative-grade bonds, momentum profits are concentrated in the UP market state, whereas losses are observed in the DOWN state. The examination of the stratified averages reported in

[24]That the temporal link between momentum and reversal may not be supported by the empirical evidence is also consistent with the results from Conrad and Yavuz (2017) for the equity market. Further, the authors find no linear relationship between the lagged market return and the momentum portfolios they consider. However, the strong state effect we document using dichotomous variables for the market state suggests that the relationship may be nonlinear.

[25]The momentum strategy in top-volume bonds is firm-based. As a given firm may issue both low and high-grade bonds, the strategy is not suitable for a subsample analysis based on credit ratings.

Panels B and C of Table 1.3 reveals that significant momentum gains principally stem from noninvestment-grade bonds formed in the UP state. There is, however, evidence of significant reversals for holding periods longer than one year, in DOWN markets, and only for investment-grade bonds.

For speculative bonds, the difference between momentum returns in UP and DOWN states is significant for all holding periods. The significance is limited to holding period horizons of one-year or longer, for high-grade bonds. Summarizing, the market state appears to matter for both credit groups.

The unconditional analysis of the momentum effect for investment-grade corporate bonds suggests that the strategy yields insignificant gains for all holding period horizons. This result appears to be in line with the findings of Jostova et al. (2013). However, the conditional analysis reveals significant momentum gains (losses) for high-grade bonds, over the long term, which are concentrated in UP (DOWN) markets.

Using a comprehensive datasets of corporate bonds, Lin et al. (2017) note that the share of speculative bonds in the US market is small, at about 8%, in value terms. They, therefore, argue that evidence that momentum gains are low for high-grade bonds, as documented in the literature, indicates that the momentum effect is weak in the bond market, overall. However, our analysis suggests that there are profits to be gained by trading on the basis of past bond returns even for the high- grade subsample, provided that the trading strategy takes the state of the market into account.

Overall, the results presented in this section show that the market state effect is stronger for speculative bonds. In particular, we note that the short-run momentum returns for low-grade corporate bonds are similar in magnitude to those documented by Cooper et al. (2004) for the equity market. For example, the six-month formation and holding period momentum portfolio in UP markets yields an average annualized return of 9.34% for speculative corporate bonds and of 11.16% for the equity market. For the same six-month formation period strategy, the return over the one-year holding period are 6.63% for low-grade bonds and 8.64% for equities.

1.4.2 Risk-Adjusted Returns

A potential explanation of the market state effect is that the winners-minus-losers portfolio compensates differently for systematic risk in the two market states. Alternatively, the systematic risk can also be state dependent. To test the robustness of the market state effect from the risk-based perspective, we re-evaluate Equations 1.2 and 1.3 using risk-adjusted momentum returns. In order to do so, we rely on a collection of eight risk factors that are documented by the literature as being priced in bond returns. To provide more details, we consider the five systematic risk factors for equity and bonds proposed in Fama and French (1993).[26] We further include the equity momentum factor (Carhart, 1997), and the liquidity innovation factor for the bond market proposed in Lin et al. (2011).[27] We also include the changes in the implied volatility index, as Chung et al. (2018) have shown that this factor is priced in the corporate bond market.

The corresponding risk-adjusted returns are reported in Table 1.4, for the whole sample and three subsamples, respectively. A comparison of the raw and risk-adjusted returns reveals that accounting for risk fails to explain the distinctive performance of the momentum strategy in UP and DOWN market states. In particular, our conclusions in this section remain unaltered when focusing on risk-adjusted momentum returns. In the remaining sections of this study, we conduct our analysis based on raw momentum returns.[28]

[26]These five factors are the stock market excess return, the value-minus-growth and size factors, and the term and default risk factors. Similarly to Jostova et al. (2013), the term factor is the first difference of the yield spread for the ten and one year Treasury, while the default risk factor is the first difference of the month-end spread between BAA and AAA-rated corporate bond yields.

[27]The liquidity factor is obtained by taking innovations from the following time-series regression: $\triangle ILLIQ_{Mt} = \alpha_0 + d_1 + d_2 + \phi_1 \triangle ILLIQ_{Mt-1} + \phi_2 \left(\frac{M_{t-1}}{M_1}\right) \triangle ILLIQ_{Mt-1} + \theta(L)\varepsilon_t$, where $\triangle ILLIQ_{Mt}$, d_1, d_2, and M_t are defined similarly to Lin et al. (2011) for their liquidity measure based on Amihud (2002). To account for the serial correlation in the residuals, the moving average term $\theta(L)\varepsilon_t$ is a MA(5) process with $L = 5$.

[28]Aside from the lack of explanatory power of the eight risk factors on the state dependence of the momentum effect, the literature provides little evidence on determining whether any of those factors are appropriate measures of systematic risk in the corporate bond market.

1.5 Sentiment

Baker and Wurgler (2006) proposed a gauge for market sentiment that they link to asset overpricing. Stambaugh et al. (2012) showed that sentiment has predictive power for the performance of key CAPM anomalies. They argue that periods of high sentiment are characterized by bursts of overconfidence, which lay the basis for the large profitability of equity trading strategies based on overpricing measures. The predictive power of sentiment is then explained by a limited arbitrage argument in that the selling activities that are meant to counter the effect of overpricing are harder to implement than the long trades used to capitalize on underpricing. Hence, departures from the fundamental valuation of assets are more marked following periods characterized by overpricing rather than by underpricing.

The extant literature yields scarce evidence on whether sentiment has a significant predictive ability for the momentum effect, or other anomalies, in the corporate bond market. Recently, Lin et al. (2017) show that the momentum effect is not sentiment-dependent for a comprehensive sample of US corporate bonds. Using momentum strategies designed to boost the information content of past yields, the authors find comparable positive momentum profits in periods following both high and low sentiment months. They also show that momentum gains are marginally stronger when sentiment is low than when sentiment is high.

Avramov et al. (2017) concludes that following periods of high sentiment, there are significant short-run returns stemming from overpricing-based trading strategies of bonds issued by publicly owned firms. These trading strategies are based on multiple firm-level gauges of overpricing, among which past equity returns. To the extent to which the profitability of the momentum strategy is linked to overpricing, the results presented in Avramov et al. (2017) appear to suggest that high sentiment may be linked to large momentum gains in the corporate bond market.

To the authors' knowledge, no previous research has been conducted on the predictive power of sentiment using the standard momentum strategy proposed in Jegadeesh and Titman (1993) for bonds issued by both publicly and privately owned firms. Hereafter we address this gap in the literature for the TRACE sample. Presently, to evaluate whether momentum profits depend on sentiment in the bond market, we focus on the cumulative returns of momentum portfolios. These cumulative returns are classified as originated in high or low sentiment months depending on the sign of the sentiment index in the month preceding portfolio formation. More precisely, the cumulative return $\mathrm{CR}_{n,t}$ at time t of a portfolio formed at time $t-n$ is in the HIGH (LOW) sentiment state when sentiment is nonnegative (negative) in month $t-n-1$.[29]

Panel D in Figure 1.2 plots the cumulative returns of the six-month formation period momentum strategy conditional on the HIGH and LOW sentiment states, for all the bonds in our sample.[30] The figure reveals that momentum portfolios formed in months following low sentiment tend to yield positive cumulative returns. In contrast, high sentiment appears to be followed mostly by reversal profits, especially over long-term holding periods. The spread between momentum returns in the LOW and HIGH sentiment states is always positive and increases almost monotonically over the length of the holding period, which suggests that the predictive power of sentiment may be best assessed over the long-run.[31]

We calculate the stratified cumulative returns on winners, losers, and on the resulting momentum portfolio in the HIGH and LOW sentiment states using the methodology employed in Section 1.4. The t-statistic values of the stratified averages are obtained by evaluating the analog of Equations 1.2 and 1.3 for the dichotomous variables that identify high and low sentiment months.

The statistical analysis confirms the impressions drawn from the visual evidence of Panel D in Figure 1.2. The stratified average returns for high-grade bonds, as reported

[29]The use of the sample median of sentiment (as in Stambaugh et al., 2012) yields equivalent results. We follow Avramov et al. (2017) and rely on the sign of the sentiment index to identify HIGH and LOW sentiment periods.

[30]Plots of the sentiment-based conditional average returns for the speculative and investment grade subsamples are available from the authors upon request.

[31]In terms of forecasting future momentum gains, the predictive content summarized by sentiment and by the market state appears to be accumulated over different time horizons. The predictive power of sentiment is weaker when conditioning on the one-year median (or average) of sentiment. Conversely, the predictive power of the sign of the one-month market return is weaker than that yielded by the one-year average market return. Chordia et al. (2017) uses the one-month market returns and, consistently, found no difference in the degrees of predictive power showed by past bond returns in predicting current returns.

in Panel B of Table 1.5, show that investment-grade bonds yield significant momentum losses for holding periods longer than one year, following months of high sentiment. In Panel C, there is also some evidence of significant momentum gains for speculative-grade bonds following low sentiment months, over the very short-run (i.e., up to three months). These dynamics aggregate in the whole sample to yield significant long-term reversal following high sentiment periods and short-term momentum following low sentiment months, as tabulated in Panel A of the same table. Further, there is some evidence of a mild but statistically significant sentiment-state effect for long-term investment horizons, with momentum returns being weaker following high sentiment.

1.5.1 Sentiment and Market State

The correlation between the one-year moving average of the return on the EW market portfolio and the sentiment index is -0.47.[32] This level of correlation is large enough to signify that the two variables are associated with the same economic reality, but sufficiently low to suggest that they may be capturing different features of the emerging market condition. A comparison of the conditional cumulative momentum returns when stratification is over the market state or sentiment, which are reported in Tables reported in Tables 1.3 and 1.5, indicate that the predictive ability of past sentiment for future momentum gains and losses is weaker than that associated with the market state.[33] We view these results as suggesting that sentiment captures different information about investor behavior than that conveyed by the market state.

However, as both variables appear to be able to discriminate momentum losses from gains, albeit to a different degree, the question arises of whether the facets of the economic reality captured by the state of the market and sentiment interact to de-

[32]The correlation is for the one-year return average on the EW index from $t-11$ to t with the sentiment index in month t.

[33]Lemmon and Portniaguina (2006) compare the predictive power of gauges of investor sentiment and of economic fundamentals and conclude that sentiment measures do not appear to forecast the momentum premium, in the US stock market. To the extent to which the sentiment series created in Lemmon et al. and the index proposed by Baker and Wurgler (2006) capture similar features of the economy, our findings suggest that sentiment has a weaker predictive power for the momentum premium than fundamental market variables for corporate bonds as well.

termine the momentum premium. In order to explore this possibility we stratify momentum returns on the basis of high and low sentiment, as well as the market state. Further, we test for significant differences between high and low sentiment momentum gains, both in the UP and DOWN market states. Details on the stratification and on the testing techniques are relegated to Appendix A.2.

The stratified momentum returns reported in Panel A.1 of Table 1.6 show that the profitability of the momentum strategy is concentrated in the UP market state, as expected, given the results on the predictive power of the market state for the momentum premium presented in Section 1.4. In UP markets momentum profits are exclusively concentrated in periods characterized by low sentiment, and there are no significant momentum gains or losses when sentiment is high. The spread between momentum returns in low and high is increasing over time, and it is significant for the holding periods from one month to two years. The return gap between momentum strategies formed in the UP market state following low and high sentiment is also economically significant, reaching about 10% at the one-year mark.

The momentum profits for low sentiment when the market state is UP are statistically significant for all the holding periods ranging from one month to two years, with the cumulative returns being broadly increasing over the holding period horizons. These conditional cumulative returns are also economically significant, yielding gains of 8.41% at the one-year mark. To compare, the momentum gains for the one-year holding period in UP markets, with no interaction with sentiment, is 5.41%, while it is an insignificant 1.46% in the unconditional analysis.

Conditioning on the market state, reveals significant reversal gains for holding period horizons longer than one year, in DOWN markets, as shown in Panel A of Table 1.3. The statistical analysis of the cumulative momentum returns stratified on the market state and HIGH and LOW sentiment, in Panel A.1 of Table 1.6, reveals momentum losses in DOWN markets that are significantly different between high and low sentiment months. The spread is broadly increasing with the holding period horizon, and it is also economically significant, as it reaches 15.2% at the two-year mark, while being above 10% starting from the 9-month holding period horizon.

The interaction with low sentiment appears to intensify, to an extreme extent, the DOWN market effect, as documented by the very large and significant momentum losses in DOWN markets, which are detectable for holding periods as short as nine months. Indeed, as documented in Panel A.1 of Table 1.6, these reversal gains reach about 15.87% at the one-year mark in DOWN markets coupled with low sentiment.[34] For comparison, the average reversal profit for the one-year holding period in DOWN markets, when the effect of sentiment is omitted, is a mere 2.69%. The return for high sentiment in DOWN markets is an insignificant 0.73%.

Summarizing, we conclude that the DOWN-market momentum losses are the result of the aggregation of reversal gains that are very large when sentiment is low but much weaker when sentiment is high. Indeed, the when the market state is DOWN, the one-year cumulative reversal gains are more than 20 times larger if sentiment is low vs. high. In UP markets, however, all momentum gains stem from periods of low sentiment. Figure 1.3 illustrates the effect of high and low sentiment in the UP and DOWN market states for the cumulative returns stemming from the momentum strategy over the holding period horizons from one month to two years.

The conditional analysis on the state of the market has shown that the momentum strategy tends to yield gains in the UP market state and losses in DOWN markets. Alternatively put, the market state discriminates between the market conditions yielding profits vs. losses for the momentum strategy. Overall, the results presented in Panel A.1 of Table 1.6 indicate that low (high) sentiment strengthens (weakens) the market state effect. Consistently, the worst and best performances of momentum are associated with low sentiment interacted with the DOWN and UP market states, respectively. Figure 1.4 plots the average cumulative returns on momentum portfolios that are sorted by the market state and by the interaction of the market state with low sentiment. The plot visually illustrates how the interaction of the market state with

[34]Incidentally, the results reported in Panel A.1 of Table 1.6 also show that reversal trading following low sentiment and DOWN markets presents an investment opportunity that strongly dominates momentum trading, in terms of long-run cumulative returns.

low sentiment amplifies the state dependence of the performance of the momentum strategy.

The stratified averages reported in Panel B and C of Table 1.6 summarize the joint effect of sentiment and the market state for the subsamples of investment and low-grade corporate bonds, separately. The analysis of the investment-grade subsample yields results that are similar to those obtained for the whole sample, in Panel A.1. This consistency is expected as high-grade bonds represent the vast majority of the securities in our sample.

Comparing the average returns for investment-grade bonds reported in Panel B of Table 1.3 with those reported in Panel B of Table 1.6 reveals that, once more, low sentiment enhances the market state effect, whereas high sentiment weakens the state dependence of the momentum profits. In particular, the momentum gains associated with the UP market state become much stronger and pervasive when focusing on periods of low sentiment. Further, the interaction with low sentiment brings about a statistically significant profitability of the momentum strategy, in UP markets, for high-grade bonds.

Sentiment appears to make a difference for the profitability of the momentum strategy in speculative bonds both in UP and DOWN markets, especially for long holding period returns. This observation is strongly substantiated by the statistical analysis of the spread between momentum returns for high and low sentiment, both in the UP and DOWN, as reported in Panel C of Table 1.6. The spread is also economically significant, especially in DOWN markets, as it reaches an impressive 17.22% at the one-year mark.

For speculative-grade bonds we find evidence of significant reversal profits in DOWN markets that are associated with low sentiment periods. These profits are comparable to those obtainable by the analogous trade for high-grade bonds. The momentum losses in the DOWN state coupled with high sentiment are however insignificant, for low-grade bonds.

The momentum gains obtained in UP markets and low sentiment for speculative bonds are much larger than those observed for investment grade bonds. For instance, at the one year mark the cumulative return on a portfolios of speculative grade bonds formed in low sentiment and UP markets yields 7.6% whereas the analogous return for high-grade bonds is about half, at about 4%.

Comparing Panel C between Table 1.3 and Table 1.6 we note that low sentiment appears to exacerbate the effect of the market state on momentum returns also for high-yield bonds. In particular, the insignificant momentum returns in DOWN markets documented in Panel C of Table 1.3 are shown to mask significant and economically large reversal gains in DOWN markets marked by low sentiment.

The literature has produced mixed evidence on the effect of sentiment on mispricing, in the bond market. This article argues that sentiment is a powerful predictor of future momentum gains, or losses, only when the market state is also taken into consideration. In particular, it is low stock market sentiment that interacts with buoyant bond markets to entail the strongest momentum gains. Low sentiment and DOWN market states couple instead to entail strong reversal profits. These momentum and reversal gains are statistically and economically significant.

1.5.2 Momentum and Underpricing

Stambaugh et al. (2012) argue that limits to arbitrage, coupled with overpricing, originate the profitability of the momentum effect, as agents face frictions in short selling overpriced loser stocks. Limits on arbitrage thus originate a positive relationship between overpricing and the difference between the strength of return continuation for winners and losers. This effect ensures that the short leg of the anomaly originates a larger share of the momentum gains than that yielded by the long side of the momentum portfolio, when sentiment (i.e., overpricing) is high. Should frictions in short-selling lay at the root of the momentum effect also in the bond market, then we should observe that momentum gains as generated mostly when overpricing is large and by the short-leg of the anomaly.

Stambaugh et al. (2012) gauge overpricing by the investor sentiment index proposed in Baker and Wurgler (2006) and find a positive relationship between momentum profits and sentiment. Using the same index, we provide empirical evidence indicating that in the corporate bond market such relationship has the opposite sign.

If we wish to retain for corporate bonds the short-selling argument used in Stambaugh et al. (2012) to justify the effect of sentiment on equity momentum, then one possibility is to assume that sentiment measures overpricing for equities, but underpricing for corporate bonds.[35] For example, following Garlappi et al. (2008) and Garlappi and Yan (2011) it can be argued that resolution of financially distressed debt may result in the equity of high-risk firms being overvalued, at the expenses of corporate bonds. In this framework, overvaluation of distressed stocks may be associated with underpricing of corporate bonds. The implication is that the sentiment index may measure stock market overpricing, but simultaneously also capture aggregate underpricing for corporate bonds.

Assuming that high (low) sentiment gauges underpricing (overpricing) in the bond market, yields precise predictions on the return pattern of past winners and losers in the bond market. Specifically, should low stock market sentiment (e.g., in this case, high bond market sentiment) gauge overpricing in the bond market then: a) the short side of the momentum portfolio should yield lower returns when sentiment is low than when it is high; b) the returns on the long-side of the momentum portfolios should not be significantly different in periods of high vs. low sentiment, and finally, c) the momentum profits should be generated by the past losers in periods of overpricing (e.g., in this case, low stock market sentiment). This pattern of returns for the two sides of the anomaly would be consistent with overpricing generating the momentum effect in the equity and bond markets.

The results reported in Panel A of Table 1.5 provide strong empirical evidence against all the three conditions listed above. Presently, the short side of the anomaly yields indistinguishable returns when sentiment is low vs. high. The only exception

[35] The sentiment index of Baker and Wurgler (2006) is a composite of six variables obtained from stock market data which are used to gauge different facets of overpricing. The resulting index is designed to gauge aggregate sentiment in the stock market. In particular, there is no direct link between the sentiment index and measures of mispricing for corporate bonds.

is for the three-month holding period return strategy for which past losers yield lower returns when sentiment is high than when it is low, a result that contradicts the prediction on the short leg of the momentum strategy.[36] Further, there is strong evidence that the returns on past winners are significantly larger when sentiment is low than when sentiment is high. This finding is documented for holding period horizons ranging from one month to two years. We note that evidence showing that the long-side of the momentum strategy yields larger returns in low vs. high sentiment periods is consistent with mispricing being linked to weaker valuations of past winners when sentiment is low, and with the resulting correction entailing an appreciation.

Last, unlike for the equity market, the gains on the momentum strategy are generated by the long leg of the portfolio in conjunction with low sentiment periods. Put differently, when the momentum effect yields significant and positive returns, these stem from past winners when sentiment is low, rather than from past losers when sentiment is high, as observed in the equity market. This conclusion is corroborated by the analysis of the returns on the winner and loser portfolios when conditioned on the interaction of market state and sentiment.

Summarizing, the analysis of the returns yielded by the short and long leg of the anomaly in Panel A of Table 1.5 rules out the conjecture that high sentiment measures overpricing in the equity market but underpricing in the bond market. Instead, the evidence is in favor of high stock market sentiment signaling overpricing both in the stock and bond markets. This conclusion is consistent with both stock and bond valuation being buoyed by inflated expectations on firm future cash-flow, which are captured, in the aggregate, by high sentiment.

As sentiment gauges the same type of mispricing across the equity and corporate bond markets, with low sentiment identifying periods of aggregate underpricing, our results can be interpreted as indicating that the momentum effect in the bond market is linked to underpricing. The role of underpricing in determining momentum prof-

[36]The return on the loser side in high and low sentiment for the three-month holding period is consistent with the return pattern of the short-side of the momentum portfolio in the equity market. In general, we note that the effect of sentiment on the short side of the anomaly appears to be smaller in the bond market than that documented in Stambaugh et al. (2012), for the equity market.

its, in the bond market, is further affirmed by the observation that momentum gains originate from past winners that are more underpriced than past losers, in a reversal of the overpricing argument employed in Stambaugh et al. (2012).

The stratified returns reported in Panel A of Table 1.6 show that momentum gains are exclusively generated by portfolios formed in UP markets coupled with low sentiment. Moreover, the effect of sentiment in UP markets depends on the returns on the long-side of the anomaly. In particular, in the UP market state the return continuation of past winners, reported in Panel A.2 of Table 1.6, is both economically and statistically stronger in low versus high sentiment, whereas there is no significant difference between the returns on past losers in low and high sentiment, as shown in Panel A.3. This asymmetric impact is the analog of the price pattern observed for equities, for which there is no significant difference between the return on past winners in low and high sentiment whereas the sentiment affects the returns on past losers. This symmetry in the conclusions of the effect of sentiment in the bond and stock markets is another piece of evidence suggesting that underpricing lays at the root of the momentum effect in the bond market.

Overall, our analysis indicates that the momentum strategy is profitable when sentiment is low because it exploits the difference in the effect of underpricing on past winners and losers, by taking a long position in deeply underpriced assets and shorting less markedly underpriced securities. Put differently, the different degree of future appreciation of past winners and losers lays at the root of the sentiment effect on the momentum strategy.

Our analysis concludes that momentum gains for corporate bonds are related to underpricing, as measured by low stock market sentiment. This feature is unique to the bond market and it suggests that underpricing cannot be counterbalanced by rational agents investing in corporate bonds as easily as done for equities.[37] Conversely, the extent to which overpricing may be originating the momentum effect in the bond market is limited.

[37] According to the evidence presented in Stambaugh et al. (2012), in the equity market, underpricing does not appear to contribute to the profitability of the momentum strategy.

Stambaugh et al. (2012) attribute the effect of overpricing to frictions on short selling, in that rational agents are unable or unwilling to exert downward pressure on prices that are inflated, relative to fundamental valuations. Güntay and Hackbarth (2010) document that short-selling constraints have limited impact on corporate bond prices. Their conclusions imply that the link between short selling restrictions and the profitability of trading strategies based on overpricing may be absent in the bond market. This argument is in accordance with our finding of no momentum gains stemming from overpricing of corporate bonds. The results of this study, therefore, suggest the need of an alternative limited arbitrage argument for mispricing-based corporate bond momentum gains. A potential explanation of an underpricing-based risk premium is that agents may not be able to assume long positions on underpriced assets, due to low liquidity.

1.6 Conclusions

Using corporate bond returns calculated on the basis of transaction data, this study documents that momentum returns are strongly dependent on the state of the market, a result that corroborates the conclusions of Cooper et al. (2004) and extends its validity from the equity to the corporate bond market. Momentum gains are concentrated in UP markets and are significant for holding period horizons ranging from the short-run up to two years. Further, the momentum strategy in DOWN markets is shown to yield insignificant losses up to the one-year horizon. Following the one-year yardstick, the winner-minus-loser portfolio entails significant losses.

That momentum returns are state dependent is consistent with an expanded version of the behavioral theory by Daniel et al. (1998) in that aggregate market gains exacerbate investors overconfidence. A market-state effect on momentum is also consistent with the bounded rationality theory by Hong and Stein (1999), where heterogeneity in the types of information structure available to market participants yields gradual information diffusion. The bounded rationality of momentum traders causes price overreaction, which entails positive profits for the momentum portfolio. In this framework, the market state effect is caused by fluctuations in the risk aversion of momentum traders, with low risk aversion being associated with the UP market state.

The empirical evidence presented in this paper indicates that the market state dominates alternative conditioning variables, in terms of predictive power for future momentum gains. For example, low levels of the sentiment index appear to be significantly associated with future momentum gains over the short-term, at least for speculative-grade bonds. However, the effect of (low) sentiment originates lower monthly returns than those yielded by conditioning on the UP market state. Similarly, gauges of risk aversion, fundamental uncertainty, and a fear index for the Treasury market, among other variables, are shown to have no, or very weak, predictive ability for future momentum gains.

We show that the interaction of sentiment with the market state strengthens the link between momentum profitability and the state of the market. In particular, there are large momentum gains also for investment grade bonds, provided that the momentum portfolio is formed in months of low sentiment coupled with UP markets.

This study's empirical results are consistent with sentiment being associated with overpricing in both the stock and bond market. As it is observed in the equity market, the returns on the short-side of the anomaly are smaller in high rather than in low sentiment months. However, our findings also show that momentum returns are high (low) when sentiment is low (high), which implies a negative relationship between momentum gains and sentiment, in the corporate bond market. A negative relationship between momentum returns and overpricing is consistent with a limited arbitrage argument that relies on frictions in correcting underpricing. In turn, the existence of these frictions would result in momentum gains being originated by the long-side of the anomaly. Consistently, the analysis of the returns on the long and short sides of the momentum strategy, conditional on sentiment, shows that it is the winner-side of the momentum portfolio that originates the largest share of the momentum profits. Summarizing, this study argues that the momentum effect in the corporate bond market is based on underpricing rather than on overpricing.

Capitalizing on the availability of transaction data in TRACE, we propose a novel design for the momentum portfolio that focuses on firm-level top-volume bonds. This alternative momentum strategy yields monthly holding period returns that are substantially larger than those offered by the strategies explored in previous studies (e.g., Gebhardt et al., 2005; Jostova et al., 2013). We argue that analyzing the momentum effect in the bond market using the momentum strategies employed for equities may cause a downward bias in the estimation of momentum returns. We conjecture that this effect may be due to significant heterogeneity in the information content of bond prices, at the issuer level (e.g., Ronen and Zhou, 2013). The examination of this conjecture is left as a challenge for future empirical and theoretical work. We note that the conclusions drawn from the conditional analysis of momentum returns for top-volume bonds are strongly consistent with those obtained for the standard six-month formation momentum strategy.

Table 1.1: Descriptive Statistics for the TRACE Corporate Bond Sample

Table 1 presents basic summary statistics for the TRACE corporate bonds in our sample, which covers the period from August 2002 to December 2014. The first column reports the count of bond-month observations in the sample, followed by the mean, standard deviation and median of the monthly returns. The last three columns list the average volume at issue (in millions of dollars), the mean coupon, and average yield at issue. Table 1 tabulates statistics for the pooled sample, for the Non-Investment Grade (NIG) and Investment Grade (IG) categories, as well as for bonds sorted into the short- medium- and long-term maturity bands.

	Count	MeanReturn (%)	St. Dev.	Median (%)	OfferedVolume (M)	Coupon (%)	YieldatIssue
Pooled	591544	0.668	0.031	0.406	552	6.203	6.120
		Subsamples by Credit Groups					
NIG	75547	0.796	0.039	0.466	484	6.631	6.390
IG	285702	0.621	0.029	0.409	647	5.698	5.715
		Subsamples by Time to Maturity					
$\leq$ 5years	288122	0.525	0.024	0.298	553	5.917	5.817
5 to 10 years	168820	0.737	0.031	0.648	611	6.214	6.012
Over 10 years	134602	0.889	0.041	0.796	477	6.802	6.863

Table 1.2: 6-month Formation Period Momentum Strategy Returns

Panel A and Panel B report the average monthly and cumulative returns on the momentum portfolios with holding periods of 1, 3, 6, 12, 18 and 24 months. The average number of bonds available in the monthly cross-section is reported in Column 2. The number of months for which momentum returns are calculated is reported in the last column of each panel. Sub-panels 1 to 4 report holding period monthly and cumulative returns for the full sample, for investment and speculative-grade bonds, as well as for the top-volume bond subsample. The time period covered is from August 2002 to December 2014.

Holding period /		**Panel A: Holding period monthly returns** $R_{n,t}$				**Panel B: Holding period cumulative returns** $CR_{n,t}$			
	#(bond) per month	Loser (P1)	Winner (P10)	Winner-Loser	Months	Loser (P1)	Winner (P10)	Winner-Loser	Months
		A.1. Whole Sample				B.1. Whole Sample			
1	3158	0.789	1.108	0.319	142	0.789	1.108	0.319	142
		(4.628)	**(6.709)**	**(2.039)**		**(4.628)**	**(6.709)**	**(2.039)**	
3	3010	0.780	1.087	0.306	142	2.336	3.192	0.856	140
		(4.629)	**(6.840)**	**(2.135)**		**(4.571)**	**(6.786)**	**(2.015)**	
6	2812	0.783	1.055	0.272	142	4.631	6.051	1.420	137
		(4.733)	**(6.756)**	**(2.006)**		**(3.448)**	**(5.715)**	(1.391)	
12	2471	0.850	0.995	0.144	142	9.806	11.266	1.460	131
		(5.267)	**(6.641)**	(1.322)		**(3.299)**	**(5.372)**	(0.701)	
18	2170	0.879	0.915	0.035	142	15.361	15.023	−0.338	125
		(5.543)	**(6.017)**	(0.362)		**(3.953)**	**(4.357)**	(−0.125)	
24	1905	0.837	0.877	0.040	142	20.499	18.836	−1.663	119
		(5.507)	**(5.594)**	(0.451)		**(3.993)**	**(4.407)**	(−0.438)	
		A.2. Investment-grade Subsample				B.2. Investment-grade Subsample			
1	1560	0.85	0.761	−0.089	142	0.85	0.761	−0.089	142
		(4.561)	**(4.610)**	(−0.621)		**(4.561)**	**(4.610)**	(−0.621)	
3	1491	0.789	0.781	−0.009	142	2.385	2.292	−0.093	140
		(4.219)	**(4.888)**	(−0.070)		**(4.599)**	**(5.421)**	(−0.272)	
6	1399	0.772	0.796	0.024	142	4.578	4.564	−0.015	137
		(4.196)	**(4.998)**	(0.200)		**(3.696)**	**(5.468)**	(−0.019)	
12	1239	0.838	0.765	−0.073	142	9.665	8.802	−0.863	131
		(4.661)	**(4.765)**	(−0.708)		**(3.838)**	**(5.000)**	(−0.601)	
18	1097	0.845	0.745	−0.100	142	14.783	12.374	−2.409	125
		(4.632)	**(4.549)**	(−1.030)		**(4.333)**	**(4.388)**	(−1.226)	
24	975	0.793	0.748	−0.045	142	19.480	16.261	−3.219	119

Holding period /		Panel A: Holding period monthly returns $R_{n,t}$				Panel B: Holding period cumulative returns $CR_{n,t}$			
	#(bond) per month	Loser (P1)	Winner (P10)	Winner-Loser	Months	Loser (P1)	Winner (P10)	Winner-Loser	Months
		(4.394)	**(4.414)**	(−0.470)		**(4.287)**	**(4.597)**	(−1.093)	
		A.3. Non-investment-grade Subsample				B.3. Non-investment-grade Subsample			
1	420	0.989	1.419	0.43	142	0.989	1.419	0.43	142
		(4.169)	**(6.247)**	**(2.080)**		**(4.169)**	**(6.247)**	**(2.080)**	
3	403	1.042	1.395	0.353	142	3.153	4.211	1.058	140
		(4.585)	**(6.356)**	**(1.847)**		**(5.005)**	**(6.462)**	**(2.012)**	
6	381	1.099	1.300	0.201	142	6.312	7.759	1.448	137
		(4.832)	**(6.300)**	(1.218)		**(3.871)**	**(5.399)**	(1.239)	
12	341	1.097	1.262	0.165	142	12.269	14.498	2.229	131
		(4.796)	**(6.407)**	(1.233)		**(3.448)**	**(5.501)**	(1.068)	
18	306	1.130	1.152	0.022	142	17.913	18.987	1.073	125
		(4.927)	**(5.779)**	(0.182)		**(3.858)**	**(4.674)**	(0.431)	
24	274	1.113	1.021	−0.092	142	23.615	22.949	−0.666	119
		(4.776)	**(5.170)**	(−0.810)		**(4.153)**	**(5.064)**	(−0.217)	
		A.4. Top Volume Subsample				B.4. Top Volume Subsample			
1	990	0.808	1.251	0.443	142	0.808	1.251	0.443	142
		(5.233)	**(8.355)**	**(3.369)**		**(5.233)**	**(8.355)**	**(3.369)**	
3	958	0.836	1.211	0.375	142				
		(5.357)	**(8.304)**	**(3.057)**					
6	917	0.841	1.162	0.321	142				
		(5.467)	**(8.215)**	**(2.867)**					
12	849	0.841	1.103	0.263	142				
		(5.812)	**(8.156)**	**(3.170)**					
18	791	0.850	1.036	0.186	142				
		(6.091)	**(7.652)**	**(2.529)**					
24	741	0.843	0.987	0.144	142				
		(6.198)	**(7.222)**	**(2.217)**					

Table 1.3: Momentum Portfolio Returns Conditional on Market State

The table reports market-state stratified averages, and their statistics, as estimated by Equations 1.2 and 1.3 using the full sample and three subsamples. Panel A shows the conditional mean returns on the winner and loser portfolios and also the resulting momentum gains in UP and DOWN markets for holding periods of 1, 3, 6, 12, 18 and 24 months, for the whole sample. Panel B and C report the analogous results for the investment and speculative grade subsamples, respectively. Panel D reports the one-month holding period average portfolio return, and its t-statistic, conditional on the market state, for the top-volume bond subsample. The time period covered is from August 2002 to December 2014.

Holding Period /		WINNER			LOSER			WINNER-LOSER		
	N (UP/DOWN)	*UP*	*DOWN*	UP-DOWN	*UP*	*DOWN*	UP-DOWN	*UP*	*DOWN*	UP-DOWN
					Panel A: Whole Sample					
1	58	1.429	0.716	(1.700)	0.71	0.786	(−0.213)	0.719	−0.07	**(2.014)**
	78	**(3.862)**	**(3.090)**		**(4.223)**	**(2.175)**		**(2.478)**	(−0.271)	
3	58	3.936	2.158	**(2.060)**	2.110	2.402	(−0.320)	1.825	−0.244	**(2.576)**
	76	**(5.490)**	**(4.056)**		**(6.183)**	**(2.745)**		**(2.980)**	(−0.456)	
6	57	7.334	4.252	**(1.941)**	3.861	5.115	(−0.540)	3.473	−0.864	**(2.273)**
	74	**(5.562)**	**(3.541)**		**(5.817)**	**(2.179)**		**(2.686)**	(−0.645)	
12	57	12.636	9.232	(1.220)	7.226	11.924	(−0.919)	5.409	−2.692	**(1.929)**
	68	**(5.053)**	**(3.815)**		**(7.599)**	**(2.211)**		**(2.478)**	(−0.839)	
18	57	16.103	12.774	(0.935)	10.885	19.668	(−1.282)	5.218	−6.894	**(2.236)**
	62	**(4.573)**	**(3.086)**		**(7.816)**	**(2.720)**		**(1.766)**	**(-1.964)**	
24	55	21.345	15.272	(1.228)	14.107	26.974	(−1.329)	7.239	−11.702	**(2.729)**
	58	**(5.713)**	**(2.665)**		**(9.573)**	**(2.705)**		**(2.596)**	**(-2.235)**	
					Panel B: Investment Grade Subsample					
1	58	0.966	0.549	(1.194)	0.799	0.84	(−0.113)	0.167	−0.292	(1.342)
	78	**(3.126)**	**(2.693)**		**(3.839)**	**(2.374)**		(0.774)	(−1.102)	
3	58	2.783	1.758	(1.299)	2.352	2.296	(0.061)	0.431	−0.538	(1.443)
	76	**(4.468)**	**(3.286)**		**(5.173)**	**(2.727)**		(0.960)	(−1.055)	
6	57	5.304	3.708	(1.211)	4.190	4.792	(−0.281)	1.114	−1.084	(1.417)
	74	**(5.112)**	**(3.407)**		**(5.003)**	**(2.273)**		(1.215)	(−0.906)	
12	57	9.801	7.694	(0.842)	7.510	11.389	(−0.914)	2.291	−3.696	**(2.010)**
	68	**(4.672)**	**(3.422)**		**(6.098)**	**(2.560)**		**(1.830)**	(−1.531)	

Holding Period /	N (UP/DOWN)	WINNER *UP*	WINNER *DOWN*	WINNER UP-DOWN	LOSER *UP*	LOSER *DOWN*	LOSER UP-DOWN	WINNER-LOSER *UP*	WINNER-LOSER *DOWN*	WINNER-LOSER UP-DOWN
18	57	13.086	10.955	(0.632)	10.901	18.164	(−1.203)	2.185	−7.210	**(2.369)**
	62	**(4.541)**	**(2.979)**		**(6.341)**	**(2.914)**		(1.194)	**(-2.601)**	
24	55	17.840	13.749	(0.861)	13.918	24.702	(−1.329)	3.922	−10.954	**(2.794)**
	58	**(5.330)**	**(2.736)**		**(7.742)**	**(2.921)**		**(2.017)**	**(-2.740)**	
					Panel C: Non-investment Grade Subsample					
1	58	1.939	0.88	**(1.849)**	1.051	0.729	(0.748)	0.888	0.151	**(1.786)**
	78	**(3.977)**	**(2.492)**		**(3.685)**	**(2.048)**		**(2.835)**	(0.474)	
3	58	5.316	2.860	**(1.952)**	2.552	2.885	(−0.333)	2.764	−0.025	**(2.905)**
	76	**(5.184)**	**(3.707)**		**(4.898)**	**(3.196)**		**(3.735)**	(−0.040)	
6	57	9.811	5.323	**(1.806)**	5.142	5.832	(−0.280)	4.668	−0.509	**(2.536)**
	74	**(5.075)**	**(3.096)**		**(6.016)**	**(2.301)**		**(3.045)**	(−0.367)	
12	57	16.446	11.410	(1.383)	9.820	12.790	(−0.532)	6.626	−1.380	**(2.140)**
	68	**(6.125)**	**(3.468)**		**(6.325)**	**(2.098)**		**(3.910)**	(−0.406)	
18	57	19.495	15.909	(0.853)	13.652	20.497	(−0.941)	5.844	−4.588	**(2.246)**
	62	**(7.270)**	**(2.953)**		**(6.684)**	**(2.451)**		**(3.197)**	(−1.161)	
24	55	25.860	18.868	(1.120)	16.699	28.067	(−1.011)	9.161	−9.199	**(2.980)**
	58	**(14.706)**	**(2.632)**		**(12.299)**	**(2.394)**		**(4.414)**	(−1.703)	
					Panel D: High Trading Volume Subsample					
1	58	1.605	0.806	**(1.999)**	0.840	0.714	(0.379)	0.765	0.092	**(1.855)**
	78	**(4.636)**	**(3.666)**		**(4.841)**	**(2.051)**		**(2.892)**	(0.381)	

Table 1.4: Risk-adjusted Momentum Returns Conditional on Market State

The table reports market-state stratified mean risk-adjusted returns, and their statistics, as estimated by Equations 1.2 and 1.3 using the full sample and three subsamples. Risk-adjusted returns are obtained as the alphas from regressing raw returns on eight risk factors. Panel A shows the conditional mean risk-adjusted returns on the winner and loser portfolios and also the resulting momentum alphas in UP and DOWN markets for holding periods of 1, 3, 6, 12, 18 and 24 months, for the whole sample. Panel B and C report the analogous results for the investment and speculative grade subsamples, respectively. Panel D reports the one-month holding period average risk-adjusted return, and its t-statistic, conditional on the market state, for the top-volume bond subsample. The time period covered is from August 2002 to December 2014.

Holding Period /		WINNER			LOSER			WINNER-LOSER		
	N (UP/DOWN)	*UP*	*DOWN*	UP-DOWN	*UP*	*DOWN*	UP-DOWN	*UP*	*DOWN*	UP-DOWN
					Panel A: Whole Sample					
1	57	1.218	0.74	(1.831)	0.484	0.826	(−1.328)	0.734	−0.086	**(2.950)**
	79	**(6.007)**	**(4.451)**		**(2.418)**	**(5.032)**		**(3.396)**	(−0.487)	
3	57	3.352	2.383	(1.322)	1.416	2.628	(−1.846)	1.936	−0.246	**(3.015)**
	77	**(5.118)**	**(6.317)**		**(3.295)**	**(5.048)**		**(3.177)**	(−0.623)	
6	56	6.794	4.397	(1.720)	3.476	4.819	(−0.764)	3.318	−0.422	**(2.241)**
	75	**(5.353)**	**(4.270)**		**(3.958)**	**(2.962)**		**(2.337)**	(−0.481)	
12	56	11.122	9.728	(0.521)	4.764	12.617	(−1.575)	6.358	−2.89	**(2.315)**
	69	**(4.715)**	**(4.251)**		**(3.927)**	**(2.567)**		**(2.915)**	(−1.022)	
18	56	14.369	13.218	(0.346)	9.276	20.138	(−1.459)	5.093	−6.92	**(2.085)**
	63	**(4.467)**	**(3.519)**		**(5.922)**	**(2.834)**		(1.495)	**(-1.916)**	
24	54	19.455	16.812	(0.637)	12.239	26.766	(−1.689)	7.215	−9.954	**(2.908)**
	59	**(6.296)**	**(3.386)**		**(8.780)**	**(3.085)**		**(3.169)**	**(-2.187)**	
					Panel B: Investment Grade Subsample					
1	57	0.772	0.631	(0.521)	0.595	0.918	(−1.091)	0.177	−0.287	(1.824)
	79	**(3.678)**	**(3.667)**		**(2.590)**	**(4.868)**		(0.895)	(−1.771)	
3	57	2.21	2.089	(0.172)	1.725	2.605	(−1.236)	0.485	−0.516	(1.564)
	77	**(3.934)**	**(4.646)**		**(3.445)**	**(4.912)**		(0.983)	(−1.276)	
6	56	4.989	3.789	(0.998)	3.992	4.509	(−0.298)	0.998	−0.721	(1.265)
	75	**(5.226)**	**(3.875)**		**(4.045)**	**(2.986)**		(0.926)	(−0.908)	
12	56	8.56	8.157	(0.160)	5.561	11.844	(−1.436)	2.999	−3.687	**(2.309)**

Holding Period /	N (UP/DOWN)	WINNER *UP*	WINNER *DOWN*	WINNER UP-DOWN	LOSER *UP*	LOSER *DOWN*	LOSER UP-DOWN	WINNER-LOSER *UP*	WINNER-LOSER *DOWN*	WINNER-LOSER UP-DOWN
	69	**(4.507)**	**(3.696)**		**(4.534)**	**(2.827)**		**(2.322)**	(−1.668)	
18	56	11.662	11.311	(0.104)	9.637	18.522	(−1.351)	2.025	−7.211	**(2.211)**
	63	**(4.335)**	**(3.206)**		**(5.774)**	**(3.006)**		(0.957)	**(-2.602)**	
24	54	16.315	14.8	(0.368)	12.422	24.666	(−1.670)	3.893	−9.866	**(2.940)**
	59	**(5.373)**	**(3.353)**		**(7.404)**	**(3.303)**		**(2.108)**	**(-2.791)**	
Panel C: Non-investment Grade Subsample										
1	57	1.615	0.899	**(2.154)**	0.769	0.768	(0.002)	0.846	0.131	**(1.958)**
	79	**(6.253)**	**(4.245)**		**(2.987)**	**(3.639)**		**(2.979)**	(0.561)	
3	57	4.654	3.023	(1.782)	1.819	3.094	(−1.717)	2.835	−0.071	**(3.312)**
	77	**(5.435)**	**(6.250)**		**(3.476)**	**(5.154)**		**(3.835)**	(−0.137)	
6	56	9.064	5.522	(1.706)	4.497	5.702	(−0.648)	4.566	−0.18	**(2.345)**
	75	**(4.813)**	**(4.315)**		**(5.240)**	**(3.106)**		**(2.823)**	(−0.156)	
12	56	14.363	12.117	(0.668)	6.902	13.588	(−1.261)	7.461	−1.47	**(2.356)**
	69	**(5.067)**	**(4.389)**		**(3.868)**	**(2.473)**		**(3.946)**	(−0.456)	
18	56	17.617	16.498	(0.282)	11.612	20.902	(−1.138)	6.005	−4.404	**(1.978)**
	63	**(7.630)**	**(3.408)**		**(5.092)**	**(2.569)**		**(2.615)**	(−1.079)	
24	54	23.673	20.149	(0.662)	14.259	28.296	(−1.374)	9.414	−8.147	**(2.982)**
	59	**(18.466)**	**(3.427)**		**(9.056)**	**(2.772)**		**(4.640)**	(−1.607)	
Panel D: High Trading Volume Subsample										
1	57	1.429	0.832	**(2.787)**	0.572	0.785	(−0.971)	0.856	0.047	**(3.525)**
	79	**(8.582)**	**(6.092)**		**(3.361)**	**(5.622)**		**(4.798)**	(0.321)	

Table 1.5: Momentum Portfolio Returns Conditional on Sentiment

The table reports sentiment- stratified averages, and their statistics, as estimated by Equations 1.2 and 1.3 using the full and three subsamples. Panel A shows the conditional mean returns on the winner and loser portfolios and also the resulting momentum gains in HIGH and LOW sentiment, for holding periods of 1, 3, 6, 12, 18 and 24 months. Panel B and C report the analogous regression coefficients and statistics for the investment and speculative grade subsamples, respectively. Panel D reports the one-month holding period average portfolio returns and t-statistics conditional on sentiment for the top-volume bond subsample. The time period covered is from August 2002 to December 2014.

Holding Period /		WINNER			LOSER			WINNER-LOSER		
	N (HIGH/LOW)	*HIGH*	*LOW*	HIGH-LOW	*HIGH*	*LOW*	HIGH-LOW	*HIGH*	*LOW*	HIGH-LOW
1	74	0.522	1.747	**(-3.105)**	0.443	1.166	(−1.661)	0.078	0.581	(−1.255)
	74	**(2.386)**	**(5.088)**		**(1.964)**	**(2.935)**		(0.620)	(1.414)	
3	73	1.304	5.248	**(-4.980)**	1.256	3.513	**(-2.409)**	0.048	1.735	**(-2.016)**
	73	**(2.822)**	**(7.921)**		**(2.241)**	**(4.446)**		(0.124)	**(2.323)**	
6	72	3.002	9.427	**(-4.078)**	2.710	6.758	(−1.634)	0.292	2.669	(−1.193)
	71	**(3.631)**	**(6.687)**		**(2.203)**	**(3.019)**		(0.374)	(1.429)	
12	71	6.763	16.594	**(-3.417)**	6.607	13.591	(−1.324)	0.156	3.002	(−0.698)
	66	**(4.193)**	**(6.868)**		**(2.534)**	**(2.770)**		(0.105)	(0.766)	
18	67	8.865	22.136	**(-3.087)**	12.981	18.110	(−0.937)	−4.115	4.026	**(-2.178)**
	64	**(3.176)**	**(6.359)**		**(4.470)**	**(2.996)**		**(-3.285)**	(0.985)	
24	64	11.683	27.159	**(-3.600)**	18.586	22.724	(−0.746)	−6.903	4.435	**(-2.903)**
	61	**(3.675)**	**(7.523)**		**(4.344)**	**(3.228)**		**(-2.507)**	(0.960)	
					Panel B: Investment Grade Subsample					
1	74	0.323	1.238	**(-2.366)**	0.408	1.331	**(-1.980)**	−0.085	−0.093	(0.021)
	74	(1.505)	**(4.079)**		**(1.765)**	**(3.305)**		(−0.814)	(−0.263)	
3	73	0.898	3.811	**(-3.895)**	1.168	3.711	**(-2.701)**	−0.270	0.100	(−0.537)
	73	**(2.059)**	**(6.041)**		**(2.122)**	**(4.613)**		(−0.859)	(0.162)	
6	72	2.443	6.912	**(-3.423)**	2.486	6.895	**(-1.957)**	−0.043	0.017	(−0.040)
	71	**(3.352)**	**(5.972)**		**(2.235)**	**(3.394)**		(−0.065)	(0.012)	
12	71	5.477	12.736	**(-3.093)**	6.641	13.243	(−1.612)	−1.163	−0.507	(−0.236)
	66	**(3.495)**	**(6.364)**		**(3.416)**	**(3.276)**		(−1.352)	(−0.182)	
18	67	7.777	17.684	**(-2.999)**	12.217	17.747	(−1.390)	−4.441	−0.063	**(-1.725)**
	64	**(3.413)**	**(6.007)**		**(4.754)**	**(3.671)**		**(-3.365)**	(−0.022)	

Holding Period	N (HIGH/LOW)	WINNER *HIGH*	WINNER *LOW*	WINNER HIGH-LOW	LOSER *HIGH*	LOSER *LOW*	LOSER HIGH-LOW	WINNER-LOSER *HIGH*	WINNER-LOSER *LOW*	WINNER-LOSER HIGH-LOW
Panel A: Whole Sample										
24	64	10.918	22.477	**(-3.351)**	17.683	21.570	(-0.936)	-6.765	0.907	**(-2.439)**
	61	**(3.963)**	**(6.947)**		**(4.321)**	**(3.798)**		**(-2.863)**	(0.249)	
Panel C: Non-investment Grade Subsample										
1	74	0.688	2.216	**(-3.210)**	0.498	1.523	**(-1.995)**	0.189	0.693	(-1.154)
	74	**(2.023)**	**(5.713)**		(1.626)	**(3.651)**		(0.731)	**(1.992)**	
3	73	1.898	6.732	**(-4.396)**	1.564	4.884	**(-2.799)**	0.334	1.847	(-1.495)
	73	**(2.410)**	**(8.278)**		**(2.292)**	**(4.952)**		(0.566)	**(2.178)**	
6	72	4.016	11.906	**(-3.968)**	2.928	10.060	**(-2.469)**	1.088	1.846	(-0.349)
	71	**(2.757)**	**(7.213)**		**(1.982)**	**(3.954)**		(1.043)	(0.906)	
12	71	9.173	20.799	**(-3.006)**	6.501	19.095	**(-2.046)**	2.673	1.704	(0.228)
	66	**(3.583)**	**(7.249)**		**(1.984)**	**(3.594)**		(1.455)	(0.434)	
18	67	11.821	27.264	**(-2.683)**	13.138	23.429	(-1.339)	-1.317	3.834	(-1.099)
	64	**(2.879)**	**(6.972)**		**(2.866)**	**(3.518)**		(-0.690)	(0.864)	
24	64	15.416	31.715	**(-3.236)**	18.970	29.021	(-1.280)	-3.554	2.694	(-1.522)
	61	**(3.516)**	**(11.215)**		**(3.346)**	**(4.023)**		(-1.574)	(0.578)	
Panel D: High Trading Volume Subsample										
1	74	0.653	1.903	**(-3.329)**	0.431	1.219	**(-1.866)**	0.222	0.684	(-1.206)
	74	**(3.114)**	**(5.842)**		**(1.963)**	**(3.270)**		(1.638)	**(1.808)**	

Table 1.6: Momentum Portfolio Returns Conditional on Sentiment and Market State

The table reports the stratified averages and associated t-statistic values of momentum returns, calculated conditional on the interaction of the HIGH and LOW sentiment indicators with the state of the market UP and DOWN variables. These conditional averages are estimate by Equations A.2.1 and A.2.2. The results are presented for the full sample and for three subsamples. Panels A.1 to A.3 tabulate the stratified average returns and t-statistics conditional on the market state and sentiment, for the momentum strategies and corresponding winner and loser deciles, for holding periods ranging from 1 month to 2 years, in the full sample. Panel B and C report only the stratified momentum profits and t-statistics for the winner-minus-loser strategies, as done in Panel A.1, for the investment and speculative-grade subsamples, respectively. The winner and loser performances can be found in the internet appendix. Panel D reports the one-month holding period stratified average momentum return, and its t-statistic, for the top-volume bond subsample. The time period covered is from August 2002 to December 2014.

Holding	High sentiment				Low sentiment				High-Low sentiment			
Period	*UP*	*t − stat*	*DOWN*	*t − stat*	*UP*	*t − stat*	*DOWN*	*t − stat*	*UP*	*t − stat*	*DOWN*	*t − stat*
	Panel A.1: Momentum Profits (Winners minus Losers) in the Whole Sample											
1	−0.221	(−0.683)	0.168	(1.385)	1.109	**(3.314)**	−0.715	(−0.821)	−1.329	**(-3.008)**	0.883	(1.206)
2	−0.719	(−1.220)	0.480	(1.720)	2.068	**(4.811)**	−1.705	**(-2.022)**	−2.787	**(-3.820)**	2.184	**(2.460)**
3	−1.072	(−1.483)	0.388	(0.928)	3.026	**(4.548)**	−2.015	(−1.361)	−4.098	**(-4.196)**	2.403	(1.573)
4	−1.005	(−0.950)	0.309	(0.560)	4.071	**(4.837)**	−2.795	(−1.284)	−5.077	**(-3.825)**	3.104	(1.393)
5	−1.058	(−0.664)	0.518	(0.751)	4.824	**(4.953)**	−4.013	(−1.399)	−5.882	**(-3.273)**	4.531	(1.554)
6	−1.004	(−0.579)	0.692	(0.806)	5.375	**(4.746)**	−5.368	(−1.494)	−6.379	**(-3.394)**	6.060	(1.660)
7	−1.354	(−0.924)	1.062	(0.988)	5.947	**(4.489)**	−6.784	(−1.565)	−7.301	**(-4.371)**	7.847	(1.789)
8	−1.737	(−1.238)	1.078	(0.867)	6.655	**(4.405)**	−8.244	(−1.674)	−8.392	**(-4.854)**	9.321	**(1.889)**
9	−1.899	(−1.386)	1.081	(0.750)	7.321	**(4.585)**	−9.916	**(-1.831)**	−9.221	**(-4.881)**	10.997	**(2.024)**
10	−1.828	(−1.454)	1.135	(0.672)	7.805	**(4.597)**	−12.142	**(-2.137)**	−9.633	**(-4.667)**	13.278	**(2.316)**
11	−1.413	(−1.171)	0.938	(0.503)	8.118	**(4.406)**	−14.795	**(-2.647)**	−9.531	**(-4.183)**	15.733	**(2.789)**
12	−1.649	(−1.424)	0.725	(0.382)	8.409	**(4.182)**	−15.870	**(-2.709)**	−10.058	**(-4.078)**	16.594	**(2.841)**
13	−1.829	(−1.486)	0.022	(0.013)	8.843	**(4.220)**	−17.204	**(-2.679)**	−10.673	**(-4.095)**	17.226	**(2.740)**
14	−2.135	(−1.702)	−0.736	(−0.438)	9.461	**(4.347)**	−18.367	**(-2.670)**	−11.597	**(-4.295)**	17.631	**(2.663)**
15	−2.017	(−1.474)	−1.564	(−1.014)	9.403	**(3.890)**	−18.433	**(-2.663)**	−11.420	**(-3.753)**	16.869	**(2.582)**
16	−2.648	(−1.857)	−2.388	(−1.650)	9.420	**(3.766)**	−18.216	**(-2.651)**	−12.068	**(-3.813)**	15.828	**(2.496)**
17	−3.340	(−1.677)	−3.293	**(-2.136)**	9.258	**(3.562)**	−18.374	**(-2.789)**	−12.598	**(-3.412)**	15.081	**(2.536)**
18	−4.046	(−1.354)	−4.139	**(-2.291)**	9.155	**(3.451)**	−18.374	**(-2.868)**	−13.201	**(-2.879)**	14.235	**(2.513)**
19	−3.884	(−1.215)	−5.287	**(-2.494)**	9.280	**(3.514)**	−18.434	**(-2.806)**	−13.164	**(-2.767)**	13.147	**(2.273)**

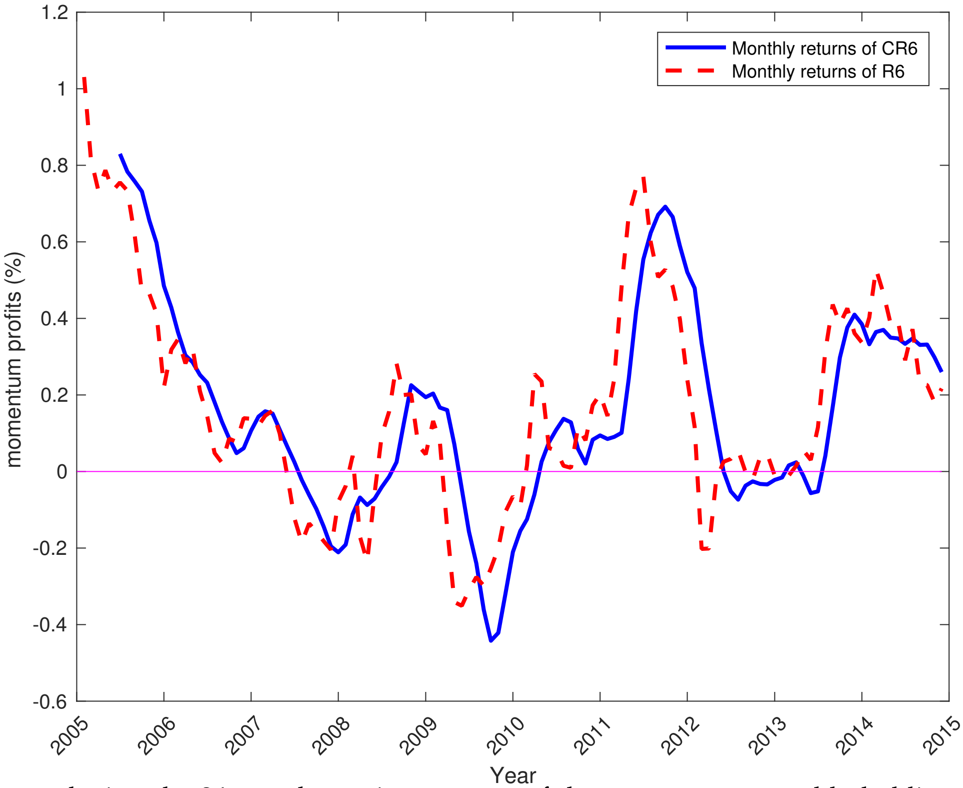
Holding	High sentiment				Low sentiment				High-Low sentiment			
Period	UP	$t-stat$	$DOWN$	$t-stat$	UP	$t-stat$	$DOWN$	$t-stat$	UP	$t-stat$	$DOWN$	$t-stat$
20	−2.853	(−0.948)	−6.489	**(-2.572)**	9.643	**(3.626)**	−19.231	**(-2.882)**	−12.496	**(-2.700)**	12.742	**(2.162)**
21	−2.361	(−0.858)	−7.337	**(-2.511)**	10.034	**(3.832)**	−20.381	**(-2.915)**	−12.395	**(-2.825)**	13.044	**(2.070)**
22	−2.167	(−0.858)	−8.171	**(-2.438)**	10.483	**(4.233)**	−21.147	**(-2.906)**	−12.650	**(-3.125)**	12.977	**(1.980)**
23	−1.813	(−0.732)	−8.615	**(-2.355)**	10.951	**(4.572)**	−23.810	**(-3.492)**	−12.764	**(-3.272)**	15.195	**(2.631)**
24	−1.627	(−0.656)	−8.811	**(-2.203)**	11.205	**(4.726)**	−24.053	**(-3.510)**	−12.832	**(-3.321)**	15.242	**(2.692)**
Panel A.2: Returns for the Long Leg of the Momentum Portfolio (Winners) in the Whole Sample												
1	0.515	(1.302)	0.524	**(2.043)**	1.808	**(4.091)**	1.237	**(3.217)**	−1.293	**(-2.180)**	−0.713	**(-1.686)**
2	0.581	(0.996)	0.934	**(2.718)**	3.592	**(6.978)**	2.922	**(4.715)**	−3.011	**(-3.873)**	−1.988	**(-2.807)**
3	0.888	(1.212)	1.431	**(2.631)**	5.199	**(6.277)**	4.195	**(3.880)**	−4.312	**(-3.885)**	−2.764	**(-2.344)**
4	1.460	**(1.919)**	2.010	**(3.105)**	6.821	**(6.346)**	5.061	**(2.905)**	−5.361	**(-4.048)**	−3.051	**(-1.761)**
5	2.301	**(2.440)**	2.474	**(3.115)**	8.066	**(6.242)**	6.241	**(2.787)**	−5.765	**(-3.583)**	−3.767	**(-1.700)**
6	3.227	**(2.754)**	2.933	**(3.021)**	9.079	**(6.098)**	8.070	**(3.057)**	−5.851	**(-3.094)**	−5.138	**(-1.923)**
7	3.572	**(2.846)**	3.655	**(3.255)**	10.232	**(6.077)**	9.921	**(3.264)**	−6.660	**(-3.240)**	−6.266	**(-1.974)**
8	3.808	**(2.403)**	4.336	**(3.426)**	11.454	**(6.189)**	11.531	**(3.334)**	−7.646	**(-3.230)**	−7.195	**(-1.992)**
9	4.148	**(2.006)**	5.134	**(3.683)**	12.648	**(6.325)**	12.878	**(3.318)**	−8.501	**(-2.968)**	−7.744	**(-1.913)**
10	4.817	**(2.203)**	5.852	**(3.893)**	13.620	**(6.298)**	14.755	**(3.606)**	−8.803	**(-2.820)**	−8.904	**(-2.084)**
11	5.628	**(2.538)**	6.405	**(3.924)**	14.567	**(6.163)**	16.792	**(4.069)**	−8.939	**(-2.722)**	−10.387	**(-2.410)**
12	5.920	**(2.607)**	7.029	**(3.931)**	15.490	**(5.914)**	17.730	**(4.258)**	−9.570	**(-2.706)**	−10.702	**(-2.466)**
13	6.352	**(2.582)**	7.369	**(3.903)**	16.506	**(5.868)**	19.785	**(5.228)**	−10.154	**(-2.655)**	−12.416	**(-3.119)**
14	6.873	**(2.624)**	7.726	**(3.877)**	17.511	**(5.960)**	22.267	**(6.460)**	−10.638	**(-2.676)**	−14.541	**(-3.906)**
15	7.826	**(2.618)**	7.975	**(3.695)**	18.014	**(5.656)**	23.685	**(6.258)**	−10.189	**(-2.228)**	−15.711	**(-3.883)**
16	7.460	**(2.011)**	8.553	**(3.720)**	18.579	**(5.609)**	24.897	**(5.898)**	−11.120	**(-2.108)**	−16.345	**(-3.694)**
17	7.113	(1.599)	9.017	**(3.691)**	19.167	**(5.617)**	26.156	**(5.724)**	−12.054	**(-2.007)**	−17.139	**(-3.616)**
18	7.748	(1.604)	9.245	**(3.389)**	19.653	**(5.498)**	27.478	**(6.056)**	−11.905	**(-1.831)**	−18.233	**(-3.801)**
19	8.753	**(1.934)**	9.264	**(2.958)**	20.423	**(5.568)**	28.281	**(6.186)**	−11.670	**(-1.868)**	−19.016	**(-3.831)**
20	10.006	**(2.285)**	9.308	**(2.770)**	21.550	**(5.799)**	28.854	**(6.195)**	−11.544	**(-1.880)**	−19.546	**(-3.805)**
21	10.703	**(2.475)**	9.676	**(2.661)**	22.449	**(5.937)**	29.293	**(6.060)**	−11.746	**(-1.921)**	−19.617	**(-3.633)**
22	11.248	**(2.951)**	10.020	**(2.594)**	23.353	**(6.179)**	29.879	**(6.113)**	−12.104	**(-2.159)**	−19.859	**(-3.609)**
23	12.240	**(3.758)**	10.552	**(2.647)**	24.091	**(6.358)**	31.890	**(7.104)**	−11.851	**(-2.331)**	−21.338	**(-3.800)**
24	13.026	**(4.610)**	11.197	**(2.764)**	25.067	**(6.643)**	32.683	**(7.020)**	−12.040	**(-2.543)**	−21.486	**(-3.717)**
Panel A.3: Returns for the Short Leg of the Momentum Portfolio (Lossers) in the Whole Sample												
1	0.736	**(2.733)**	0.356	(1.288)	0.699	**(3.279)**	1.953	**(2.065)**	0.037	(0.104)	−1.596	**(-1.799)**

Holding	High sentiment				Low sentiment				High-Low sentiment			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
2	1.299	**(3.627)**	0.454	(0.993)	1.524	**(5.979)**	4.627	**(4.025)**	−0.225	(−0.511)	−4.173	**(-3.373)**
3	1.959	**(3.504)**	1.042	(1.491)	2.173	**(5.112)**	6.209	**(2.860)**	−0.214	(−0.305)	−5.167	**(-2.317)**
4	2.465	**(2.827)**	1.701	**(1.944)**	2.750	**(4.755)**	7.856	**(2.247)**	−0.284	(−0.276)	−6.154	**(-1.777)**
5	3.359	**(2.895)**	1.956	(1.675)	3.242	**(4.987)**	10.253	**(2.183)**	0.117	(0.091)	−8.298	**(-1.777)**
6	4.232	**(3.358)**	2.240	(1.476)	3.704	**(5.418)**	13.438	**(2.279)**	0.528	(0.404)	−11.198	**(-1.888)**
7	4.925	**(3.855)**	2.593	(1.363)	4.284	**(6.101)**	16.705	**(2.353)**	0.641	(0.510)	−14.113	**(-1.958)**
8	5.545	**(3.949)**	3.258	(1.505)	4.799	**(6.758)**	19.775	**(2.436)**	0.746	(0.567)	−16.516	**(-2.017)**
9	6.047	**(3.743)**	4.053	(1.642)	5.327	**(7.433)**	22.795	**(2.521)**	0.720	(0.469)	−18.741	**(-2.054)**
10	6.645	**(4.055)**	4.716	(1.687)	5.815	**(7.566)**	26.898	**(2.831)**	0.829	(0.532)	−22.181	**(-2.304)**
11	7.041	**(4.275)**	5.467	**(1.821)**	6.450	**(7.643)**	31.587	**(3.362)**	0.592	(0.379)	−26.120	**(-2.754)**
12	7.569	**(4.336)**	6.304	**(1.973)**	7.081	**(7.615)**	33.600	**(3.468)**	0.488	(0.288)	−27.296	**(-2.817)**
13	8.181	**(4.041)**	7.347	**(2.272)**	7.663	**(7.463)**	36.989	**(3.758)**	0.519	(0.258)	−29.642	**(-3.063)**
14	9.008	**(4.040)**	8.462	**(2.587)**	8.050	**(7.657)**	40.633	**(4.113)**	0.958	(0.444)	−32.171	**(-3.384)**
15	9.843	**(3.850)**	9.538	**(2.917)**	8.611	**(8.152)**	42.118	**(4.121)**	1.232	(0.510)	−32.580	**(-3.370)**
16	10.107	**(3.266)**	10.941	**(3.390)**	9.159	**(8.278)**	43.114	**(4.094)**	0.948	(0.322)	−32.173	**(-3.310)**
17	10.453	**(3.328)**	12.310	**(3.807)**	9.909	**(8.639)**	44.529	**(4.188)**	0.544	(0.183)	−32.219	**(-3.356)**
18	11.794	**(4.298)**	13.384	**(3.847)**	10.498	**(8.389)**	45.851	**(4.360)**	1.296	(0.515)	−32.468	**(-3.490)**
19	12.637	**(5.106)**	14.551	**(3.881)**	11.143	**(8.459)**	46.715	**(4.326)**	1.494	(0.681)	−32.164	**(-3.429)**
20	12.860	**(5.057)**	15.797	**(3.996)**	11.908	**(8.736)**	48.085	**(4.364)**	0.952	(0.420)	−32.289	**(-3.430)**
21	13.064	**(4.875)**	17.013	**(3.968)**	12.416	**(8.509)**	49.675	**(4.319)**	0.648	(0.259)	−32.662	**(-3.331)**
22	13.415	**(5.349)**	18.191	**(3.738)**	12.869	**(8.149)**	51.026	**(4.319)**	0.546	(0.226)	−32.836	**(-3.282)**
23	14.053	**(6.458)**	19.167	**(3.506)**	13.140	**(7.946)**	55.700	**(5.160)**	0.913	(0.437)	−36.534	**(-3.984)**
24	14.654	**(7.417)**	20.008	**(3.330)**	13.862	**(8.236)**	56.736	**(5.218)**	0.792	(0.399)	−36.728	**(-3.992)**
Panel B: Momentum Profits (Winners minus Losers) in Investment Grade Subsample												
1	−0.107	(−0.524)	−0.079	(−0.676)	0.281	(0.972)	−0.869	(−0.922)	−0.388	(−1.086)	0.791	(0.988)
2	−0.646	(−1.381)	0.143	(0.609)	0.663	**(1.990)**	−1.843	**(-2.021)**	−1.309	**(-2.279)**	1.986	**(2.109)**
3	−1.060	**(-1.865)**	−0.030	(−0.087)	1.048	**(1.936)**	−1.962	(−1.251)	−2.108	**(-2.719)**	1.932	(1.209)
4	−0.824	(−0.904)	−0.103	(−0.253)	1.575	**(2.169)**	−2.773	(−1.225)	−2.399	**(-2.120)**	2.670	(1.173)
5	−0.831	(−0.613)	0.098	(0.186)	1.779	**(2.169)**	−3.732	(−1.313)	−2.609	**(-1.737)**	3.830	(1.349)
6	−0.955	(−0.602)	0.238	(0.335)	1.994	**(2.354)**	−4.911	(−1.441)	−2.949	**(-1.845)**	5.150	(1.498)
7	−1.519	(−1.164)	0.418	(0.482)	2.353	**(2.559)**	−6.218	(−1.539)	−3.872	**(-3.137)**	6.636	(1.634)
8	−1.861	(−1.453)	0.195	(0.213)	2.723	**(2.642)**	−7.533	**(-1.681)**	−4.585	**(-3.734)**	7.728	**(1.733)**
9	−2.099	(−1.586)	0.013	(0.014)	3.224	**(3.193)**	−9.029	**(-1.895)**	−5.323	**(-3.985)**	9.042	**(1.905)**

Holding	High sentiment				Low sentiment				High-Low sentiment			
Period	UP	$t-stat$	$DOWN$	$t-stat$	UP	$t-stat$	$DOWN$	$t-stat$	UP	$t-stat$	$DOWN$	$t-stat$
10	−1.992	(−1.546)	−0.098	(−0.085)	3.530	**(3.473)**	−11.058	**(-2.378)**	−5.522	**(-3.834)**	10.960	**(2.352)**
11	−1.429	(−1.147)	−0.544	(−0.453)	3.793	**(3.563)**	−13.274	**(-3.019)**	−5.222	**(-3.316)**	12.730	**(2.921)**
12	−1.679	(−1.418)	−1.001	(−0.900)	3.979	**(3.408)**	−14.090	**(-3.174)**	−5.657	**(-3.331)**	13.089	**(3.019)**
13	−1.782	(−1.412)	−1.765	**(-1.817)**	4.306	**(3.412)**	−14.942	**(-3.247)**	−6.088	**(-3.292)**	13.177	**(3.002)**
14	−1.905	(−1.431)	−2.500	**(-2.706)**	4.795	**(3.456)**	−15.419	**(-3.112)**	−6.700	**(-3.322)**	12.920	**(2.769)**
15	−1.610	(−1.148)	−3.317	**(-3.584)**	4.592	**(2.864)**	−15.753	**(-3.291)**	−6.202	**(-2.658)**	12.436	**(2.849)**
16	−1.659	(−1.184)	−3.947	**(-3.695)**	4.624	**(2.742)**	−15.936	**(-3.450)**	−6.282	**(-2.620)**	11.989	**(2.911)**
17	−2.166	(−1.223)	−4.460	**(-3.456)**	4.441	**(2.509)**	−16.210	**(-3.742)**	−6.607	**(-2.447)**	11.751	**(3.112)**
18	−2.791	(−1.071)	−5.002	**(-3.270)**	4.300	**(2.331)**	−16.410	**(-3.898)**	−7.091	**(-2.083)**	11.408	**(3.171)**
19	−2.677	(−1.022)	−5.809	**(-3.215)**	4.314	**(2.181)**	−16.485	**(-3.716)**	−6.991	**(-2.042)**	10.677	**(2.785)**
20	−2.043	(−0.814)	−6.654	**(-3.258)**	4.576	**(2.224)**	−17.244	**(-3.760)**	−6.619	**(-1.996)**	10.590	**(2.643)**
21	−1.338	(−0.633)	−7.364	**(-3.185)**	4.979	**(2.405)**	−17.897	**(-3.638)**	−6.317	**(-2.119)**	10.533	**(2.382)**
22	−1.278	(−0.658)	−8.019	**(-2.952)**	5.409	**(2.627)**	−18.396	**(-3.599)**	−6.687	**(-2.443)**	10.377	**(2.224)**
23	−1.267	(−0.621)	−8.477	**(-2.856)**	5.943	**(3.000)**	−20.351	**(-4.312)**	−7.210	**(-2.668)**	11.874	**(2.851)**
24	−1.437	(−0.694)	−8.692	**(-2.738)**	6.320	**(3.242)**	−20.616	**(-4.408)**	−7.757	**(-2.914)**	11.924	**(2.916)**
Panel C: Momentum Profits (Winners minus Losers) in Non-investment Grade Subsample												
1	−0.086	(−0.152)	0.271	(0.884)	1.292	**(4.173)**	−0.175	(−0.221)	−1.377	**(-2.258)**	0.446	(0.559)
2	−0.273	(−0.380)	0.602	(1.402)	2.751	**(5.300)**	−1.088	(−1.339)	−3.024	**(-3.413)**	1.690	**(1.838)**
3	−0.228	(−0.218)	0.505	(0.739)	4.005	**(4.998)**	−1.507	(−1.264)	−4.233	**(-3.297)**	2.012	(1.487)
4	0.556	(0.361)	0.359	(0.404)	4.896	**(4.576)**	−2.484	(−1.473)	−4.340	**(-2.455)**	2.843	(1.490)
5	0.729	(0.371)	0.633	(0.605)	5.667	**(4.365)**	−3.606	(−1.544)	−4.938	**(-2.341)**	4.239	(1.649)
6	1.044	(0.536)	1.102	(0.960)	6.209	**(3.897)**	−5.170	(−1.691)	−5.165	**(-2.495)**	6.272	**(1.916)**
7	1.454	(0.803)	1.737	(1.367)	6.444	**(3.424)**	−5.910	(−1.531)	−4.990	**(-2.478)**	7.647	**(1.897)**
8	1.545	(0.928)	1.884	(1.300)	6.945	**(3.342)**	−7.902	(−1.639)	−5.400	**(-2.709)**	9.786	**(1.981)**
9	1.974	(1.404)	1.925	(1.160)	7.406	**(3.598)**	−9.776	**(-1.821)**	−5.433	**(-2.905)**	11.701	**(2.163)**
10	3.122	**(2.552)**	1.922	(1.021)	7.334	**(3.489)**	−11.636	**(-1.931)**	−4.212	**(-2.089)**	13.558	**(2.238)**
11	3.622	**(2.893)**	2.036	(0.962)	7.551	**(3.487)**	−13.845	**(-2.228)**	−3.929	**(-1.737)**	15.881	**(2.513)**
12	4.288	**(3.248)**	2.164	(0.947)	7.620	**(3.616)**	−15.053	**(-2.393)**	−3.332	(−1.394)	17.217	**(2.695)**
13	3.881	**(2.910)**	1.619	(0.708)	7.867	**(3.686)**	−15.655	**(-2.252)**	−3.986	(−1.574)	17.274	**(2.474)**
14	3.307	**(2.382)**	1.172	(0.490)	8.403	**(3.878)**	−17.198	**(-2.437)**	−5.096	**(-1.868)**	18.370	**(2.574)**
15	2.989	**(2.082)**	1.008	(0.408)	8.238	**(3.889)**	−16.142	**(-2.133)**	−5.249	**(-1.889)**	17.150	**(2.245)**
16	1.489	(0.877)	0.353	(0.143)	8.417	**(4.275)**	−16.778	**(-2.235)**	−6.927	**(-2.336)**	17.131	**(2.260)**
17	0.604	(0.315)	−0.608	(−0.225)	8.230	**(4.599)**	−16.947	**(-2.261)**	−7.626	**(-2.495)**	16.339	**(2.150)**

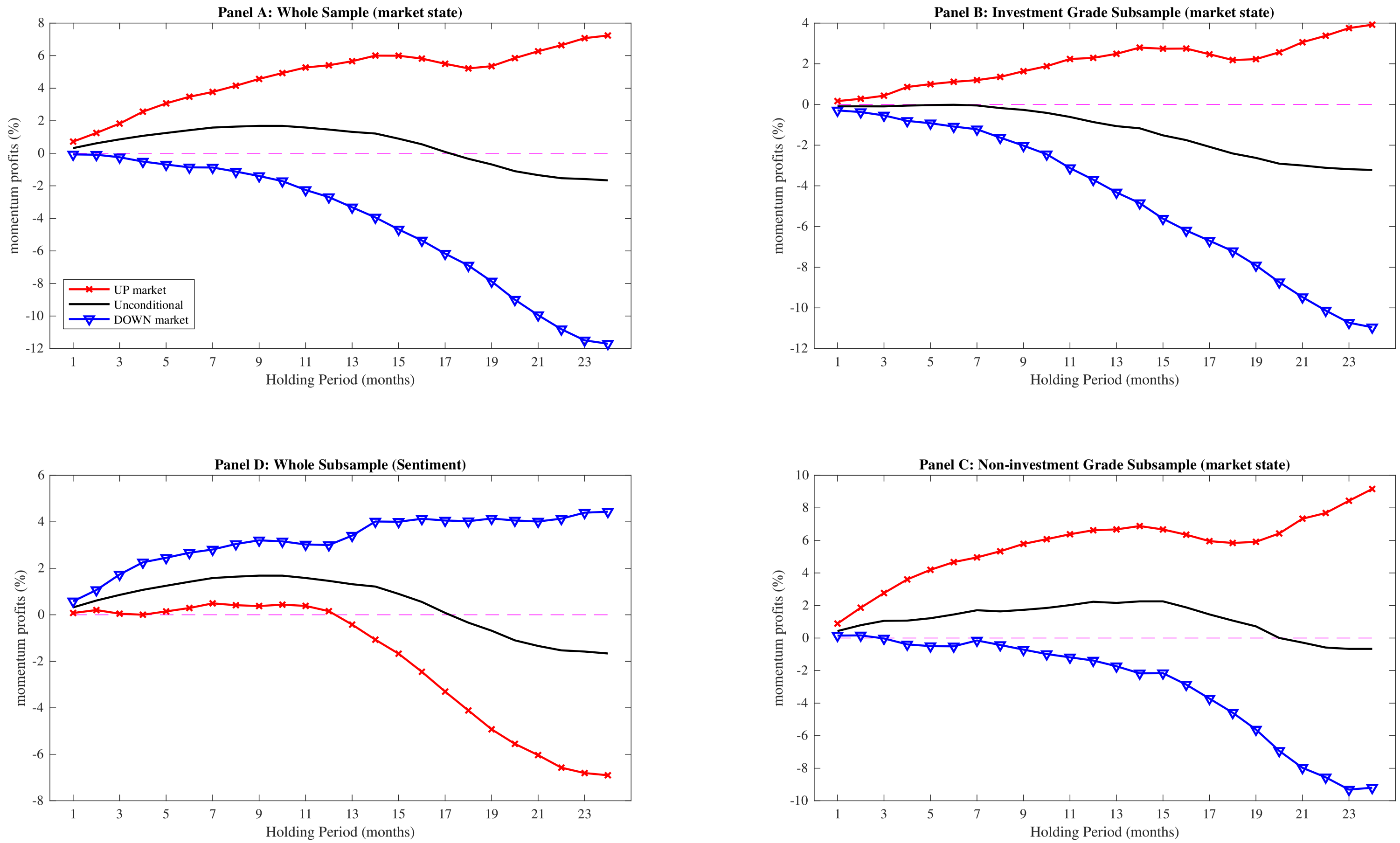
Holding Period	High sentiment UP	t − stat	DOWN	t − stat	Low sentiment UP	t − stat	DOWN	t − stat	High-Low sentiment UP	t − stat	DOWN	t − stat
18	−0.004	(−0.002)	−1.763	(−0.621)	8.329	**(4.533)**	−16.357	**(-2.129)**	−8.333	**(-2.355)**	14.593	**(1.899)**
19	0.378	(0.135)	−2.961	(−0.979)	8.265	**(5.016)**	−16.491	**(-2.158)**	−7.887	**(-2.023)**	13.530	**(1.751)**
20	1.711	(0.611)	−4.298	(−1.347)	8.482	**(4.632)**	−17.679	**(-2.421)**	−6.771	**(-1.704)**	13.381	**(1.812)**
21	2.601	(0.922)	−5.196	(−1.535)	9.398	**(4.743)**	−19.092	**(-2.755)**	−6.796	**(-1.680)**	13.896	**(1.940)**
22	2.128	(0.731)	−5.807	(−1.514)	10.106	**(5.381)**	−19.336	**(-2.682)**	−7.978	**(-1.985)**	13.530	**(1.792)**
23	2.500	(0.787)	−6.258	(−1.566)	11.025	**(6.002)**	−22.373	**(-3.597)**	−8.525	**(-1.997)**	16.115	**(2.572)**
24	3.302	(0.981)	−6.034	(−1.407)	11.781	**(5.714)**	−22.722	**(-3.512)**	−8.479	**(-1.830)**	16.688	**(2.632)**
					Panel D: Momentum Profits (Winners minus Losers) in Firm-level Top Volume Subsample							
1	−0.044	(−0.151)	0.301	**(2.036)**	1.101	**(3.553)**	−0.476	(−0.662)	−1.145	**(-2.895)**	0.777	(1.156)

Figure 1.1: 24-month Moving Average Momentum Profits Over Time



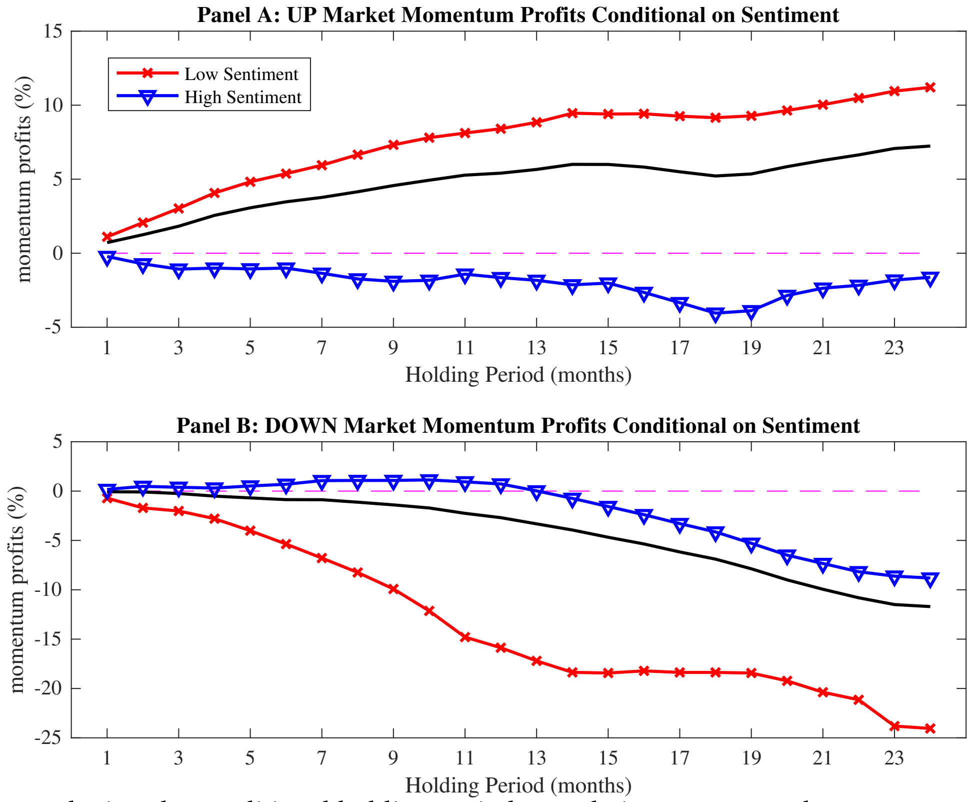
The figure depicts the 24-month moving average of the momentum monthly holding period returns ($R_{6,t}$) and cumulative returns ($CR_{6,t}$), where the latter series is converted into monthly returns. The time-period spans August 2002 to December 2014.

Figure 1.2: Conditional Cumulative Momentum Profits Over Time



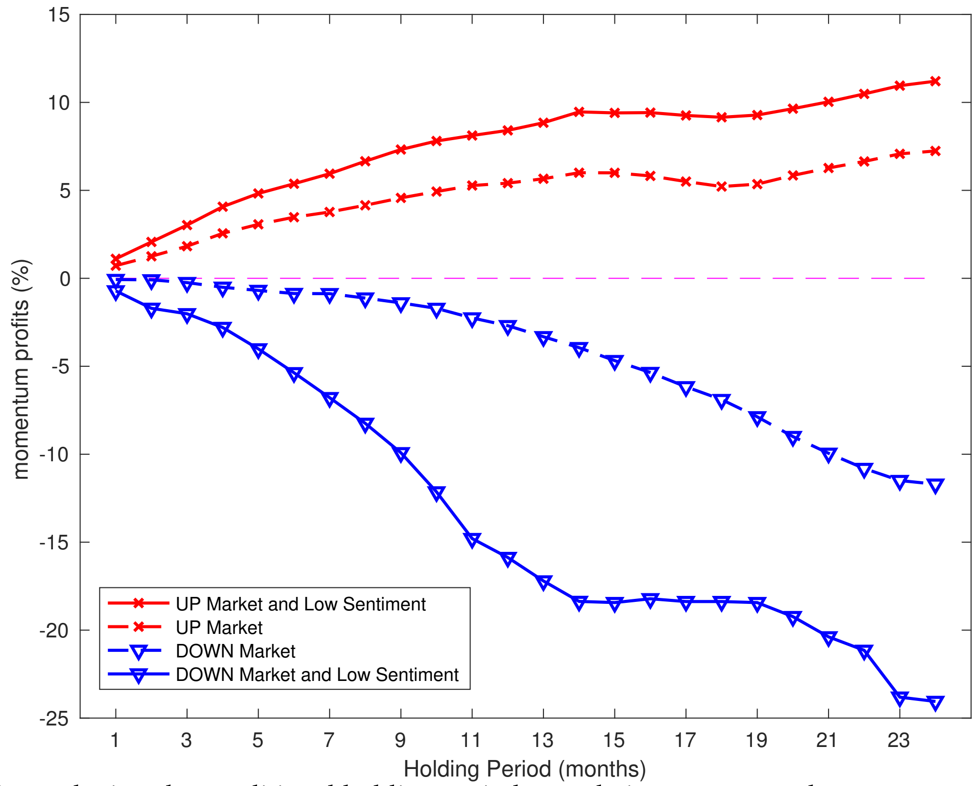
Panel A depicts the unconditional cumulative returns stemming from the six-month formation momentum portfolio with holding period horizons ranging from 1 month to 2 years, as well as the corresponding momentum returns stratified on the state of the market. Panel B and C represent the analogous time series, for the investment-grade and noninvestment-grade subsamples, respectively. Panel D plots the stratified momentum cumulative returns on sentiment. The time-period ranges from August 2002 to December 2014.

Figure 1.3: Effect of Sentiment on Momentum in UP and DOWN markets



The figure depicts the conditional holding period cumulative returns on the momentum portfolio for holding periods ranging from one month to two years. In Panel A, the conditional returns obtained when the market state is UP are sorted by high and low sentiment. In Panel B, the DOWN-market conditional returns are sorted by high and low sentiment. The time-period spans August 2002 to December 2014.

Figure 1.4: Momentum Effect Conditional on Market State in Low Sentiment



The figure depicts the conditional holding period cumulative returns on the momentum portfolio for holding periods ranging from 1 month to two years. The conditional returns in dotted lines are obtained by sorting on market states alone. This is the same series shown in Panel A of Figure 1.2. The solid lines represents momentum gains and losses conditional on the interaction of the market state and LOW sentiment. The time-period spans August 2002 to December 2014.

Chapter 2

The momentum effect for Canadian corporate bonds

2.1 Introduction

A recent report by the board of the International Organization of Securities Commissions (IOSCO) reckons that the number of issuances of Canadian corporate bonds has been steadily growing over the recent decade.[1] In 2016, the value of new corporate issuances in the US and Canada were $1.73 trillion and about $340 billion US dollars, respectively, which makes the value of the Canadian issuances about a fifth of that of the US. As of the end of the same year, the value of Canadian corporate bond outstanding amounted to about $1.13 trillion US dollars, whereas the equivalent figure for the US was around $8.1 trillion.[2]

While the Canadian corporate bond market is dwarfed by that of the US, a slightly different picture emerges when debt levels are compared to the respective levels of Gross Domestic Product (GDP). Debt outstanding for the Canadian corporate bond market was a solid 14% of that of its Southern neighbor, at the end of 2016. In contrast,

[1] Figures on issuances are from the February 2017 IOSCO report which is available at the following website: http://www.iosco.org/library/pubdocs/pdf/IOSCOPD558.pdf, last accessed on April 18, 2017.

[2] To provide further terms of comparison, the corporate debt stock for the UK hovered around $1.6 trillion US dollars, at the end of 2016. Data on country-level debt outstanding are from Bloomberg L.P.

over the same year, the Canadian GDP was about 8% of that of the US. Put differently, the size of the market for Canadian corporate bonds is larger than that of the US, in relative terms.

The literature on Canadian corporate bonds is rather sparse, despite the substantial size of the market. This study contributes to fill this gap by discussing the profitability of the asset pricing anomaly momentum in the Canadian setting, using bond-level data. The examined time period, spanning from August 1987 to December 2016, is only slightly short of three decades, and it is exceptionally long for the standards of the literature on Canadian financial markets. The sample includes 2,424 bonds issued by 389 firms which are spread over ten industries.

While being interesting in its own right, this study's analysis of the momentum effect for Canadian corporate bonds can also be viewed as an out-of-sample validation of the results obtained for the US corporate bond market (e.g., Jostova et al., 2013; Lin et al., 2017). Comparing countries in which investors operate in similar environments assuages concerns of conclusions being driven by unobservable market or institutional norms. From this perspective, choosing Canada for an out-of-sample analysis of the momentum effect for US corporate bonds is favored by the many similarities between the two markets, which have been most recently highlighted in Patel and Yang (2015).[3]

A momentum strategy exploits price trends, by taking long positions on past winners and short positions on past losers, where winners and losers are identified by ranking assets on the basis of their historical performance. The continuation of the historical price trends makes the momentum strategy profitable during the holding period. The expectation of a significant momentum effect in the market for Canadian corporate bonds is created by the conclusions in Asness et al. (2013) who document the pervasiveness of momentum gains across several countries as well as asset classes. While their empirical analysis does not cover the Canadian corporate bond market, the authors find some momentum gains for indexes of Canadian equities and govern-

[3]The institutional linkages between the Canadian and US financial markets are further reinforced by the considerable proportion of large companies listed on the Canadian stock market that are owned by US institutional investors (Tinic et al., 1987; Mittoo, 2003).

ment bonds. Along the same lines of inquiry, Schmidt et al. (2015) and Cleary and Inglis (1998), provide empirical evidence showing that Canadian stocks yield significant momentum gains. To the extent to which investors participating in the Canadian financial market are subject to similar market forces and investor biases, evidence of significant momentum gains for Canadian equities and government bonds suggests that the momentum effect should be relevant also for the pricing of Canadian fixed income securities.

The first round of results presented in this study documents that the momentum strategy for Canadian corporate bonds yields significant gains. These profits are markedly persistent, as we find significant and positive momentum returns for holding period horizons ranging from one month to two years. The comparison with the momentum gains documented in Jostova et al. (2013) for US corporate bonds suggests that the momentum effect is slightly weaker for Canadian bonds. The difference is however not extreme, as the spread is less than 20% of the annualized momentum returns for US bonds.[4]

Gebhardt et al. (2005) find that the momentum effect is not significant using a sample of investment-grade US corporate bonds, a result that is confirmed in Jostova et al. (2013). Our empirical analysis shows that there are no significant returns stemming from unconditional momentum strategies of investment-grade bonds also in the Canadian market. In particular, we find no momentum gains for holding periods ranging from one month up to two years.

Jostova et al. (2013) argue that there are significant momentum gains to be had in the US corporate bond market, which are however concentrated on speculative-grade bonds. Given the similarities between the Canadian and US corporate bond markets, these findings yield the expectation that the profitability of the momentum strategy for Canadian bonds should stem from the return continuation of low-grade securities. Unfortunately, the sparseness of Canadian speculative bonds prevents a direct exami-

[4]For the six-month holding period, Jostova et al. (2013) documents an annualized return of 4.44%, over a sample ranging from 1973 to 2011, whereas, we find that the corresponding rate for Canadian bonds is 3.67% over the period from 1987 to 2016.

nation of the profitability of the momentum strategy, for high-yield bonds. Indeed, for most of the months in our 1987-2016 sample, there are simply not enough low-grade Canadian bonds in the cross-section to form the decile (or even quintile) portfolios that define the momentum strategy. The marked paucity of Canadian speculative bonds is also documented in Patel and Yang (2015).

An examination of the composition of the short and long legs of the momentum portfolio suggests that the top and bottom deciles are characterized by high return dispersions as well as by large shares of speculative bonds, relative to the remaining deciles. While this finding is suggestive, the numerosity of the speculative-grade sample is too low to allow drawing any firm conclusion on the link between credit risk and momentum profits.

The momentum effect has been shown to be state-dependent in the US equity market, with momentum gains stemming exclusively from portfolios formed in months following periods of aggregate market gains (Cooper et al., 2004). In this study, we examine whether conditioning on the market state yields predictive power for the profitability of the momentum strategy also in the Canadian corporate bond market. Following Cooper et al. (2004), we define two states, namely the "UP" and "DOWN" market states, on the basis of the performance of the aggregate market index, here an equally weighted portfolio of the corporate bonds included in the sample. Momentum returns are classified as stemming from UP or DOWN markets on the basis of the market state in the portfolio formation month.

Our empirical results show that the market state effect is very significant in the Canadian corporate bond market. Significant momentum gains are obtained exclusively in UP markets. Further, subsequent testing shows that the difference between the performance of the momentum strategy in the UP and DOWN market states is statistically significant. The state effect is observed for holding period horizons ranging from one month up to two years. Conditioning on the market state has non-trivial implications for the profitability of the momentum effect, as forming the portfolio in UP market months yields gains that are twice as large as those entailed by the unconditional momentum strategy. To illustrate, the six-month formation period momentum strategy generates a significant monthly return of 0.63% for UP markets but an unconditional 0.30%, over the six-month holding period horizon.

A comparison of the conditional momentum returns documented in Cooper et al. (2004) for US equities and their analog for Canadian corporate bonds reveals strong similarities between the market state effect for the two asset classes. Momentum gains can be obtained only in UP markets. The empirical evidence also shows that the UP-market momentum gains are about a third weaker for Canadian bonds than for US equities.[5] Further, momentum portfolios formed in DOWN market state yield insignificant returns over the short run. However, different from that observed for equities, momentum portfolios of Canadian corporate bonds formed in DOWN markets fail to yield significant reversal gains for longer holding periods.

As done in Cooper et al. (2004) for the equity market, we regard our evidence of a market state effect on momentum as being consistent both with an extended version of the behavioral theory developed by Daniel et al. (1998) and of the limited rationality argument proposed in Hong and Stein (1999). The market state influences investors' overconfidence (e.g., Gervais and Odean, 2001), which originates the momentum effect in Daniel et al. (1998). Hong and Stein (1999) argue that a decrease in risk aversion of momentum traders entails stronger momentum gains. The effect of the market state on agents' risk aversion can be linked to wealth fluctuations in the habit formation framework by Campbell and Cochrane (1999). To the extent to which buoyant markets are associated with a reduced risk aversion, due to wealth increases, positive market gain may be associated with stronger underreaction to news and thus with stronger momentum gains.

In the market for Canadian corporate bonds, momentum profits appear to reach their highest values in the early part of the sample. These gains appear to decrease to lower levels starting from the early nineties. This shift coincides with a period

[5] A potential explanation of this cross-market difference may reside in the definition of the market states employed. Using equity market data, we show in an appendix that the definition of the market states in this study makes harder to detect state dependence than the one used in Cooper et al. (2004).

during which the Canadian financial market underwent institutional changes which profoundly altered the market environment. We explore the possibility that the momentum effect may be radically different before and after this wave of institutional changes by examining the profitability of the strategy in a subsample starting in 1994. For the time being, it suffices to note that the conclusions drawn on the basis of the full sample are confirmed from the subsample analysis.

The Canadian market for corporate bonds is dominated by institutional investors, in terms of trading volume. A natural question that then arises is whether the trading activities of institutional investors are associated with the significant momentum effect documented in this article. Unfortunately, the type of data that would allow separating the trades of institutional and retail investors is not available for Canadian corporate bonds, as yet.[6]

Using transaction-based quotes for US corporate bonds, Ronen and Zhou (2013) have shown that the trading activities of institutional investors tend to focus on a handful of bonds per issuer, these being termed the top bonds. Building on their insights, this study proposes a way around data unavailability by identifying top bonds with on-the-run issues.[7] The empirical analysis shows that the momentum effect is insignificant for portfolios of on-the-run issues, both unconditionally and conditionally on the state of the market. This finding is consistent with institutional investors being largely unaffected by the behaviors that have been invoked in the theoretical literature to explain the momentum effect. However, while our analysis gives a first stab to the challenge of identifying the momentum traders in the market for Canadian bonds, we feel that more research is warranted before firm conclusions can be drawn.

The rest of the paper is organized as follows. The next section describes the sample and offers basic summary statistics for the Canadian corporate bonds used in this

[6] As of November 2015, all fixed income trades in Canada have to be reported to the Investment Industry Regulatory Organization of Canada (IIROC). Starting from July 2016, a subset of the IIROC corporate bond transaction data has been made available to researchers. However, this promising data source cannot be employed to analyze the momentum strategy, as the time span covered is too limited.

[7] In another study of the Canadian corporate bond market, Cao et al. (2017) showed that on-the-run issues magnify the predictive power of bond yield changes for future stock returns, at the issuer level. This result is consistent with the prices of top bonds as being informationally richer than those of the remaining bonds in the cross-section.

study. Section 2.3 describes the momentum strategies employed to gauge the momentum effect. The unconditional assessment of the profitability of the momentum effect in the Canadian corporate bond market is in Section 2.4. The effect of the market state on momentum returns is documented in Section 2.5. The analysis of the 1994-2016 subsample can be found in Section 2.6. The evaluation of the momentum effect for on-the-run bonds is in Section 2.7. A short summary of the findings conclude.

2.2 Data

Our sample covers monthly bond-level data over a period slightly shorter than three decades, ranging from August 1987 to December 2016, for 20,988 corporate bonds issued in Canada. The sample includes information on individual bonds monthly closing prices and yields. For each bond, we obtain the coupon, coupon frequency, the first coupon payment date, volume at issue, date of issue, and maturity date, as well as the issuer's industry code. Data are sourced from Bloomberg. Credit ratings are from DBRS (Dominion Bond Rating Service), the reference rating agency for long samples of Canadian securities.[8] We refer to issuer-level credit ratings when assigning rates to bond-month observations.[9]

We exclude from the sample all bonds denominated in currencies other than the Canadian dollar, and also bonds that have contingency provisions.[10] We obtain a subset of 4,249 bullet bonds, i.e. fixed-coupon bonds with no contingency provisions attached, issued in Canadian dollars. We further exclude all bonds that have less than six observations. We also discard bonds for which relevant information (e.g., issue date) is unavailable or incomplete. For each bond, prices falling within six months of the bond maturity date are discarded from the sample, as these prices are typically particularly

[8]Whenever the DBRS ratings are not available we use the rating of Standard & Poor's. The two agencies use the same rating scale. For bonds requiring ratings earlier than 2000, we refer to Canadian Bond Rating Service (CBRS), which became a subsidiary of S&P in 2000.

[9]When the credit rating of an issuer is not available, then we employ its rating for senior unsecured debt. For bond issuers that have only one bond, which is neither senior nor unsecured, we use bond-level ratings, whenever possible.

[10]In particular, we exclude from the sample callable, putable, convertible, sinkable bonds, and bonds with floating coupon rate.

unreliable. To alleviate data quality concerns, especially for the early years of the sample, we winsorize returns at the 1% level. This procedure allows discarding outliers that are most likely to be associated with incorrect data entries. The conclusions of this study remain unaltered when we use unwinsorized data.

In the raw data, the total number of monthly prices after filtering is 120,945, for 2,428 bonds. Of the total number of observations, 108,299, i.e., slightly less than 90%, belong to bonds paying coupons semiannually, while 10,145, i.e., about 8.4%, are for bonds yielding annual coupons. The remaining observations are associated with quarterly or monthly coupon frequencies, or with zero-coupon bonds. We calculate monthly returns for each bond in the refined sample based on their monthly closing (last) prices. To calculate returns we define:

$$r_{i,t+1} = \frac{(P_{i,t+1} + AI_{i,t+1} + C_{i,t+1}) - (P_{i,t} + AI_{i,t})}{P_{i,t} + AI_{i,t}} \tag{2.1}$$

where, $r_{i,t+1}$ is the return on bond i for the one-month holding period from t to $t+1$, and $P_{i,t+1}$ is the last price of bond i at time $t+1$. The variable $C_{i,t+1}$ is the amount of coupon paid between time t and $t+1$, if any, and it is calculated as the ratio of annual coupon rate of bond i to the coupon frequency. The accrued interest $AI_{i,t+1}$ is defined as follows:

$$AI_{i,t+1} = C_{i,t+1}\left(\frac{d_{t+1}}{D_{t+1}}\right)$$

where d_{t+1} is the number of days between time $t+1$ and the last coupon payment date, and D_{t+1} is the number of days between two consecutive coupon payments enclosing time $t+1$. When dealing with the calculation of accrued interests, we take into account that calendar months contain different numbers of days. After filtering, our sample contains 113,155 return observations for 2,424 bonds issued by 389 firms from 10 industries. Table 2.1 tabulates basic descriptive statistics for our sample.

Panel A in Table 2.1 reports basic summary statistics for the whole sample, as well as for investment-grade and speculative bonds, separately. In the pooled sample, the coupon level is about 6%, while the average yield is about 4.6%. Meanwhile, the average volume at issue, per bond, is 297 million Canadian dollars. The average monthly return is 50 bps, which amounts to about 6%, in terms of annualized return. The median monthly return is slightly lower, by 14 bps, which suggests the presence of a heavy right tail of the distribution. After sorting all bonds in our sample by their issue year, we calculate that about C$ 20 billions of new corporate bonds are issued per year (untabulated) from 1971 to 2016.

The second and third rows of results in Panel A reports summary statistics for bond-month observations sorted into the investment and non-investment grade categories.[11] The vast majority of the monthly returns in our sample belong to bonds issued by firms rated at, or above, the BBB low threshold. Of the 102,195 observations for which credit rating is available, only 1,002 are associated with the pricing of high-yield bonds. Hence, there are roughly 100 bond-month returns in the investment-grade category for each bond-month observation in the low-grade group. Untabulated statistics show that an overwhelming majority of the returns on high-grade bonds (i.e., 49,279 observations) falls into the "A"-rating category, whereas the low-grade category of BB accounts for 68% of the non-investment-grade bond returns. The sparseness of high-yield bonds in our sample is consistent with the observations of Patel and Yang (2015).

To shed further light on the structure of the Canadian market for corporate bonds, we calculate basic summary statistics for the sub-sample of bonds for which we can obtain a return-at-issue.[12] The yields and returns of the bonds in this sub-sample offer an approximation of the at-issue cost of borrowing for Canadian firms tapping the domestic corporate bond market.[13] The at-issue sub-sample includes 1,066 returns and yields for 254 firms. This sub-sample of bonds are sorted into maturity bands to gather stylized facts on the effect of maturity length on bond borrowing costs. Detailed summary statistics for at-issue bonds are reported in Panel B of Table 2.1. The statistics in

[11]For 10,960 of the 113,155 observations in our sample (i.e., about 10%), credit ratings are not available.

[12]In the literature on municipal bond offerings, many studies employ yields at issue (e.g., Butler, 2008).

[13]To calculate the return-at-issue, we use the first two available end-of-the-month prices, within the first two months following the date of issue.

Panel B indicate that Canadian corporate bonds are issued with an average maturity of about nine years, with more than half of the issues maturing in 5 to 10 years. Coupons and yields appear to be increasing with maturity length.

2.3 The Momentum Strategies

We form the momentum portfolio of bonds as already done in Gebhardt et al. (2005) and Jostova et al. (2013) who in turn rely on the six-month formation period momentum strategy introduced by Jegadeesh and Titman (1993). Presently, the momentum portfolio formed in month t is obtained after sorting bonds into deciles on the basis of their historical cumulative returns over the formation period, which consists of six months.[14] An equally weighted portfolio of the bonds in the top (bottom) decile identifies the long (short) leg of the momentum anomaly. For all strategies, we skip a month between the formation and holding periods. This month is henceforth called the formation month. We consider holding period horizons spanning from one month up to two years.

To foster consistency with previous studies on the conditional and unconditional momentum effect, we consider two types of returns, these being holding period monthly returns and cumulative returns. Following Jegadeesh and Titman (1993), for each holding period n, the holding period monthly return is the cross-sectional average at time t of the returns on n overlapping momentum portfolios. Each of this overlapping strategies is formed in one of the n months preceding time t. The series of the n-month holding period monthly returns is denoted by $\mathrm{R}_{n,t}$.

Later on in this study, we shall perform a conditional analysis of the return on the momentum strategy using cumulative rather than monthly holding period returns. The time-t cumulative return of a portfolio formed at time $t-n$, which is denoted by $\mathrm{CR}_{n,t}$, is the sum of the n monthly returns stemming from the portfolio in the months

[14] All the results presented in this paper are robust when we consider momentum portfolios that are symmetric in the length of the formation and holding periods, ranging from one to 24 months. The results are available upon request.

ranging from $t-n+1$ to t.

Holding period monthly returns are cross-sectional averages of overlapping momentum portfolios which are formed in different months. Because the formation months are staggered, it is unclear the degree to which the returns on the overlapping portfolios are influenced by any given realization of a conditioning variable. In contrast, cumulative returns are calculated for momentum portfolios that are formed in a given month, and thus they can be linked to a unique realization of the conditioning variable under consideration. This key difference between cumulative and monthly holding period returns make the latter less suitable than the former to perform a conditional analysis of the predictive type. Consistently, this study's conditional analysis of the performance of the momentum strategy focuses on cumulative returns. In doing so, we are following the approach proposed in Cooper et al. (2004) to analyze the predictive ability of the market state for future momentum gains, in the US equity market.[15]

The impact of rebalancing on portfolio performance may be particularly relevant in the corporate bond market, due to high transaction costs.[16] The buy-and-hold portfolios generating cumulative returns are thus potentially more cost-efficient than the monthly rebalanced portfolios yielding the holding period monthly returns. From this perspective, an additional advantage of considering cumulative rather than holding period monthly returns is that the estimated profits are less susceptible to be wiped away by transaction costs.

[15]Recent literature has examined the conditional profitability of the momentum strategy for the one-month holding period (e.g., Lin et al., 2017), an approach that does not require the use of overlapping portfolios. However, using cumulative returns allows evaluating conditional profitability for holding period horizons longer than one month.

[16]To the authors' knowledge there is no scholarly evidence on the role of transaction costs in the Canadian bond market. For the US market, Edwards et al. (2007) note that transaction costs for corporate bonds are substantially higher than those of equities.

2.4 Profitability of the Momentum Strategy

Panel A.1 of Table 2.2 reports the (unconditional) monthly holding period returns for the momentum strategy with six-month formation period. The results indicate that the momentum strategy yields significant gains for holding period horizons ranging from one month up to two years. These returns are comparable to those documented for the US in Jostova et al. (2013), in which the authors document a significant momentum profit, of 37 bps per month, for the six-month holding period return. The analog portfolio for Canadian bonds yields the very similar rate of return of 35 bps.[17] This monthly return rate appears to be increasing with the holding period. Considering cumulative returns, in Panel B.1, rather than monthly holding period rates, does not modify the assessment of the profitability of the momentum effect for Canadian corporate bonds. For instance, the cumulative return of the strategy at the two-year mark is 6.65%, which corresponds to a monthly return of 28 bps.

The analysis of the (unconditional) profitability of the momentum strategy summarized in Panel A.2 of Table 2.2 reveals that there are no momentum gains for high-grade corporate bonds. Panel B.2 of the same table confirms that the use of cumulative returns does not alter this conclusion. Evidence of no momentum gains for high-grade bonds is consistent with the conclusions of Gebhardt et al. (2005) and Jostova et al. (2013) for the US corporate bond market. Getting ahead of ourselves, however, we note that the conditional analysis will reveal that these insignificant cumulative returns are partially the result of the aggregation of significantly different levels of momentum profitability across the market states.

Jostova et al. (2013) show that the profitability of the winners-minus-losers strategy for US corporate bonds is concentrated in low-grade securities. Given that we find no evidence of unconditional momentum gains in the investment-grade subsample, we

[17] In this chapter, we rely on price quotes, rather than transaction-based prices. As quote-based prices may reflect the judgment of dealers on the value of the assets, it is conceivable that dealers who extrapolate quotes from benchmarks with similar bond features may generate spurious momentum returns. Jostova et al. (2013) document that, in the US market, the momentum strategy generates similar returns using both transaction-based and quote based prices. The authors conclude that strategies based on price quotes are not identifying spurious momentum profits. For the Canadian market, transaction-based prices are not available for a time interval that is sufficiently long to test this conjecture.

conjecture that low-grade bonds also appear to drive the unconditional momentum effect in the Canadian market. However, whether there are significant momentum profits in Canadian high-yield bonds cannot be directly investigated with the available data, as the size of the market for Canadian speculative bonds is negligible compared to that of high-grade bonds. As reported in Table 2.1, only 1% of the bond-month observations in our sample are associated with low-grade bonds. Furthermore, about 92% of the bond issuers in our sample are rated above BBB low, across the entire sample period. The small scale of the high-yield bond market in Canada renders unfeasible the formation of momentum portfolios for speculative-grade bonds.

The separate examination of the short and long legs of the 6-month formation and holding period momentum portfolio in Table 2.3 reveals that the past winner (decile 10) portfolio includes about 3.5 times as many speculative-grade bonds than the past loser side (decile 1 portfolio). The percentage of non-investment grade bonds is also multiple times larger in the top decile portfolio than in the remaining deciles. The winner and loser decile portfolios are also exceptional in terms of return dispersion. The cross-sectional standard deviation of formation period returns in the top and bottom deciles are at least one order of magnitude larger than that observed for other deciles. This evidence suggests that a high concentration of speculative bonds may matter in determining the strength of the momentum effect. However, we cannot form a firm conclusion on this matter with the currently available sample.

2.5 UP and DOWN Markets

The possibility that a small fraction of high-yield bonds is entirely accountable for the momentum gains in Canadian corporate bonds implies that the momentum effect may be negligible in the Canadian corporate bond market. However, the weak momentum effect, especially in the investment-grade bond subsample, could simply be the result of the aggregation of significant gains and losses over different sub-periods. For instance, Cooper et al. (2004) find that the momentum effect in the US stock market is exclusive to holding periods following positive aggregate stock market performance, while the momentum strategy is unprofitable in periods of negative market performance.

Figure 2.1 plots the 48-month moving average of the returns on the six-month formation and holding period momentum strategy. The plot reveals that momentum returns in Canadian corporate bonds have been fluctuating over time. A time-varying profitability of the momentum strategy begets the question of whether there is an observable conditioning variable (e.g., the bond market state) that is able to account for periods of high and low momentum profits. In this section, we investigates whether a similar market state effect is detectable for Canadian corporate bonds, and whether, upon conditioning on market states, the analysis of the momentum effect can bring about significant gains also for Canadian investment-grade bonds.

To commence, a month t is in the UP (DOWN) market state if the overall market performance over the year preceding month t is above (below) the sample average of the return on the equally weighted (EW) market portfolio.[18] More precisely, at time t the market is in the UP (DOWN) state if the average of all the monthly bond returns available for the time-period from $t-12$ to $t-1$ is above (below) the sample average of the return on the EW index.[19] The market is in an UP state in 141 months of the 341 months in our sample. Table 2.4 tabulates the descriptive statistics for the UP and DOWN periods of the sample.

To evaluate the predictive ability of the market state, we follow Cooper et al. (2004) and focus on the cumulative returns of the six-month formation period momentum portfolio. A momentum return is categorized as in the UP (DOWN) market state when the market state in the formation month is UP (DOWN). Hence the series of cumulative returns on portfolios with six-month formation and holding periods, namely $CR_{6,t}$, is in the UP state at time t if at time $t-6$ the market is in the UP (DOWN) state.

[18]In each month, the equally weighted market portfolio includes all the bonds in the cross-section of the final sample, i.e., the sample used to construct the momentum portfolios.

[19]The use of the median, rather than the average, of the monthly returns on the EW market index does not alter the conclusion of this paper. Further details and a discussion of the definition of the market states are presented in the appendix.

In Figure 2.2, we plot the conditional and unconditional momentum cumulative returns for the six-month formation period strategy, where conditioning is on the market state in the portfolio formation month. The plot clearly suggests that the unconditional momentum gains documented in Panel B.1 of Table 2.2 are the result of the aggregation over market states of a very state-dependent return series. Indeed, the most striking feature of the conditional momentum return series, as plotted in Figure 2.2, is their diverging paths. In particular, the figure shows that the spread between the momentum returns in UP versus DOWN markets increases over time, in an almost perfectly monotonic fashion.

The visual evidence is corroborated by the results of the statistical analysis, which is conducted following the approach proposed in Cooper et al. (2004) to foster consistency with the literature on the momentum effect. Presently, to ascertain whether momentum gains are zero in UP or DOWN market states, we evaluate a linear model of the cumulative returns on the six-month formation strategy $\mathrm{CR}_{n,t}$ as a function of the dichotomous variables identifying the market states. Formally, the equation is:

$$CR_{n,t} = \beta_{UP} D^{UP}_{t-n} + \beta_{DOWN} D^{D}_{t-n} + \varepsilon_t, \tag{2.2}$$

where $t-n$ is the formation month, the variable D^{UP}_t is one if at t the market is UP and zero otherwise, the variable D^D_t is one if at t the market is DOWN and zero otherwise, and ε_t are zero-mean disturbances. Further, to ascertain whether momentum gains are different conditionally on market state, we evaluate a second linear model in which the momentum series of $\mathrm{CR}_{n,t}$ is modeled as a function of a constant and of the UP market indicator for the formation month. Formally, the model is:

$$CR_{n,t} = \alpha + \gamma_{UP} D^{UP}_{t-n} + \nu_t \tag{2.3}$$

where once more $t-n$ is the formation month and ν_t are zero-mean error terms. Since the $\mathrm{CR}_{n,t}$ series are the summation of overlapping returns, we employ a heteroskedasticity-and-autocorrelation consistent (HAC) estimator for the variance of the coefficients in equations 2.2 and 2.3 (e.g., Gallant, 1987; West and Newey, 1987; Cooper et al., 2004). The number of lags is set equal to the number of overlapping months in the holding period (i.e., for the series $CR_{n,t}$ then we consider $n-1$ lags). The regression approach preserves the time-series structure of the data and yields standard errors that are robust for autocorrelation.

The stratified averages and corresponding t-statistics of the cumulative returns on the momentum strategy, as well as for the long and short side of the momentum portfolio, are reported in Panel A of Table 2.5 for the full sample and in Panel B for the investment-grade subsample. The table also includes the assessment of the significance of the coefficient γ_{UP} from equation 2.3.

The estimates reported in Panel A of Table 2.5 indicate that there are significant momentum profits associated with the six-month formation momentum strategy, but only if the market state is UP. Insignificant returns are associated with DOWN markets. Further, the coefficient γ_{UP} from equation 2.3 is significant, thus indicating that the returns of the momentum strategy are indeed statistically different across the two market states. These conclusions are strongly supported by the empirical analysis for holding periods ranging from one month to two-years.

The comparison of the conditional and unconditional stratified returns in Panel B.1 of Table 2.2 and Panel A of Table 2.5 shows that the stratified momentum profits in UP states are about twice as large as the corresponding unconditional average returns. Taken together, the empirical evidence presented in Table 2.5 indicate that momentum gains are concentrated in periods following buoyant market conditions, a conclusion that is consistent with the finding of Cooper et al. (2004).

The comparison of the conditional momentum returns documented in Cooper et al. (2004) for US equities and their analog for Canadian corporate bonds reveals strong similarities between the market state effect for the two asset classes. Momentum gains can be obtained only in UP markets. However, for US equities there are significant reversal profits, i.e., momentum losses, for holding periods longer than one year. It appears not to be the case for Canadian corporate bonds, as the positive and significant momentum gains in UP markets as documented in Panel A of Table 2.5 extend up to the two-year horizon.

The empirical evidence also shows that the UP-market momentum gains are weaker for Canadian bonds than for US equities.[20] While being smaller than those observed for equities, the conditional returns stemming from momentum portfolios of Canadian corporate bonds are economically relevant. In UP markets, the six-month formation period momentum strategy generates a significant monthly return of 63 bps, over a six-month holding period horizon. To compare, for US equities the analog rate is 93 bps, as estimated in Cooper et al. (2004).

In the DOWN market state, Cooper et al. (2004) show that US equities yield significant reversal gains for holding period horizons longer than one year, as well as insignificant momentum losses over the short-run. We document that in the market for Canadian bonds, in DOWN markets, neither reversal nor momentum gains are detectable, for all the holding periods considered.

Figure 2.3 represents the cumulative return on the six-month formation strategy for investment-grade bonds, conditional on the UP and DOWN market states. The plot also reports the unconditional cumulative returns on the same portfolio. At a glance it stands out that the spread between momentum returns in UP and DOWN markets is consistently large, starting from the six-month holding period horizon. Further, the figure shows that the momentum profits stem solely from the UP market state, and that, for most of the months, the strategy yields very small losses in the DOWN market state. The statistical analysis, in Panel B of Table 2.5, broadly confirms the conclusions suggested by the visual evidence. Overall, the conditional analysis reveals that there are significant momentum profits to be gained also for high-grade corporate bonds, albeit weak ones, in the UP market state. These gains appear to be concentrated around the one-year holding period horizon.

Evidence of a significant market state dependence of the momentum effect in the

[20] A potential explanation of this cross-market difference may reside in the definition of market state employed. Using equity market data, we show in an appendix that the definition of the market states in this study makes harder to detect state-dependence than the one used in Cooper et al. (2004).

Canadian corporate bond market may be interpreted in view of the limited rationality argument proposed in Hong and Stein (1999) as well as the behavioral theory developed by Daniel et al. (1998). Buoyant markets are associated with reduced risk aversion of momentum traders, which causes increased spells of underreaction to information, resulting in stronger momentum gains. From this standpoint, the distinctive performances of the momentum strategy across market states can be viewed as evidence that the marginal investor in the Canadian corporate bond market is a momentum trader, and that the risk aversion of momentum traders declines following enduring market gains. An alternative explanation for the market state effect is that upbeat markets increase investors' overconfidence, which in turns yields larger momentum gains. From this perspective, the results discussed in this section are consistent with investors overconfidence increases following good market runs.

Viewing from the perspective of the behavioral theory of Daniel et al. (1998), the results discussed in this section are consistent with the market state being a good gauge of investors' overconfidence, which originates the momentum effect. The literature, however, has proposed alternative measures of overconfidence, where this behavioral bias is measured by aggregate overpricing. The BW sentiment measure proposed in Baker and Wurgler (2006), in particular, has been shown to be linked to the profitability of several anomalies, among which is the momentum strategy in the US equity market (Stambaugh et al., 2012). In an unreported analysis, we find that the BW sentiment measure, which is constructed using US data, has no predictive power for future momentum returns in the Canadian corporate bond market.

In Panel A of Table B.5 in the Appendix B, we explore the market state effect for US corporate bonds using transaction data from the Trade Reporting and Compliance Engine (TRACE) database. As TRACE was launched in 2002 the sample is shorter than the one analyzed in this study of the Canadian market for corporate bonds. Nevertheless, significant similarities do emerge. The momentum effect is profitable exclusively in the UP state in both the US and Canadian corporate bond markets. These momentum gains are significantly different from the momentum returns associated with

DOWN markets, which in turn are either negative (for the US sample) or insignificant (for Canadian bonds).

In Panel B of Table B.5, we restrict our sample to the period defined by the availability of TRACE data. The results show that the profitability of the momentum strategy in UP markets is lower in the short-run for Canadian corporate bonds than for the US corporate bonds. For instance, the six-month formation period momentum strategy yields a monthly return of 46 bps and 58 bps for Canadian and US bonds, respectively, for the holding period of six months. However, over the long-run, the momentum returns in UP markets tend to converge to about 30 bps for both markets. Previous evidence shows that both US equities and corporate bonds yield significant reversal gains in the long-run, but not momentum profits, in DOWN markets. In contrast, both the momentum and reversal effects appear to be absent when the market state is DOWN for Canadian bonds, both for the 1987-2016 and the TRACE-defined time period.

2.6 Subsample Analysis (1994-2016)

The plot of momentum average returns documented in Figure 2.1 reveals that the momentum strategy used to be particularly profitable in the early years of the sample, reaching values as large as 12% in terms of annualized return rate. Gauging from the visual evidence, the assessment of the profitability of the momentum strategy conducted for the 1987-2016 sample could be profoundly conditioned from the strong momentum returns observed in the early years. Additionally, we note that the market for Canadian corporate bonds was extremely small during those early years of the sample. As a result, early price quotes might carry a large liquidity premium which is difficult to assess, in the absence of reliable bid and ask prices. Taken together, these considerations suggest that the robustness of the results discussed up to this point should be verified through a subsample analysis.

Landon (2009) examines the effective tax rate on Government of Canada bonds and shows that following a wave of institutional amendments, the composition of the investor pool in Canada might have changed around the year 1993. Relying on his conclusions, we identify the cut-off point defining the early and most recent subsamples as the end of 1993.

The results reported in Panel A.1 of Table 2.6 for the 1994-2016 sample indicate that the momentum strategy yields significant holding period monthly returns over horizons ranging from one month to two years, as it is the case in the full sample. However, the momentum effects appear to be weaker in the reduced sample. Similar conclusions can be drawn considering cumulative returns, reported in Panel B.1 of Table 2.6.

Weaker momentum average returns in the most recent sample may be attributed to many causes. For instance, the momentum effect in the corporate bond market may be vanishing in recent years because of its exposure to the scholarly debate. Indeed, McLean and Pontiff (2016) have suggested that once the academic literature identifies an abnormally profitable strategy, its gains enter a descending trajectory, as more traders crowd the profitable positions.[21] However, such line of argumentation may be less than compelling for Canadian corporate bonds, as this article is the first to explore the momentum effect for Canadian corporate bonds.

At this stage of our investigation, we are unable to explain the drop in momentum gains occurred in the early nineties. We, however, conjecture that the changes in the pool of investors documented by Landon (2009) for Government of Canada bonds may have also affected the market for corporate bonds. From this perspective, the possibility exists that momentum traders, *a la* Hong and Stein (1999) have become less prevalent following the wave of institutional reforms that characterized the first part of the sample. The exploration of this possibility is left for future research.

As reported in Table 2.7, the conditional analysis of returns on the momentum strategy in the 1994-2016 subsample reveals that momentum gains are exclusive to UP

[21] The first paper to discuss momentum gains in the corporate bond market, for the US, dates back to 2005 by Gebhardt et al. (2005).

markets, as observed for the full sample. While the conditional returns in the subsample are smaller than those obtained for the full sample, as it was the case for the unconditional subsample analysis, they are economically and statistically meaningful. In Panel A of Table 2.7, across holding periods ranging from one month to two years, the strategy yields a monthly return of about 40 bps, which is smaller but comparable to the analog rate of 0.55 observed for the full sample. Interestingly, however, in Panel B of Table 2.7, the momentum gains yielded by investment-grade bonds in UP market turn out to be small but significant for the full range of holding period horizons considered. These returns are economically significant, at least over the short-run. For instance, the annualized rate of return for the six month holding period strategy in UP markets is 4.12% in Panel B of Table 2.7. These rates are much larger than the corresponding returns reported in Panel B of Table 2.5 for high-grade bonds in UP markets when the full time period sample is considered. Put differently, conditioning on the market state brings about significant gains for investment-grade bonds. These conditional profits appear to have been increasing over time.

We find it puzzling that the subsample analysis yields evidence of opposite trends in the returns on momentum portfolios of investment-grade bonds versus those of momentum strategies that rely on the full cross-section of bonds, in UP markets. We propose that a potential explanation resides in the dynamic of credit ratings, in the subsamples.

Empirically, we find that there is an overall declining trend for the cross-sectional average of the credit ratings assigned to investment-grade bonds in the 1994-2016 subsample. Put differently, the post-1994 ratings in our sample suggest that the credit quality of high-grade bonds has been declining over time. Figure 2.4 visually confirm the statistical analysis, by showing the fitted trend regression lines for the monthly cross-sectional average of credit ratings in the pre-1994 and 1994-2016 subsamples, under the convention that lower credit quality corresponds to larger values of the credit risk measure.

Declines in the average rating of investment-grade bonds may cause market participants to view these securities as increasingly similar to speculative securities. Should the momentum effect be particularly marked for speculative bonds in Canada, as it is the case in the US corporate bond market, then declining credit scores would be positively associated with an increase in momentum gains for high-grade bonds. The effect is only visible in UP markets, as in DOWN market the analysis reveals that the momentum effect yields insignificant returns. From this perspective, the documented higher momentum gains for investment-grade bonds in the most recent subsample are consistent with an overall decline in credit ratings of investment-grade bonds. The effect is less marked in the full sample, as ratings appear to have been on an upward trend in the early years of the period under consideration.[22] Consistently, a comparison between the full and reduced sample shows that significant momentum gains for investment-grade bonds are larger in the 1994-2016 subsample. This result is also confirmed by the point-estimates of the unconditional returns.[23]

In the 1994-2016 subsample, although the momentum effect in the whole sample has decreased, the higher momentum gains in UP markets for investment-grade bonds suggest that it is more plausible to implement the state-dependent momentum strategy in the post-1994 period. We argue that, when conditioning on market states, the performance of the momentum strategy may improve with increased returns and decreased volatility. Particularly, the average unconditional momentum returns summarize periods over which the momentum strategy performs poorly with periods of strong performance. Hence, returns on the unconditional momentum strategy are associated with large variations. Consistently, in the 1994-2016 subsample, the annual Sharpe ratio for the unconditional momentum strategy is 0.8, compared with 3.25 for the conditional UP market strategy, considering the standard six-month formation and holding period strategy. For comparison, the Sharpe ratio of the reversal strategy in the DOWN market is 0.17. When the six-month formation and holding period strategy is implemented in investment-grade bonds, the annual Sharpe ratio increased from

[22] An univariate regression of the cross-sectional rating (with high values meaning lower ratings) on a time-trend, and a constant, yields a positive and statistically significant trend coefficient in the sub-sample. The analog coefficient for the 1987-1993 sample is negative.

[23] Compare Panels A.2 and B.2 of Tables 2.2 and Table 2.6.

0.45 for the unconditional portfolio to 0.77 in UP markets.

2.7 Momentum in Top-Bonds

Institutional traders dominate the market for Canadian corporate bonds, with retail investors accounting for only 3% of the trading volume in 2016 (e.g., Devani and Zhang, 2017). Further, this study documents a significant, and persistent, momentum effect for Canadian corporate bonds. These two pieces of evidence, taken together, raise the question of whether institutional investors operating in the Canadian market for corporate bonds are momentum traders. Momentum profits stemming from the trades of institutions would not be surprising, as previous literature has shown that, at least in the US, institutional investors do enact momentum strategies in their portfolios (e.g., Grinblatt et al., 1995; Sias, 2004).

Unfortunately, the type of data that could be used to separate the trades of institutional and retail investors is not yet available for Canadian corporate bonds. However, this study proposes a way around this obstacle by capitalizing on the findings of Ronen and Zhou (2013) to identify bonds traded by institutional investors.

Using transaction-based quotes for US corporate bonds, Ronen and Zhou (2013) have shown that the trading activities of institutional investors tend to focus on a handful of bonds per issuer, these being termed the top bonds. The authors show that for US firms issuing only investment grade bonds, the most recent issues are the top bonds in a remarkable 94% of the instances (e.g., see Table 6 in Ronen and Zhou, 2013). Building on this characterization of top bonds, in this study we identify the top bond of each issuer with its most recently issued bond (i.e., with the on-the-run issue).[24] This identification strategy is supported by the observation that about 90% of the bonds in our sample are issued by firms that are rated at or above the BBB low

[24] In cases where a firm issued multiple bonds on the same date, the top bond is the one with the longest time to maturity. This selection protocol is corroborated by the finding that in 84.18% of the instances firms' top bonds are those on-the-run issues with the longest maturity (Ronen and Zhou, 2013).

threshold for the entire lifespan of the bond.[25]

We cull from our sample a subsample of on-the-run issues. Past winners and losers are then identified ranking into deciles firms on the basis of the cumulative returns of their top bonds, over the six months preceding the formation month. Hence, the strategy identifies a set of firms, rather than a set of bonds, as past winners and past losers. In this sense, the top-bond momentum strategy is firm-based, as it is the case for the momentum strategy in the equity market.

The empirical results, reported in Table 2.8, show that the momentum effect is insignificant for portfolios of on-the-run issues. Furthermore, unreported results also document insignificant momentum returns for top bonds both in the UP and DOWN market states. To the extent to which the returns on top bonds capture the trades of institutional investors, these findings are consistent with institutional investors in the Canadian bond market being largely unaffected by the biases that have been proposed to explain the momentum effect, in the theoretical literature. This result would leave retail investors responsible for the momentum effect. However, given the small trade volume associated with retail investing, we feel that this conclusion needs further scrutiny. We leave this challenge for future research.

For the year 2016, Devani and Zhang (2017) show that Canadian corporate bonds attract most of the trades in the first two weeks after issuances. Moreover, the bond-level trade volume drops dramatically after one week from issuance. On the basis of these pieces of information, we conclude that the on-the-run issue is the most liquid bond in the cross-section of bonds, at the issuer level, also in the Canadian market. From this perspective, thus, focusing on momentum portfolios in top bonds is also a way to examine whether liquidity has some bearing on the strength of the momentum effect. The empirical evidence appears to suggest that the momentum effect may be associated with low-liquidity bonds.[26]

[25] About 65% (162 bonds) of the remaining 10% have no ratings over their lifespan. Only eight bonds issued by three firms are rated low-grade over the entire time period under examination.

[26] An analysis of the impact of liquidity on the momentum effect in the Canadian corporate bond market will benefit from the availability of the IIROC database and it is left for further research. However, we note that, at a monthly frequency, low liquidity of the bonds in the momentum portfolio does not necessarily imply that the strategy is impractical.

2.8 Conclusions

In this paper, we investigate the momentum effect in the market for Canadian corporate bonds, over a period of about 30 years spanning from August 1987 to December 2016. The examined time period is exceptionally long for the standards of the literature on Canadian financial markets. Our sample includes 2,424 bullet Canadian corporate bonds issued by 389 firms. Our analysis concludes that the momentum strategy is significantly profitable in the market for Canadian corporate bonds, as it yields gains that are comparable to those observed in the much larger market for US corporate bonds.

Cooper et al. (2004) find that momentum profits vary with the state of the market, and they explain their findings within the framework proposed by the theoretical works of Daniel et al. (1998) and Hong and Stein (1999). Our analysis reveals a strong and persistent market state effect also for Canadian corporate bonds. Conditioning on the market state doubles the returns on the momentum portfolio for holding periods ranging from one month to two years. Further, these gains are exclusive to periods following above-average market gains (i.e., in UP markets), as it is the case for US equities. The conditional momentum profits for Canadian bonds are sizeable, at about two third of the analogous gains for US equities, in UP markets.

Previous research on the momentum effect for US corporate bonds has shown that momentum gains are driven by speculative-grade bonds. In contrast, high-grade bonds appear not to be associated with profitable momentum strategies. The lack of significant gains for investment grade bonds is confirmed by this study's results for the Canadian market. However, the conditional analysis highlights that the state of the market brings about sizeable momentum returns also for investment grade bonds, especially in the most recent years of the sample.

We note that both the unconditional and conditional momentum effects documented in this study disappear for on-the-run bonds. Recent work by the authors indicates that, in the US corporate bond market, the momentum effect is very short lived for bonds that heavily attract trades of institutional investors. In particular, strategies with six month-formation period are not profitable for bonds attracting the highest volumes of institutional-sized trades, a subsample of which consists of one-the-run issues. However, significant momentum gains are identified in bonds that, although less likely to be on-the-run bonds, are actively traded by retail investors. Thus, in the US market, the momentum effect in off-the-run bonds is not likely to be the result of illiquidity. Whether the same conclusion can be reached also for Canadian corporate bonds is left for future exploration, once transaction-level data becomes available.

Table 2.1: Descriptive Statistics

Panel A presents basic summary statistics for the Canadian corporate bonds in our sample, for the pooled sample and for the Non-Investment Grade (NIG) and Investment Grade (IG) categories. The covered time period is August 1987 to December 2016. The first column reports the count of bond-month observations in the sample, followed by the average yield and return, as well as the standard deviation and median of the monthly returns. The last two columns list the mean volume at issue (in millions of Canadian dollars) and the average coupon. Panel B reports the summary statistics (including time-to-maturity) for the subset of bonds for which the return at-issue is available. These bonds are also categorized into maturity bands. Data from Bloomberg L.P.

Panel A: Descriptive Statistics for the 1987-2016 Sample

	Count	Yield (%)	Return (%)	St. Dev.	Median (%)	Volume (M)	Coupon (%)
Pooled	113,155	4.593	0.50	0.013	0.36	297	6.064
			Subsamples by credit rating bands				
NIG	1,002	7.704	0.71	0.013	0.66	174	6.954
IG	101,193	4.549	0.52	0.013	0.37	300	6.079

Panel B: Descriptive Statistics for Bonds at Issue

Count	Yield (%)	Return (%)	St. Dev.	Median (%)	Volume (M)	Coupon (%)	Time to Maturity (months)
Pooled							
1,066	5.267	0.66	0.014	0.58	410	5.222	102
Maturity at issue less than 5 years							
164	3.931	0.46	0.008	0.42	409	3.941	38
5 to 10 years							
593	5.178	0.73	0.012	0.63	467	5.038	67
Over 10 years							
309	6.126	0.61	0.019	0.57	301	6.254	206

Table 2.2: Unconditional Returns on the 6-month Formation Period Momentum Strategy

Panel A and Panel B report the average monthly and cummulative returns on the momentum portfolios with holding periods of 1, 3, 6, 12, 18 and 24 months. Since the $CR_{n,t}$ series are the summation of overlapping returns, we employ a heteroskedasticity-and-autocorrelation consistent (HAC) estimator for the t-statistics reported in Panel B. The average number of bonds available in the monthly cross-section, denoted by N is reported in Column 2. The number of months for which momentum returns are calculated is reported in the last column of each panel. Sub-panels 1 and 2 report holding period monthly and cumulative returns for the pooled sample and for the investment grade subsample. The time period covered is from August 1987 to December 2016.

		Panel A: Holding period monthly returns $R_{n,t}$				**Panel B: Holding period cumulative returns $CR_{n,t}$**			
Holding Period	N	Loser (P1)	Winner (P10)	Winner-Loser	Months	Loser (P1)	Winner (P10)	Winner-Loser	Months
		A.1. Pooled Sample				B.1. Pooled Sample			
1	251	0.63	0.969	0.34	341	0.63	0.969	0.34	341
		(9.202)	**(11.284)**	**(4.520)**		**(9.202)**	**(11.284)**	**(4.520)**	
3	236	0.638	0.971	0.333	341	1.889	2.799	0.910	339
		(9.567)	**(11.264)**	**(4.729)**		**(10.630)**	**(12.234)**	**(5.014)**	
6	215	0.633	0.983	0.350	341	3.785	5.588	1.803	336
		(9.667)	**(11.144)**	**(5.123)**		**(9.986)**	**(10.050)**	**(4.295)**	
12	181	0.640	1.051	0.410	341	7.630	11.082	3.452	330
		(9.836)	**(11.805)**	**(6.349)**		**(9.754)**	**(8.044)**	**(3.430)**	
18	151	0.644	1.089	0.445	341	11.686	16.800	5.114	324
		(10.305)	**(12.130)**	**(6.957)**		**(9.352)**	**(6.690)**	**(2.858)**	
24	125	0.653	1.116	0.463	341	15.714	22.359	6.646	318
		(10.429)	**(12.581)**	**(7.459)**		**(8.982)**	**(5.675)**	**(2.347)**	
		A.2. Investment-grade Subsample				B.2. Investment-grade Subsample			
1	227	0.652	0.724	0.073	334	0.652	0.724	0.073	334
		(9.188)	**(8.404)**	(0.954)		**(9.188)**	**(8.404)**	(0.954)	
3	213	0.661	0.709	0.048	334	1.941	2.117	0.176	332
		(9.547)	**(8.443)**	(0.719)		**(10.420)**	**(10.106)**	(1.066)	
6	194	0.658	0.704	0.046	334	3.812	4.175	0.363	329
		(9.753)	**(8.390)**	(0.763)		**(9.670)**	**(9.572)**	(1.142)	
12	162	0.649	0.712	0.063	334	7.569	8.273	0.705	323
		(9.893)	**(8.628)**	(1.264)		**(8.899)**	**(9.758)**	(1.471)	
18	136	0.656	0.706	0.050	332	12.030	12.599	0.569	315
		(9.993)	**(8.770)**	(1.177)		**(9.148)**	**(9.787)**	(0.772)	
24	112	0.667	0.713	0.046	332	16.099	16.536	0.438	309

	(9.964)	**(9.262)**	(1.278)	**(8.654)**	**(9.205)**	(0.421)

Table 2.3: Credit Rating Distribution Across Decile Portfolios

The table reports, for each of the 6-month holding period decile portfolio, the average number of bonds included, the standard deviation of the cumulative returns in the formation period (six months), the sample mean of the cross-sectional averge share of investment grade bonds, during the portfolio formation month, as well as the corresponding shares of non-investment grade bonds and of bonds that are not rated.

	P1 (Loser)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (Winner)
mean (bondN)	21.6	21.4	21.6	21.5	21.8	21.3	21.6	21.5	21.6	21.5
std (formation-rtn)	0.01	0.002	0.002	0.001	0.001	0.001	0.002	0.002	0.003	0.036
mean (%IG)	88.1	87.8	90.7	91.7	92.7	93.6	93.6	92.8	90.8	84.9
mean (%NIG)	0.4	0.2	0.1	0.2	0.2	0.2	0.2	0.3	0.6	1.4
mean (%non-rated)	11.5	12	9.2	8.1	7.1	6.2	6.2	6.9	8.6	13.7

Table 2.4: Descriptive Statistics in UP and DOWN states

The table presents basic summary statistics for the pooled sample and for the Investment Grade (IG) bond subsample in periods of UP and DOWN market states, respectively. The covered time period is August 1987 to December 2016. The first column reports average bond number per month in each sample and market state, followed by the average return, standard deviation and median of the monthly returns.

	N(bond/month)	Return (%)	St. Dev.	Median (%)
UP market state (n=141)				
Pooled	234	0.79	0.013	0.66
IG	192	0.94	0.013	0.81
DOWN market state (n=199)				
Pooled	399	0.56	0.009	0.42
IG	369	0.43	0.010	0.40

Table 2.5: Momentum Portfolio Returns Conditional on Market States

The table reports market-state stratified averages, and their statistics, as estimated by Equation 2.2 for the pooled sample (Panel A) and the investment-grade subsample (Panel B) . Each panel tabulates the conditional mean returns and their t-statistics for the winner and loser portfolios, as well as for the resulting momentum strategy in UP and DOWN markets. The portfolio holding periods are of 1, 3, 6, 12, 18 and 24 months. Each UP-DOWN column reports the t-statistics of the γ coefficient from Equation 2.3. This coefficient evaluates whether the stratified returns are statistically different across the market states. Panel B reports the analogous results for the investment-grade subsample. The time period covered is from August 1987 to December 2016.

Holding Period /		LONG			SHORT			LONG-SHORT		
N (UP/DOWN)		UP	DOWN	UP-DOWN	UP	DOWN	UP-DOWN	UP	DOWN	UP-DOWN
Panel A: Pooled Sample										
1	141	1.228	0.764	**(2.181)**	0.625	0.64	(-0.085)	0.603	0.124	**(2.960)**
	199	**(7.168)**	**(6.196)**		**(4.649)**	**(6.218)**		**(4.711)**	(1.266)	
3	141	3.506	2.281	**(2.755)**	1.830	1.933	(-0.293)	1.675	0.347	**(3.883)**
	197	**(9.446)**	**(8.613)**		**(6.861)**	**(8.233)**		**(6.416)**	(1.519)	
6	141	7.346	4.311	**(3.185)**	3.551	3.971	(-0.577)	3.795	0.340	**(5.181)**
	194	**(9.086)**	**(7.096)**		**(6.785)**	**(7.593)**		**(7.054)**	(0.763)	
12	141	14.099	8.850	**(2.775)**	6.940	8.181	(-0.933)	7.158	0.669	**(4.818)**
	188	**(8.214)**	**(6.233)**		**(8.022)**	**(7.159)**		**(5.293)**	(0.917)	
18	141	21.345	13.342	**(2.774)**	11.005	12.273	(-0.656)	10.340	1.068	**(4.564)**
	182	**(7.099)**	**(5.694)**		**(8.013)**	**(7.008)**		**(4.625)**	(0.838)	
24	137	28.404	17.853	**(2.254)**	15.014	16.329	(-0.537)	13.390	1.524	**(3.422)**
	180	**(5.493)**	**(5.413)**		**(7.473)**	**(7.189)**		**(3.717)**	(0.707)	
Panel B: Investment Grade Subsample										
1	141	1.042	0.509	**(2.918)**	0.971	0.435	**(3.381)**	0.071	0.074	(-0.017)
	199	**(7.069)**	**(4.772)**		**(7.890)**	**(4.481)**		(0.538)	(0.801)	
3	141	3.478	1.184	**(6.154)**	3.018	1.203	**(5.119)**	0.460	-0.019	(1.488)
	197	**(12.299)**	**(4.769)**		**(10.498)**	**(5.713)**		**(1.782)**	(-0.092)	
6	141	6.630	2.467	**(6.829)**	5.318	2.764	**(3.935)**	1.311	-0.297	**(2.995)**
	194	**(14.184)**	**(5.332)**		**(8.927)**	**(7.266)**		**(2.940)**	(-0.800)	
12	141	10.804	6.456	**(3.496)**	9.092	6.474	**(1.990)**	1.712	-0.019	**(2.594)**
	188	**(9.923)**	**(7.816)**		**(7.362)**	**(7.592)**		**(2.619)**	(-0.039)	
18	141	15.119	10.733	**(2.349)**	13.499	10.942	(1.389)	1.620	-0.208	**(1.854)**
	182	**(9.991)**	**(7.780)**		**(8.221)**	**(7.514)**		**(1.873)**	(-0.243)	

24	137	19.407	14.452	**(2.135)**	17.913	14.781	(1.340)	1.494	-0.330	(1.266)
	180	**(9.763)**	**(7.617)**		**(8.359)**	**(7.119)**		(1.465)	(-0.242)	

Table 2.6: Unconditional Returns on the 6-month Formation Period Momentum Strategy (1994-2016)

Panel A and Panel B report the average monthly and cummulative returns on the momentum portfolios with holding periods of 1, 3, 6, 12, 18 and 24 months. Since the $CR_{n,t}$ series are the summation of overlapping returns, we employ a heteroskedasticity-and-autocorrelation consistent (HAC) estimator for the t-statistics reported in Panel B. The average number of bonds available in the monthly cross-section, denoted by N is reported in Column 2. The number of months for which momentum returns are calculated is reported in the last column of each panel. Sub-panels 1 and 2 report holding period monthly and cumulative returns for the pooled sample and for the investment grade subsample. The time period covered is from January 1994 to December 2016.

		Panel A: Holding period monthly returns $R_{n,t}$				**Panel B: Holding period cumulative returns $CR_{n,t}$**			
Holding Period	N	Loser (P1)	Winner (P10)	Winner-Loser	Months	Loser (P1)	Winner (P10)	Winner-Loser	Months
		A.1. Subsample 1994-2016				B.1. Subsample 1994-2016			
1	294	0.506	0.692	0.186	276	0.506	0.692	0.186	276
		(7.598)	**(8.095)**	**(2.298)**		**(7.598)**	**(8.095)**	**(2.298)**	
3	276	0.525	0.678	0.153	276	1.589	2.071	0.482	276
		(7.984)	**(8.011)**	**(2.044)**		**(9.333)**	**(9.709)**	**(2.527)**	
6	252	0.533	0.666	0.132	276	3.275	4.179	0.904	276
		(8.345)	**(7.758)**	**(1.907)**		**(8.726)**	**(9.090)**	**(2.338)**	
12	211	0.537	0.683	0.146	276	6.772	8.62	1.847	276
		(8.429)	**(8.239)**	**(2.488)**		**(9.408)**	**(8.542)**	**(2.467)**	
18	176	0.549	0.691	0.142	276	10.546	13.331	2.785	276
		(8.957)	**(8.301)**	**(2.752)**		**(9.772)**	**(7.509)**	**(2.096)**	
24	145	0.556	0.694	0.138	276	14.332	18.094	3.762	276
		(8.893)	**(8.620)**	**(2.918)**		**(9.565)**	**(6.330)**	(1.664)	
		A.2. IG Subsample 1994-2016				B.2. IG Subsample 1994-2016			
1	266	0.531	0.657	0.125	276	0.531	0.657	0.125	276
		(7.908)	**(7.489)**	(1.537)		**(7.908)**	**(7.489)**	(1.537)	
3	249	0.545	0.643	0.098	276	1.636	1.934	0.298	276
		(8.225)	**(7.408)**	(1.297)		**(9.414)**	**(9.086)**	(1.576)	
6	227	0.56	0.623	0.063	276	3.329	3.813	0.484	276
		(8.637)	**(7.146)**	(0.894)		**(8.693)**	**(8.600)**	(1.307)	
12	189	0.551	0.638	0.088	276	6.798	7.706	0.908	276
		(8.916)	**(7.395)**	(1.494)		**(9.052)**	**(9.855)**	(1.681)	
18	157	0.572	0.64	0.068	276	10.942	11.73	0.788	276
		(9.126)	**(7.599)**	(1.347)		**(9.871)**	**(10.268)**	(0.966)	
24	129	0.579	0.644	0.065	276	14.716	15.417	0.701	276

	(8.892)	**(8.076)**	(1.516)		**(9.619)**	**(9.839)**	(0.613)

Table 2.7: Momentum Portfolio Returns Conditional on Market State (1994-2016)

The table reports market-state stratified averages, and their statistics, as estimated by Equation 2.2 for the pooled sample (Panel A) and the investment-grade subsample (Panel B) . Each panel tabulates the conditional mean returns and their t-statistics for the winner and loser portfolios, as well as for the resulting momentum strategy in UP and DOWN markets. The portfolio holding periods are of 1, 3, 6, 12, 18 and 24 months. Each UP-DOWN column reports the t-statistics of the γ coefficient from Equation 2.3. This coefficient evaluates whether the stratified returns are statistically different across the market states. Panel B reports the analogous results for the investment-grade subsample. The time period covered is from January 1994 to December 2016.

Holding Period /	N (UP/DOWN)	LONG UP	LONG DOWN	LONG UP-DOWN	SHORT UP	SHORT DOWN	SHORT UP-DOWN	LONG-SHORT UP	LONG-SHORT DOWN	LONG-SHORT UP-DOWN
				Panel A: Subsample 1994-2016						
1	88	0.796	0.643	(0.727)	0.371	0.569	(-1.485)	0.425	0.074	**(1.972)**
	188	**(4.395)**	**(6.034)**		**(3.902)**	**(6.108)**		**(2.844)**	(0.753)	
3	90	2.316	1.953	(0.780)	1.235	1.761	(-1.658)	1.081	0.192	**(2.274)**
	186	**(5.739)**	**(8.022)**		**(5.404)**	**(7.865)**		**(3.341)**	(0.846)	
6	93	5.156	3.683	(1.689)	2.495	3.672	**(-1.828)**	2.661	0.011	**(4.005)**
	183	**(6.739)**	**(7.233)**		**(6.097)**	**(7.166)**		**(5.020)**	(0.027)	
12	99	10.563	7.533	**(2.003)**	5.405	7.537	**(-1.832)**	5.158	-0.005	**(4.655)**
	177	**(7.715)**	**(7.061)**		**(9.389)**	**(7.113)**		**(4.963)**	(-0.008)	
18	105	16.514	11.377	**(2.397)**	9.315	11.302	(-1.144)	7.199	0.076	**(4.884)**
	171	**(7.796)**	**(6.457)**		**(9.805)**	**(7.055)**		**(4.678)**	(0.071)	
24	107	22.389	15.374	(1.632)	12.978	15.189	(-0.924)	9.411	0.185	**(2.812)**
	169	**(5.294)**	**(6.021)**		**(8.306)**	**(7.143)**		**(3.049)**	(0.097)	
				Panel B: IG Subsample 1994-2016						
1	88	1.026	0.484	**(2.792)**	0.739	0.434	**(2.204)**	0.287	0.049	(1.308)
	188	**(6.348)**	**(4.623)**		**(7.120)**	**(4.827)**		**(1.852)**	(0.521)	
3	90	3.45	1.2	**(5.878)**	2.418	1.257	**(3.317)**	1.031	-0.057	**(2.823)**
	186	**(11.243)**	**(5.049)**		**(8.296)**	**(6.268)**		**(3.113)**	(-0.267)	
6	93	6.57	2.412	**(6.733)**	4.511	2.729	**(2.563)**	2.059	-0.317	**(3.775)**
	183	**(14.062)**	**(5.257)**		**(6.941)**	**(7.085)**		**(3.686)**	(-0.813)	
12	99	10.501	6.143	**(4.274)**	8.032	6.108	**(1.807)**	2.469	0.035	**(3.424)**
	177	**(12.923)**	**(7.723)**		**(8.166)**	**(7.455)**		**(3.400)**	(0.070)	
18	105	14.482	10.039	**(2.815)**	12.263	10.131	(1.329)	2.219	-0.091	**(2.094)**
	171	**(12.722)**	**(7.943)**		**(9.375)**	**(7.729)**		**(2.250)**	(-0.101)	

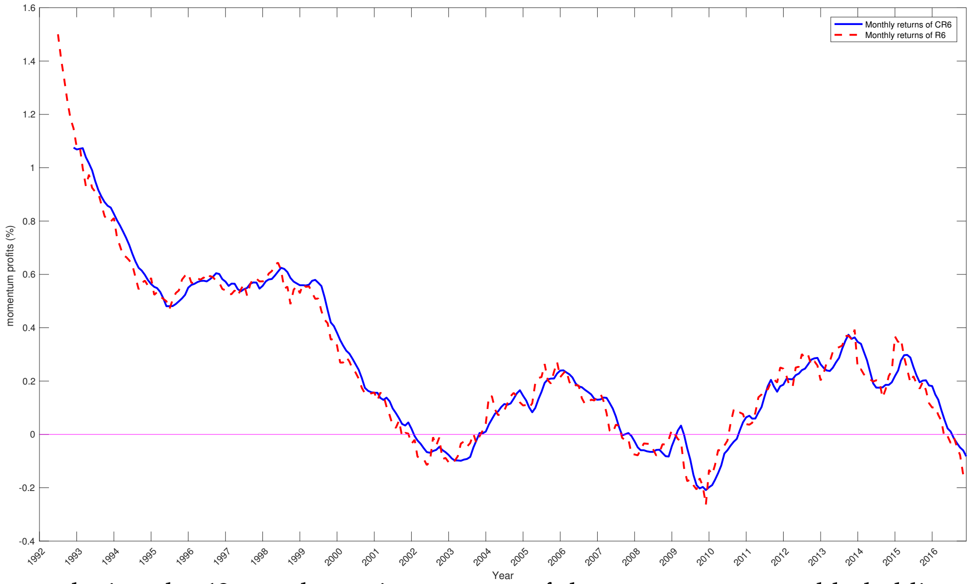
24	107	18.564	13.424	**(2.442)**	16.392	13.654	(1.327)	2.172	-0.23	(1.564)
	169	**(11.178)**	**(7.973)**		**(10.201)**	**(7.302)**		**(1.994)**	(-0.159)	

Table 2.8: Unconditional Momentum Returns for Top Bonds

Panel A and Panel B report the average monthly and cummulative returns on the momentum portfolios for top bonds with holding periods of 1, 3, 6, 12, 18 and 24 months. Since the $CR_{n,t}$ series are the summation of overlapping returns, we employ a heteroskedasticity-and-autocorrelation consistent (HAC) estimator for the t-statistics reported in Panel B. The average number of bonds available in the monthly cross-section, denoted by N, is reported in Column 2. The number of months for which momentum returns are calculated is reported in the last column of each panel. The time period covered is from August 1987 to December 2016.

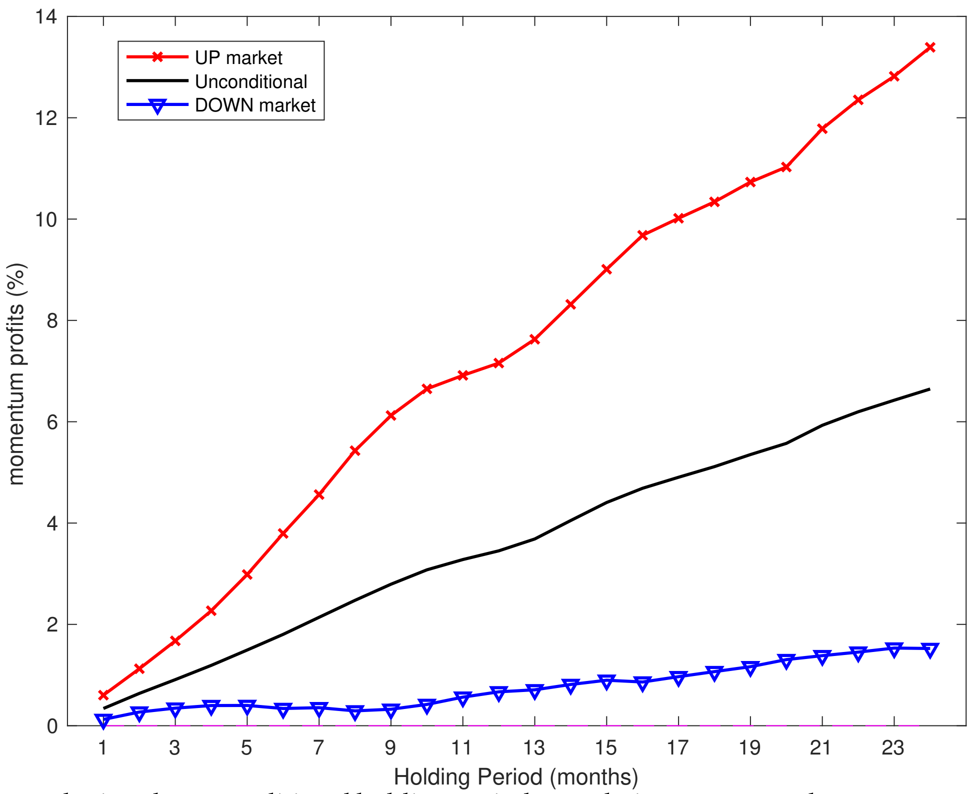
Holding Period	N	Loser (P1)	Winner (P10)	Winner-Loser	Months
Panel A: Holding period monthly returns ($R_{n,t}$)					
1	84	0.666	0.72	0.055	340
		(9.363)	**(8.548)**	(0.780)	
3	81	0.682	0.694	0.012	340
		(9.930)	**(8.362)**	(0.193)	
6	77	0.666	0.686	0.021	340
		(9.936)	**(8.322)**	(0.376)	
12	70	0.667	0.706	0.038	340
		(10.214)	**(9.035)**	(0.851)	
18	64	0.666	0.690	0.024	338
		(10.674)	**(9.008)**	(0.647)	
24	58	0.669	0.681	0.012	338
		(10.805)	**(9.169)**	(0.355)	
Panel B: Holding period cummulative returns ($CR_{n,t}$)					
1	84	0.666	0.72	0.055	340
		(9.363)	**(8.548)**	(0.780)	
3	81	2.025	2.081	0.057	338
		(10.964)	**(10.041)**	(0.352)	
6	77	3.960	4.197	0.237	335
		(10.646)	**(10.175)**	(0.863)	
12	70	7.931	8.290	0.360	329
		(10.901)	**(10.247)**	(0.856)	
18	64	11.828	12.035	0.207	321
		(10.421)	**(9.420)**	(0.378)	
24	58	15.492	15.277	-0.214	315
		(9.476)	**(7.895)**	(-0.277)	

Figure 2.1: 48-month Moving Average Momentum Profits Over Time



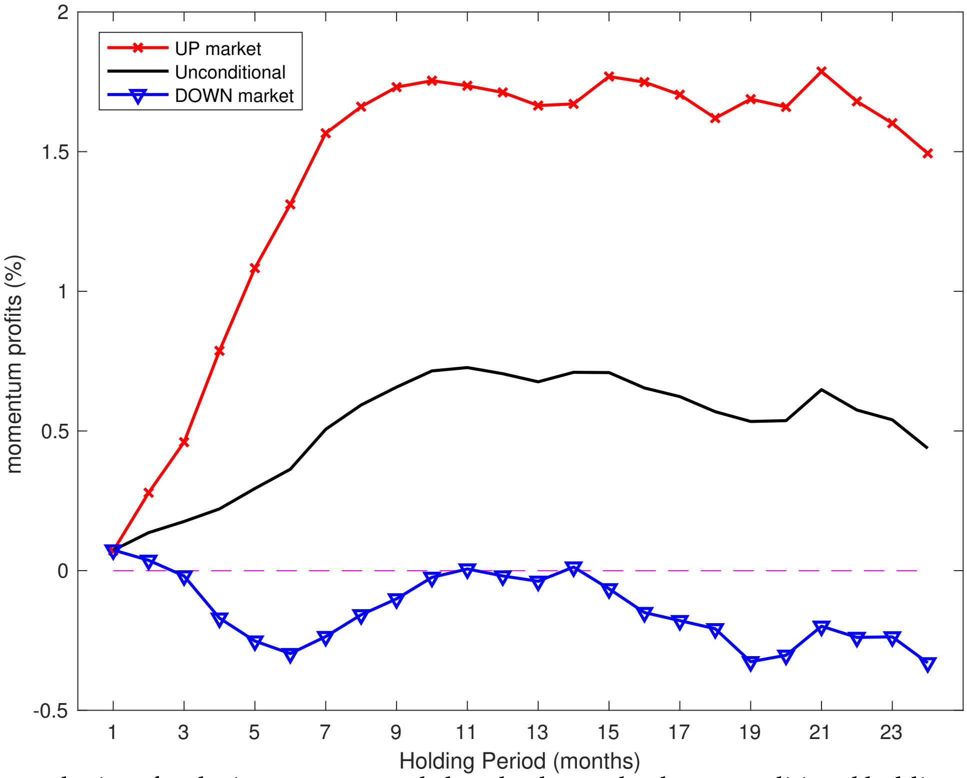
The figure depicts the 48-month moving average of the momentum monthly holding period returns ($R_{6,t}$) and cumulative returns ($CR_{6,t}$), where the latter series is converted into monthly returns. The sample ranges from August 1987 to December 2016.

Figure 2.2: Conditional Cummulative Momentum Profits Over Time



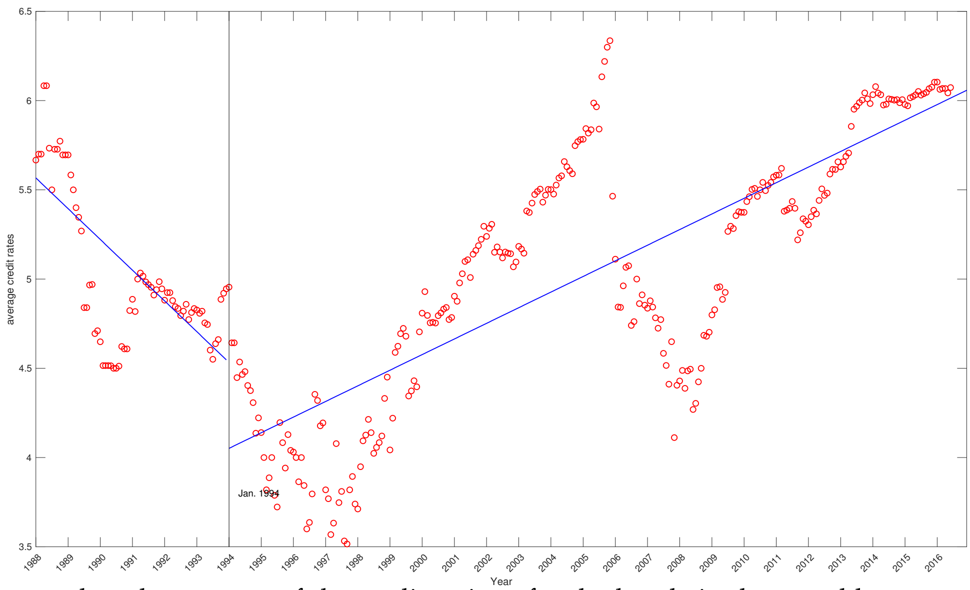
The figure depicts the unconditional holding period cumulative returns on the momentum portfolio for holding period horizons ranging from 1 month to 2 years, as well as the corresponding momentum returns stratified on the state of the market. The time period covered ranges from August 1987 to December 2016.

Figure 2.3: Conditional Cummulative Momentum Profits for Investment-grade Bonds



The figure depicts, for the investment-grade bond subsample, the unconditional holding period cumulative returns on the momentum portfolio for holding period horizons ranging from 1 month to 2 years, as well as the corresponding momentum returns stratified on the state of the market. The time period covered ranges from August 1987 to December 2016.

Figure 2.4: Pre- and Post- 1994 Credit Rating Trends



The figure plots the average of the credit ratings for the bonds in the monthly cross-section, under the convention that lower credit quality corresponds to larger values. Hence the highest DBRS rating, namely AAA, corresponds to value 1 whereas the lowest category, namely D, corresponds to level 22. The figure also depicts the pre-1994 and post-1994 fitted trends of the credit ratings. The time period covered is from August 1987 to December 2016.

Chapter 3

Seasonality in Canadian corporate bonds

3.1 Introduction

The seasonality in asset returns arises when the mean return appears to be abnormally high/low in a given calendar period. A well-known calendar seasonality is the so-called January effect (or more broadly the monthly effect), according to which returns are exceptionally high in the month of January (e.g., Wachtel, 1942; Rozeff and Kinney, 1976; Keim, 1983; Lakonishok and Smidt, 1984; Tinic and West, 1984; Al-Khazali, 2001).[1] Recently, calendar anomalies, including the monthly effect, have been found to be time-varying, being waxing and waning in different subperiods, for stock portfolios and indexes (e.g., Urquhart and McGroarty, 2014; Agnani and Aray, 2011). However, less is known on the time variations of the monthly effect in the corporate bond market. This paper aims to fill this gap by examining the existence and variations of the monthly effect in the Canadian corporate bond market. The main findings in this paper support the conclusion that changes in market condition driven by phenomenal

[1]Other calendar effects include the day-of-the-week effect (Gibbons and Hess, 1981; Flannery and Protopapadakis, 1988; Jordan and Jordan, 1991; Wang et al., 1997, etc.), the turn-of-month effect (e.g., Ogden, 1990), the Halloween effect (e.g., Bouman and Jacobsen, 2002; Athanassakos, 2008), the holiday effect (e.g., Ariel, 1990; Frieder and Subrahmanyam, 2004), and the lunar effect (Rotton and Rosenberg, 1984; Dichev and Janes, 2003; Yuan et al., 2006, etc.).

financial events, i.e., the 2007-09 global financial crisis, can wipe away, existing, yet undiscovered, anomalies while offering alternative profit opportunities in the form of new anomalies.

Using a large sample of individual bonds sourced from the Bloomberg database for the period of 1987 to 2016, I show that the Canadian corporate bond returns are subject to the January effect. Further, there is also a significant decline in returns in March followed by a significant return boost in July. By convention, I define the two monthly effects as the March effect and the July effect, respectively. Importantly, the three monthly effects are not concurrent. The March effect can only be detected in samples ending before the 2007-09 global financial crisis, while the two positive January and July effects are exploitable through the post-crisis sample period. In the subsample before the crash, the negative March effect dominates, both economically and statistically, that of other months by at least 20 bps in absolute terms, reaching -56 bps, while no obvious return patterns were found for January and July over the same time period. In contrast, as markets recovered from the crash, the March effect disappeared as gains for both January and July become significant. Specifically, the average monthly excess return in January dwarfs those of non-January returns by 72 bps, a level that is 50% higher than the aggregated January effect of 48 bps for the full sample. Likewise, the abnormally high average excess return in July yields significant returns of a significant 58 bps per month in the post-crisis subsample.

I identify two leading causes for the changes in the monthly anomalies. Presently, the pre-crisis negative March effect can be linked to the seasonality in the changes of the 10-year US Treasury monthly yield. The January and July effects are attributable to an intensive reinvestment of received coupons, with a majority paid in December and June, during the long period of declining interest rates in the post-crisis period.

To illustrate, the monthly change in the US Treasury yields is found to be strongly and negatively related to the monthly return variations of the Canadian corporate bonds across the entire sample period, which is consistent with the finding in Landon and Smith (2006) for the Canadian provincial bonds.[2] Therefore, seasonal patterns in the US Treasury yield changes is transmitted, inversely, to the Canadian corporate bond return changes. Notably, I find that the US Treasury yield changes exhibit a positive March effect before the crisis, which turns insignificant afterward. Hence, the negative March effect documented in this paper for the Canadian corporate bonds stems from seasonal variations in the US long-run borrowing cost, prior to the financial crisis. The US Treasury yield changes, however, do not account for the post-crisis January and July effects documented in this paper, as there is no analogous pattern in Treasuries.

To explain the significant January and July gains in the post-crisis Canadian corporate bond market, I refer to the conclusions of theoretical studies that seasonal variations in asset prices and returns. From the demand and supply perspective, the January effect on stock returns is often viewed as the result of a rebound in demand in January following the year-end portfolio rebalancing behavior of investors. The tax-loss selling pressure hypothesis (formalized in Wachtel, 1942; Roll, 1983) and the window dressing theory (e.g., Lakonishok et al., 1991) are two commonly cited reasons for the year-end portfolio rebalancing behavior. The tax-loss selling pressure hypothesis postulates that investors sell poorly performed stocks at the end of the tax year to realize capital losses and reduce the tax liability. Whereas the window dressing behavior is observed among fund managers, in time of annual evaluations. The behavior consists in selling the riskiest assets in their portfolios to improve the perceived stability of the fund.[3] The high return in January obtains when investors, or fund managers, buy back the depreciated assets sold at the end of the previous year. The empirical analysis in this paper, however, fails to provide evidence in support of the two theories.

Recognizing a unique feature regarding the uneven distribution of coupon pay-

[2]This finding is not as surprising as it appears, given the high integration between the US and Canadian financial markets (e.g., Mittoo, 2003; Mittoo and Zhang, 2010), and the large proportion (about 50%) of Canadian corporate bonds issued in the US market (e.g., Anderson et al., 2003; Patel and Yang, 2015).

[3]For empirical evidence supporting the tax-loss selling pressure hypothesis, see Wachtel (1942), Lakonishok and Smidt (1984), Berges et al. (1984), Chang and Pinegar (1986) and Tinic et al. (1987), etc. Empirical evidence supporting the window dressing theory can be found in Cooper and Shulman (1994), Maxwell (1998) and Dbouk et al. (2013) for the US (high-yield) corporate bonds.

ments in the bond market, DeRosa-Farag (1996) proposes the coupon-based payment flow theory to explain the January effect. The theory states that the demand of corporate bonds surges following months of heavy coupon payments, so that the increase in demand is driven by the need for the coupon reinvestment. The author argues that, given that the highest level of coupon payments often occurs in December, the share of demand increase that is due to coupon reinvestment should be at its highest level in January, which results in the January effect. However, the literature, so far, offers little empirical evidence in support of the explanatory power of this theory (e.g., Fridson and Garman, 1995a,b; Barnhill et al., 1997; Dbouk et al., 2013). In this paper, I show that the coupon-based payment flow theory can be extended to explain both the January and July effects documented for the Canadian corporate bonds, once two assumptions implied by the theory are satisfied. The first assumption requires that coupons are paid unevenly over the year with the majority payments concentrate in a few months. This assumption can be validated by examining the monthly distribution of coupon payments, from all the bonds in the sample. In this study, coupon payments are at their highest in December and June, in terms of both frequency and volume.

In months with intensive coupon payments, the received coupon funds need to be reinvested to push up the demand in the next month, which is the second assumption underlying the coupon-based explanation for the seasonal gains. The reliance on this assumption, however, is not made explicit in the coupon-based payment flow theoretical studies, and it was essentially overlooked by previous literature. To fill this gap, I uncover a link between the coupon-based payment flow theory and the expectation of future interest rate. When the long-term interest rate is expected to fall, the values of corporate bonds are likely to increase, making investing in corporate bonds more attractive.[4] Therefore, due to increased demand from new investments and coupon reinvestments, corporate bond returns should increase in periods when the expected future interest rate declines. In this scenario, if coupons are paid unevenly, return increases in months following the most intensive coupon payments should be the high-

[4]This relationship tends to be stronger for bonds with low credit risks (i.e., investment grade bonds) and long time-to-maturities.

est during the year. Over time, if the same month frequently receives the highest amount of coupon payments, then on average, the following-month bond returns will be significantly higher than those in the rest months of the year, which leads to the calendar month seasonality. As most coupons are paid in December and June for Canadian bonds, in a downward trending expected interest rate environment, bond returns in January and July should be significantly higher. In contrast, when the interest rate is expected to increase, the risk of having to sell the corporate bond at a price lower than the purchase price also increases. Therefore, investors may choose to divert their coupon funds to other channels that offer higher expected returns than those offered by the corporate bond market.

The Canadian market during the period studied in this paper provides a natural experiment for the verification of the conjecture on the role of expected interest rate in affecting the explanatory power of the coupon-based payment flow theory. The post-crisis Canadian economy is marked by a sustained low interest rate environment, in comparison to the period before the financial crisis. In this study, I use the monthly change in the price of the ten-year Government of Canada bond futures to measure the adjusted expectation on the future long-term interest rate (i.e., positive price change implies that the long-term interest rate is expected to decline). An analysis of the monthly coupon payment frequency reveals that the post-crisis period identifies months (i.e., December and June) with the highest average monthly total numbers of bonds paying coupons, when the following months are associated with a lower expected interest rate. While for the pre-crisis declining expected interest rate periods, previous-month coupon payments are lower and less uneven. The prediction then is that the coupon reinvestment effect should be more evident in the post-crisis Canadian corporate bond market than before the onset of the crisis.

The empirical analysis in this paper confirms that the post-crisis coupon payment in December significantly increases January bond returns by 78 bps, and the corresponding effect on returns in July from the post-crisis coupon reinvestment in June is 30 bps. Further, upon controlling for the monthly price change of the ten-year Treasury futures in the whole sample, bond return increases due to the coupon effect are significantly higher than those caused solely by the decreased expected interest rate, with the differences reaching 18.7 bps and 12.6 bps for January and July returns, respectively. Therefore, the conclusion is that the coupon-based payment flow theory, when taken into consideration of expected interest rate variations, contributes significantly to explain the seasonality in Canadian corporate bond returns.

Despite the high level of institutional and regulatory structure similarity and close integration, the Canadian corporate bond market has been shown to be less liquid (Mittoo and Zhang, 2010), and characterized by a higher share of investment-grade to high-yield bonds (Patel and Yang, 2015), than the US market. Further, the correlation of corporate bond credit spreads between the two countries is found to be very low (Champagne et al., 2017), suggesting the possibility of distinct seasonal variations in corporate bond prices and returns in Canada and the US. Therefore, the study of return seasonality in the Canadian corporate bond market offers more than an out of sample validation of results documented for the US market. In fact, Dbouk et al. (2013) document a January effect for the US corporate bond returns during a sample period of 1995 to 2010, while during the same time period, the Canadian corporate bond returns feature a negative March effect. Therefore, the study in this paper is characterized by several novel contributions to the literature.

First, this study contributes to the literature on various market efficiency tests. The classic theory of efficient market hypothesis (EMH) proposed by Fama (1991) states that the asset market is at least weakly efficient if historical price patterns have no predictability on future prices and returns. The literature has documented numerous asset pricing anomalies that weaken the EMH as, to name a few, the January effect, the Halloween effect, the momentum and reversal effects (first documented in Bondt and Thaler, 1985; Jegadeesh and Titman, 1993, respectively), as well as the cross-sectional seasonality documented in Heston and Sadka (2008). However, it has been established that once the academic literature identifies an abnormally profitable strategy, its gains enter a descending trajectory, as more traders crowd the profitable positions (e.g., Chordia et al., 2014; McLean and Pontiff, 2016; Jones and Pomorski, 2017), a result that is consistent with the Adaptive Markets Hypothesis (AMH) proposed in Lo (2004). The AMH states that any anomaly can be more profitable in certain market environments, and less so in others.[5] As the market condition changes, e.g., as a new anomaly is discovered, new profitable portfolios can be created, while existing profit opportunities may disappear. The AMH broadens the application of the EMH by viewing the various anomalies from the behavioral perspective as temporary adaptation and adjustment of investors to a changing environment. The finding in this paper on the switch of different monthly effects incurred by the 2007-09 global financial crisis, a dramatic change of market environment, offers concrete empirical evidence in support of the AMH theory.

The use of a large sample of bond-level corporate bond data in this paper also contributes to the sparse literature on the studies of seasonal effects in the Canadian financial markets. Different seasonal patterns have been documented for Canadian federal and provincial government bonds, as well as stocks. For instance, Athanassakos (2008) provides evidence of opposite Halloween effects for Canadian size-based equity portfolios and Treasury bond indexes. Berges et al. (1984), Tinic et al. (1987), and more recently L'Her et al. (2004) examine the Canadian equity seasonality and report a January effect similar to that documented for the US stocks. Landon and Smith (2006) examine seasonal patterns for bonds issued by the provincial governments of Canada and document a negative March effect.

However, no analogous studies are available for Canadian corporate bonds, despite the substantial size of the market, a situation most likely due to the paucity of the available data.[6] This study contributes to filling this gap by analyzing the size and

[5]Consistently, Li and Galvani (2018) find that, in the US corporate bond market, the momentum effect is only profitable following up market states coupled with low investors sentiment, while reversal strategies perform significantly better in down market and low sentiment states than other periods. The second chapter of my dissertation documents that momentum returns are higher for the Canadian investment-grade corporate bonds in a subperiod when the average credit rating of bond issuers deteriorates, compared to the period when the entire period (i.e., from 1987 to 2016) is considered.

[6]At the end of 2016, the Canadian GDP was about 8% of that of the US, in contrast, debt outstanding for the Canadian corporate bond market was a solid 14% of that of its Southern neighbor. Put differently, the size of the market for Canadian corporate bonds is larger than that of the US, in relative terms.

variations of the monthly effect in Canadian corporate bond returns, using bond-level data. The sample is the largest ever explored in the literature as it includes 2,317 bullet bonds issued by 381 firms which are spread over ten industries. The examined time period, spanning from August 1987 to December 2016, is only slightly short of three decades, and it is exceptionally long for the standards of the literature on Canadian financial markets. The findings of this paper reveal that the pre-crisis return seasonal pattern for Canadian corporate bonds resembles that of provincial bonds (i.e., both exhibit a negative March effect) more than that of stocks. However, no parallel comparisons are available in the literature for the period following the crisis.

Lastly, the improvement in the explanatory power of the extended coupon-based payment flow theory contributes to the theoretical literature for asset price seasonalities. I show that the lack of empirical evidence in supporting the explanatory power of the coupon-based payment flow theory is in part due to lack of recognition of expected long-term interest rate changes in shaping the coupon reinvestment behavior of investors. More importantly, the empirical tests in this paper indicate that two theories developed in the stock market, i.e., the tax-loss selling pressure hypothesis and the window-dressing hypothesis, yield to the coupon-based payment flow theory in explaining the January effect (and more broadly the positive monthly effects). Given that the foundation of the latter relies on the coupon payment feature of the fixed income market, the finding of this paper thus suggests that return seasonal variations in the corporate bond market should not simply be treated as a seasonality spillover from the stock market.

The rest of the paper is organized as follows: Section 3.2 describes the corporate bond sample employed in this study along with data summary statistics. Detailed examination of the monthly return seasonal variations for the Canadian corporate bonds and the subsample analysis is conducted in Section 3.3. Section 3.4 explores different explanations to the existence and transition of the monthly effects documented in this paper. Section 3.5 concludes.

3.2 Data

This study's analysis of seasonal effects in the Canadian corporate bond market is an original contribution to the literature on Canadian corporate bonds, which is, unfortunately, rather sparse. The main reason for the thinness of the literature on this subject is that, up to recent years, there has been limited readily available data, especially those covered by Bloomberg, which is the primary data source on this market.[7] This study focuses on bullet bonds issued in Canadian dollars by Canadian corporations.

From the Bloomberg database, I extract all the Canadian dollar denominated corporate bonds that have been issued in Canada between July 1987 to December 2016, excluding the bonds that have contingency provisions or unusual coupons (e.g., bonds that are callable, puttable, convertible, sinkable, or bonds with floating coupon rate). The resulting sample offers closing prices and yields for 4,249 individual bullet bonds at the monthly frequency.[8] For each bond in the sample, I also extract information on bond characteristics from the Bloomberg database and obtain coupon rate and frequency, first and second coupon payment dates, bond issue and maturity dates, volume at issue, and issuer's industry code. Bond credit ratings are collected from DBRS (Dominion Bond Rating Service), the reference rating agency for long samples of Canadian securities.[9] I refer to issuer-level credit ratings when assigning rates to bond-month observations.[10] Notice that prices and yields of the Canadian corporate bonds in this sample are not based on individual transactions but prices obtained from dealer quotes, which, sometimes, are produced relying on the practice of matrix pric-

[7] As of November 2015, all fixed income trades in Canada have to be reported to the Investment Industry Regulatory Organization of Canada. Starting from July 2016, a subset of corporate bond transaction data has been made available to researchers. However, this promising data source cannot be employed to analyze the seasonal effect, as the time span covered is too limited.

[8] From 1987 to 2016, the Bloomberg database records information for 20,988 individual corporate bonds issued in Canada.

[9] Whenever the DBRS ratings are not available, I use the rating of Standard & Poor's. The two agencies use the same rating scale. For bonds requiring ratings earlier than 2000, we refer to Canadian Bond Rating Service (CBRS), which became a subsidiary of S&P in 2000.

[10] When the overall rating of an issuer is not available, I employ the rating of any issue that is classified as a senior unsecured debt. For bond issuers that have only one bond, which is neither senior nor unsecured, I use bond-level ratings, whenever possible.

ing by the data providing agency.[11]

I further refine the sample by discarding bonds with unavailable or incomplete information (e.g., missing issue date). Short-lived bonds that have less than six observations during the entire sample period are also discarded. For each bond, prices falling within six months of the bond maturity date are typically deemed unreliable and thus eliminated from the sample. After the filtering, there are 120,945 monthly price observations for 2,428 bonds that are matched with bond characteristics. Of the total observations, 108,299, i.e., slightly less than 90%, belong to bonds paying coupons semi-annually, while 10,145, i.e., about 8.4%, are for bonds yielding annual coupons. The remaining observations are associated with quarterly or monthly coupon frequencies, or with zero-coupon bonds. Relying on the monthly price data and bond characteristics, monthly returns are calculated as follows:

$$r_{i,t+1} = \frac{(P_{i,t+1} + AI_{i,t+1} + C_{i,t+1}) - (P_{i,t} + AI_{i,t})}{P_{i,t} + AI_{i,t}} \tag{3.1}$$

where, $r_{i,t+1}$ is the return on bond i for the one-month holding period from t to $t+1$, and $P_{i,t+1}$ is the price of bond i at time $t+1$. The variable $C_{i,t+1}$ is the amount of coupon paid between time t and $t+1$, if any, and it is calculated as the ratio of annual coupon rate of bond i to the coupon frequency.[12] The accrued interest $AI_{i,t+1}$ is defined as follows:

$$AI_{i,t+1} = C_{i,t+1}\left(\frac{d_{t+1}}{D_{t+1}}\right),$$

where d_{t+1} is the number of days between time $t+1$ and the last coupon payment date, and D_{t+1} is the number of days between two consecutive coupon payments enclosing time $t+1$. The day count convention used is the actual number of days between coupon payment dates. The final sample contains 113,155 return observations

[11] Due to the high illiquidity of most corporate bonds, matrix pricing is commonly used by broker agencies to evaluate bond values. The mechanism behind it is to price bonds with similar features (such as credit ratings and coupons) using certain yield benchmarks and adjust accordingly using predetermined and standardized formulas. Therefore, the obtained bond prices are not actual transaction prices and thus do not reflect all the specific information of the bond issuers and the supply and demand of the bonds in the market.

[12] The coupon rate is the coupon amount for \$100 face value. Bond prices are also quoted for a face value of \$100.

for 2,317 bonds issued by 381 firms from 10 industries. The time span, slightly short of three decades, ranges from August 1987 to December 2016. To alleviate data quality concerns, especially for the early years of the sample, I winsorize returns at the 1% level. This procedure allows discarding outliers that are most likely to be associated with incorrect data entries.[13] Table 3.1 tabulates basic descriptive statistics for the final sample.

In the pooled sample, as shown in row one of Panel A, the coupon level is at about 6%, while the average yield is about 4.6%. Meanwhile, the average volume at issue, per bond, is 297 million Canadian dollars. The average monthly return is 50 bps, which amounts to about 6%, in terms of annualized return. The median monthly return is slightly lower, by 14 bps, which suggests the presence of a heavy right tail of the distribution. A stylized fact on the Canadian corporate bond market that is confirmed in Panel A is that the vast majority of the issues are rated at, or above, the BBB low threshold.[14] The second and third rows of results in Panel A reports summary statistics for bond-month observations sorted into the investment and non-investment grade categories.[15] Of the 102,195 observations for which credit rating is available, only 1,002 are associated with the pricing of high-yield bonds. Hence, there are roughly 100 bond-month returns in the investment-grade category for each bond-month observation in the low-grade group. Untabulated statistics show that an overwhelming majority of the returns on high-grade bonds (i.e., 49,279 observations) falls into the "A"-rating category, whereas the low-grade category of BB accounts for 68% of the non-investment-grade bond returns.

To get a sense of the features of the Canadian corporate bond market that captures the cost of borrowing borne by firms, Panel B presents basic summary statistics for the sub-sample of bonds for which returns-at-issue are available.[16] The sub-sample

[13] The conclusions of this study remain unaltered when unwinsorized returns are used.

[14] The sparseness of high-yield bonds in the sample is consistent with the observations of Patel and Yang (2015).

[15] For 10,960 of the 113,155 observations in the sample (i.e., about 10%), credit ratings are not available.

[16] In the literature on municipal bond offerings, many studies employ yields at issue (e.g., Butler, 2008).

includes 1,066 at-issue returns and yields on 1,066 bonds issued by 254 firms.[17] The average yield at issue is about 5%, and the average return at issue is 0.66%, which offer an approximation of the at-issue cost of borrowing for Canadian firms tapping the domestic corporate bond market. Bonds in the sub-sample are then sorted into maturity bands to gather stylized facts on the effect of maturity length on at issue borrowing yields. The results reported in Panel B indicate that Canadian corporate bonds are issued with an average maturity of about nine years, with more than half of the issues maturing in five to ten years. Coupons and yields appear to be increasing with maturity length.

3.3 The Calendar Monthly Effects

The test of asset price anomalies provides evidence on whether the asset market is at least weakly efficient, in which case historical price patterns have no predictability on future prices and returns (Fama, 1991). In this study, I test the market efficiency in the Canadian corporate bond market by exploring the less costly and more persistent monthly effect, among which is the well-known January effect. Even though monthly seasonality has been documented for several types of assets and investment strategies, the literature on the monthly effect in the corporate bond market is rather thin, with most studies focusing on credit-based bond indexes instead of individual corporate bonds.[18] From a practical view, implementing strategies capitalizing abnormal returns in a given month requires less frequent asset rebalancing and therefore lower transaction costs, compared to other seasonal anomalies such as the Monday effect as documented in Gibbons and Hess (1981), Flannery and Protopapadakis (1988), Wang et al. (1997), etc. In this section, I perform regression analysis in the whole sample and also several subsamples, segmented by the 2007-09 global financial crisis.

[17] To calculate the return-at-issue, I use the first two available end-of-the-month prices, within the first two months following the date of issue.

[18] One exception is the study by Dbouk et al. (2013) who examine the January effect for the US individual corporate bonds.

3.3.1 Methodology

To evaluate whether being in a particular calendar month causes significant variations in Canadian corporate bond returns, I perform twelve regressions, one for each month, of monthly corporate bond returns in excess of T-Bill (Canada) returns (i.e. the excess returns $r_{b,t}$ of bond b in month t) on a month indicator, D_m, as in Model 1:

$$r_{b,t} = \alpha_0 + \alpha_1 MAT_{b,t} + \alpha_2 CR_{b,t} + \alpha_m D_{m,t} + \sum_{y=1988}^{2015} \alpha_y D_{y,t} + \sum_{i=2}^{10} \alpha_i D_{b,i} + \sum_{b=2}^{2317} \alpha_b D_b + \varepsilon_{b,t}$$

$$m = 1, 2, \ldots, 12 \qquad \text{(Model 1)}$$

For the month m regression, the indicator D_m equals one if the return $r_{b,t}$ is obtained in month m, and zero otherwise. In each of the twelve regressions, several variables are added to control for any cross-sectional and non-month time-series return variations. Specifically, $MAT_{b,t}$ is a time-varying and bond-specific discrete variable that counts the months left from month $t+1$ until the bond b matures (i.e., time to maturity). This variable captures the return premium associated with maturity length. $CR_{b,t}$ is a time-varying and firm-specific discrete variable that represents the DBRS credit rating of the firm issuing bond b in month t. The range of the variable CR is from 1 to 19, with one corresponds to the rating scale of AAA, while 19 is assigned to the rating scale of C low, which is the lowest rating in the sample.[19] The three groups of dichotomous variables, $D_{y,t}$ ($= 1$ if the month t of $r_{b,t}$ is in the year y), $D_{b,i}$ ($= 1$ if the bond b is in the industry i), and D_b ($= 1$ for bond b offering the excess return $r_{b,t}$), control for the year, industry and bond fixed effects, respectively.[20] $\varepsilon_{b,t}$ are zero-mean disturbances. To allow for correlations among error terms within each month, year, or firm, I rely on three-way clustered standard errors.[21] The estimated 12 coefficients, $\widehat{\alpha}_m$, measure the

[19]Not all returns in the sample have a corresponding credit rating assigned. Therefore, the variable CR will be dropped in the regressions whenever the full sample is employed in the analysis.

[20]Controlling for the firm fixed effect in the model does not alter the size and significance of all the other estimators.

[21]The three clustering variables are chosen as the aggregated levels of nested variables in the model while allowing for a reasonable number of clusters. I employ the "reghdfe" package in STATA to perform the three-way clustering, which implements the methodology described in Correia (2016).

individual monthly effect in explaining bond returns.

As a variation of Model 1, the pooled regression of monthly bond excess returns on eleven monthly indicators allows to compare the relative performance of bond returns in each calendar month to that in the base month (i.e., January). As displayed in Model 2 below, the single dichotomous variable D_m in Model 1 is replaced by a group of eleven monthly indicators for the months of February through December, with the month January as the base month. Similarly, the time to maturity variable $MAT_{b,t}$, the credit rating variable $CR_{b,t}$, and groups of year, industry and bond indicator variables are added to account for the maturity risk premium, the credit risk premium, and common factors in the year, industry and bond dimensions.[22] Standard errors are once again three-way clustered on the month, year and firm dimensions:

$$\begin{aligned} r_{b,t} = \alpha_0 + \alpha_1 MAT_{b,t} + \alpha_2 CR_{b,t} + \sum_{m=2}^{12} \alpha_m D_{m,t} + \sum_{y=1988}^{2015} \alpha_y D_{y,t} + \sum_{i=2}^{10} \alpha_i D_{b,i} \\ + \sum_{b=2}^{2317} \alpha_b D_b + \varepsilon_{b,t} \end{aligned} \quad \text{(Model 2)}$$

where $r_{b,t}$ is the excess return on bond b in months t, and $D_{m,t}$ for $m = 2, 3, 4, \ldots, 12$ are indicators of the eleven calendar months (with the month January as the baseline) that are meant to capture the relative seasonal effect. $\varepsilon_{b,t}$ are zero-mean disturbances. Implications of whether there exists a January effect or any other monthly effect on returns of Canadian corporate bonds can be inferred from the estimates of the coefficients α_m in both Model 1 and Model 2.

3.3.2 Empirical Results

The estimated α_m for each month from January to December in twelve regressions of Model 1 and from February to December in Model 2 are plotted in Figure 3.1. The partial effect of individual calendar month on monthly bond returns, shown in Panel A, reaches its highest values for January and July, and its minimum for March. The results

[22] The Model 2 is analogous to the one employed in Landon and Smith (2006), which tests the seasonal return variations for the Canadian Provincial bonds by controlling for time to maturity, and year, province and bond level fixed effects.

suggest that, other than the conventional January effect, there also exist a positive July effect and a negative March effect for Canadian corporate bonds. Interestingly, Landon and Smith (2006), who study the seasonality of Canadian provincial bond returns, also document an economically and statistically significant March effect, where provincial bond returns are much lower in March relative to their December baseline.

Panel A in Figure 3.1 also plots the deviations of averaged excess returns in each month from the sample mean, and they map the partial effects estimated in Model 1 rather closely, with a significant correlation of 0.988. Therefore, the plot in Panel A implies that the fixed effects and other control variables included in Model 1, albeit significant in some cases, contribute little to the monthly pattern of bond excess returns. Specifically, the seasonality of excess returns identified in January, July, and March is not entirely due to any particular year, industry or groups of bonds. Therefore, Panel A of Figure 3.1 suggests that there may be seasonal variations in Canadian corporate bond returns, and that the seasonal variations seem to be especially evident in the months of January, March, and July.

Focusing on the January effect, as depicted in Panel B, the relative performance of bond excess returns in non-January months estimated by Model 2 are uniformly dwarfed by that in January. Specifically, excess returns in January outperform all the other month, but July, by at least 18 bps (65 bps in the case of March), which is rather impressive when compared with the sample excess return average of 33 bps. The statistical significance of the estimated coefficients α_m in Model 1, Model 2, and their variations can be found in Table 3.2.

The visual evidence in Panel A of Figure 3.1 is confirmed by the statistical results of Panel B in Table 3.2, which displays the estimated α_m and corresponding statistical significance for twelve regressions of Model 1 (one for each month). Even after controlling for fixed effects and relying on three-way clustered standard errors, the partial effects of the three identified months (i.e., January, March, and July) on bond excess returns are still highly significant. Moreover, they are at least 10 bps higher in magnitude than the estimates obtained for the remaining months. For instance, the January effect, as tabulated in Panel B, almost doubles the size of the significant negative effect of April on the excess returns, with April being the most significant month among the remaining months. Thus, both the economic and statistical evidence supports the conclusion that Canadian corporate bond excess returns tend to be high in January and July, while low in March. In addition to the three monthly effects, the variable CR in Model 1 also has a significant impact on bond excess returns, in that one notch lower in the credit rating significantly increases excess returns by 5 bps. As credit ratings are absent for 10% bonds in the sample, the regression results for Model 1, evaluated in the full sample, exclude the variable CR, and are reported in Panel A of Table 3.2. Results in Panel A confirms that the effects of January, March, and July are robust regardless of whether credit ratings are controlled for in the model.

The results of the estimation of Model 2 are tabulated in Panel C of Table 3.2. Panel C displays the impact of different months, relative to January, on raw or excess returns of Canadian corporate bonds for the full sample, as well as for the CR-available and investment-grade subsamples. The results for raw (excess) returns in the three (sub)samples are reported in columns 1 to 3 (4 to 6), respectively. For instance, Columns 1 and 4 report the results for raw and excess returns in the full sample, after excluding the variable CR from the estimation of Model 2.

The full sample regression results in column 1 of Panel C indicate that raw returns in January uniformly outperform the remaining eleven months, with 8 out of the 11 cases being statistically significant, confirming the existence of the January effect. Meanwhile, compared to the results for raw returns, the estimated non-January effects for excess returns, albeit being smaller in magnitude, are again all negative, with a majority being statistically significant (e.g., column 4).

The conclusions drawn from the full sample remain robust when the analysis, after adding the credit risk to the model, is conducted for the CR-available and investment-grade subsamples. Specifically, as shown in columns 2 and 3, bond raw returns in non-January months are lower than in January, with the differences being significant, at the 10% level, in 7 out of 11 months for both subsamples. Notably, returns in March significantly underperform those in January by about 67 bps for both subsamples, which is higher than the all-month sample mean of 50 bps, for the raw returns. Further, returns in the previous three months (i.e., October to December) on average are lower than those in January by about 35 to 53 bps, which implies a possibility of tax-loss selling behavior from investors.[23] Similar results are obtained for excess returns in the two subsamples, as reported in columns 5 and 6 in Panel C.[24] Overall, the credit risk effect, while being significant, only marginally weakens the January effect for both the raw and excess returns.

Previous studies of the January effect in the US corporate bond market reveal that the January effect is generally significant only for low quality corporate bond indexes (e.g., Smirlock, 1985; Chang and Huang, 1990; Fama and French, 1993; Al-Khazali, 2001). The explanations link lower credit quality to smaller firm size and argue that high-yield bonds are more likely to be the target of the tax-loss selling (Chang and Pinegar, 1986) or sold by institutional investors to fulfill their "window-dressing" purposes of raising the portfolio quality (Maxwell, 1998) towards year-end. However, the analysis of the empirical results in this section suggests that there exists a significant January effect also for the Canadian investment-grade corporate bonds.

3.3.3 The Subsample Analysis

The sample in this study covers the 2007-09 financial crisis, a period during which the yield spread between Canadian investment-grade corporate bonds with respect to Treasury securities dramatically widened (Patel and Yang, 2015).[25] The dramatic change in the yield spread suggests the possibility of a structural break in the seasonal pattern of returns on Canadian corporate bonds, a majority of which fall in the investment grade. As recognized by Cooper et al. (2006), periods containing very unusual levels of return may affect the reliability of the analysis of seasonal effects. The reason

[23] The formal test of the tax-loss selling pressure hypothesis is discussed in Section 3.4.1.
[24] Column 5 of Panel C corresponds to the plot of Panel B in Figure 3.1.
[25] According to Patel and Yang (2015), between 2003 to 2013, the investment grade corporate option-adjusted spread (OAS) in Canada increased by 300 bps to 500 bps during the financial crisis, compared to before and after the crisis levels.

for this concern is intuitive: the presence of a month in a given year over which returns are extremely large or small may distort the evaluation of the seasonal effect as these extreme returns lend significance to the seasonality associated with the months of their occurrence.

In view of these considerations, it is necessary to explore whether the identified seasonal pattern in Section 3.3.2 can be attributed to the abnormally high yield spread during the financial crisis. One way to test this conjecture is to split the sample into pre- and post-crisis subperiods and examine the robustness of the identified seasonality within these subsamples. Throughout this study, the financial crisis period is taken to range between May 2007 to December 2008.[26] The evaluation of Model 1 and Model 2 is repeated in three subsamples, i.e., the pre-crisis subsample that covers the period prior to May 2007, the post-crisis subsample from January 2009 to December 2016, inclusive, as well as in the combined subsample, that is in the sample obtained excluding the financial crisis period.

Panel A of Table 3.3 reports selective estimates, for each subsample, from the twelve regressions described by Model 1. Strikingly, the pre- and post-crisis subsamples exhibit fundamentally different seasonal patterns for Canadian corporate bonds, as displayed in Parts A and B of Panel A. To illustrate, the average excess return in January prior to the financial crisis is no exception compared to that in other months. However, it significantly dwarfs those non-January returns by 72 bps after the crisis, a level that is 50% higher than the aggregated effect of 48 bps found in the full sample. Put differently, the January effect was absent in the Canadian corporate bond market before the outbreak of the financial crisis, while it has manifested itself thereafter. Likewise, the abnormally high average excess return in July as depicted in Panel A of Figure 3.1 mostly originates from the post-crisis subsample, reaching a significant 58 bps per month. On the contrary, the negative March effect dominated, both economically and statistically, that of other months by at least 20 bps in size before the hit of the slump, with its strength being waning after the crisis. Overall, the significantly abnormal ex-

[26]The conclusions in this section, and also the following sections, remain robust if the financial crisis period is expanded to include the year of 2009.

cess returns in January, July, and March, as observed in Part C of Panel A for the combined subsample, as well as those reported in Panel B of Table 3.2 for the full sample, appear to be the aggregation of distinctive seasonal patterns in the pre- and post-crisis subsamples.[27]

A closer look at the January effect in Model 2, as displayed in Panel B of Table 3.3, confirms the shift of seasonal patterns around the financial crisis. Before the onset of the crisis, both the average raw and excess returns in January, while overperformed those in March, were dominated by August returns and they were no higher than returns in other months, indicating no sign of a January effect. However, when Model 2 is evaluated for the post-crisis subsample, both the raw and excess returns in non-January months turn out to be smaller than those in January, with 7 out of 11 estimated differences being statistically significant at the 10% level. Panel B of Table 3.3, therefore, indicates that the global financial crisis induced a January effect in the market for Canadian corporate bonds.

Explanations for the transition from a negative March effect to strong January and July gains for Canadian corporate bonds around the financial crisis can be related to the Adaptive Markets Hypothesis (AMH) proposed in Lo (2004). The AMH states that any anomaly can be more profitable in certain market environments, and less so in others. As the market condition changes, new profitable anomalies can be created, while existing profit opportunities disappear. The change of market conditions in the wake of the financial crisis is likely to create new profit opportunities in January and July for investors trading Canadian corporate bonds. Nonetheless, the AMH offers no explanation on why the significant pre-crisis March effect ceases to be profitable under the new environment. Consistently with the predictions of the AMH, the literature documents that the discovery of an anomaly contributes to the descending trajectory of its profitability, as more traders crowd the profitable positions (e.g., Chordia et al., 2014; McLean and Pontiff, 2016; Jones and Pomorski, 2017). However, the weakened

[27] Notably, the impact of the credit rating variable on excess returns becomes insignificant in the post-crisis subsample, which may be explained by the increased importance of the liquidity risk relative to the credit risk in explaining corporate bond yield spreads after the onset of the crisis (e.g., Dick-Nielsen et al., 2012).

March effect in the post-crisis era is hardly due to over-exploitation of the opportunity, as this article is the first, at least in the scholarly literature, to explore the calendar month effect for Canadian corporate bonds. I notice that the documented negative March effect for Canadian provincial government bonds in Landon and Smith (2006) may provide some evidence supporting the over-exploitation argument, though the two types of bonds are not perfectly substitutable. Moreover, how the AMH can be applied to explain the fact that the market condition before the crisis favors the profitability of the January effect for Canadian stocks (e.g., Berges et al., 1984; Tinic et al., 1987; L'Her et al., 2004) but not corporate bonds needs further scrutiny. Detailed analysis of the origins of the calendar month seasonality for Canadian corporate bonds is discussed in the next section.

Trading the Post-crisis Seasonal Effects

The aftermath of the financial crisis brought a shift in seasonal patterns for Canadian corporate bond returns, which suggests a change in seasonal trading strategies for corporate bond investors. Specifically, the profit opportunity of trading the negative March effect was replaced by trading the January and July effects.

As shown in Table 3.3, the post-crisis average return in January exceeds all the other months by about 90 bps (or 60 to 126 bps pairwise, excluding July), which is more than twice the post-crisis sample average of 37 bps. The average return in July, albeit lower than that in January, is still 53 bps above the average of all the other months, which is combined with the low returns observed for June.

The profitability of a trading portfolio timing the January and July effects can be evaluated by comparing its annual returns with those on a buy-and-hold strategy. To do this, I select a subset of corporate bonds in the sample for which monthly returns can be calculated throughout the period from 2009 to 2016. There are eleven bonds in the sample satisfying this criterion. An equally-weighted (EW) portfolio consisting of these eleven bonds is then formed to evaluate the different performance of the seasonal and buy-and-hold strategies.

The seasonal strategy requires that, at the end of each year in the post-crisis subsample, investors buy the constructed portfolio and hold it for one month in January, then sell it at the month-end to capitalize on the January effect. The portfolio is again repurchased in June, held for another month, and sold at the end of July to profit from the July effect. For the remaining months of the year, investors hold the Treasury. A buy-and-hold strategy is instead to buy and hold the EW portfolio of the eleven bonds throughout the year and sell it at the year-end. The annual returns on the two strategies are calculated, in each year, as the annualized average of the monthly returns.

Table 3.4 tabulates annual returns on the two strategies for the year 2010 to 2016, as well as the corresponding net returns that take into account a round-trip transaction cost of 85 bps.[28] Overall, the seasonal trading strategy outperforms the buy-and-hold strategy in four of the seven years.[29] However, the calculated annual Sharpe ratio for the seasonal strategy is 1.03, while the corresponding ratio for the buy-and-hold strategy, at 1.47, is about 50% higher. Therefore, given the small sample size of 7 years after the crisis, exploiting the January and July seasonality is riskier than a simple buy-and-hold strategy.

3.4 Determinants of the Time-series Seasonality

In this section, I explore possible explanations for the shift of the seasonal effects documented in this paper. The standard demand-supply theory states that price adjusts to changes in demand and supply. Therefore, seasonal variations in corporate bond prices (and returns) can be related to changes in corporate bond supply and demand due to investors' seasonal portfolio rebalancing behavior. Investors rebalance their portfolios for various reasons. The literature on the January effect describes two types of portfolio rebalancing behaviors of investors, i.e., the tax-loss selling and window dressing behaviors.

[28] Devani and Zhang (2017) estimate that the round-trip transaction costs for Canadian liquid and non-liquid corporate bonds in Q4 2016 range from 15 bps to 85 bps, based on three different calculations. I rely on the most conservative of their estimated transaction costs.

[29] Given the small sample size, the statistical significance of the differences is not tabulated.

Investors sell high-yield assets, or those that performed poorly during the year, to realize capital losses and to cut their tax liabilities, a behavior that is called the tax-loss selling (Wachtel, 1942; Roll, 1983). Tax-loss sellings often occur at the end of the tax year (December in Canada) and are followed by buybacks of the depreciated assets in January, which increases the demand and pushes up the price. These year-end shifts in demand may explain the January effect. Empirical studies have shown that the tax-loss selling hypothesis explains at least partially the January effect for Canadian stocks (e.g., see Berges et al., 1984; Tinic et al., 1987).

Institutional investors rebalance their portfolios also for the purpose of window dressing (e.g., Lakonishok et al., 1991), which is typically linked to periods over which fund managers are evaluated on their performance. Specifically, institutional portfolio managers tend to sell riskiest assets (e.g., high-yield bonds) in their portfolio at the year-end to decrease portfolio risk (to the eye of the evaluators) while maintaining the proceeds of previous risk taking. Managers then increase their demand for risky assets in the following January to capture higher expected returns over the coming year.

The window-dressing explanation of the January effect has been documented for the US (high-yield) corporate bonds (e.g., Cooper and Shulman, 1994; Maxwell, 1998; Dbouk et al., 2013). The window-dressing argument, however, suggests that the selling pressure at the end of the year, and consequent price appreciation in January, should be concentrated within high-yield bonds. Given the large share of investment-grade bonds in the Canadian market, as well as the significant January effect in the investment-grade subsample (e.g., Table 3.2), the window-dressing hypothesis is expected to be less relevant in explaining the seasonality for Canadian corporate bonds.

Specific to explaining corporate bond monthly seasonalities, DeRosa-Farag (1996) proposes the coupon-based payment flow theory, which I introduce to explain the joint January and July seasonalities. The theory states that the demand for corporate bonds surges following the month in which coupons are heavily paid, and the increase in demand is driven by the need for coupon reinvestment. Given that coupons are paid unevenly during the year, with a sizable amount of bonds paying coupons in

December, the theory thus suggests that the January effect may be explained by an increased coupon-based fund flow in December.

I note that, of the 2317 Canadian corporate bonds sampled in this paper, over 90% pay coupons semiannually. If a bond in the sample pays coupons in December, it is likely that the bond also pays a coupon in the following June. Since majority bonds in the sample pay their coupons in December, the theory states that reinvestment of coupon cash flows in December may explain the observed January effect. By the same token, the cash flows from coupon payments in the following June are reinvested to push up bond prices in July, thus the positive July effect. Note that, however, the literature so far offers little empirical evidence in support of the coupon-based payment flow theory (e.g., Fridson and Garman, 1995a,b; Barnhill et al., 1997; Dbouk et al., 2013).

The theories introduced above offer possible explanations for the documented January and July effects observed in the post-crisis sample. The explanation for the negative March effect, however, draws insights from the study by Landon and Smith (2006). Using a sample of Canadian provincial government bonds from 1983 to 2003, Landon and Smith identify a significant March effect where returns in March are lower by 11.9% at an annual rate relative to the December baseline. Interestingly, the authors document a significant causal relationship between the US 10-year Treasuries and Canadian provincial government bonds, which accounts for the March seasonality. The important role played by the US 10-year Treasuries, a major indicator for the cost of borrowing in the US, suggests a high level of integration between the Canadian and the US financial markets, a feature that has been already pointed out in Berges et al. (1984) and Tinic et al. (1987). Using December (instead of January) as the baseline, I re-examine Model 2 employing the pre-crisis subsample and find a significant March effect also for the Canadian corporate bonds. The results (untabulated) indicate that, for corporate bonds, March returns are 8.76% lower than returns in December, at an annual rate. Given the similar seasonal variations in the pre-crisis Canadian provincial and corporate bond returns, the natural question is to ask whether the US 10-year

Treasuries also help explain the negative March effect documented for Canadian corporate bond returns.

3.4.1 The Reversal Effect

Both the tax-loss selling and window-dressing behaviors target bonds with low returns during the previous year (tax-loss selling) or the previous month (window dressing), with those bonds most likely to be sold in December and bought back in January. Therefore, the lower the price of a bond is in December, or during the year, the more likely it is that it will be sold at the year-end. The price depreciation in December is then reversed due to the increased demand for the bond, because of portfolio rebalancing, in the following January. Put differently, the portfolio rebalancing behavior of investors, either motivated by the need of realizing capital losses or making portfolios appear less risky, offers a testable prediction that the January effect should be negatively related to returns in preceding months, particularly in December, as proposed in Roll (1983) and Cooper and Shulman (1994). In this section, I test possible reversal relations between returns in January and previous months by adapting the two-step regression procedure employed in Heston and Sadka (2008).

Heston and Sadka (2008) document that returns on US stocks tend to follow a periodical pattern with same-stock returns in the same calendar month being strongly correlated over one or more preceding years, which results in periodic spikes, every twelve lags, among the averaged return responses to lagged returns. The authors dub this pattern the cross-sectional seasonality, since it describes a periodicity in the relative performance of stocks, at any given moment in time. In Appendix C, I conduct a similar two-step procedure proposed in Heston and Sadka (2008) to test the cross-sectional seasonality and find no such pattern for Canadian corporate bonds.[30] However, the two-step procedure can be modified to test the reversal effect on January returns, given past price information over a period of twelve months. Specifically, for

[30] The two-step procedure resembles the Fama-MacBeth regression (Fama and MacBeth, 1973) with known betas (i.e. excluding the time-series regression stage). Details on the methodology of the two-step procedure can be found in Appendix C.

each January in year y of the sample, and each given k lag (for $k = 1, 2, \ldots, 12$), I consider the following cross-sectional regression:

$$r_{b,y} = \alpha_{k,y} + \gamma_{k,y} r_{b,y-k} + e_{b,y} \text{ for } b = 1, 2.... \text{ given } y \text{ and } k, \qquad \text{(Model 3)}$$

where, $r_{b,y}$ is the January excess return on the bond b in year y, and $e_{b,y}$ are zero-mean disturbances. Standard errors in the model are adjusted for cross-sectional heterogeneity. Here, $\gamma_{k,y}$ is defined as the "return effect" following Heston and Sadka (2008), and measures cross-sectional responses of January returns in year y to those in lag-k month of last year.

To illustrate, the negative response of year-y January returns to previous December returns, i.e. the reversal effect, is measured by the estimated $\gamma_{1,y}$ in the cross-sectional regression, where returns on any bond available in January of year y are regressed on their lagged one month returns (i.e., December returns in year $y - 1$) and a constant.[31] If the reversal effect lies at the root of the January effect, then a) a majority of the estimated $\gamma_{1,y}$, and, further, the average of all the responses, $\overline{\gamma_1} = \sum_{y=1991}^{2016} \widehat{\gamma_{1,y}}$, should be negative and statistically significant. Given that both the tax-loss selling and window dressing investors focus on selling bonds that yield low returns in December, then b) one should observe a dip in the time-series of $\overline{\gamma_k}$ at lag one ($k = 1$).[32]

Figure 3.2 depicts the estimated $\gamma_{1,y}$ over time and $\overline{\gamma_k}$ for k from 1 to 12. Panel A of Figure 3.2 indicates that there is not enough evidence to support prediction a). In fact, of all the estimated $\gamma_{1,y}$ for $y = 1991, \ldots, 2016$, there are 15 out of 26 years in which returns in January response positively to the previous December returns.[33] Further, prediction b) is visually refuted by Panel B of Figure 3.2, where January returns respond to last January returns ($k = 12$) more negatively than to December ones

[31] For the cross-sectional regression in any year, I require that the bonds included in the analysis have at least 50 bond-month observations. The earlier years of the sample (i.e., from 1987 to 1990) with less than 50 bonds available are excluded from the analysis.

[32] For the tax-loss selling pressure hypothesis, investors sell bonds with capital losses during the year. However, since those bonds are sold in December, the price is likely to be pushed further down, thus one would expect the reversal effect to be the strongest in December.

[33] This number for the post-crisis subsample, in which the January effect originally thrived, is 4 out of 8.

($k = 1$).

Still, as the estimated average $\overline{\gamma_1}$ is negative in Panel B of Figure 3.2, one can not conclude that December returns are irrelevant to the January effect without referring to the statistical significance. Moreover, Panel B implies that the January returns may respond to returns in other months of the previous year. Therefore, the statistical significance of the averaged return responses can be useful for further inference. Table 3.5 tabulates, for January, values of $\overline{\gamma_k}$ for k from 1 to 12 along with their heterogeneity corrected t-statistics. Regression results pertaining to March and July are provided for comparison. Consistent with Figure 3.2, Table 3.5 indicates that the last December returns have negative but statistically insignificant impact on the following January returns. In fact, the abnormal returns in January do not seem to stem from bond price depreciation in any month of the previous year.

Overall, the empirical results indicate that the January effect is not likely to be caused by a reversal effect originated from investors' behaviors like tax-loss selling and window dressing. As both the tax-loss selling and window-dressing hypotheses have been developed to explain the January effect in the equity market, their weak explanatory power for the January effect in corporate bonds implies that return seasonal variations in the corporate bond market should not simply be viewed as seasonality spillovers from the stock market.

3.4.2 The Coupon Effect

The coupon-based payment flow theory, which has been developed for the fixed income market, may provide a suitable explanation for the post-crisis January and July positive returns in the Canadian corporate bond market. The premise of this theory lies in two assumptions. One is that corporate bond coupon payments are unevenly distributed, with a majority concentrated in December. The second assumption requires investors to accumulate received coupon funds by reinvesting the cash back to the corporate bond market (i.e., on the same class of asset) instead of investing on other assets. Taken together, the theory predicts that the demand for corporate bonds in January will soar following an influx of coupon funds in December, which leads to the January effect.[34] To determine whether the coupon-based payment flow theory accounts for the January and perhaps also the July seasonalities identified in this paper, I first provide supporting evidence for the premise of the theory in the Canadian corporate bond market.

Panel A of Figure 3.3 plots the annual distribution of coupon payments from all the bonds in the sample, by month. It is evident from the plot that coupon payments in the sample are indeed unevenly distributed, with December and June showing the two highest frequencies and volumes on average. Further analysis (unreported) shows that splitting the sample around the financial crisis does not change the distribution pattern. I note that over 90% of bonds in the sample pay coupons semiannually, among which, 21% pay coupons in both December and June. Therefore, the likelihood of a bond paying coupons in December-June is higher than the share of 1/6 in an even distribution, which originates the double-peaked coupon distribution.[35] One implication of the coupon-based payment flow theory is that the more coupons are paid in a month, the higher demand for corporate bonds will be in the following month, which then results in higher prices and thus higher returns.[36] The concentration of coupon payments in December and June over the sample period, as shown in Panel A of Figure 3.3, thus suggests that returns in January and July are likely to be higher than those in other months for Canadian bonds. Arguably, this prediction holds if the coupon funds released in December and June flow back into the bond market in the following months, i.e., in January and July.

The coupon-based payment flow theory does not specify the market condition in which coupon reinvestments actually lead to increased bond demand in the following

[34]The argument that intensive coupon payments pump up bond demand in the following month instead of current month is consistent with the finding that frequent portfolio rebalancing may lead to excessive transaction costs and low returns (e.g., Ahmadi et al., 2007; Cuthbertson et al., 2016). Particularly, in the corporate bond market, reinvesting received coupons whenever available is impractical, given the high transaction costs associated with frequent and small-sized trades (e.g., Edwards et al., 2007; Feldhütter, 2011).

[35]The corresponding figures for the pre-crisis (post-crisis) subsample are 84% and 20% (98% and 21%), respectively.

[36]The possible consideration for a delayed and perhaps lump-sum coupon reinvestment is to reduce transaction costs.

months, if they are not redirected to other asset classes. However, if previous-month coupon reinvestments lie at the root of the documented post-crisis January and July effects, one can argue that the theory agrees more with the post-crisis than the pre-crisis market environment. Particularly, in the post-crisis period, as coupon payments in December and June are not exceptionally higher than their pre-crisis counterparts, reinvesting coupon funds back to the bond market is likely to be more attractive than in the period leading to the crisis. Therefore, for the theory to be applicable in explaining the post-crisis seasonality, the occurrence of a coupon payment in December (June) should have a significantly positive effect on the January (July) return of the coupon-bearing bond, only for the post-crisis subsample.

Testing the Coupon Effect

In this section, I perform a formal test on the predictive power of the coupon-based payment flow theory in different market states segmented by the financial crisis. Specifically, I re-evaluate Model 1 by adding a dichotomous variable indicating the occurrence of a coupon payment in December or June, along with its interaction term with a post-crisis dummy variable, for regressions assessing the January and July effects respectively. The revised model is displayed in Model 1-1:

$$\begin{aligned} r_{b,t} =& \alpha_0 + \alpha_1 MAT_{b,t} + \alpha_2 CR_{b,t} + \alpha_c CPN_{b,t} + \alpha_{post} D_{post,t} + \alpha_{c*p} CPN_{b,t} \times D_{post,t} \\ & + \alpha_m D_{m,t} + \sum_{y=1988}^{2016} \alpha_y D_{y,t} + \sum_{i=2}^{10} \alpha_i D_{b,i} + \sum_{b=2}^{2317} \alpha_b D_b + \varepsilon_{b,t} \quad m = 1,7 \end{aligned} \tag{Model 1-1}$$

where, in the regression of the January effect ($m = 1$), for bond b in month t, the dichotomous variable $CPN_{b,t}$ is one only if the previous month, month $t-1$, is December and it is the month in which bond b paid a coupon, and zero otherwise. Similarly, in the regression of the July effect ($m = 7$), the variable $CPN_{b,t}$ is one only if the previous month is June and has a coupon payment. The post-crisis dummy variable $D_{post,t}$ is one if month t comes later than December 2008.

I expect the estimated α_c to be insignificant or significantly negative, while the estimated coefficient on the interaction term, i.e., α_{c*p}, is expected to be significantly positive. Essentially, the estimated α_{c*p} offers an empirical validation for the conjecture that the significant return gains in January and July, in the post-crisis Canadian corporate bond market, are attributable to the increased demand of reinvesting coupons paid in December and June. As a comparison, I also perform two regressions of Model 1-1 for the month December and June by changing the variable $CPN_{b,t}$ to a current month December/June coupon payment dichotomous variable. The estimated results for the four regressions are tabulated in Table 3.6.

Consistent with the conjecture, the estimated α_{c*p} in table 3.6 for both the January (column 1) and July (column 2) regressions are positive and statistically significant at the 5% level. Economically, the post-crisis coupon payment in December increases bond return in January by 78 bps, and the corresponding effect on returns from the post-crisis coupon reinvestment in July is 30 bps. Interestingly, the coupon effect prior to the financial crisis, i.e., α_c in the two regressions, is significantly negative, which seems to suggest that the demand for bonds following coupon payments decreases in periods before the crisis. I note that the estimated seasonal effect in January and July are still highly significant, after controlling for the coupon reinvestment effect. Therefore, the conclusion, based on the empirical results in table 3.6, is that the coupon-based payment flow theory does (partially) explain the January-July seasonal gains for Canadian corporate bonds.

The results of the December and June regressions, as tabulated in column 3 and 4 of Table 3.6, seem to complement the results of January and July regressions. Specifically, in the post-crisis period, coupon payments decrease bond returns in the current month but increase returns in the following month, while the opposite holds for the pre-crisis period.

The Role of Expected Future Interest Rate

A possible explanation for the opposite effect of lagged December and June coupon payments on bond returns can be linked to different interest rate environments before and after the financial crisis. Investing in (high-quality) corporate bonds, especially those with long-term maturities, is highly attractive when interest rates are expected to decrease in the long run, as the value of the bond will increase after the purchase. As shown in Panel B of Figure 3.3, the trading price on the contracts tracking deliverable ten-year Government of Canada bonds has been increasing since 2000, with an long-term upward trend commencing around 2005.[37] The increased price for trading the ten-year Treasury Futures implies that investors expect the long-term interest rate to follow a downward trend, which is particularly evident in the post-crisis period, as benchmark interest rates are eventually set close to zero, or even negative, by central banks, to counter the aftermath of the financial crisis. In contrast, the expected long-term interest rate is more volatile during the pre-crisis period, making the expected return on investing in corporate bonds less predictable. Therefore, reinvesting coupon payments in corporate bonds is more profitable and practical in the post-crisis period.

If the demand for corporate bonds decreases with the expected long-term interest rate, one should expect higher bond returns in months when the expected Treasury price increases, regardless of the occurrence of coupon payments in previous months. However, intensive coupon payments provide extra funds for investors to capitalize on their expectations of a declining interest rate. As December and June are associated with the highest amounts of coupon payments over time, one should expect that, on average, there are significant boosts in January and July returns in periods of declining expected long-term interest rate. Therefore, to explain the January and July significant gains by referring to the coupon-based payment flow theory, one should expect that a) bond returns increase with the current month expected change in the ten-year Treasury price, and b) this relationship significantly increases when there are

[37] The ten–year Government of Canada bond futures are traded at the Canadian Derivatives Exchange. The price time series is obtained from the Bloomberg database.

extensive coupon payments in the previous month (i.e., in December and June). To test these two hypotheses, I re-evaluate the four regressions of Model 1-1 by replacing the post-crisis dichotomous variable with the first difference of the ten-year Treasury futures price. An F-test is performed, for each regression, to test whether the positive coupon reinvestment effect is still significant after controlling for the expected price change in the long-term Treasuries. The regression and test results are tabulated in Table 3.7.

The first two columns address the effect of coupon payments in December and June on the following month bond returns. The future Treasury price change, when there is no coupon paid in the previous month, has a significantly positive effect on the current month corporate bond returns. This effect is as expected, given an increase in the futures price is equivalent to a decrease in the expected long-term interest rate, which improves expected returns on investing in (investment-grade) corporate bonds. Notably, controlling for future interest rate expectations largely reduced the marginal effect on the two monthly dummies of January and July, as compared to regression results reported in the first two columns of Table 3.6. Further, the positive effect of the future Treasury price change increases by 73% (48%) when there are intensive coupon payments in December (June). The increase can be attributed to the coupon reinvestment pushing up bond demand in the following months, i.e., the coupon effect. Based on the F-test results, the coupon effect is significant for both regressions assessing the January and July seasonalities.[38] Conversely, the intensive coupon payments in December and June fail to enhance the confirming effect of lower future expected interest rate on current month corporate bond returns, as indicated by the F-test results in columns 3 and 4 of Table 3.7. In conclusion, the documented post-crisis January and July effects are due to increased bond demand from reinvesting coupons paid in the previous months, when the long-term interest rate is expected to decline for a sustained time period, which characterizes the period following the financial crisis.

However, the empirical evidence in Table 3.7 does not suffice to explain the absence

[38]The test for the coupon effect in July is only significant at 10% level.

of coupon-driven seasonal gains in the pre-crisis period. As shown in Panel B of Figure 3.3, the pre-crisis period also identifies occasional downward trends in the expected long-term interest rate. In this regard, I argue that, during the pre-crisis period, the frequency of coupon payments in a particular month, when averaged across periods of decreasing expected interest rate, is not high enough to yield significant abnormal gains in the following months. Indeed, as shown in Table 3.8, conditioning on expected future interest rate being lower, the post-crisis coupon payments more than double, except in one month, that in the pre-crisis period. In particular, the previous-month average monthly total coupon payments for January and July are the highest, at 152, among all the months when considering both the previous and current month coupon payments.

Overall, the analysis in this section validates the coupon-based payment flow theory in explaining positive seasonal effects in the corporate bond market, but the explanatory power of the theory needs the support of a market environment in which investors expect a downward trending long-term interest rate, in this case, the period after the financial crisis in Canada. A sustained and extremely-low interest rate environment following the financial crisis is a salient feature of the world economy as a whole. Under this circumstance, it may be reasonable to extrapolate that the conclusion drawn in this section also applies to the post-crisis corporate bond market in other countries. This extrapolation remains a research question for future explorations.

3.4.3 Out-of-the-system Drivers

Following the approach in Landon and Smith (2006), I test, in this section, whether the US 10-year Treasury yield changes help explain any of the three monthly effects in the Canadian corporate bond returns. The empirical test is performed in two steps. First, an adapted version of Model 2 is evaluated multiple times, one for each year, to obtain the marginal return change in each month of a year, as summarized by the coefficients γ_m^y for month m in year y in Model 2-1.

$$r^y_{b,t} = \gamma^y_1 MAT_{b,t} + \sum_{m=1}^{12} \gamma^y_m D_{m,t} + \sum_{i=1}^{I^y-1} \gamma^y_i D_{b,i} + \sum_{f=1}^{F^y-1} \gamma^y_b D_{b,f} + \varepsilon_{b,t} \qquad \text{(Model 2-1)}$$

$$y = 1988, 1989, \ldots, 2016$$

In Model 2-1, for a given year y, excess returns are regressed on twelve monthly dummies (with no constant and the baseline month) to obtain twelve estimated coefficients γ^y_m, one for each month in the year, controlling for the maturity risk, and the industry and firm fixed effects.[39] The exclusion of the bond fixed effect in Model 2-1 is because that, in each yearly regression, the number of return observations belonging to any bond is at most twelve, which makes the return variation of one bond hardly distinguishable from that of another. Therefore, the fixed effect controlled in Model 2-1 is firm level instead of bond level. The parameters F^y and I^y in Model 2-1 represent the numbers of firms, and the industries they belong to, that issue the bonds available in the subsample of year y. The 348 estimated γ^y_m on the monthly dummies (12 per year for 29 years) are stored for the next step.

Figure 3.4 plots the variations of the estimated γ^y_m over the year, for the months of January, March, and July (i.e., the ones in which significant seasonality patterns are detected), respectively. As Model 2-1 is estimated separately for each year, the estimated monthly effects vary over time.

In the second stage, I regress the pooled 348 $\widehat{\gamma}^y_m$ on a set of macroeconomic and stock market factors that have potential influence on the Canadian corporate bond returns, after controlling for a constant, the year and month fixed effects, and two financial crisis dummies, as displayed in Model 4:

[39] Regressions in this step do not control for the credit risk to keep also bond-month observations with no credit ratings in the regression. Adding the credit rating variable to the model has limited impact on the regression results and does not alter the conclusion (results available upon request).

$$\widehat{\gamma}_m^y = \beta_0 + \beta_1 Z_{m,y} + \beta_{crisis} D_{crisis} + \beta_{postcrisis} D_{postcrisis} + \sum_{y=1988}^{2016} \beta_{2y} D_y + \sum_{m=2}^{12} \beta_{3m} D_m + u_{m,y} \quad \text{(Model 4)}$$

where, factors $Z_{m,y}$ include the three US market variables employed in Landon and Smith (2006), i.e., the first difference in the US 3-month Treasury Bill yield, the first difference in the US 10-year Treasury bond yield, and the excess return on the S&P 500 stock index. Further, the high level of integration between the Canadian and the US financial markets (e.g., Mittoo and Zhang, 2010; Patel and Yang, 2015) implies that shocks to the CDN/US exchange rate, represented by the first difference of the exchange rate, could also play a role in explaining the seasonal variations in Canadian corporate bond returns. To control for the impact of the stock market, I also add as factors the monthly rate of the excess return on the Canadian Financial Markets Research Center (CFMRC) TSX stock market Value Weighted (VW) Index and the Amihud illiquidity measure (Amihud, 2002) for the Canadian stock market.[40] The Amihud illiquidity measure is constructed with individual stock data for the Canadian market. It is included to examine whether illiquidity in the Canadian stock market accounts for seasonal variations in corporate bond returns.[41] As Canada is a resource exporting economy, I also include the first difference of the Bank of Canada total Commodity Price Index (BCPI) to control for seasonal commodity price changes.

The seven factors that are included in the matrix $Z_{m,y}$ in Model 4 are retrieved from five different sources: the US 3-month Treasury Bill (secondary market) yields and 10-year constant maturity Treasury bond yields are from the Board of Governors of the Federal Reserve System website; the S&P 500 value-weighted return (including dividends) and the US risk-free rate is from WRDS Database (the difference of the two

[40] The CFMRC VW index includes all TSX (the Toronto Stock Exchange) listed domestic common equities in the CFMRC database.

[41] The time-series of the Amihud measure is constructed for the period of May 1993 to October 2015. Therefore regressions including the Amihud illiquidity measure are conducted on the 1993-2015 subsample.

variables is the excess return of the S&P 500 Index). From the CHASS Data Centre, I obtain the Canadian CFMRC Monthly VW Index, the 91 Day T-Bill Rate (the difference of the two variables is the excess return of the TSX VW Index), and the CDN/US Foreign Exchange Rate. The total Commodity Price Index is from the Bank of Canada, while the TSX stock prices, volumes, and returns that are needed for calculating the Amihud illiquidity measure are downloaded from Datastream. Table 3.9 reports basic summary statistics for the seven variables included in $Z_{m,y}$.

Columns Mdl1, Mdl2 and Mdl3 in Table 3.10 tabulate the estimated coefficients on the variables included in three specifications for $Z_{m,y}$ in Model 4. The three specifications are the combinations of factors with and without the Amihud illiquidity measure, and the one excluding both the Amihud illiquidity measure and the excess return on the S&P 500 index. The Amihud illiquidity measure is excluded to allow the coverage of the entire sample, while the excess return on the S&P 500 index is dropped to mitigate the collinearity problem, as the correlation between the US and Canadian stock market index excess return variables reaches 0.773, as shown in Table 3.9.

Columns Mdl4 and Mdl5 in Table 3.10 also report selective estimates, for two of the specifications of $Z_{m,y}$, in an adapted version of Model 4, in which all factors are interacted with three dichotomous variables indicating the financial crisis months, and the pre- and post-crisis months. This adapted version of Model 4 allows to analyze the time variations of the coefficients on the factors included in each specification of $Z_{m,y}$.

As shown in Table 3.10, throughout the entire sample period from 1988 to 2016, the first difference of the 10-year US Treasury bond yield is the only factor that has a significant and negative effect on the estimated monthly return variations, γ_m^y, and the effect is persistent across sub-periods and for different model variations. Specifically, a 1% increase in the change of the US Treasury yields decreases the monthly return seasonal variations by about 2%, for the Canadian corporate bonds. The negative relationship is as expected, as an increase in the yield on US Treasuries would be expected to lead to a rise in the yield on Canadian corporate bonds, and a fall in the holding period returns. This finding reinforces the conclusion in Landon and Smith (2006) that changes in the 10-year US Treasury yields have a significant impact on the Canadian fixed income return seasonalities. Table 3.10 also indicates that the excess return on the Canadian stock market index has a positive impact on γ_m^y before and during the financial crisis, as a rise in the TSX excess return would be expected to coincide with a rise in the yield on Canadian corporate bonds. However, this impact disappears in the wake of the crisis. The rest of the factors included in the model have no explanatory power on the seasonal variation of the Canadian corporate bond returns.[42]

The empirical results in Table 3.10 establish a negative link between the monthly changes in the US Treasury yield and Canadian corporate bond returns, thus any seasonal pattern pertaining to the US Treasury yield changes may be transmitted, inversely, to Canadian corporate bond return changes. Therefore, if the long-run US market borrowing cost lies at the root of the seasonal variations of the Canadian corporate bond returns, one should expect the US Treasury yield changes to be subject to a positive pre-crisis March effect and negative post-crisis January and July effects. Similar mechanism also applies to the pre-crisis effect of the TSX excess return.[43]

Table 3.11 reports the seasonal variations for both the US Treasury yield changes and the Canadian stock market index returns, specific to the months of January, March, and July. It can be shown that the monthly yield changes in the 10-year US Treasury exhibit a significantly positive March effect during the pre-crisis period, with no evidence of a January or July effect after the crisis. No seasonal patterns are detected for the Canadian stock market excess returns. Therefore, the positive March effect on the US long-run borrowing cost should, at least partially, explain the negative March effect documented for the Canadian corporate bond returns, with the causality being detectable exclusively before the outset of the 2007-09 financial crisis.[44] Further, neither the US Treasury yield monthly changes or the excess returns on the Canadian stock market index are responsible for the post-crisis January and July effects docu-

[42]The estimated coefficient on the exchange rate in Mdl4 before the crisis is significant only at 10% level.

[43]As noted in Fama and French (1993), if a variable is to explain a seasonal effect, it should be characterized by seasonality.

[44]Results in Table 3.11 seem to suggest that the March effect is also present during the crisis. However, this conclusion is supported by too few observations to be reliable.

mented in this paper. Note that, in Table 3.11, the crisis dummy variable alone has no explanatory power to the two time series examined.

Overall, among the seven variables employed in Model 4, only the factor linked to the US 10-year Treasury yield is found to be relevant in explaining the seasonality in Canadian corporate bond returns. Further, the explanatory power of the US Treasury yield is limited to the pre-crisis period. The fact that the US long-run borrowing cost exerts a persistent impact on the Canadian corporate bond market is not as surprising as it appears, given that Canadian firms borrow heavily in the US debt market: approximately 50% of Canadian firms' debt capital is raised in the US market (e.g., Anderson et al., 2003; Patel and Yang, 2015).

3.5 Conclusion

In this paper, I document a negative March seasonal effect and positive January and July effects in Canadian corporate bond returns, during a period spanning from 1987 to 2016. Importantly, the 2007-09 financial crisis played a crucial role in switching the documented seasonal patterns, with the March effect being significant only before the crisis, while the January and July effects become exploitable only in the post-crisis subsample.

Further, I provide explanations for this transition of monthly seasonality patterns. Consistent with the finding in Landon and Smith (2006) for Canadian provincial bonds, I show that the monthly change of the 10-year US Treasury yield is significantly, and negatively, linked to the monthly return variations in Canadian corporate bonds, over the entire sample period. A further investigation indicates that the 10-year US Treasury yield changes used to increase significantly in March, but only before the financial crisis. Consequently, a significant increase in the change of the 10-year US Treasury yield will induce significant decreases in the Canadian corporate bond returns, which offers an explanation for the negative pre-crisis March effect documented in this paper. Landon and Smith (2006) found a similar March effect for the Canadian provincial bond returns, for the period of 1983 to 2003, and the authors attribute their finding to the monthly change in the US 10-year Treasury yields. Their conclusion, if extended to the post-crisis sample, is likely to be modified given the fading March effect in the US Treasury yield changes.

One salient and widely observed market environment change following the financial crisis is the sustained low levels of benchmark interest rates. I show that, in a declining interest rate environment, the coupon-based payment flow theory (DeRosa-Farag, 1996) is suitable to explain the January and July effects for Canadian corporate bonds. The argument is that when investors expect the long-term interest rate to follow a downward trend, investing in corporate bonds becomes highly attractive, which facilitates coupon reinvestments in the corporate bond market. Therefore, according to the coupon-based payment flow theory, frequent coupon reinvestments in the post-crisis period will result in strong upward pressure on corporate bond returns in months following massive coupon payments. As the highest levels of coupon payments in the analyzed sample occur in December and June, the coupon-based payment flow theory, after taking into account the interest rate consideration, successfully explains the significant gains in January and July for Canadian corporate bonds. I argue that the limited role of the coupon-based payment flow theory in explaining the January effect as documented in the literature is unjustified, because the appropriate condition for applying the theory is ignored.

Finally, the Adaptive Markets Hypothesis (Lo, 2004) states that, depending on changes in the market conditions, any anomaly can be more profitable in certain market conditions, and less so in others. The research conducted in this paper for Canadian corporate bonds provides further supporting evidence to this hypothesis.

Table 3.1: Descriptive Statistics

Panel A presents basic summary statistics for the Canadian corporate bonds studied in this paper, for the pooled sample and the Non-Investment Grade (NIG) and Investment Grade (IG) categories. The covered sample period is from August 1987 to December 2016. The first column reports the count of bond-month observations in the sample, followed by the average yield and return, as well as the standard deviation and median of the monthly returns. The last two columns list the mean volume at issue (in millions of Canadian dollars) and the average coupon rate. Panel B reports the same summary statistics for the subset of bonds for which the return at-issue is available. These bonds are also categorized into maturity bands. The last column adds the average number of months until maturity for each category.

Panel A: Descriptive Statistics for the 1987-2016 Sample

	N	Yield (%)	Return (%)	St. Dev.	Median (%)	Volume (M)	Coupon (%)
Pooled	113,155	4.593	0.50	0.013	0.36	297	6.064
			Subsamples by credit rating bands				
NIG	1,002	7.704	0.71	0.013	0.66	174	6.954
IG	101,193	4.549	0.52	0.013	0.37	300	6.079

Panel B: Descriptive Statistics for Bonds at Issue

	N	Yield (%)	Return (%)	St. Dev.	Median (%)	Volume (M)	Coupon (%)	Time to Maturity (months)
Pooled								
	1,066	5.267	0.66	0.014	0.58	410	5.222	102
Maturity at issue less than 5 years								
	164	3.931	0.46	0.008	0.42	409	3.941	38
5 to 10 years								
	593	5.178	0.73	0.012	0.63	467	5.038	67
Over 10 years								
	309	6.126	0.61	0.019	0.57	301	6.254	206

Table 3.2: Monthly Seasonality in Canadian Corporate Bond Returns

Panel A tabulates estimated α_m in Model 1 (without the credit risk variable) from twelve regressions, one for each calendar month from January to December. The first column of results displays the estimated coefficient on the monthly indicator for January, which predicts whether January is different from all the other months in explaining corporate bond excess returns. Columns 2 to 12 correspond to estimates for February to December, respectively. Corresponding regression results when the credit risk variable is included are reported in Panel B. Panel C displays the estimated coefficients on the 11 monthly indicators of Model 2, with January as the base month, for both raw and excess returns. The first column of results in Panel C tabulates regression results for raw returns in the whole sample. Results for raw returns in the credit-rating-available subsample and the investment-grade subsample are reported in Columns 2 and 3, respectively. Columns 4 to 6 display regression results for excess returns in each subsample. All regressions control for year, industry, and bond fixed effects, as well as maturity risk (and credit risk when possible). Results for controlling variables are not tabulated. Standard errors are adjusted using three-way clustering by month, year, and firm. The time period covered is from August 1987 to December 2016.

Panel A: Individual Monthly Effect

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Month	0.441^{+}	-0.0612	-0.382**	-0.273*	0.117	-0.208^{+}	0.392**	0.217*	-0.0355	-0.176^{+}	-0.0576	0.0474
Effect	(0.240)	(0.163)	(0.0390)	(0.120)	(0.0915)	(0.0975)	(0.0479)	(0.0793)	(0.0527)	(0.0954)	(0.0999)	(0.0972)
N	112908	112908	112908	112908	112908	112908	112908	112908	112908	112908	112908	112908
FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
3-way Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Individual Monthly Effect with Credit Ratings

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Credit	0.0585**	0.0585**	0.0585**	0.0587**	0.0584**	0.0587**	0.0593**	0.0584**	0.0585**	0.059**	0.0585**	0.0586**
Effect	(0.00620)	(0.00501)	(0.00533)	(0.00617)	(0.00941)	(0.0159)	(0.00974)	(0.0102)	(0.00667)	(0.00576)	(0.00492)	(0.00506)
Month	0.475*	-0.029	-0.36**	-0.269*	0.085	-0.246*	0.371**	0.214*	-0.052	-0.181	0.0604	0.019
Effect	(0.198)	(0.152)	(0.101)	(0.121)	(0.0904)	(0.0987)	(0.0602)	(0.0911)	(0.0416)	(0.119)	(0.109)	(0.125)
N	101893	101893	101893	101893	101893	101893	101893	101893	101893	101893	101893	101893

FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
3-way Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel C: Relative Return Performance across Different Months

	Raw	Raw	IG	ExcessR	ExcessR	ExcessR IG
Credit		0.0591**	0.0484*		0.0595**	0.0494*
		(0.0168)	(0.0180)		(0.0165)	(0.0170)
February	-0.391*	-0.379*	-0.381*	-0.375^{+}	-0.363*	-0.365*
	(0.171)	(0.155)	(0.157)	(0.173)	(0.156)	(0.158)
March	-0.679**	-0.665**	-0.671**	-0.660**	-0.647**	-0.653**
	(0.192)	(0.179)	(0.180)	(0.189)	(0.176)	(0.177)
April	-0.622^{+}	-0.615^{+}	-0.619^{+}	-0.594^{+}	-0.588^{+}	-0.592^{+}
	(0.291)	(0.284)	(0.288)	(0.285)	(0.279)	(0.282)
May	-0.275	-0.294	-0.294	-0.265	-0.283	-0.283
	(0.175)	(0.169)	(0.170)	(0.172)	(0.165)	(0.167)
June	-0.579*	-0.592*	-0.598*	-0.573*	-0.587*	-0.593*
	(0.230)	(0.218)	(0.219)	(0.228)	(0.215)	(0.217)
July	-0.0400	-0.0243	-0.0207	-0.0386	-0.0243	-0.0205
	(0.141)	(0.155)	(0.155)	(0.143)	(0.157)	(0.157)
August	-0.221	-0.180	-0.179	-0.215	-0.176	-0.174
	(0.224)	(0.238)	(0.240)	(0.221)	(0.235)	(0.237)
September	-0.468^{+}	-0.429	-0.432	-0.456^{+}	-0.420	-0.423
	(0.241)	(0.260)	(0.262)	(0.237)	(0.256)	(0.257)
October	-0.584**	-0.530*	-0.533*	-0.585**	-0.531*	-0.534*
	(0.181)	(0.212)	(0.214)	(0.181)	(0.212)	(0.213)
November	-0.512**	-0.352*	-0.354*	-0.498**	-0.340*	-0.342*
	(0.113)	(0.140)	(0.141)	(0.114)	(0.140)	(0.141)
December	-0.433**	-0.377*	-0.376*	-0.434**	-0.379*	-0.378*
	(0.111)	(0.145)	(0.146)	(0.110)	(0.143)	(0.144)
N	112908	101893	100901	112908	101893	100901
FE	YES	YES	YES	YES	YES	YES
3-way Cluster	YES	YES	YES	YES	YES	YES

[1] Standard errors in parentheses
[2] $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 3.3: Seasonality and the Financial Crisis

The table reports regression results for the pre- and post-crisis subsamples and also for the sample combining these two periods. The financial crisis is identified by the dates between May 2007 to December 2008. The pre-crisis subsample covers the period prior to May 2007, and the post-crisis subsample is from 2009 to 2016, inclusive. Panel A tabulates estimated α_m in Model 1 for twelve regressions, one for each month, conducted on the three subsamples, respectively. The first column of results displays the estimated coefficient on the monthly indicator of January, which predicts whether January is different from all the other months in explaining corporate bond excess returns. Columns 2 to 12 correspond to estimates for February to December, respectively. Panel B displays, for the three subsamples, the estimated coefficients on the 11 monthly indicators of Model 2, with January as the base month. Columns 1, 3, and 5 report results for raw returns in the three subsamples, respectively. Columns 2, 4, and 6 show corresponding results for excess returns. All regressions control for year, industry, and bond fixed effects, as well as maturity risk and credit risk. Estimates for controlling variables are not tabulated. Standard errors are adjusted using three-way clustering by month, year, and firm.

Panel A: Individual Monthly Effect

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
					Part A: Subsample prior to the Financial Crisis [1987.08 - 2007.05)							
Credit Effect	0.0612**	0.0618**	0.0606**	0.0615**	0.0603**	0.0611**	0.0617**	0.0606**	0.0610**	0.0613*	0.0614**	0.0611**
	(0.0163)	(0.0163)	(0.0162)	(0.0157)	(0.0151)	(0.0181)	(0.0153)	(0.0148)	(0.0154)	(0.0245)	(0.0155)	(0.0151)
Monthly Effect	0.138	0.288^{+}	-0.559**	-0.263^{+}	0.169	0.0436	0.183^{+}	0.367**	-0.0407	-0.152	-0.153^{+}	0.00574
	(0.216)	(0.155)	(0.0874)	(0.121)	(0.113)	(0.0938)	(0.0884)	(0.0722)	(0.0928)	(0.122)	(0.0851)	(0.149)
N	43574	43574	43574	43574	43574	43574	43574	43574	43574	43574	43574	43574
					Part B: Subsample post the Financial Crisis [2009 - 2016]							
Credit Effect	0.0183	0.0168	0.0195	0.0197	0.0187	0.0198	0.0202^{+}	0.0190	0.0190	0.0187	0.0194	0.0191
	(0.0127)	(0.0125)	(0.0146)	(0.0148)	(0.0134)	(0.0154)	(0.00907)	(0.0153)	(0.0254)	(0.0175)	(0.0266)	(0.0187)
Monthly Effect	0.715^{+}	-0.347*	-0.247	-0.278	0.136	-0.435*	0.578**	0.0650	0.0183	-0.185	0.202	-0.0809
	(0.366)	(0.132)	(0.179)	(0.200)	(0.127)	(0.161)	(0.0531)	(0.178)	(0.0293)	(0.213)	(0.157)	(0.189)
N	52150	52150	52150	52150	52150	52150	52150	52150	52150	52150	52150	52150

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Part C: Subsample excluding the Financial Crisis [1987.08 - 2007.05) & [2009-2016]												
Credit Effect	0.0612**	0.0609**	0.0610**	0.0615**	0.0606**	0.0612**	0.0620**	0.0609**	0.0611**	0.0612**	0.0611**	0.0610**
	(0.00899)	(0.00810)	(0.00821)	(0.00868)	(0.00898)	(0.0153)	(0.00975)	(0.00990)	(0.0105)	(0.00921)	(0.00806)	(0.00802)
Monthly Effect	0.463$^+$	-0.0577	-0.388**	-0.276*	0.143	-0.238*	0.399**	0.208$^+$	-0.00736	-0.167	0.0385	-0.0401
	(0.211)	(0.150)	(0.101)	(0.123)	(0.0938)	(0.106)	(0.0611)	(0.0984)	(0.0349)	(0.128)	(0.115)	(0.126)
N	95741	95741	95741	95741	95741	95741	95741	95741	95741	95741	95741	95741
FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
3-way Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Relative Return Performance across Different Months

	[1987.08 - 2007.05)		[2009 - 2016]		excluding the Crisis	
	Raw Return	Excess Return	Raw Return	Excess Return	Raw Return	Excess Return
Credit	0.0605	0.0612	0.0190	0.0194	0.0614**	0.0619**
	(0.0391)	(0.0394)	(0.0348)	(0.0359)	(0.0191)	(0.0193)
February	0.133	0.153	-0.811*	-0.801*	-0.392*	-0.378*
	(0.159)	(0.160)	(0.252)	(0.254)	(0.158)	(0.159)
March	-0.535**	-0.503**	-0.790$^+$	-0.772$^+$	-0.685**	-0.664**
	(0.115)	(0.114)	(0.386)	(0.379)	(0.186)	(0.183)
April	-0.248	-0.239	-0.872	-0.843	-0.606$^+$	-0.590$^+$
	(0.194)	(0.185)	(0.563)	(0.554)	(0.295)	(0.288)
May	0.169	0.176	-0.524$^+$	-0.512$^+$	-0.234	-0.229
	(0.261)	(0.249)	(0.271)	(0.268)	(0.184)	(0.180)
June	0.0953	0.0940	-1.068*	-1.058*	-0.579*	-0.579*
	(0.187)	(0.180)	(0.337)	(0.335)	(0.232)	(0.230)
July	0.260$^+$	0.251	-0.167	-0.154	0.00393	-0.000546
	(0.137)	(0.141)	(0.357)	(0.365)	(0.165)	(0.167)

	[1987.08 - 2007.05)		[2009 - 2016]		excluding the Crisis	
	Raw Return	Excess Return	Raw Return	Excess Return	Raw Return	Excess Return
August	0.436**	0.442**	-0.670	-0.655	-0.188	-0.186
	(0.0905)	(0.0960)	(0.400)	(0.394)	(0.251)	(0.249)
September	0.0905	0.103	-0.749	-0.731	-0.394	-0.388
	(0.175)	(0.171)	(0.487)	(0.482)	(0.278)	(0.275)
October	0.0501	0.0400	-0.944*	-0.933*	-0.519*	-0.529*
	(0.129)	(0.132)	(0.383)	(0.380)	(0.220)	(0.219)
November	0.0552	0.0760	-0.675*	-0.656*	-0.377*	-0.369*
	(0.122)	(0.112)	(0.224)	(0.224)	(0.140)	(0.139)
December	0.224	0.227	-0.916**	-0.902**	-0.430*	-0.435**
	(0.148)	(0.137)	(0.160)	(0.161)	(0.140)	(0.137)
N	43574	43574	52150	52150	95741	95741
FE	YES	YES	YES	YES	YES	YES
3-way Cluster	YES	YES	YES	YES	YES	YES

[1] Standard errors in parentheses
[2] $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 3.4: Comparison between Trading Strategies

The table reports annual returns on two trading strategies and their transaction-cost adjusted return differences, in the post-crisis subsample. The seasonal trading strategy capitalizes on the January and July effects, in that an equally-weighted eleven-bond portfolio is held two months in January and July. When the portfolio is sold at the end of January or July, it is replaced by investing on Treasury Bills during the remaining months of the year. The buy-and-hold strategy, instead, buy and hold the same eleven-bond portfolio throughout the year. The eleven corporate bonds selected are the ones for which monthly returns can be calculated for each month of the period from 2009 to 2016.

	Annual Returns (%)						
	Y2010	Y2011	Y2012	Y2013	Y2014	Y2015	Y2016
Buy-and-Hold	10.515	11.207	7.149	-0.035	8.069	2.107	3.441
Seasonal Trading	13.844	8.759	9.383	-0.052	9.9	11.5	2.602
	Transaction-cost Adjusted Differences in Annual Returns (%)						
Difference	2.479	-3.298	1.384	-0.867	0.981	8.543	-1.689

Table 3.5: The Reversal Effect

The table displays averaged responses of returns in January, March, and July, respectively, on their lagged returns. The reported values are the mean and t-statistics (in parentheses) of the estimated gammas from Model 3, for lags ranging from 1 (column $t-1$) to 12 (column $t-12$). For returns in January, $t-1$ corresponds to last December, while $t-12$ means previous January. For returns in March (July), $t-1$ is the month of last February (June), and $t-12$ refers to last March (July). The standard errors are adjusted for heterogeneity. The sample period is from August 1987 to December 2016.

	t-1	t-2	t-3	t-4	t-5	t-6	t-7	t-8	t-9	t-10	t-11	t-12
January	-0.006	0.085	0.283**	-0.001	0.1	0.184$^+$	0.162	0.134	0.165$^+$	0.097	0.24**	-0.083
	(-0.055)	(0.971)	(3.080)	(-0.006)	(0.885)	(1.783)	(1.371)	(1.236)	(1.738)	(0.932)	(2.960)	(-0.709)
March	-0.14$^+$	0.183*	0.05	0.038	0.075	0.074	-0.087	-0.036	0.103	-0.017	0.18$^+$	0.183*
	(-1.738)	(2.292)	(0.842)	(0.451)	(1.203)	(0.989)	(-1.285)	(-0.384)	(1.215)	(-0.251)	(1.780)	(2.320)
July	0.148	0.248*	0.047	-0.105	0.234*	-0.019	0.093	0.181*	0.125	0.107	0.146$^+$	0.276$^+$
	(1.202)	(2.185)	(0.495)	(-0.914)	(2.277)	(-0.177)	(1.221)	(2.102)	(1.351)	(0.911)	(1.669)	(1.803)

[1] Standard errors in parentheses

[2] $^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 3.6: The Effect of Coupon Payments on the Seasonality

The table displays regression results of Model 1-1 for four regressions. The Column January (July) reports results for regressing excess returns on the monthly indicator for January (July), the dummy variable indicating whether the previous month is December (June) and had a coupon payment. The coupon dummy variable is also interacted with a post-crisis dummy variable to distinguish high versus low interest rate environments. The Column December (June) tabulates results for regressing excess returns on the monthly indicator for December (June), the dummy variable indicating whether the current month is December (June) and had a coupon payment, as well as the interaction term with the post-crisis dummy variable. All four regressions control for year, industry and bond fixed effects as well as maturity and credit risks. Results for controlling variables are not tabulated. Standard errors are adjusted using three-way clustering by month, year and firm. The time period covered is from August 1987 to December 2016.

	January	July	December	June
Credit	0.0600**	0.0612**	0.0585**	0.0585*
Effect	(0.00724)	(0.0108)	(0.00617)	(0.0215)
Monthly	0.494*	0.357**	0.0144	-0.254*
Effect	(0.201)	(0.0599)	(0.126)	(0.1000)
L.coupon	-0.445*	-0.114^{+}		
	(0.162)	(0.0571)		
L.coupon×post	0.779*	0.297*		
	(0.283)	(0.123)		
coupon			0.265**	0.256*
			(0.0851)	(0.100)
coupon×post			-0.533**	-0.434*
			(0.145)	(0.167)
N	96687	96687	101893	101893
FE	YES	YES	YES	YES
3-way Cluster	YES	YES	YES	YES

[1] Standard errors in parentheses

[2] $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 3.7: The Effect of Coupon Payments and Expected Interest Rates

The table displays regression results of modified Model 1-1 for four regressions. The Column January (July) reports results for regressing excess returns on the monthly indicator for January (July), the interaction between a dummy variable indicating whether the previous month is December (June) and had a coupon payment, and the first difference of price on the ten-year Government of Canada bond futures. The Column December (June) tabulates results for regressing excess returns on the monthly indicator for December (June), the interaction between a dummy variable indicating whether the current month is December (June) and had a coupon payment, and the first difference of the futures price. All four regressions control for year, industry and bond fixed effects as well as maturity and credit risks. Results for controlling variables are not tabulated. Standard errors are adjusted using three-way clustering by month, year and firm. The time period covered is from September 1989 to December 2016.

	January	July	December	June
Credit	0.0557**	0.0562**	0.0554**	0.0552**
Effect	(0.00878)	(0.00900)	(0.0108)	(0.0145)
Monthly	0.105	0.137*	0.324**	-0.504**
Effect	(0.123)	(0.0606)	(0.0935)	(0.106)
W/O Coupon (A)	0.257**	0.262**	0.266**	0.270**
	(0.0709)	(0.0725)	(0.0735)	(0.0709)
With Coupon (B)	0.444**	0.388**	0.322**	0.268**
	(0.0177)	(0.0221)	(0.0286)	(0.0462)
F-test (A=B)	12.22**	3.63^{+}	0.77	0.01
Reject H0	YES	YES	NO	NO
N	96269	96269	101443	101443
FE	YES	YES	YES	YES
3-way Cluster	YES	YES	YES	YES

[1] Standard errors in parentheses

[2] $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 3.8: Coupon Payment Frequency in Periods of Lower Expected Interest Rates

The table displays, for each month t, the average total number of bonds with coupon payments in the month $t-1$ (columns 1 and 2) and month$t$ (columns 3 and 4), respectively. In column 1 (3), the monthly total number of bonds paying coupons in month $t-1$ (t) is averaged across years, before the financial crisis, in which the expected long-term interest rate drops in month t. In column 2 (4), the monthly total number of bonds paying coupons in month $t-1$ (t) is averaged across post-crisis years in which the expected long-term interest rate drops in month t. The time period covered is from September 1989 to December 2016.

	Previous Month Coupon		Current Month Coupon	
	Pre-crisis	Post-crisis	Pre-crisis	Post-crisis
January	56	152	33	94
February	36	86	37	84
March	12	35	19	43
April	41	87	38	86
May	33	106	36	151
June	31	142	43	143
July	44	152	31	92
August	41	87	39	89
September	29	48	38	62
October	28	121	27	122
November	41	86	37	126
December	27	142	53	145

[1] Standard errors in parentheses

[2] $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 3.9: Descriptive Statistics and Correlations for the Seven Factors

The table presents summary statistics for the seven explanatory factors employed in Model 4. The time span for the Amihud illiquidity measure variable is from May 1993 to October 2015. The time series of the remaining six variables start from January 1988 to December 2016. Panel A reports, for each time series, the average, standard deviation, median, minimum and maximum values, and skewness. Panel B lists the correlation matrix for the seven factors, and the significance is at the 5 percent level.

Panel A: Descriptive Statistics [1]

	Mean	St. Dev.	Median	Max	Min	Skewness
Amihud Illiquidity Measure	0.354	0.632	0.083	5.670	0.011	3.937
3-M d.T-bill Yield (Var2)	-0.015	0.186	0.000	0.460	-0.860	-1.113
10-Y d.T-bond Yield (Var3)	-0.019	0.225	-0.033	0.641	-1.110	-0.137
S&P Excess Return (Var4)	-2.219	4.703	-1.933	10.881	-19.212	-0.281
TSX Excess Return (Var5)	-3.370	5.279	-2.632	11.290	-24.115	-0.720
d.BCPI (Var6)	0.421	22.031	1.045	57.620	-141.180	-1.457
Exchange Rate Shock (Var7)	0.000	0.020	-0.000	0.126	-0.074	0.388

Panel B: Correlations [2]

	Var1	Var2	Var3	Var4	Var5	Var6
Var2	0.094					
Var3	0.002	0.380*				
Var4	-0.159*	0.010	0.017			
Var5	-0.176*	0.093	0.023	0.773*		
Var6	0.021	0.103	0.219*	0.091	0.184*	
Var7	0.061	-0.063	-0.021	-0.217*	-0.246*	-0.467*

[1] Footnote 1: No. of observations for all variables are 348 except for the illiquidity measure, which is 270.

[2] Footnote 2: The variables in the correlation matrix follow the ordering of Panel A.

[3] * 0.05 significance level

Table 3.10: The Role of the Seven Factors

The table tabulates estimated coefficients on the seven factors, for five variations of Model 4. Mdl1 reports results for Model 4 including all the seven factors and two crisis dummies. The sample period covered is from 1993 to 2015 (270 observations). Mdl2 repeats the regression of Mdl1 but excludes the Amihud Illiquid measure, and the sample is extended and covers the period from 1988 to 2016 (348 observations). Mdl3 further excludes the excess return on the S&P index from Mdl2. Mdl 4 and Mdl5 correspond to regression specifications of Mdl1 and Mdl3, except that the factor variables are replaced by their interactions with three dummies variables indicating the pre-crisis months, the months of the crisis, and the post-crisis months. All regressions control for year and month fixed effects. Results for controlling variables are not tabulated.

	Mdl1	Mdl2	Mdl3	Mdl4			Mdl5		
				prior	crisis	post	prior	crisis	post
Amihud Illiquidity Measure	0.00206			-0.00967	0.0274	9.147			
	(0.124)			(0.171)	(0.106)	(9.214)			
3-M d.T-bill Yield	0.186	-0.132	-0.144	0.350	-0.190	-2.029	0.0534	-0.400	-1.087
	(0.310)	(0.396)	(0.394)	(0.496)	(0.286)	(3.520)	(0.571)	(0.271)	(2.777)
10-Y d.T-bond Yield	-1.592**	-2.102**	-2.097**	-1.593**	-1.269**	-1.555*	-2.326**	-1.288**	-1.624**
	(0.248)	(0.269)	(0.266)	(0.306)	(0.383)	-0.0188	(0.340)	(0.390)	(0.623)
S&P Excess Return	-0.0220	0.00623		-0.00766	-0.0227	(0.0424)			
	(0.0186)	(0.0220)		(0.0231)	(0.0376)	(0.0459)			
TSX Excess Return	0.0588**	0.0529*	0.0576**	0.0591**	0.0858+	0.00989	0.0704**	0.0708**	-0.00486
	(0.0199)	(0.0217)	(0.0149)	(0.0224)	(0.0458)	(0.0590)	(0.0178)	(0.0241)	(0.0372)
d.Total Commodity Price Index	-0.000685	0.000478	0.000373	-0.00208	0.00258	0.000833	-0.00231	0.00309	0.00203
	(0.00196)	(0.00214)	(0.00205)	(0.00357)	(0.00316)	(0.00423)	(0.00354)	(0.00324)	(0.00415)
d.CDN/US Exchange Rate	-1.947	-2.162	-2.217	-5.558+	6.999	0.489	-5.359	7.365	0.347
	(2.730)	(3.154)	(3.140)	(2.996)	(5.712)	(7.490)	(4.015)	(5.661)	(5.928)
crisis07-09	-0.125	-0.393	-0.395	-0.0307			-0.240		
	(0.349)	(0.384)	(0.382)	(0.342)			(0.392)		
postcrisis	-0.562	-0.277	-0.287	-1.085			-0.263		
	(0.581)	(0.409)	(0.419)	(0.749)			(0.438)		
Constant	1.103+	0.524	0.529	1.167+			0.569		
	(0.570)	(0.468)	(0.475)	(0.670)			(0.482)		
Observations	270	348	348	270			348		
R-squared	0.323	0.335	0.335	0.354			0.357		
Adjusted R-squared	0.202	0.233	0.236	0.187			0.235		
Year FE	YES	YES	YES	YES			YES		
Month FE	YES	YES	YES	YES			YES		

[1] Standard errors in parentheses
[2] $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 3.11: The Seasonal Variations of the Two Significant Factors

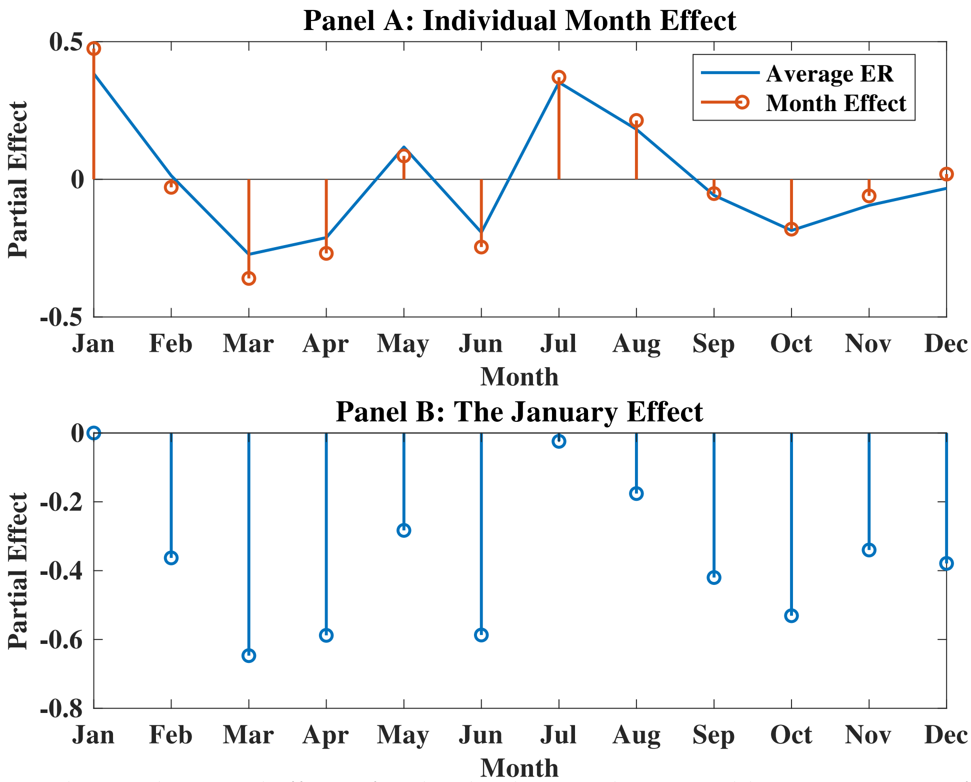
The table provides return changes attributed to the months of January, March, and July for the two significant factors employed in Model 4, i.e., "dUSYL" (the first difference of the US 10Y T-bond Yield) and "TSX" (the excess return on the TSX index), respectively. For the regressions testing the January effect (Columns 1 and 4), monthly returns on the two factors are separately regressed on three financial-crisis-related dichotomous variables and their interaction terms with the January dummy variable, also controlling for the year fixed effect. The three dichotomous variables indicating the pre-crisis, during-crisis, and post-crisis periods, where the financial crisis is identified as between May 2007 to December 2008. Regressions for tests of the March effect (Columns 2 and 5) and the July effect (Columns 3 and 6) are conducted in the same fashion. Results for the controlled year fixed effect are not tabulated.

	dUSYL			TSX		
	Jan	Mar	Jul	Jan	Mar	Jul
The crisis dummy	-0.101	-0.0774	-0.109	-0.733	-0.939	-0.647
	(0.107)	(0.124)	(0.113)	(1.339)	(1.324)	(1.397)
		Monthly Effect				
Before the crisis	0.0233	0.118*	-0.0175	0.625	-0.198	0.0376
	(0.0475)	(0.0553)	(0.0550)	(0.917)	(0.889)	(0.821)
During the crisis	-0.256*	-0.213^{+}	0.0311	-4.277^{+}	2.214	-1.975
	(0.123)	(0.128)	(0.0960)	(2.354)	(2.360)	(1.692)
Post the crisis	-0.0235	-0.0922	-0.0379	-1.474	1.177	1.036
	(0.0809)	(0.0734)	(0.0781)	(1.596)	(1.308)	(0.992)
N	348	348	348	348	348	348
R-sq	0.128	0.140	0.127	0.472	0.471	0.471
adj. R-sq	0.040	0.053	0.038	0.418	0.417	0.417
YEAR FE	YES	YES	YES	YES	YES	YES

[1] Standard errors in parentheses

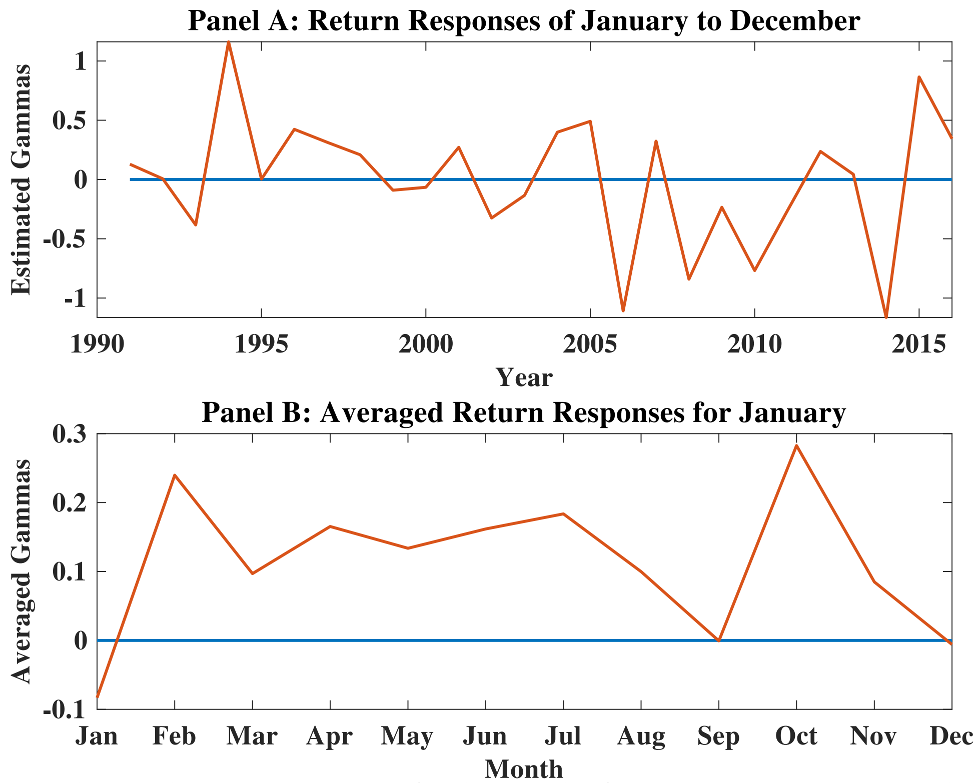
[2] $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Figure 3.1: Time-series Seasonality in the Canadian Corporate Bond Market



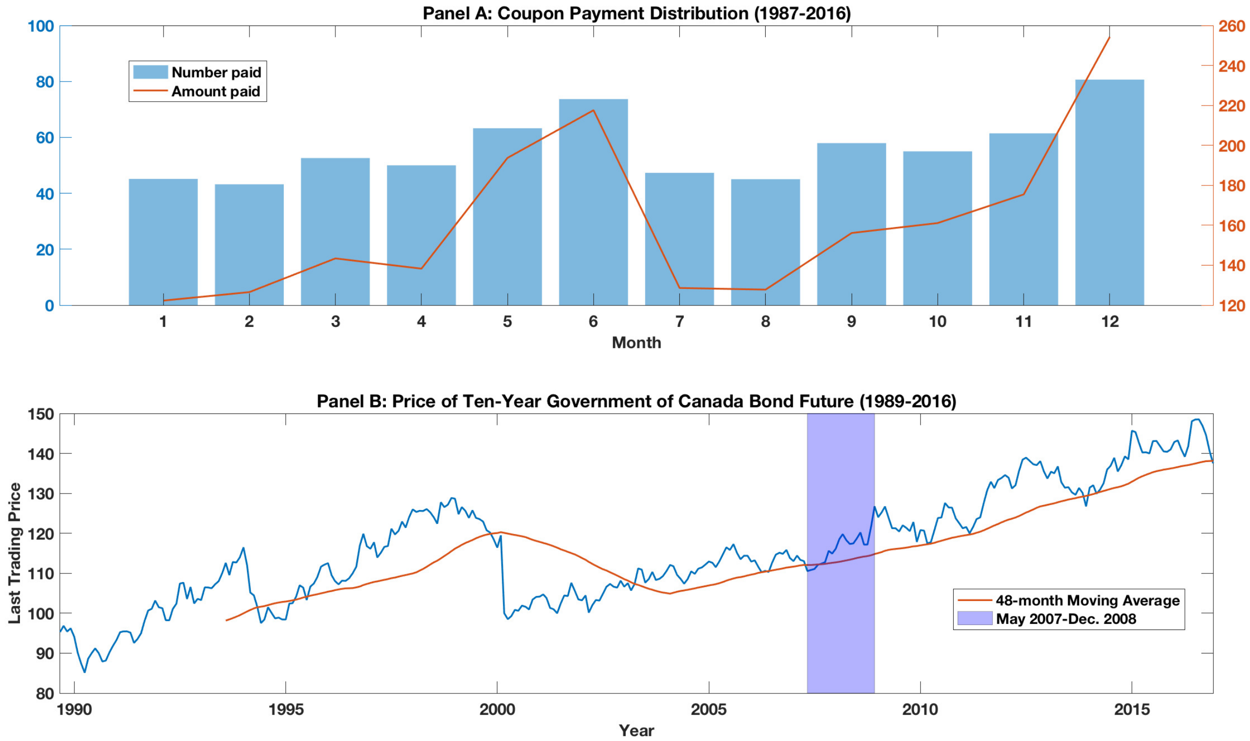
The figure depicts the partial effects of each calendar month on monthly excess returns of Canadian corporate bond, by controlling for maturity risk premium, credit risk premium, and common factors in the year, industry and bond dimensions. Panel A shows the partial effect of each month accompanied by the difference between average excess returns by month and the sample mean excess return. Panel B plots the relative impact of months from February through December compared to the month January. The time-period covered spans from August 1987 to December 2016.

Figure 3.2: Responses of January Returns on Returns of the Past Year



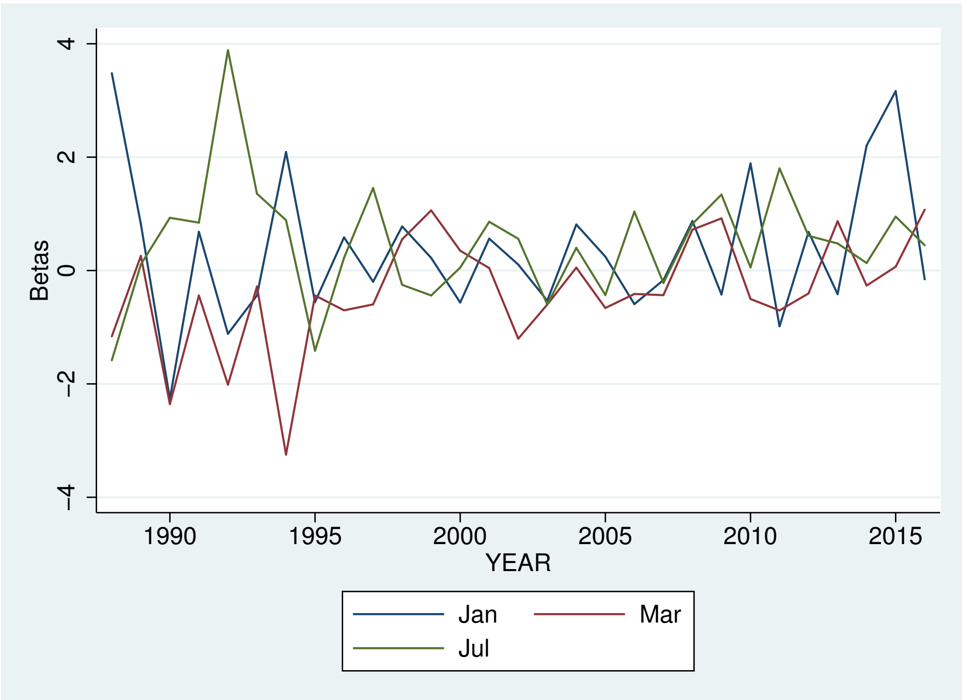
The figure depicts the return responses for the month of January on returns in months of the previous year. Panel A plots the responses of January returns in each year, from 1991 to 2016, on their one-period lagged December returns. Panel B shows the responses of January returns to returns in months from January to December in the previous year. The responses in Panel B are averaged over the years from 1991 to 2016.

Figure 3.3: Coupon Payment Distribution in the Sample and the Interest Rate



Panel A of the figure plots the annual coupon payment distribution for all bonds in the sample, in terms of frequency (i.e., the average total number of bonds paying coupons in each month) and volume (i.e., the average total dollar amount per $100 face value paid in each month). Panel B depicts the price variation of the Ten-Year Government of Canada Bond Futures over the time-period from September 1989 to December 2016, along with its 48-month moving average. The shaded area marks the period of the 2007-09 financial crisis.

Figure 3.4: The Monthly Effect Over Time



The figure plots the variations of the estimated γ_m^y in Model 2-1 over the year, for the months of January, March, and July, respectively.

Concluding Remarks

Studies exploring various types of market inefficiency, i.e., anomalies, are mostly conducted in the equity market. Less is know about the existence and time variations of these anomalies in the corporate bond market, which has grown to be increasingly important for both lenders and borrowers. The three chapters of my thesis evaluate the performance of two well-studied types of anomalies, namely the momentum effect and the calendar effect, in the corporate bond market.

The first two chapters study the conditional performance of the momentum effect in the US and Canadian corporate bond markets. We find that, in both markets, the momentum effect (i.e., abnormal gains from buying past winners and selling past losers) is significantly positive (negative) following above (below) average bond market returns. That momentum returns are state dependent is consistent with an expanded version of the behavioral theory by Daniel et al. (1998) in that aggregate market gains exacerbate investors overconfidence, which renders return continuation. A market-state effect on momentum is also consistent with the bounded rationality theory by Hong and Stein (1999), if linked to wealth fluctuations in the habit formation framework by Campbell and Cochrane (1999). Specifically, buoyant markets foster low levels of risk aversion among momentum traders. Therefore, strong momentum gains are obtained when momentum traders overreact aggressively to the price trend caused by gradual information diffusion.

For the US market, empirical results are consistent with investors' sentiment being associated with overpricing in both the stock and bond markets. Further, we show that investors' sentiment interacts with the market state to exacerbate the dichotomous trends of the momentum effect in the corporate bond market, and the exacerbation occurs only in low sentiment periods. Notably, the conditional momentum gains and losses are driven by winners being significantly more underpriced than losers, which is in contrary to what is documented for the equity market, where anomalies are originated from short legs (or losers) being significantly more overpriced than long legs (or winners) (e.g., Stambaugh et al., 2012). Further, we show that significant momentum gains and losses in different market and sentiment states are also detectable for the US investment-grade bonds, for which previous studies have documented insignificant momentum profits employing the standard strategy (e.g., Gebhardt et al., 2005; Jostova et al., 2013).

For the Canadian market, we document a stronger market state effect on momentum returns for investment-grade bonds in the post-1994 subsample, compared to that obtained for the pre-1994 subsample. The stronger market state effect is linked to a deterioration of issuer credit qualities following structural reforms to the Canadian bond market around 1993 (Landon, 2009).

Using quote-based price data sourced from Bloomberg, Chapter 3 documents a negative March seasonal effect and positive January and July effects in Canadian corporate bond returns, during a period spanning from 1987 to 2016. Importantly, the 2007-09 financial crisis played a crucial role in switching the documented seasonal patterns, with the March effect being present only before the crisis, while the January and July effects become significant in the post-crisis subsample.

I show that, in a declining interest rate environment, the coupon-based payment flow theory (DeRosa-Farag, 1996) is suitable for explaining the January and July gains. This finding suggests a re-examination of the limited role of the coupon-based payment flow theory documented in the literature, as previous studies fail to recognize the role of expected long-term interest rate changes in shaping the coupon reinvestment behavior of investors. Further, I show that, in the pre-crisis period, the 10-year US Treasury yield changes increased significantly in March, which, through the negative link between the US long-term borrowing cost and the monthly return variations in Canadian corporate bonds, explains the pre-crisis March effect documented for Canadian corporate bonds in this chapter.

To summarize, the key findings of this thesis are that the profitability of strategies separately exploiting the momentum and seasonality effects is highly state-dependent, and the underlying mechanisms originating the two anomalies in the corporate bond markets are fundamentally different from those in the equity markets.

Bibliography

Agnani, B. and H. Aray (2011). The january effect across volatility regimes. *Quantitative Finance 11*(6), 947–953.

Ahmadi, H., J. Khoroujik, and R. B. Rafiq (2007). Do under-managed portfolios outperform over-managed portfolios? *Journal of Business & Economics Research 5*(4).

Al-Khazali, O. M. (2001). Does the january effect exist in high-yield bond market? *Review of Financial Economics 10*(1), 71–80.

Amihud, Y. (2002). Illiquidity and Stock Returns: Cross-section and Time-series Effects. *Journal of Financial Markets 5*(1), 31–56.

Anderson, S., R. Parker, and A. Spence (2003). Development of the canadian corporate debt market: Some stylized facts and issues. *Bank of Canada Financial System Review*, 35–41.

Ariel, R. A. (1990). High stock returns before holidays: Existence and evidence on possible causes. *The Journal of Finance 45*(5), 1611–1626.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen (2013). Value and Momentum Everywhere. *The Journal of Finance 68*(3), 929–985.

Athanassakos, G. (2008). Seasonal patterns in canadian financial markets and the impact of professional portfolio rebalancing: Evidence of profitable opportunities. *Journal of Financial and Economic Practice 9*(1), 73–96.

Avramov, D., T. Chordia, G. Jostova, and A. Philipov (2017). Bonds, stocks, and sources of mispricing.

Baele, L., G. Bekaert, K. Inghelbrecht, and M. Wei (2014). Flights to Safety. *Finance and Economics Discussion Series of Federal Reserve Board* (2014-46).

Baker, M. and J. Wurgler (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance 61*(4), 1645–1680.

Bansal, R. and A. Yaron (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *The Journal of Finance 59*(4), 1481–1509.

Bao, J., J. Pan, and J. Wang (2011). The illiquidity of corporate bonds. *The Journal of Finance 66*(3), 911–946.

Barnhill, T., F. Joutz, and W. Maxwell (1997). Factors affecting the yield of noninvestment grade bond indices. Technical report, George Washington University Working Paper 97-46 (August).

Barroso, P. and P. Santa-Clara (2015). Momentum has its moments. *Journal of Financial Economics 116*(1), 111–120.

Bekaert, G. and M. Hoerova (2014). The vix, the variance premium and stock market volatility. *Journal of Econometrics 183*(2), 181–192.

Bekaert, G. and M. Hoerova (2016). What do asset prices have to say about risk appetite and uncertainty? *Journal of Banking & Finance 67*, 103–118.

Bekaert, G., M. Hoerova, and M. L. Duca (2013). Risk, Uncertainty and Monetary Policy. *Journal of Monetary Economics 60*(7), 771–788.

Berges, A., J. McConnell, and G. G. Schlarbaum (1984). The turn-of-the-year in canada. *The Journal of Finance 39*(1), 185–192.

Bollerslev, T., G. Tauchen, and H. Zhou (2009). Expected stock returns and variance risk premia. *The Review of Financial Studies 22*(11), 4463–4492.

Bondt, W. F. and R. Thaler (1985). Does the stock market overreact? *The Journal of finance 40*(3), 793–805.

Bouman, S. and B. Jacobsen (2002). The halloween indicator," sell in may and go away": Another puzzle. *The American Economic Review 92*(5), 1618–1635.

Brugler, J. A., C. Comerton-Forde, and J. S. Martin (2016). Do you see what i see? transparency and bond issuing costs. *Working Paper (November 24, 2016). Available at SSRN: https://ssrn.com/abstract=2875165*.

Butler, A. W. (2008). Distance still matters: Evidence from municipal bond underwriting. *Review of Financial Studies 21*(2), 763–784.

Cai, N., J. Helwege, and A. Warga (2007). Underpricing in the corporate bond market. *The Review of Financial Studies 20*(6), 2021–2046.

Campbell, J. Y. and J. H. Cochrane (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of political Economy 107*(2), 205–251.

Cao, N., V. Galvani, and S. Gubellini (2017). Firm-specific stock and bond predictability: New evidence from canada. *International Review of Economics & Finance*.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance 52*(1), 57–82.

Champagne, C., F. Coggins, and A. Sodjahin (2017). Corporate bond market interdependence: credit spread correlation between and within us and canadian corporate bond markets. *The North American Journal of Economics and Finance 41*, 1–17.

Chan, L. K., N. Jegadeesh, and J. Lakonishok (1996). Momentum strategies. *The Journal of Finance 51*(5), 1681–1713.

Chang, E. C. and R. D. Huang (1990). Time-varying return and risk in the corporate bond market. *Journal of Financial and Quantitative analysis 25*(03), 323–340.

Chang, E. C. and J. M. Pinegar (1986). Return seasonality and tax-loss selling in the market for long-term government and corporate bonds. *Journal of Financial Economics 17*(2), 391–415.

Chordia, T., A. Goyal, Y. Nozawa, A. Subrahmanyam, and Q. Tong (2017). Are capital market anomalies common to equity and corporate bond markets? an empirical investigation. *Journal of Financial and Quantitative Analysis 52*(4), 1301–1342.

Chordia, T., A. Subrahmanyam, and Q. Tong (2014). Have capital market anomalies attenuated in the recent era of high liquidity and trading activity? *Journal of Accounting and Economics 58*(1), 41–58.

Chung, K. H., J. Wang, and C. Wu (2018). Volatility and the cross-section of corporate bond returns.

Cleary, S. and M. Inglis (1998). Momentum in canadian stock returns. *Canadian Journal of Administrative Sciences/Revue Canadienne des Sciences de l'Administration 15*(3), 279–291.

Conrad, J. and M. D. Yavuz (2017). Momentum and reversal: Does what goes up always come down?*. *Review of Finance 21*(2), 555–581.

Cooper, M. J., R. C. Gutierrez, and A. Hameed (2004). Market states and momentum. *The Journal of Finance 59*(3), 1345–1365.

Cooper, M. J., J. J. McConnell, and A. V. Ovtchinnikov (2006). The other january effect. *Journal of Financial Economics 82*(2), 315–341.

Cooper, R. A. and J. M. Shulman (1994). The year-end effect in junk bond prices. *Financial Analysts Journal 50*(5), 61–65.

Correia, S. (2016). Linear models with high-dimensional fixed effects: An efficient and feasible estimator. Technical report. Working Paper.

Cuthbertson, K., S. Hayley, N. Motson, and D. Nitzsche (2016). What does rebalancing really achieve? *International Journal of Finance & Economics 21*(3), 224–240.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam (1998). Investor psychology and security market under-and overreactions. *The Journal of Finance 53*(6), 1839–1885.

Daniel, K. and T. J. Moskowitz (2016). Momentum crashes. *Journal of Financial Economics 122*(2), 221–247.

Dbouk, W., I. Jamali, and L. Kryzanowski (2013). The january effect for individual corporate bonds. *International Review of Financial Analysis 30*, 69–77.

De Bondt, W. F. and R. H. Thaler (1987). Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance*, 557–581.

DeRosa-Farag, S. (1996). 1995 high yield market review. *New York Chase Securities, New York*.

Devani, B. and Y. Zhang (2017, August). Corporate Bond Markets: Liquidity Determination and Overview. *Investment Industry Regulatory Organization of Canada (IIROC)*.

Dichev, I. D. and T. D. Janes (2003). Lunar cycle effects in stock returns. *The Journal of Private Equity 6*(4), 8–29.

Dick-Nielsen, J. (2014). How to clean enhanced trace data. *Available at SSRN: https://ssrn.com/abstract=2337908 or http://dx.doi.org/10.2139/ssrn.2337908*.

Dick-Nielsen, J., P. Feldhütter, and D. Lando (2012). Corporate bond liquidity before and after the onset of the subprime crisis. *Journal of Financial Economics 103*(3), 471–492.

Edwards, A. K., L. E. Harris, and M. S. Piwowar (2007). Corporate bond market transaction costs and transparency. *The Journal of Finance 62*(3), 1421–1451.

Fama, E. F. (1991). Efficient capital markets: Ii. *The journal of finance 46*(5), 1575–1617.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics 33*(1), 3–56.

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *The journal of political economy*, 607–636.

Feldhütter, P. (2011). The same bond at different prices: identifying search frictions and selling pressures. *The Review of Financial Studies 25*(4), 1155–1206.

Flannery, M. J. and A. A. Protopapadakis (1988). From t-bills to common stocks: Investigating the generality of intra-week return seasonality. *The journal of finance 43*(2), 431–450.

Fontaine, J.-S. and R. Garcia (2011). Bond liquidity premia. *The Review of Financial Studies 25*(4), 1207–1254.

Fridson, M. and C. Garman (1995a). January effect: Probably not a function of coupon flows. *This Week in High Yield 47*, 1–3.

Fridson, M. and C. Garman (1995b). January effect: The longer-term evidence. *This Week in High Yield (December)*, 4–6.

Frieder, L. and A. Subrahmanyam (2004). Nonsecular regularities in returns and volume. *Financial Analysts Journal 60*(4), 29–34.

Gallant, A. R. (1987). *Nonlinear Statistical Models*. New York: Wiley.

Garlappi, L., T. Shu, and H. Yan (2008). Default risk, shareholder advantage, and stock returns. *The Review of Financial Studies 21*(6), 2743–2778.

Garlappi, L. and H. Yan (2011). Financial distress and the cross-section of equity returns. *The Journal of Finance 66*(3), 789–822.

Gebhardt, W. R., S. Hvidkjaer, and B. Swaminathan (2005). Stock and bond market interaction: Does momentum spill over? *Journal of Financial Economics 75*(3), 651–690.

Gervais, S. and T. Odean (2001). Learning to be overconfident. *The Review of Financial Studies 14*(1), 1–27.

Gibbons, M. R. and P. Hess (1981). Day of the week effects and asset returns. *Journal of business*, 579–596.

Griffin, J. M., X. Ji, and J. S. Martin (2003). Momentum investing and business cycle risk: Evidence from pole to pole. *The Journal of Finance 58*(6), 2515–2547.

Grinblatt, M., S. Titman, and R. Wermers (1995). Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *The American economic review*, 1088–1105.

Güntay, L. and D. Hackbarth (2010). Corporate bond credit spreads and forecast dispersion. *Journal of Banking & Finance 34*(10), 2328–2345.

Heston, S. L. and R. Sadka (2008). Seasonality in the cross-section of stock returns. *Journal of Financial Economics 87*(2), 418–445.

Hong, H. and J. C. Stein (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance 54*(6), 2143–2184.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance 48*(1), 65–91.

Jones, C. S. and L. Pomorski (2017). Investing in disappearing anomalies. *Review of Finance 21*(1), 237–267.

Jordan, S. D. and B. D. Jordan (1991). Seasonality in daily bond returns. *Journal of Financial and Quantitative Analysis 26*(02), 269–285.

Jostova, G., S. Nikolova, A. Philipov, and C. W. Stahel (2013). Momentum in corporate bond returns. *Review of Financial Studies 26*(7), 1649–1693.

Jurado, K., S. C. Ludvigson, and S. Ng (2015). Measuring uncertainty. *The American Economic Review 105*(3), 1177–1216.

Keim, D. B. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of financial economics 12*(1), 13–32.

Lakonishok, J., A. Shleifer, R. Thaler, and R. Vishny (1991). Window dressing by pension fund managers. Technical report, National Bureau of Economic Research.

Lakonishok, J. and S. Smidt (1984). Volume and turn-of-the-year behavior. *Journal of Financial Economics 13*(3), 435–455.

Landon, S. (2009). The capitalization of taxes in bond prices: Evidence from the market for government of canada bonds. *Journal of Banking & Finance 33*(12), 2175–2184.

Landon, S. and C. Smith (2006). Seasonality in canadian bond returns: The role of international factors. *Canadian Journal of Administrative Sciences/Revue Canadienne des Sciences de l'Administration 23*(4), 352–366.

Lee, C. and B. Swaminathan (2000). Price momentum and trading volume. *The Journal of finance 55*(5), 2017–2069.

Lemmon, M. and E. Portniaguina (2006). Consumer confidence and asset prices: Some empirical evidence. *The Review of Financial Studies 19*(4), 1499–1529.

L'Her, J.-F., T. Masmoudi, and J.-M. Suret (2004). Evidence to support the four-factor pricing model from the canadian stock market. *Journal of International Financial Markets, Institutions and Money 14*(4), 313–328.

Li, L. and V. Galvani (2018). Market states, sentiment, and momentum in the corporate bond market. *Journal of Banking & Finance 89*, 249–265.

Lin, H., J. Wang, and C. Wu (2011). Liquidity risk and expected corporate bond returns. *Journal of Financial Economics 99*(3), 628–650.

Lin, H., C. Wu, and G. Zhou (2017). Does momentum exist in bonds of different ratings? *Available at SSRN: https://ssrn.com/abstract=2872382 or http://dx.doi.org/10.2139/ssrn.2872382*.

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *Journal of Portfolio Management 30*, 15–29.

Maxwell, W. F. (1998). The january effect in the corporate bond market: A systematic examination. *Financial Management*, 18–30.

McLean, R. D. and J. Pontiff (2016). Does academic research destroy stock return predictability? *The Journal of Finance 71*(1), 5–32.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *The Journal of Finance 32*(4), 1151–1168.

Mittoo, U. R. (2003). Globalization and the value of us listing: Revisiting canadian evidence. *Journal of Banking & Finance 27*(9), 1629–1661.

Mittoo, U. R. and Z. Zhang (2010). Bond market access, credit quality, and capital structure: Canadian evidence. *Financial Review 45*(3), 579–602.

Mueller, P., A. Vedolin, Y.-m. Yen, et al. (2012). *Bond variance risk premia*. Financial Markets Group, London School of Economics and Political Science.

Ogden, J. P. (1990). Turn-of-month evaluations of liquid profits and stock returns: A common explanation for the monthly and january effects. *The Journal of Finance 45*(4), 1259–1272.

Patel, T. and K. Yang (2015). The canadian fixed income market report 2014. *the Ontario Securities Commission (OSC)*.

Roll, R. (1983). {Vas ist das? The turn-of-the-year effect and the return premia of small firms}. *J. Portfolio Management 9*(2), 18–28.

Ronen, T. and X. Zhou (2013). Trade and information in the corporate bond market. *Journal of Financial Markets 16*(1), 61–103.

Rotton, J. and M. Rosenberg (1984). Lunar cycles and the stock market: Time-series analysis for environmental psychologists. *Unpublished Manuscript, Florida International University*.

Rozeff, M. S. and W. R. Kinney (1976). Capital market seasonality: The case of stock returns. *Journal of financial economics 3*(4), 379–402.

Schmidt, P. S., A. Schrimpf, U. von Arx, A. Wagner, and A. Ziegler (2015). Size and momentum profitability in international stock markets. Technical report, CEPR Discussion Papers.

Sias, R. W. (2004). Institutional herding. *The Review of Financial Studies 17*(1), 165–206.

Smirlock, M. (1985). Seasonality and bond market returns*. *The Journal of Portfolio Management 11*(3), 42–44.

Stambaugh, R. F., J. Yu, and Y. Yuan (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics 104*(2), 288–302.

Tinic, S., G. Barone-Adesi, and R. West (1987). Seasonality in canadian stock prices: A test of the "tax-loss-selling" hypothesis. *Journal of Financial and Quantitative Analysis 22*(01), 51–63.

Tinic, S. M. and R. R. West (1984). Risk and return: Janaury vs. the rest of the year. *Journal of Financial Economics 13*(4), 561–574.

Tsai, H.-J. (2014). The informational efficiency of bonds and stocks: The role of institutional sized bond trades. *International Review of Economics & Finance 31*, 34–45.

Urquhart, A. and F. McGroarty (2014). Calendar effects, market conditions and the adaptive market hypothesis: Evidence from long-run us data. *International Review of Financial Analysis 35*, 154–166.

Wachtel, S. B. (1942). Certain observations on seasonal movements in stock prices. *The journal of business of the University of Chicago 15*(2), 184–193.

Wang, K., Y. Li, and J. Erickson (1997). A new look at the monday effect. *The Journal of Finance 52*(5), 2171–2186.

West, K. D. and W. K. Newey (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–708.

Whaley, R. (2000). The investor fear gauge. *The Journal of Portfolio Management 26*(3), 12–17.

Yuan, K., L. Zheng, and Q. Zhu (2006). Are investors moonstruck? lunar phases and stock returns. *Journal of Empirical Finance 13*(1), 1–23.

Appendices

Appendix A: Robustness Check

Appendix A.1: Market States

In this study, the market is in the UP (DOWN) state in month t when the average of the monthly returns of the market aggregate portfolio, over the year preceding month t, is above or equal (below) the sample average of the EW market portfolio monthly returns.

In conducting our empirical analysis, we strived to foster consistency with the literature by focusing on commonly studied momentum strategies and examining their conditional performance according to the methodologies proposed in preceding studies. While the conditional evaluation of the momentum effect on the basis of stock market variables (e.g., sentiment) can be conducted deploying the methodologies used in preceding literature, the use of bond market conditioning variables requires some market-specific adjustments. In particular, the approach proposed by Cooper et al. (2004), to categorize market states turns out being not applicable in our 2002-2014 sample.

For a given month t, Cooper et al. (2004) define the UP and DOWN states on the basis of the market average return over the three-year preceding month t. The market is in the UP state if the three-year average is nonnegative, whereas the DOWN state occurs when the average is negative. The authors also show that using the one-year and the three-year market averages yield consistent results on the market state dependence of the momentum effect. For the time period examined in this study, which covers 149 months, there are very few periods in which the average return on the EW (corporate bond market) index return is negative. In particular, no month is categorized as a DOWN state if we use the sign of the three-year average return on the EW index to define UP and DOWN states, as done in Cooper et al. (2004).

The paucity of DOWN states is not unique to the three-year average: only four months in the sample are characterized by a negative one-year average market return. Further, the use of the median of the returns yielded by the EW market portfolio identifies only six months with negative bond returns, thus ruling out also the use of the median market return to discriminate market states. The scarcity of low-performance periods appears to be specific to the bond market. To provide a comparison with the equity market, the months characterized by one-year negative (average or median) market returns are about a third of those yielding market gains over the 2002-2014 sample.

To evaluate the implications of this study's departure from the approach proposed in Cooper et al. (2004) to classify market states, we examine the state dependence of the benchmark equity momentum portfolio, which is available on Kenneth French's webpage.[45] Table A.1 reports the stratified averages of the stock market momentum factor according to four definitions of the UP and DOWN market states. What we find is that the methodology employed in this study makes harder to detect state dependence of the momentum factor. Presently, using the grand and one-year average returns of the market portfolio to define the market states yields a smaller spread between equity momentum in the UP vs. DOWN market states than the corresponding spread when the definition of UP and DOWN markets proposed in Cooper et al. (2004) is used. The annualized equity momentum gains stand at 4.29% and -10.13%, respectively in the UP and DOWN states, as defined in this study, over the August 2002-2014 sample.[46] Over the same period, the corresponding returns for the UP and DOWN states, where these are defined as in Cooper et al. (2004), are 6.89 and -19.66, again in annualized

[45] We use the methodology of Stambaugh et al. (2012), and condition the returns on the momentum factor on the month preceding the holding period monthly return.

[46] Correspondingly, for 1929-2016 sample, equity momentum gains are 9.4% and 3.9% respectively using this study's definition of UP and DOWN states.

Table A.1: State Dependence of the Stock Market Momentum Factor

Note: The table reports the stratified average returns on the equity market momentum factor, as obtained from Professor French's website. Stratification is according to the UP and DOWN market states that are defined, in the first row, by comparing the one-year average (first column) and three-year average (second column) return on the EW market portfolio with the sample average of the monthly returns on the same index. In the second row, the UP and DOWN market states are defined by the sign of the one-year average (first column) and three-year average (second column) of the monthly returns on the EW index. In this appendix, the monthly returns are gauged by the returns on the CRSP EW market portfolio for US equities.

	1-year		3-year	
Grand Average	UP	DOWN	UP	DOWN
	4.29	-10.13	10.18	-9.88
Sign (Average)	UP	DOWN	UP	DOWN
	7.43	-27.03	6.89	-19.66

percent terms.[47]

Further, we also find that the use of the one-year average market return to define the market state makes harder to detect state dependence, with respect to the use of the three-year average, employed in Cooper et al. (2004).[48] To illustrate, we consider the returns on the momentum equity factor in UP and DOWN states where the market states are defined comparing the grand average of market returns with the three-year versus the one-year average return. Using the three-year average market return yields a spread between the average momentum gains in the UP vs. DOWN market states that is about 39% larger than the spread obtained using the one-year market return series over the 2002-2014 sample.[49]

Summarizing, the use of the sample average of the return on the EW market index as a threshold for the one-year market return, to discriminate UP from DOWN markets, makes harder to provide evidence of state dependence for momentum than the sign of the (one or three-year) average of the EW market index return.

[47]The stratified momentum returns when the UP and DOWN states are defined as in Cooper et al. (2004) are 9.87% and -13.32% respectively, in the UP and DOWN states, over the 1929-2016 sample.

[48]As noted Cooper et al. (2004), the use of the market return average over longer vs. shorter time periods identifies market states that are more (less) extreme. However, using longer time periods also decrease the number of observations.

[49]For the 1929-2016 sample using the three-year average market returns yields a UP-minus-DOWN effect that is about 60.5% larger than that obtained relying on the one-year market average return.

Turning our attention back to the corporate bond market, we note that in this article the market states are defined on the basis of the comparison of the one-year average return on the EW portfolio of the bonds in our sample with the sample average of the returns on the same index. Clearly, the latter average is only available ex-post, and it is not in the information set of real-time investors. The use of an ex-post benchmark in defining the market states thus raises the concern that the robustness of our conclusions may be weakened by a look-ahead bias. In order to address this concern, we evaluate the market state effect using return cut-offs defined solely on the basis of information that is available to real-time investors, at the time of portfolio formation.

To begin with, we define the UP and DOWN states on the basis of the average of the monthly returns on the S&P 500 bond index sampled from its inception (in January 1995) to the month preceding the start of the TRACE-based return series (July 2002).[50] A portfolio formed in months t is deemed to be formed in an UP (DOWN) market if the 12-month average return (from $t-12$ to $t-1$) of the EW portfolio of the bonds in our sample is above (below) the average of the 1995-2002 average of the monthly returns on the S&P 500 bond index.[51] The results, reported in Panel A of Table A.2, strongly support the significance of the market state effect on the profitability of the momentum strategy.

As an additional robustness check, the time-t return threshold defining the UP and DOWN states is defined by the average return on the EW portfolio of the bonds in our sample over the months spanning from August 2002 to $t-1$. A momentum portfolio formed at time t is then deemed to be formed in the UP (DOWN) market state when the EW index one-year average return (from $t-12$ to $t-1$) is above (below) the corresponding time-t return cut-off. Once more, the results, reported in Panel B of Table A.2, strongly support our conclusions.

[50] The S&P 500 bond index is the corporate-bond counterpart of the S&P 500 equity index. Relying on the S&P 500 bond index has the advantage of dispensing with the assumption that agents have access to the full TRACE dataset when identifying the market state.

[51] The grand average of the returns employed as the cut-off to define the market state in the paper is 0.65% whereas for the S&P 500 bond index the return threshold is 0.89%.

Table A.2: Conditional Momentum Returns Using Alternative Market States Definitions

The table reports market-state stratified averages (in percentage terms) and their t-statistics, as estimated by Equations 1.2 and 1.3, for two alternative market state defitions. In Panel A, the benchmark separating the UP and DOWN states is the average of the monthly returns on the S&P 500 bond index sampled from its inception (in January 1995) to the month preceding the start of the TRACE-based return series (July 2002). In Panel B, the benchmark is instead the average return on the EW portfolio of the bonds in our sample over the months spanning from August 2002 to the month proceeding the portfolio formation. The returns of the momentum strategy are for the sample from August 2002 to December 2014.

Holding Period /		WINNER			LOSER			WINNER-LOSER		
	N (UP/DOWN)	*UP*	*DOWN*	UP-DOWN	*UP*	*DOWN*	UP-DOWN	*UP*	*DOWN*	UP-DOWN
					Return of S&P 500 Bond Index as the Benchmark					
1	27	2.179	0.733	**(2.583)**	0.878	0.723	(0.489)	1.301	0.01	**(2.621)**
	109	**(4.055)**	**(3.618)**		**(4.464)**	**(2.521)**		**(2.912)**	(0.051)	
3	27	5.608	2.251	**(2.862)**	2.376	2.251	(0.158)	3.232	0	**(3.065)**
	107	**(5.128)**	**(4.945)**		**(5.098)**	**(3.458)**		**(3.351)**	(0.001)	
6	27	10.076	4.429	**(2.998)**	3.751	4.782	(−0.558)	6.325	−0.353	**(3.925)**
	104	**(5.845)**	**(4.358)**		**(5.217)**	**(2.730)**		**(4.691)**	(−0.337)	
12	27	17.992	8.798	**(3.390)**	6.685	10.635	(−1.043)	11.307	−1.837	**(4.375)**
	98	**(7.505)**	**(4.438)**		**(8.275)**	**(2.691)**		**(6.334)**	(−0.833)	
18	27	22.814	11.89	**(3.068)**	10.277	16.982	(−1.321)	12.537	−5.093	**(4.460)**
	92	**(7.774)**	**(3.456)**		**(10.952)**	**(3.193)**		**(5.751)**	**(-2.059)**	
24	27	27.295	15.381	**(2.850)**	13.735	22.901	(−1.389)	13.561	−7.52	**(4.224)**
	86	**(8.232)**	**(3.578)**		**(8.541)**	**(3.225)**		**(7.158)**	**(-1.991)**	
					Panel B: Expanding Sample Market Average as the Benchmark					
1	37	1.576	0.812	(1.618)	0.783	0.743	(0.123)	0.793	0.07	**(1.774)**
	99	**(3.561)**	**(3.656)**		**(4.410)**	**(2.379)**		**(2.237)**	(0.324)	
3	37	4.444	2.349	**(2.232)**	2.313	2.262	(0.065)	2.131	0.087	**(2.327)**
	97	**(5.297)**	**(4.713)**		**(6.688)**	**(3.159)**		**(2.776)**	(0.186)	
6	36	7.845	4.739	**(1.768)**	4.152	4.728	(−0.301)	3.693	0.011	**(1.965)**
	95	**(4.705)**	**(4.472)**		**(6.372)**	**(2.500)**		**(2.303)**	(0.010)	
12	36	13.62	9.637	(1.233)	6.88	10.956	(−1.015)	6.74	−1.319	**(1.976)**
	89	**(4.069)**	**(4.715)**		**(6.554)**	**(2.593)**		**(2.353)**	(−0.529)	

Holding Period /		WINNER			LOSER			WINNER-LOSER		
N (UP/DOWN)		*UP*	*DOWN*	UP-DOWN	*UP*	*DOWN*	UP-DOWN	*UP*	*DOWN*	UP-DOWN
18	36	16.966	13.242	(1.008)	10.369	17.669	(−1.354)	6.597	−4.428	**(2.075)**
	83	**(3.614)**	**(3.971)**		**(6.468)**	**(3.116)**		**(1.738)**	(−1.528)	
24	35	23.263	15.969	(1.683)	14.007	23.719	(−1.268)	9.256	−7.751	**(2.960)**
	78	**(5.318)**	**(3.462)**		**(7.707)**	**(3.023)**		**(3.050)**	(−1.743)	

Appendix A.2: Two-way stratification of cumulative returns.

Portfolios formed in month t are classified as formed in periods following high (low) sentiment if the value of sentiment in the month $t-1$ is nonnegative (negative). Market state at the time of portfolio formation is defined as described in Section 1.4. The two-way stratified averages are evaluate using a linear model of the series $\mathrm{CR}_{n,t}$ as a function of four dichotomous variables, each identifying one of the market states and sentiment realizations. Formally, the model is:

$$CR_{n,t} = \beta^{H}_{UP} D^{UP}_{t-n} * D^{H}_{t-n} + \beta^{L}_{UP} D^{UP}_{t-n} * D^{L}_{t-n} + \beta^{H}_{D} D^{D}_{t-n} * D^{H}_{t-n} + \beta^{L}_{D} D^{UP}_{t-n} * D^{L}_{t-n} + \varepsilon_t, \tag{A.2.1}$$

where $t-n$ is the formation month, and ε_t are zero-mean disturbances. The variables D^H_t and D^L_t identify high and low sentiment months. If t is the formation month of a portfolios then D^H_t equals 1 when in month $t-1$ the sentiment was non-negative, and zero otherwise. The variable D^L_t is defined analogously for negative values of sentiment. To evaluate whether momentum gains are different conditionally on market state and sentiment levels, we use the following linear model of the cumulative returns observed at time t:

$$CR_{n,t} = \gamma_{UP} D^{UP}_{t-n} + \gamma_{DOWN} D^{D}_{t-n} + \gamma^{H}_{UP} D^{UP}_{t-n} * D^{H}_{t-n} + \gamma^{H}_{DOWN} D^{DOWN}_{t-n} * D^{H}_{t-n} + \nu_t \tag{A.2.2}$$

where, $t-n$ is the formation month and ν_t are zero-mean error terms. Since the $\mathrm{CR}_{n,t}$ series use overlapping returns, we employ a heteroskedasticity-and-autocorrelation consistent (HAC) estimator for the variance of the coefficients in equations 1.2 and 1.3 (e.g., Gallant, 1987; Cooper et al., 2004). The number of lags is set equal to the number of overlapping months in the holding period (i.e., $n-1$ for the returns series $\mathrm{CR}_{n,t}$). The regression approach preserves the time-series structure of the data and yields standard errors that are robust for autocorrelation.

Appendix A.3: Other Conditioning Variables

The evidence presented in this study shows that sentiment has a lower predictive power than the market state for the profitability of the momentum strategy. Further, we find substantial empirical evidence that conditioning on the market state dominates a host of other market indicators in terms on discriminating between momentum gains and losses. Instead, these indicators interact with the market state to heighten or weaken state dependence, although to a lesser degree than sentiment.[52] The empirical results supporting this section's conclusions are in the internet appendix.

Hereafter, we briefly discuss the use of three volatility-based market indicators to forecast momentum gains and losses. These conditioning variables are the risk aversion and fundamental uncertainty indicators proposed in Bekaert et al. (2013) and Bekaert and Hoerova (2016), where the former is empirically indistinguishable from the volatility premium defined in Bekaert and Hoerova (2014), and the implied volatility index for Treasuries used by Mueller et al. (2012).[53]

Varying risk aversion has been invoked to explain several aspects of the dynamic of asset valuation usually within the framework of the familiar rational asset pricing model with habit-formation proposed in Campbell and Cochrane (1999). Bansal and Yaron (2004) allow for fluctuations in consumption volatility, which are meant to model uncertainty, and show that uncertainty is yet another fundamental market characteristic affecting asset prices. Whaley (2000) argued that the implied volatility index VIX captures both a variance risk premium and stock market uncertainty. Consistently, Bekaert and Hoerova (2016) gauge risk aversion and fundamental uncertainty by decomposing VIX index into the volatility premium and a residual.[54] They proceed then to validate these measures by comparing them with a large sample of indicators that have been proposed in previous studies to capture fluctuations in risk aversion

[52]We created the equivalent of the UP and DOWN states for market indicators including the excess return of the value-weighted stock market portfolio, the bond liquidity factor proposed in Fontaine and Garcia (2011), and the 10-year Treasury return, among others. All these have been shown to yield an inferior predictive power than the market state for momentum gains and losses.

[53]Detailed results are relegated to the internet appendix.

[54]Whaley (2000) argued that the VIX index captures both stockmarket uncertainty and a variance risk premium.

and uncertainty. They document that the gauge of risk aversion is strongly correlated with the volatility premium (Bollerslev et al., 2009; Bekaert and Hoerova, 2014). The measure of fundamental uncertainty is instead strongly correlated with the macroeconomic uncertainty measures based by Jurado et al. (2015), but its dynamic is even closer to that of the flight-to-safety indicator proposed in Baele et al. (2014). As documented in Bekaert and Hoerova (2016), both the risk aversion and the uncertainty gauge are not strongly correlated with sentiment.

Panels A and B of Table A.3 summarize the conditional analysis of momentum returns for risk aversion and fundamental uncertainty.[55] The statistical evidence indicates that there is no significant difference between the momentum profits yielded by portfolios formed on months characterized by high vs. low levels of the conditioning variable. Further, as documented in the internet appendix, the interaction of risk aversion and of fundamental uncertainty with the market state appear to yield some predictive power for momentum returns. In particular, high risk aversion and uncertainty interact with the UP market state to amplify the market state effect. The analysis of the state dependence of the momentum effect shows that momentum gains are mostly concentrated in UP markets. Interacting the UP state with high risk aversion or uncertainty yields much stronger returns than the ones obtained for UP markets alone. The interaction effect is similar, in terms of the size of the returns to that observed for the interaction of sentiment with the market state documented in Panel A.1 of Table 1.6. The interaction of the market state with fundamental uncertainty is more effective than risk aversion in discriminating momentum gains and losses, but less so than sentiment.

The implied volatility index (VIX)—also dubbed the "investors' fear index"—is typically considered a good gauge of aggregate uncertainty or risk aversion. Mueller et al. (2012) propose an equivalent of the implied volatility index for the Treasury mar-

[55] Following the approach of Stambaugh et al. (2012) to assess the predictive power of sentiment, momentum portfolios formed in month t are classified as formed in a high (low) risk aversion month if the risk aversion index in month $t-1$ is above (below) its sample median. An analogous definition applies to high and low fundamental uncertainty, the TIV index, and the bond illiquidity measure.

ket, the Treasury Implied Volatility index (TIV).[56] The TIV index is negatively correlated with stock market sentiment, at -0.5 in our sample.

The stratified averages reported Panel C of Table A.3 summarize the conditional analysis of momentum returns for the TIV index. The results suggest that suggest that the TIV index fails to separate future momentum gains and losses.[57] However, the two-way sorting obtained considering high and low TIV index coupled with the UP and DOWN market states yields very strong results. For any holding period horizon, momentum gains are concentrated in periods following market gains and high TIV index periods. DOWN market coupled with high TIV index yields strong reversal over the medium and long-term horizons. Put differently, conditioning on the interaction of the market state and the TIV index yields momentum returns that are the opposite of those obtained using the interaction with sentiment. The empirical evidence thus suggests that the two indexes interact symmetrically with the overall market state to determine future momentum payoffs.[58]

Sentiment and the TIV index originate from different streams of the literature, with the use of sentiment being justified by behavioral theories and the interpretation of the TIV index being associated with the variance risk premium. At the moment it is unclear why the fear index in the bond market and sentiment interact symmetrically with the market state to predict momentum gains.

[56] As of its name, the TIV series consists of estimates of the volatility implied by prices of derivative written on Treasuries. More precisely, the index is calculated using high-frequency prices of options and futures written on benchmark Treasuries with maturities of 5, 10 and 30 years. The estimation techniques deployed in Mueller et al. (2012) are similar to those employed used to estimate the VIX index.

[57] Using the one-year average for the TIV index yields the same result.

[58] The predictability of sentiment and the TIV index follows a symmetric pattern also in the subsamples of investment and speculative grade bonds. See the internet appendix.

Table A.3: Momentum Portfolio Returns Conditional on Volatility-based Variables

The table reports the conditional average returns, as well as their t-statistics, as estimated in Equations 1.2 and 1.3 using the full sample. The returns are stratified on the risk aversion and fundamental uncertainty measures discussed in (Bekaert and Hoerova (2014) and Bekaert and Hoerova (2016)), and the Treasury Implied Volatility index (TIV, Mueller et al. (2012)). Panel A shows the conditional mean returns on the winner and loser portfolios and also the resulting momentum gains following HIGH and LOW risk aversion periods, for holding period of 1, 3, 6, 12, 18 and 24 months, for the full sample. Panel B and C report the analogous results for fundamental uncertainty and the TIV index, respectively. The time period covered is from August 2002 to December 2014.

Holding Period /		WINNER			LOSER			WINNER-LOSER		
	N (HIGH/LOW)	*HIGH*	*LOW*	HIGH-LOW	*HIGH*	*LOW*	HIGH-LOW	*HIGH*	*LOW*	HIGH-LOW
Panel A: Whole Sample Momentum Conditional on Risk Aversion										
1	75	1.491	0.747	(1.534)	1.139	0.459	(1.487)	0.352	0.288	(0.153)
	73	**(3.162)**	**(4.351)**		**(2.655)**	**(2.631)**		(0.868)	**(2.296)**	
3	75	4.360	2.056	**(2.584)**	3.003	1.688	(1.305)	1.357	0.368	(1.181)
	71	**(5.397)**	**(5.207)**		**(3.258)**	**(3.992)**		**(1.732)**	(1.159)	
6	74	8.156	3.976	**(2.186)**	5.914	3.367	(0.987)	2.242	0.609	(0.842)
	69	**(4.541)**	**(5.419)**		**(2.375)**	**(4.100)**		(1.210)	(0.846)	
12	73	15.028	7.328	**(2.629)**	12.436	7.052	(1.066)	2.591	0.275	(0.570)
	64	**(5.361)**	**(5.075)**		**(2.405)**	**(5.715)**		(0.664)	(0.249)	
18	72	20.847	8.507	**(2.628)**	20.497	9.615	**(1.860)**	0.350	−1.107	(0.278)
	59	**(5.508)**	**(2.759)**		**(3.549)**	**(5.649)**		(0.073)	(−0.531)	
24	71	25.700	10.574	**(2.542)**	27.745	11.777	**(2.209)**	−2.045	−1.203	(−0.143)
	54	**(6.263)**	**(2.671)**		**(3.933)**	**(8.258)**		(−0.344)	(−0.416)	
Panel B: Whole Sample Momentum Conditional on Uncertainty										
1	75	1.486	0.752	(1.460)	1.026	0.565	(1.000)	0.46	0.186	(0.646)
	73	**(3.025)**	**(4.601)**		**(2.338)**	**(3.575)**		(1.114)	(1.520)	
3	74	4.460	1.993	**(2.736)**	3.019	1.691	(1.296)	1.441	0.302	(1.358)
	72	**(5.442)**	**(5.133)**		**(3.201)**	**(4.135)**		**(1.820)**	(0.982)	
6	74	8.203	3.930	**(2.249)**	5.812	3.467	(0.895)	2.391	0.463	(0.993)
	69	**(4.547)**	**(5.572)**		**(2.314)**	**(4.179)**		(1.297)	(0.624)	
12	74	14.675	7.586	**(2.381)**	11.963	7.477	(0.846)	2.711	0.109	(0.654)
	63	**(5.025)**	**(5.654)**		**(2.260)**	**(6.326)**		(0.709)	(0.094)	

Holding Period /		WINNER			LOSER			WINNER-LOSER		
N (HIGH/LOW)		*HIGH*	*LOW*	HIGH-LOW	*HIGH*	*LOW*	HIGH-LOW	*HIGH*	*LOW*	HIGH-LOW
18	73	20.551	8.636	**(2.727)**	19.872	10.149	(1.656)	0.679	−1.513	(0.431)
	58	**(5.513)**	**(2.875)**		**(3.428)**	**(5.995)**		(0.144)	(−0.733)	
24	72	25.481	10.561	**(2.562)**	27.519	11.757	**(2.142)**	−2.038	−1.195	(−0.146)
	53	**(6.419)**	**(2.591)**		**(3.949)**	**(7.212)**		(−0.347)	(−0.419)	
Panel C: Whole Sample Momentum Conditional on Treasury Implied Volatility (TIV)										
1	75	1.535	0.705	**(1.755)**	1.066	0.528	(1.216)	0.47	0.177	(0.748)
	73	**(3.266)**	**(4.132)**		**(2.484)**	**(3.696)**		(1.249)	(1.136)	
3	75	4.312	2.103	**(2.533)**	3.062	1.630	(1.478)	1.250	0.473	(0.972)
	71	**(5.369)**	**(5.371)**		**(3.293)**	**(4.643)**		(1.680)	(1.297)	
6	75	7.824	4.251	**(1.915)**	5.718	3.528	(0.869)	2.106	0.723	(0.722)
	68	**(4.452)**	**(5.327)**		**(2.310)**	**(4.918)**		(1.144)	(1.026)	
12	75	15.445	6.615	**(3.633)**	12.702	6.583	(1.298)	2.743	0.032	(0.765)
	62	**(6.526)**	**(4.024)**		**(2.643)**	**(4.075)**		(0.762)	(0.029)	
18	75	20.861	7.829	**(3.057)**	20.350	9.213	**(1.771)**	0.511	−1.384	(0.409)
	56	**(6.477)**	**(2.399)**		**(3.461)**	**(4.426)**		(0.115)	(−0.724)	
24	73	25.200	10.637	**(2.846)**	27.162	11.913	**(1.986)**	−1.962	−1.277	(−0.116)
	52	**(6.892)**	**(2.802)**		**(3.559)**	**(8.819)**		(−0.336)	(−0.422)	

Internet Appendix

Table IA.1: Winners and Losers Conditional on Sentiment and Market State for (Non)Investment Grade Subsamples

The table reports the stratified averages and associated t-statistic values of winner and loser portfolio returns, calculated conditional on the interaction of the HIGH and LOW sentiment indicators with the state of the market UP and DOWN variables. These conditional averages are estimate by Equations A.2.1 and A.2.2. The results are presented for the investment grade and non-investment grade subsamples. Panels A.1 and A.2 tabulate the stratified average returns and t-statistics conditional on the market state and sentiment, for the winner and loser deciles constructed on investment grade bonds, for holding periods ranging from 1 month to 2 years. Panel B.1 and B.2 report the analogous returns and t-statistics for non-investment grade bonds. The time period covered is from August 2002 to December 2014.

Holding	High sentiment				Low sentiment				High-Low sentiment			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
Panel A.1: Returns for the Long Leg of the Momentum Portfolio (Winners) in the Investment Grade Subsample												
1	0.645	**(1.943)**	0.227	(0.898)	1.099	**(2.697)**	1.424	**(3.966)**	−0.455	(−0.876)	−1.197	**(-2.523)**
2	0.748	(1.475)	0.457	(1.248)	2.393	**(5.062)**	3.112	**(4.565)**	−1.646	**(-2.374)**	−2.656	**(-3.432)**
3	0.981	(1.401)	0.873	(1.686)	3.53	**(4.540)**	4.235	**(3.939)**	−2.549	**(-2.462)**	−3.363	**(-2.902)**
4	1.58	**(1.944)**	1.43	**(2.499)**	4.701	**(4.665)**	4.844	**(3.095)**	−3.121	**(-2.468)**	−3.414	**(-2.181)**
5	2.559	**(3.103)**	1.793	**(2.611)**	5.484	**(4.674)**	6.202	**(3.377)**	−2.925	**(-2.147)**	−4.409	**(-2.347)**
6	3.283	**(3.223)**	2.184	**(2.583)**	6.164	**(4.904)**	8.122	**(3.769)**	−2.881	**(-1.936)**	−5.938	**(-2.640)**
7	3.391	**(2.604)**	2.778	**(2.794)**	7.08	**(5.230)**	9.665	**(3.945)**	−3.689	**(-2.208)**	−6.887	**(-2.630)**
8	3.443	**(1.966)**	3.278	**(2.853)**	8.049	**(5.585)**	11.06	**(4.026)**	−4.606	**(-2.289)**	−7.781	**(-2.665)**
9	3.544	(1.501)	4	**(3.203)**	9.125	**(5.946)**	11.961	**(3.851)**	−5.581	**(-2.172)**	−7.961	**(-2.455)**
10	4.045	(1.559)	4.694	**(3.511)**	10.032	**(6.023)**	13.207	**(3.994)**	−5.987	**(-2.103)**	−8.513	**(-2.508)**
11	4.751	**(1.707)**	5.154	**(3.493)**	10.967	**(5.957)**	14.831	**(4.505)**	−6.217	**(-2.031)**	−9.676	**(-2.885)**
12	4.997	**(1.712)**	5.629	**(3.500)**	11.843	**(5.755)**	15.659	**(4.580)**	−6.845	**(-2.068)**	−10.03	**(-2.936)**
13	5.478	**(1.758)**	5.84	**(3.428)**	12.743	**(5.794)**	17.448	**(5.436)**	−7.264	**(-2.055)**	−11.608	**(-3.622)**
14	6.116	**(1.849)**	6.134	**(3.475)**	13.664	**(5.944)**	19.614	**(6.934)**	−7.548	**(-2.056)**	−13.48	**(-4.728)**
15	7.13	**(2.041)**	6.362	**(3.429)**	14.053	**(5.561)**	20.663	**(6.045)**	−6.923	(−1.679)	−14.3	**(-4.299)**
16	6.87	**(1.702)**	7.077	**(3.662)**	14.59	**(5.561)**	21.435	**(5.438)**	−7.72	(−1.632)	−14.359	**(-3.870)**
17	6.536	(1.482)	7.655	**(3.864)**	15.137	**(5.657)**	22.529	**(5.211)**	−8.601	(−1.679)	−14.874	**(-3.760)**
18	7.287	(1.672)	7.943	**(3.538)**	15.551	**(5.485)**	23.504	**(5.414)**	−8.264	(−1.598)	−15.561	**(-3.887)**

Holding Period	High sentiment *UP*	$t-stat$	*DOWN*	$t-stat$	Low sentiment *UP*	$t-stat$	*DOWN*	$t-stat$	High-Low sentiment *UP*	$t-stat$	*DOWN*	$t-stat$
19	8.132	**(2.073)**	8.039	**(3.156)**	16.212	**(5.428)**	24.274	**(5.614)**	−8.08	**(-1.708)**	−16.235	**(-4.085)**
20	8.99	**(2.301)**	8.345	**(3.112)**	17.205	**(5.510)**	24.594	**(5.589)**	−8.214	**(-1.735)**	−16.249	**(-4.093)**
21	9.837	**(2.614)**	8.968	**(3.015)**	18.066	**(5.547)**	24.71	**(5.306)**	−8.23	**(-1.764)**	−15.743	**(-3.721)**
22	10.475	**(3.284)**	9.474	**(2.928)**	18.852	**(5.579)**	25.06	**(5.233)**	−8.377	**(-2.015)**	−15.586	**(-3.565)**
23	11.235	**(4.054)**	9.985	**(2.861)**	19.596	**(5.657)**	26.65	**(5.951)**	−8.361	**(-2.196)**	−16.665	**(-3.663)**
24	11.844	**(4.908)**	10.584	**(2.924)**	20.523	**(5.747)**	27.272	**(6.014)**	−8.68	**(-2.369)**	−16.689	**(-3.559)**

Panel A.2: Returns for the Short Leg of the Momentum Portfolio (Lossers) in the Investment Grade Subsample

1	0.752	**(2.543)**	0.305	(1.095)	0.819	**(3.029)**	2.293	**(2.429)**	−0.067	(−0.168)	−1.988	**(-2.130)**
2	1.394	**(3.522)**	0.314	(0.705)	1.73	**(5.228)**	4.956	**(4.133)**	−0.336	(−0.652)	−4.642	**(-3.629)**
3	2.041	**(2.753)**	0.903	(1.363)	2.481	**(4.390)**	6.197	**(3.007)**	−0.44	(−0.473)	−5.295	**(-2.505)**
4	2.404	**(2.046)**	1.533	**(2.042)**	3.126	**(4.136)**	7.617	**(2.328)**	−0.722	(−0.522)	−6.085	**(-1.874)**
5	3.39	**(2.254)**	1.695	**(1.712)**	3.705	**(4.495)**	9.934	**(2.301)**	−0.316	(−0.191)	−8.239	**(-1.912)**
6	4.238	**(2.553)**	1.945	(1.524)	4.17	**(4.937)**	13.033	**(2.462)**	0.068	(0.040)	−11.088	**(-2.071)**
7	4.91	**(2.964)**	2.361	(1.531)	4.727	**(5.522)**	15.884	**(2.523)**	0.183	(0.115)	−13.523	**(-2.112)**
8	5.304	**(2.906)**	3.084	**(1.819)**	5.326	**(6.124)**	18.593	**(2.632)**	−0.022	(−0.013)	−15.509	**(-2.177)**
9	5.643	**(2.713)**	3.987	**(2.108)**	5.902	**(6.687)**	20.99	**(2.718)**	−0.258	(−0.136)	−17.003	**(-2.191)**
10	6.036	**(2.874)**	4.792	**(2.233)**	6.502	**(6.781)**	24.265	**(3.113)**	−0.465	(−0.242)	−19.473	**(-2.486)**
11	6.18	**(2.882)**	5.698	**(2.546)**	7.174	**(6.702)**	28.105	**(3.795)**	−0.994	(−0.500)	−22.407	**(-3.048)**
12	6.676	**(3.086)**	6.629	**(2.846)**	7.864	**(6.528)**	29.748	**(3.950)**	−1.188	(−0.567)	−23.119	**(-3.148)**
13	7.26	**(3.075)**	7.605	**(3.222)**	8.437	**(6.305)**	32.39	**(4.303)**	−1.177	(−0.503)	−24.785	**(-3.468)**
14	8.021	**(3.149)**	8.634	**(3.548)**	8.87	**(6.436)**	35.034	**(4.628)**	−0.848	(−0.346)	−26.4	**(-3.784)**
15	8.74	**(3.074)**	9.68	**(3.875)**	9.461	**(6.750)**	36.416	**(4.584)**	−0.722	(−0.269)	−26.736	**(-3.759)**
16	8.529	**(2.540)**	11.024	**(4.253)**	9.966	**(6.782)**	37.372	**(4.505)**	−1.437	(−0.447)	−26.348	**(-3.636)**
17	8.702	**(2.605)**	12.114	**(4.321)**	10.696	**(7.097)**	38.739	**(4.613)**	−1.994	(−0.633)	−26.625	**(-3.716)**
18	10.078	**(3.498)**	12.945	**(4.056)**	11.251	**(7.109)**	39.913	**(4.785)**	−1.173	(−0.457)	−26.968	**(-3.857)**
19	10.809	**(3.953)**	13.847	**(3.920)**	11.898	**(7.353)**	40.759	**(4.733)**	−1.089	(−0.460)	−26.912	**(-3.803)**
20	11.033	**(4.154)**	14.999	**(3.950)**	12.628	**(7.484)**	41.838	**(4.733)**	−1.595	(−0.683)	−26.839	**(-3.755)**
21	11.174	**(4.174)**	16.332	**(3.915)**	13.087	**(7.588)**	42.607	**(4.523)**	−1.913	(−0.761)	−26.275	**(-3.441)**
22	11.753	**(4.844)**	17.493	**(3.762)**	13.444	**(7.475)**	43.456	**(4.456)**	−1.691	(−0.750)	−25.963	**(-3.311)**
23	12.501	**(5.763)**	18.462	**(3.594)**	13.653	**(7.322)**	47.002	**(5.210)**	−1.151	(−0.590)	−28.54	**(-3.876)**
24	13.281	**(6.450)**	19.276	**(3.458)**	14.203	**(7.394)**	47.888	**(5.322)**	−0.923	(−0.480)	−28.613	**(-3.876)**

Panel B.1: Returns for the Long Leg of the Momentum Portfolio (Winners) in the Non-Investment Grade Subsample

Holding	High sentiment				Low sentiment				High-Low sentiment			
Period	UP	$t-stat$	$DOWN$	$t-stat$	UP	$t-stat$	$DOWN$	$t-stat$	UP	$t-stat$	$DOWN$	$t-stat$
1	0.479	(0.603)	0.75	**(2.170)**	2.544	**(5.365)**	1.234	**(2.196)**	−2.065	**(-2.177)**	−0.485	(−0.935)
2	0.761	(0.711)	1.447	**(2.811)**	4.897	**(7.439)**	3.07	**(3.487)**	−4.136	**(-3.291)**	−1.622	(−1.591)
3	1.328	(0.795)	2.071	**(2.398)**	6.97	**(6.539)**	5.068	**(3.856)**	−5.642	**(-2.857)**	−2.997	**(-2.002)**
4	2.21	(0.998)	2.659	**(2.464)**	8.933	**(6.640)**	6.184	**(2.827)**	−6.723	**(-2.646)**	−3.525	(−1.630)
5	3.357	(1.188)	3.209	**(2.453)**	10.754	**(6.805)**	7.443	**(2.585)**	−7.396	**(-2.395)**	−4.234	(−1.519)
6	4.566	(1.470)	3.846	**(2.447)**	12.039	**(6.680)**	9.6	**(2.829)**	−7.473	**(-2.278)**	−5.754	**(-1.708)**
7	5.926	**(1.923)**	4.541	**(2.533)**	13.254	**(6.461)**	12.506	**(3.291)**	−7.328	**(-2.304)**	−7.964	**(-1.994)**
8	6.636	**(2.202)**	5.352	**(2.711)**	14.558	**(6.466)**	14.433	**(3.602)**	−7.923	**(-2.555)**	−9.081	**(-2.132)**
9	7.5	**(2.601)**	6.273	**(2.939)**	16.035	**(6.480)**	16.06	**(3.655)**	−8.535	**(-2.696)**	−9.787	**(-2.054)**
10	9.127	**(3.515)**	6.949	**(2.937)**	16.729	**(6.215)**	18.879	**(4.351)**	−7.602	**(-2.381)**	−11.93	**(-2.432)**
11	10.365	**(4.133)**	7.667	**(3.122)**	17.749	**(6.122)**	21.873	**(5.263)**	−7.385	**(-2.193)**	−14.206	**(-2.984)**
12	11.461	**(4.065)**	8.453	**(3.022)**	18.564	**(6.134)**	22.814	**(5.158)**	−7.103	**(-1.873)**	−14.362	**(-2.785)**
13	12.121	**(4.143)**	8.753	**(2.875)**	19.577	**(6.129)**	25.486	**(6.590)**	−7.456	**(-1.828)**	−16.733	**(-3.519)**
14	12.765	**(4.558)**	9.117	**(2.858)**	20.852	**(6.202)**	28.291	**(8.390)**	−8.087	**(-1.932)**	−19.174	**(-4.358)**
15	13.55	**(4.475)**	9.782	**(2.928)**	21.263	**(6.341)**	30.125	**(8.448)**	−7.713	**(-1.725)**	−20.343	**(-4.363)**
16	13.022	**(3.492)**	10.429	**(2.963)**	21.717	**(6.783)**	31.181	**(8.097)**	−8.695	(−1.696)	−20.752	**(-4.195)**
17	13.018	**(2.683)**	10.964	**(2.966)**	21.988	**(7.299)**	33.049	**(8.361)**	−8.97	(−1.484)	−22.085	**(-4.348)**
18	13.299	**(2.348)**	11.319	**(2.852)**	22.129	**(7.813)**	35.034	**(9.749)**	−8.83	(−1.293)	−23.715	**(-4.775)**
19	14.951	**(2.701)**	11.442	**(2.657)**	22.461	**(8.748)**	35.943	**(9.591)**	−7.51	(−1.132)	−24.501	**(-4.733)**
20	16.383	**(3.078)**	11.49	**(2.566)**	23.633	**(9.772)**	36.497	**(8.278)**	−7.25	(−1.113)	−25.007	**(-4.374)**
21	17.132	**(3.209)**	11.872	**(2.579)**	24.977	**(11.238)**	36.915	**(6.955)**	−7.845	(−1.200)	−25.044	**(-3.949)**
22	17.685	**(3.603)**	12.25	**(2.581)**	26.203	**(13.096)**	37.977	**(6.854)**	−8.518	(−1.414)	−25.727	**(-3.963)**
23	19.235	**(4.488)**	12.772	**(2.611)**	27.201	**(15.441)**	40.146	**(7.652)**	−7.966	(−1.495)	−27.375	**(-4.135)**
24	20.182	**(5.178)**	13.692	**(2.743)**	28.4	**(18.585)**	40.984	**(7.724)**	−8.218	**(-1.709)**	−27.292	**(-4.059)**
Panel B.2: Returns for the Short Leg of the Momentum Portfolio (Lossers) in the Non-investment Grade Subsample												
1	0.565	(0.931)	0.479	(1.446)	1.252	**(4.175)**	1.409	(1.624)	−0.688	(−1.035)	−0.931	(−1.020)
2	1.034	(1.341)	0.846	(1.595)	2.147	**(5.798)**	4.158	**(3.409)**	−1.112	(−1.301)	−3.312	**(-2.490)**
3	1.556	(1.453)	1.567	**(1.979)**	2.965	**(5.279)**	6.575	**(3.008)**	−1.409	(−1.159)	−5.008	**(-2.180)**
4	1.654	(1.505)	2.3	**(2.092)**	4.037	**(5.906)**	8.668	**(2.465)**	−2.383	**(-1.837)**	−6.368	**(-1.781)**
5	2.628	**(1.904)**	2.575	**(1.841)**	5.087	**(5.970)**	11.049	**(2.287)**	−2.458	(−1.508)	−8.474	**(-1.736)**
6	3.522	**(2.243)**	2.744	(1.555)	5.831	**(6.223)**	14.77	**(2.416)**	−2.309	(−1.245)	−12.026	**(-1.937)**
7	4.471	**(2.609)**	2.805	(1.270)	6.81	**(6.193)**	18.416	**(2.510)**	−2.338	(−1.156)	−15.611	**(-2.069)**
8	5.091	**(2.766)**	3.467	(1.381)	7.614	**(6.031)**	22.335	**(2.634)**	−2.523	(−1.151)	−18.867	**(-2.173)**

Holding	High sentiment				Low sentiment				High-Low sentiment			
Period	UP	$t-stat$	$DOWN$	$t-stat$	UP	$t-stat$	$DOWN$	$t-stat$	UP	$t-stat$	$DOWN$	$t-stat$
9	5.526	**(2.747)**	4.348	(1.565)	8.628	**(6.263)**	25.836	**(2.740)**	−3.102	(−1.330)	−21.488	**(-2.232)**
10	6.006	**(2.995)**	5.027	(1.590)	9.395	**(6.604)**	30.515	**(3.046)**	−3.39	(−1.462)	−25.488	**(-2.468)**
11	6.742	**(3.244)**	5.631	(1.611)	10.199	**(6.750)**	35.718	**(3.559)**	−3.456	(−1.435)	−30.087	**(-2.895)**
12	7.174	**(2.760)**	6.289	(1.623)	10.944	**(6.494)**	37.867	**(3.615)**	−3.771	(−1.274)	−31.578	**(-2.914)**
13	8.24	**(2.836)**	7.133	**(1.768)**	11.711	**(6.237)**	41.141	**(3.856)**	−3.47	(−1.048)	−34.007	**(-3.115)**
14	9.458	**(3.170)**	7.945	**(1.866)**	12.449	**(6.433)**	45.489	**(4.405)**	−2.991	(−0.903)	−37.544	**(-3.549)**
15	10.56	**(3.107)**	8.774	**(1.991)**	13.025	**(6.967)**	46.267	**(4.211)**	−2.464	(−0.680)	−37.493	**(-3.335)**
16	11.533	**(2.767)**	10.076	**(2.273)**	13.3	**(7.331)**	47.959	**(4.291)**	−1.768	(−0.409)	−37.883	**(-3.345)**
17	12.414	**(2.524)**	11.573	**(2.558)**	13.758	**(7.739)**	49.996	**(4.399)**	−1.344	(−0.268)	−38.424	**(-3.366)**
18	13.303	**(2.608)**	13.082	**(2.766)**	13.8	**(7.972)**	51.391	**(4.587)**	−0.496	(−0.096)	−38.308	**(-3.434)**
19	14.573	**(3.237)**	14.402	**(2.787)**	14.196	**(8.365)**	52.434	**(4.633)**	0.377	(0.081)	−38.031	**(-3.370)**
20	14.672	**(3.422)**	15.788	**(2.996)**	15.15	**(8.883)**	54.176	**(4.644)**	−0.479	(−0.110)	−38.389	**(-3.357)**
21	14.531	**(3.153)**	17.068	**(3.010)**	15.58	**(8.975)**	56.007	**(4.598)**	−1.049	(−0.225)	−38.939	**(-3.253)**
22	15.557	**(3.823)**	18.057	**(2.816)**	16.097	**(9.911)**	57.313	**(4.528)**	−0.54	(−0.128)	−39.256	**(-3.150)**
23	16.735	**(5.076)**	19.03	**(2.704)**	16.177	**(11.032)**	62.519	**(5.506)**	0.558	(0.159)	−43.49	**(-3.794)**
24	16.879	**(5.995)**	19.726	**(2.601)**	16.618	**(10.821)**	63.706	**(5.476)**	0.261	(0.081)	−43.98	**(-3.758)**

Table IA.2: Momentum Portfolio Returns Conditional on Risk Aversion and Market State

The table reports the stratified averages and associated t-statistic values of momentum returns, calculated conditional on the interaction of the HIGH and LOW risk aversion with the state of the market UP and DOWN variables. These conditional averages are estimate by Equations A.2.1 and A.2.2. Panels A to C tabulate the stratified average returns and t-statistics conditional on the market state and risk aversion, for the momentum strategies and corresponding winner and loser deciles, for holding periods ranging from 1 month to 2 years, in the full sample. The time period covered is from August 2002 to December 2014.

Holding	High RA				Low RA				High-Low RA			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
Panel A: Momentum Profits (Winners minus Losers) in the Whole Sample												
1	1.164	**(2.959)**	−0.913	(−1.546)	0.042	(0.169)	0.402	**(2.827)**	1.122	**(2.454)**	−1.314	**(-2.210)**
2	1.978	**(3.625)**	−1.135	(−1.488)	0.145	(0.344)	0.511	**(2.452)**	1.832	**(2.655)**	−1.645	**(-2.081)**
3	3.067	**(3.859)**	−1.65	(−1.337)	−0.065	(−0.103)	0.576	(1.690)	3.132	**(3.170)**	−2.226	**(-1.753)**
4	3.9	**(3.859)**	−2.441	(−1.414)	0.422	(0.427)	0.62	(1.253)	3.478	**(2.590)**	−3.061	**(-1.726)**
5	4.528	**(3.662)**	−2.886	(−1.163)	0.75	(0.596)	0.545	(0.858)	3.778	**(2.434)**	−3.432	(−1.349)
6	4.831	**(3.122)**	−2.855	(−0.873)	1.312	(0.957)	0.28	(0.370)	3.519	**(1.984)**	−3.135	(−0.936)
7	5.14	**(2.817)**	−2.684	(−0.632)	1.589	(1.092)	0.191	(0.221)	3.551	**(1.750)**	−2.875	(−0.664)
8	5.845	**(2.807)**	−3.141	(−0.622)	1.459	(0.925)	0.088	(0.095)	4.386	**(1.879)**	−3.229	(−0.629)
9	6.286	**(2.749)**	−3.592	(−0.617)	1.843	(1.086)	−0.051	(−0.050)	4.443	(1.637)	−3.541	(−0.600)
10	6.809	**(2.792)**	−3.91	(−0.589)	1.946	(1.123)	−0.329	(−0.304)	4.862	(1.655)	−3.582	(−0.533)
11	7.325	**(2.851)**	−4.987	(−0.669)	2.014	(1.181)	−0.601	(−0.557)	5.311	**(1.713)**	−4.386	(−0.584)
12	7.508	**(2.655)**	−5.966	(−0.766)	2.071	(1.136)	−0.665	(−0.613)	5.437	(1.571)	−5.301	(−0.675)
13	8.195	**(2.846)**	−7.475	(−0.965)	1.627	(0.918)	−0.686	(−0.742)	6.568	**(1.909)**	−6.789	(−0.868)
14	8.652	**(2.770)**	−8.968	(−1.197)	1.788	(0.990)	−0.675	(−0.853)	6.864	**(1.864)**	−8.293	(−1.094)
15	8.496	**(2.462)**	−10.339	(−1.472)	2.023	(1.005)	−0.904	(−1.061)	6.473	(1.581)	−9.435	(−1.300)
16	8.268	**(2.222)**	−11.491	**(-1.707)**	1.928	(0.922)	−1.423	(−1.460)	6.34	(1.429)	−10.068	(−1.414)
17	8.056	**(2.071)**	−12.826	**(-2.110)**	1.437	(0.579)	−1.784	(−1.435)	6.619	(1.338)	−11.042	(−1.657)
18	8.148	**(2.091)**	−13.995	**(-2.479)**	0.556	(0.181)	−2.097	(−1.322)	7.592	(1.389)	−11.898	**(-1.840)**
19	8.331	**(2.153)**	−15.266	**(-2.908)**	0.619	(0.195)	−2.74	(−1.254)	7.712	(1.370)	−12.526	**(-1.914)**
20	8.599	**(2.259)**	−17.14	**(-3.590)**	1.266	(0.418)	−3.339	(−1.293)	7.333	(1.328)	−13.801	**(-2.149)**
21	8.916	**(2.326)**	−18.659	**(-4.172)**	1.863	(0.659)	−3.722	(−1.269)	7.054	(1.303)	−14.936	**(-2.331)**
22	9.143	**(2.391)**	−20.054	**(-4.865)**	2.477	(0.902)	−4.013	(−1.259)	6.665	(1.237)	−16.042	**(-2.546)**
23	9.74	**(2.665)**	−21.299	**(-5.594)**	2.638	(1.008)	−4.07	(−1.286)	7.102	(1.384)	−17.228	**(-2.874)**
24	10.091	**(2.784)**	−22.349	**(-6.584)**	2.62	(1.019)	−3.636	(−1.200)	7.471	(1.468)	−18.713	**(-3.402)**

Holding	High RA				Low RA				High-Low RA			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
	Panel B: Returns for the Long Leg of the Momentum Portfolio (Winners) in the Whole Sample											
1	2.105	**(4.734)**	0.376	(0.667)	0.4	(0.983)	0.906	**(6.160)**	1.705	**(2.865)**	−0.53	(−0.919)
2	3.828	**(6.878)**	1.124	(1.525)	1.006	**(1.816)**	1.636	**(6.215)**	2.822	**(3.593)**	−0.512	(−0.654)
3	5.569	**(6.329)**	1.835	(1.451)	1.45	**(1.923)**	2.346	**(5.817)**	4.119	**(3.600)**	−0.511	(−0.386)
4	7.09	**(6.173)**	2.619	(1.417)	2.25	**(2.586)**	2.926	**(5.254)**	4.84	**(3.372)**	−0.307	(−0.160)
5	8.457	**(6.112)**	3.583	(1.447)	2.989	**(3.125)**	3.42	**(4.927)**	5.468	**(3.311)**	0.163	(0.064)
6	9.51	**(5.768)**	4.648	(1.551)	3.872	**(3.520)**	4.024	**(4.966)**	5.638	**(2.871)**	0.623	(0.201)
7	10.391	**(5.400)**	6.207	**(1.839)**	4.832	**(3.783)**	4.609	**(4.975)**	5.559	**(2.455)**	1.598	(0.460)
8	11.47	**(5.288)**	7.603	**(2.003)**	5.521	**(3.576)**	5.094	**(4.773)**	5.95	**(2.281)**	2.509	(0.646)
9	12.339	**(4.994)**	8.861	**(2.135)**	6.572	**(3.625)**	5.663	**(4.837)**	5.767	**(1.861)**	3.198	(0.758)
10	13.44	**(5.055)**	10.187	**(2.313)**	7.104	**(3.930)**	6.235	**(4.826)**	6.336	**(1.938)**	3.952	(0.887)
11	14.67	**(5.196)**	11.813	**(2.545)**	7.498	**(4.319)**	6.517	**(4.371)**	7.172	**(2.132)**	5.296	(1.151)
12	15.471	**(4.885)**	12.984	**(2.821)**	8.126	**(4.419)**	6.91	**(4.088)**	7.345	**(1.939)**	6.074	(1.361)
13	16.836	**(5.180)**	13.779	**(2.880)**	8.134	**(4.338)**	7.242	**(4.058)**	8.702	**(2.293)**	6.537	(1.433)
14	17.721	**(5.112)**	14.709	**(2.951)**	8.957	**(4.615)**	7.549	**(3.951)**	8.764	**(2.190)**	7.16	(1.518)
15	18.288	**(4.896)**	15.822	**(3.090)**	9.706	**(4.470)**	7.577	**(3.465)**	8.582	**(1.930)**	8.246	**(1.711)**
16	18.84	**(4.751)**	17.965	**(3.477)**	9.573	**(3.470)**	7.548	**(3.086)**	9.267	**(1.818)**	10.418	**(2.166)**
17	19.299	**(4.614)**	19.391	**(3.784)**	9.643	**(2.853)**	7.604	**(2.795)**	9.656	(1.658)	11.786	**(2.415)**
18	19.981	**(4.684)**	20.343	**(3.903)**	9.933	**(2.733)**	7.659	**(2.445)**	10.047	(1.630)	12.684	**(2.455)**
19	20.878	**(4.844)**	21.344	**(4.106)**	10.681	**(3.165)**	7.215	**(1.915)**	10.197	(1.678)	14.129	**(2.557)**
20	21.815	**(5.040)**	21.93	**(4.167)**	11.764	**(3.537)**	7.058	**(1.706)**	10.051	(1.661)	14.872	**(2.497)**
21	22.708	**(5.152)**	22.63	**(4.267)**	12.51	**(3.741)**	7.149	(1.593)	10.198	(1.659)	15.481	**(2.441)**
22	23.345	**(5.073)**	23.529	**(4.503)**	13.567	**(4.469)**	7.096	(1.489)	9.779	(1.586)	16.434	**(2.519)**
23	24.238	**(5.367)**	24.303	**(4.612)**	14.252	**(5.578)**	7.247	(1.465)	9.986	**(1.738)**	17.056	**(2.541)**
24	25.281	**(5.674)**	25.168	**(4.749)**	14.972	**(6.736)**	7.775	(1.574)	10.309	**(1.866)**	17.394	**(2.577)**
	Panel C: Returns for the Short Leg of the Momentum Portfolio (Losers) in the Whole Sample											
1	0.941	**(4.961)**	1.289	(1.331)	0.358	(1.377)	0.505	**(2.604)**	0.583	(1.811)	0.784	(0.810)
2	1.851	**(6.978)**	2.259	**(1.856)**	0.861	**(2.895)**	1.126	**(3.252)**	0.99	**(2.484)**	1.133	(0.895)
3	2.502	**(5.896)**	3.485	(1.607)	1.515	**(2.877)**	1.77	**(3.326)**	0.987	(1.456)	1.715	(0.771)
4	3.191	**(5.545)**	5.06	(1.526)	1.828	**(2.685)**	2.306	**(3.119)**	1.363	(1.604)	2.754	(0.816)
5	3.93	**(6.017)**	6.47	(1.362)	2.239	**(2.782)**	2.874	**(3.149)**	1.691	**(1.845)**	3.595	(0.748)
6	4.679	**(6.650)**	7.502	(1.230)	2.56	**(3.061)**	3.744	**(3.604)**	2.119	**(2.415)**	3.758	(0.610)
7	5.251	**(6.922)**	8.891	(1.185)	3.243	**(3.887)**	4.418	**(3.818)**	2.008	**(2.446)**	4.473	(0.592)

Holding	High RA				Low RA				High-Low RA			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
8	5.625	**(7.009)**	10.744	(1.230)	4.062	**(4.381)**	5.006	**(4.027)**	1.563	**(1.857)**	5.738	(0.655)
9	6.052	**(6.891)**	12.453	(1.261)	4.729	**(4.922)**	5.714	**(4.301)**	1.324	(1.426)	6.739	(0.683)
10	6.631	**(7.162)**	14.098	(1.286)	5.158	**(5.457)**	6.564	**(4.682)**	1.474	(1.626)	7.534	(0.690)
11	7.344	**(7.365)**	16.8	(1.398)	5.483	**(5.974)**	7.118	**(4.827)**	1.861	**(2.086)**	9.681	(0.818)
12	7.963	**(7.631)**	18.95	(1.538)	6.055	**(5.625)**	7.575	**(4.604)**	1.908	**(1.788)**	11.375	(0.949)
13	8.641	**(7.681)**	21.254	**(1.708)**	6.507	**(4.995)**	7.927	**(4.693)**	2.133	(1.622)	13.327	(1.108)
14	9.069	**(7.710)**	23.677	**(1.917)**	7.17	**(4.962)**	8.224	**(4.514)**	1.899	(1.359)	15.453	(1.302)
15	9.792	**(8.465)**	26.162	**(2.190)**	7.683	**(4.549)**	8.481	**(4.370)**	2.109	(1.383)	17.681	(1.548)
16	10.571	**(8.998)**	29.457	**(2.528)**	7.645	**(3.847)**	8.971	**(4.637)**	2.926	(1.637)	20.486	**(1.851)**
17	11.243	**(9.879)**	32.217	**(2.960)**	8.207	**(3.916)**	9.388	**(4.978)**	3.037	(1.612)	22.829	**(2.212)**
18	11.832	**(9.890)**	34.338	**(3.309)**	9.377	**(5.092)**	9.756	**(5.021)**	2.455	(1.596)	24.582	**(2.506)**
19	12.547	**(10.550)**	36.609	**(3.753)**	10.063	**(5.879)**	9.954	**(4.979)**	2.485	**(1.866)**	26.655	**(2.893)**
20	13.216	**(10.567)**	39.07	**(4.309)**	10.498	**(6.086)**	10.397	**(5.514)**	2.718	**(2.008)**	28.673	**(3.346)**
21	13.792	**(11.060)**	41.289	**(4.806)**	10.647	**(5.776)**	10.871	**(6.219)**	3.145	**(2.057)**	30.418	**(3.745)**
22	14.203	**(10.813)**	43.584	**(5.361)**	11.089	**(6.231)**	11.108	**(6.601)**	3.113	**(2.012)**	32.476	**(4.227)**
23	14.499	**(10.500)**	45.602	**(5.836)**	11.614	**(7.640)**	11.318	**(6.095)**	2.884	**(2.241)**	34.284	**(4.650)**
24	15.19	**(11.521)**	47.517	**(6.371)**	12.352	**(9.086)**	11.411	**(5.647)**	2.838	**(2.600)**	36.107	**(5.119)**

Table IA.3: Momentum Portfolio Returns Conditional on Uncertainty and Market State

The table reports the stratified averages and associated t-statistic values of momentum returns, calculated conditional on the interaction of the HIGH and LOW uncertainty with the state of the market UP and DOWN variables. These conditional averages are estimate by Equations A.2.1 and A.2.2. Panels A to C tabulate the stratified average returns and t-statistics conditional on the market state and uncertainty, for the momentum strategies and corresponding winner and loser deciles, for holding periods ranging from 1 month to 2 years, in the full sample. The time period covered is from August 2002 to December 2014.

Holding	High UC				Low UC				High-Low UC			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
Panel A: Momentum Profits (Winners minus Losers) in the Whole Sample												
1	1.222	**(3.153)**	−0.652	(−1.108)	0.007	(0.026)	0.274	**(1.922)**	1.215	**(2.596)**	−0.927	(−1.557)
2	2.214	**(4.400)**	−1.031	(−1.333)	−0.113	(−0.233)	0.451	**(2.204)**	2.327	**(3.328)**	−1.482	**(-1.853)**
3	3.207	**(4.198)**	−1.553	(−1.225)	−0.132	(−0.226)	0.519	(1.528)	3.339	**(3.672)**	−2.072	(−1.578)
4	4.051	**(4.014)**	−2.146	(−1.178)	0.349	(0.418)	0.447	(0.923)	3.701	**(3.082)**	−2.593	(−1.373)
5	4.642	**(3.700)**	−2.507	(−1.008)	0.745	(0.690)	0.392	(0.606)	3.897	**(2.801)**	−2.899	(−1.127)
6	5.194	**(3.599)**	−2.661	(−0.826)	0.927	(0.679)	0.23	(0.292)	4.267	**(2.617)**	−2.891	(−0.869)
7	5.605	**(3.311)**	−2.491	(−0.601)	1.056	(0.707)	0.134	(0.149)	4.55	**(2.414)**	−2.625	(−0.618)
8	6.424	**(3.445)**	−2.91	(−0.590)	0.794	(0.483)	0.014	(0.014)	5.63	**(2.761)**	−2.924	(−0.580)
9	6.968	**(3.457)**	−3.346	(−0.587)	1.029	(0.596)	−0.129	(−0.121)	5.939	**(2.609)**	−3.217	(−0.553)
10	7.403	**(3.388)**	−3.734	(−0.573)	1.279	(0.726)	−0.361	(−0.323)	6.124	**(2.441)**	−3.374	(−0.508)
11	7.735	**(3.252)**	−4.368	(−0.615)	1.639	(0.886)	−0.81	(−0.672)	6.096	**(2.143)**	−3.559	(−0.491)
12	7.901	**(2.921)**	−5.364	(−0.718)	1.727	(0.940)	−0.821	(−0.676)	6.174	**(1.943)**	−4.543	(−0.593)
13	8.322	**(2.871)**	−6.728	(−0.898)	1.726	(0.996)	−0.874	(−0.831)	6.596	**(1.996)**	−5.854	(−0.761)
14	9.249	**(3.119)**	−8.015	(−1.092)	1.203	(0.711)	−0.94	(−1.046)	8.046	**(2.467)**	−7.075	(−0.938)
15	9.397	**(2.904)**	−9.398	(−1.370)	0.972	(0.584)	−1.106	(−1.196)	8.425	**(2.424)**	−8.292	(−1.162)
16	9.454	**(2.696)**	−10.357	(−1.616)	0.452	(0.237)	−1.467	(−1.308)	9.002	**(2.226)**	−8.89	(−1.291)
17	9.174	**(2.459)**	−11.572	**(-1.954)**	0.071	(0.030)	−1.841	(−1.240)	9.104	**(1.949)**	−9.731	(−1.460)
18	9.063	**(2.429)**	−12.979	**(-2.284)**	−0.466	(−0.159)	−2.201	(−1.261)	9.529	**(1.855)**	−10.778	(−1.635)
19	9.162	**(2.443)**	−14.183	**(-2.681)**	−0.275	(−0.092)	−2.863	(−1.231)	9.436	**(1.772)**	−11.32	**(-1.713)**
20	9.517	**(2.580)**	−16.019	**(-3.305)**	0.181	(0.064)	−3.419	(−1.250)	9.335	**(1.791)**	−12.6	**(-1.942)**
21	9.836	**(2.668)**	−17.371	**(-3.733)**	0.761	(0.294)	−3.871	(−1.229)	9.075	**(1.810)**	−13.5	**(-2.042)**
22	9.834	**(2.600)**	−18.677	**(-4.306)**	1.711	(0.680)	−4.172	(−1.236)	8.123	(1.586)	−14.506	**(-2.254)**
23	10.31	**(2.794)**	−19.923	**(-4.948)**	2.079	(0.853)	−4.157	(−1.255)	8.231	(1.645)	−15.766	**(-2.612)**
24	10.517	**(2.840)**	−20.9	**(-5.683)**	2.321	(0.959)	−3.69	(−1.172)	8.196	(1.634)	−17.21	**(-3.113)**

Holding	High UC				Low UC				High-Low UC			
Period	*UP*	*t − stat*	*DOWN*	*t − stat*	*UP*	*t − stat*	*DOWN*	*t − stat*	*UP*	*t − stat*	*DOWN*	*t − stat*
Panel B: Returns for the Long Leg of the Momentum Portfolio (Winners) in the Whole Sample												
1	2.121	**(4.470)**	0.405	(0.756)	0.449	(1.101)	0.9	**(5.844)**	1.672	**(2.646)**	−0.495	(−0.902)
2	3.902	**(6.968)**	1.118	(1.514)	1.019	**(1.861)**	1.64	**(6.259)**	2.883	**(3.680)**	−0.523	(−0.667)
3	5.753	**(6.543)**	1.899	(1.501)	1.362	**(1.898)**	2.309	**(5.637)**	4.391	**(3.907)**	−0.411	(−0.309)
4	7.158	**(6.114)**	2.698	(1.457)	2.361	**(2.776)**	2.88	**(5.119)**	4.796	**(3.290)**	−0.182	(−0.094)
5	8.582	**(6.123)**	3.489	(1.454)	3.043	**(3.479)**	3.472	**(5.023)**	5.539	**(3.436)**	0.017	(0.007)
6	9.806	**(6.148)**	4.576	(1.575)	3.679	**(3.489)**	4.055	**(5.005)**	6.127	**(3.275)**	0.521	(0.173)
7	10.661	**(5.604)**	6.182	**(1.873)**	4.674	**(4.044)**	4.588	**(4.936)**	5.987	**(2.753)**	1.594	(0.467)
8	11.979	**(5.851)**	7.461	**(1.982)**	5.027	**(3.603)**	5.127	**(4.839)**	6.952	**(2.983)**	2.334	(0.601)
9	12.951	**(5.666)**	8.602	**(2.068)**	5.917	**(3.589)**	5.757	**(4.952)**	7.035	**(2.613)**	2.845	(0.664)
10	13.904	**(5.599)**	9.936	**(2.235)**	6.693	**(3.983)**	6.308	**(4.925)**	7.211	**(2.514)**	3.628	(0.796)
11	14.737	**(5.354)**	11.219	**(2.410)**	7.709	**(4.369)**	6.664	**(4.558)**	7.028	**(2.219)**	4.554	(0.964)
12	15.588	**(5.086)**	12.145	**(2.525)**	8.271	**(4.512)**	7.193	**(4.586)**	7.317	**(2.113)**	4.953	(1.030)
13	16.645	**(5.076)**	12.868	**(2.547)**	8.795	**(4.641)**	7.56	**(4.678)**	7.85	**(2.147)**	5.308	(1.067)
14	18.15	**(5.441)**	13.898	**(2.698)**	8.705	**(4.942)**	7.77	**(4.350)**	9.445	**(2.647)**	6.128	(1.233)
15	19.022	**(5.494)**	15.008	**(2.862)**	8.995	**(4.622)**	7.748	**(3.724)**	10.027	**(2.655)**	7.26	(1.459)
16	19.559	**(5.216)**	16.484	**(3.151)**	8.912	**(3.581)**	7.832	**(3.287)**	10.647	**(2.359)**	8.652	**(1.742)**
17	19.86	**(4.971)**	17.818	**(3.434)**	9.234	**(2.953)**	7.852	**(2.885)**	10.626	**(2.026)**	9.966	**(1.979)**
18	20.28	**(4.958)**	19.237	**(3.618)**	9.928	**(2.892)**	7.787	**(2.469)**	10.351	**(1.867)**	11.45	**(2.169)**
19	21.153	**(5.044)**	20.397	**(3.920)**	10.718	**(3.359)**	7.135	**(1.843)**	10.434	**(1.891)**	13.262	**(2.386)**
20	22.18	**(5.338)**	21.057	**(4.064)**	11.657	**(3.719)**	6.876	(1.594)	10.523	**(1.958)**	14.181	**(2.371)**
21	23.151	**(5.595)**	21.857	**(4.247)**	12.289	**(3.875)**	6.843	(1.437)	10.862	**(2.048)**	15.014	**(2.331)**
22	23.613	**(5.418)**	22.786	**(4.510)**	13.598	**(4.542)**	6.696	(1.315)	10.015	**(1.868)**	16.09	**(2.399)**
23	24.37	**(5.501)**	23.67	**(4.684)**	14.503	**(5.514)**	6.698	(1.258)	9.867	**(1.886)**	16.972	**(2.440)**
24	25.391	**(5.830)**	24.523	**(4.825)**	15.277	**(6.591)**	7.215	(1.360)	10.114	**(2.050)**	17.307	**(2.466)**
Panel C: Returns for the Short Leg of the Momentum Portfolio (Lossers) in the Whole Sample												
1	0.899	**(4.423)**	1.057	(1.116)	0.442	**(1.714)**	0.626	**(3.499)**	0.457	(1.383)	0.431	(0.454)
2	1.688	**(6.677)**	2.148	**(1.740)**	1.133	**(3.282)**	1.189	**(3.605)**	0.555	(1.298)	0.96	(0.751)
3	2.546	**(6.344)**	3.452	(1.569)	1.494	**(2.891)**	1.79	**(3.474)**	1.052	(1.686)	1.662	(0.736)
4	3.107	**(5.940)**	4.843	(1.430)	2.012	**(2.690)**	2.432	**(3.400)**	1.095	(1.308)	2.411	(0.697)
5	3.94	**(6.489)**	5.996	(1.285)	2.298	**(2.630)**	3.08	**(3.422)**	1.642	**(1.766)**	2.916	(0.614)
6	4.612	**(6.892)**	7.236	(1.214)	2.751	**(2.954)**	3.824	**(3.645)**	1.86	**(1.964)**	3.412	(0.564)
7	5.056	**(7.111)**	8.673	(1.183)	3.618	**(3.578)**	4.454	**(3.768)**	1.438	(1.427)	4.219	(0.569)

Holding	High UC				Low UC				High-Low UC			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
8	5.555	**(7.071)**	10.371	(1.209)	4.233	**(4.129)**	5.113	**(4.024)**	1.323	(1.331)	5.258	(0.607)
9	5.984	**(7.229)**	11.948	(1.223)	4.888	**(4.193)**	5.886	**(4.400)**	1.096	(0.923)	6.062	(0.616)
10	6.501	**(7.339)**	13.671	(1.256)	5.414	**(4.733)**	6.669	**(4.797)**	1.087	(0.936)	7.002	(0.640)
11	7.002	**(7.344)**	15.587	(1.335)	6.07	**(4.771)**	7.474	**(5.102)**	0.933	(0.691)	8.113	(0.694)
12	7.688	**(7.203)**	17.51	(1.434)	6.544	**(5.078)**	8.014	**(5.238)**	1.143	(0.794)	9.496	(0.780)
13	8.323	**(7.006)**	19.596	(1.571)	7.069	**(4.718)**	8.434	**(5.521)**	1.254	(0.726)	11.162	(0.900)
14	8.9	**(7.298)**	21.913	**(1.768)**	7.501	**(4.701)**	8.71	**(5.212)**	1.399	(0.809)	13.203	(1.083)
15	9.625	**(7.933)**	24.406	**(2.041)**	8.023	**(4.472)**	8.854	**(4.830)**	1.602	(0.886)	15.552	(1.338)
16	10.106	**(8.834)**	26.841	**(2.343)**	8.46	**(3.714)**	9.299	**(5.146)**	1.645	(0.748)	17.542	(1.581)
17	10.686	**(9.583)**	29.39	**(2.706)**	9.163	**(3.915)**	9.693	**(5.542)**	1.523	(0.699)	19.698	**(1.872)**
18	11.217	**(10.062)**	32.216	**(3.036)**	10.394	**(4.620)**	9.988	**(5.432)**	0.823	(0.418)	22.228	**(2.187)**
19	11.991	**(11.017)**	34.58	**(3.484)**	10.993	**(5.143)**	9.998	**(5.003)**	0.998	(0.568)	24.582	**(2.601)**
20	12.663	**(11.709)**	37.075	**(4.023)**	11.476	**(5.062)**	10.295	**(5.256)**	1.188	(0.641)	26.781	**(3.056)**
21	13.315	**(13.052)**	39.228	**(4.475)**	11.528	**(4.749)**	10.714	**(5.819)**	1.787	(0.877)	28.514	**(3.419)**
22	13.779	**(13.073)**	41.463	**(4.983)**	11.886	**(5.009)**	10.867	**(5.899)**	1.892	(0.967)	30.596	**(3.855)**
23	14.06	**(12.518)**	43.593	**(5.480)**	12.424	**(5.775)**	10.855	**(5.201)**	1.636	(1.015)	32.738	**(4.288)**
24	14.874	**(13.918)**	45.423	**(5.936)**	12.956	**(6.681)**	10.906	**(4.865)**	1.918	(1.442)	34.517	**(4.640)**

Table IA.4: Momentum Portfolio Returns Conditional on Treasury Implied Volatility (TIV) and Market State

The table reports the stratified averages and associated t-statistic values of momentum returns, calculated conditional on the interaction of the HIGH and LOW TIV index with the state of the market UP and DOWN variables. These conditional averages are estimate by Equations A.2.1 and A.2.2. Panels A to C tabulate the stratified average returns and t-statistics conditional on the market state and TIV index, for the momentum strategies and corresponding winner and loser deciles, for holding periods ranging from 1 month to 2 years, in the full sample. The time period covered is from August 2002 to December 2014.

Holding	High TIV				Low TIV				High-Low TIV			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
Panel A: Momentum Profits (Winners minus Losers) in the Whole Sample												
1	1.175	**(3.361)**	−0.515	(−0.890)	0.117	(0.311)	0.208	(1.482)	1.058	**(2.191)**	−0.723	(−1.207)
2	2.223	**(4.775)**	−0.871	(−1.184)	−0.032	(−0.057)	0.412	**(2.020)**	2.255	**(3.094)**	−1.283	(−1.681)
3	2.937	**(4.060)**	−1.44	(−1.249)	0.357	(0.428)	0.535	(1.624)	2.58	**(2.500)**	−1.975	(−1.672)
4	3.629	**(3.512)**	−2.108	(−1.287)	1.083	(1.053)	0.536	(1.113)	2.546	**(1.968)**	−2.644	(−1.579)
5	4.248	**(2.855)**	−2.254	(−0.987)	1.449	(1.351)	0.353	(0.583)	2.799	**(1.724)**	−2.606	(−1.125)
6	4.599	**(2.505)**	−2.231	(−0.750)	1.924	(1.624)	0.069	(0.097)	2.675	(1.403)	−2.3	(−0.765)
7	5.119	**(2.480)**	−1.934	(−0.501)	1.914	(1.406)	−0.132	(−0.168)	3.205	(1.503)	−1.801	(−0.464)
8	5.649	**(2.405)**	−2.169	(−0.474)	2.095	(1.403)	−0.376	(−0.452)	3.554	(1.478)	−1.792	(−0.390)
9	6.292	**(2.639)**	−2.576	(−0.491)	2.205	(1.362)	−0.535	(−0.570)	4.087	**(1.707)**	−2.041	(−0.389)
10	6.958	**(2.917)**	−3.07	(−0.521)	2.146	(1.281)	−0.69	(−0.649)	4.812	**(2.095)**	−2.38	(−0.406)
11	7.678	**(3.236)**	−3.935	(−0.627)	1.971	(1.160)	−0.961	(−0.807)	5.707	**(2.661)**	−2.975	(−0.479)
12	8.198	**(3.364)**	−4.909	(−0.758)	1.575	(0.883)	−0.942	(−0.770)	6.623	**(3.225)**	−3.967	(−0.625)
13	8.497	**(3.355)**	−6.283	(−0.987)	1.76	(0.933)	−0.918	(−0.849)	6.736	**(3.219)**	−5.364	(−0.867)
14	8.996	**(3.396)**	−7.457	(−1.195)	1.886	(0.939)	−1.013	(−1.213)	7.11	**(3.227)**	−6.444	(−1.066)
15	9.114	**(3.135)**	−8.704	(−1.488)	1.712	(0.837)	−1.228	**(-1.807)**	7.402	**(2.965)**	−7.476	(−1.315)
16	9.058	**(2.921)**	−9.736	**(-1.786)**	1.371	(0.644)	−1.492	**(-2.257)**	7.688	**(2.807)**	−8.244	(−1.538)
17	9.012	**(2.775)**	−10.666	**(-2.051)**	0.674	(0.282)	−2.074	**(-2.343)**	8.338	**(2.637)**	−8.592	(−1.637)
18	8.99	**(2.738)**	−11.639	**(-2.331)**	0.032	(0.011)	−2.446	**(-1.917)**	8.957	**(2.412)**	−9.192	**(-1.793)**
19	9.073	**(2.823)**	−12.701	**(-2.616)**	0.24	(0.079)	−3.201	**(-1.744)**	8.833	**(2.405)**	−9.499	**(-1.848)**
20	9.43	**(3.001)**	−14.218	**(-2.967)**	0.711	(0.245)	−3.941	(−1.699)	8.719	**(2.468)**	−10.277	**(-1.972)**
21	9.861	**(3.236)**	−16.019	**(-3.358)**	1.121	(0.408)	−4.264	(−1.572)	8.74	**(2.649)**	−11.755	**(-2.223)**
22	9.897	**(3.386)**	−17.022	**(-3.478)**	1.975	(0.728)	−4.805	(−1.599)	7.922	**(2.553)**	−12.218	**(-2.284)**
23	10.159	**(3.451)**	−18.78	**(-3.797)**	2.654	(1.012)	−4.698	(−1.600)	7.505	**(2.449)**	−14.082	**(-2.732)**
24	10.219	**(3.508)**	−19.694	**(-3.976)**	2.768	(1.051)	−4.243	(−1.467)	7.451	**(2.459)**	−15.451	**(-3.165)**

Holding	High TIV				Low TIV				High-Low TIV			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
Panel B: Returns for the Long Leg of the Momentum Portfolio (Winners) in the Whole Sample												
1	2.116	**(4.208)**	0.582	(1.043)	0.523	(1.282)	0.8	**(4.909)**	1.593	**(2.566)**	−0.218	(−0.380)
2	4.021	**(7.053)**	1.322	**(1.819)**	0.978	(1.897)	1.532	**(6.546)**	3.042	**(3.957)**	−0.21	(−0.275)
3	5.528	**(5.868)**	2.018	(1.677)	1.834	**(2.288)**	2.249	**(5.722)**	3.694	**(3.076)**	−0.231	(−0.183)
4	6.75	**(5.294)**	2.752	(1.566)	3.121	**(3.174)**	2.852	**(5.326)**	3.629	**(2.371)**	−0.1	(−0.055)
5	8.038	**(5.036)**	3.604	(1.599)	4.021	**(3.677)**	3.395	**(4.920)**	4.017	**(2.208)**	0.208	(0.089)
6	9.155	**(5.069)**	4.715	**(1.749)**	4.83	**(3.476)**	3.936	**(4.730)**	4.325	**(2.039)**	0.78	(0.278)
7	10.32	**(5.180)**	6.343	**(2.131)**	5.392	**(3.287)**	4.402	**(4.404)**	4.929	**(2.072)**	1.94	(0.627)
8	11.465	**(5.156)**	7.713	**(2.347)**	6.023	**(3.243)**	4.836	**(4.080)**	5.442	**(2.030)**	2.877	(0.846)
9	12.76	**(5.519)**	8.834	**(2.480)**	6.474	**(3.103)**	5.449	**(4.173)**	6.286	**(2.213)**	3.386	(0.925)
10	13.983	**(5.984)**	10.326	**(2.832)**	6.884	**(3.243)**	5.834	**(3.886)**	7.099	**(2.582)**	4.492	(1.205)
11	15.275	**(6.215)**	11.94	**(3.364)**	7.262	**(3.535)**	5.876	**(3.123)**	8.013	**(2.983)**	6.064	(1.648)
12	16.444	**(6.277)**	13.175	**(3.777)**	7.4	**(3.527)**	6.119	**(2.845)**	9.044	**(3.322)**	7.056	**(1.921)**
13	17.377	**(6.258)**	13.965	**(3.823)**	8.116	**(3.539)**	6.384	**(2.801)**	9.26	**(3.156)**	7.581	**(1.982)**
14	18.397	**(6.342)**	14.965	**(3.947)**	8.757	**(3.643)**	6.54	**(2.625)**	9.64	**(3.094)**	8.424	**(2.083)**
15	19.292	**(6.355)**	16.032	**(4.065)**	9.04	**(3.652)**	6.455	**(2.262)**	10.252	**(3.140)**	9.577	**(2.173)**
16	19.884	**(6.334)**	17.399	**(4.275)**	8.908	**(3.062)**	6.516	**(2.098)**	10.976	**(3.025)**	10.883	**(2.289)**
17	20.408	**(6.159)**	18.423	**(4.316)**	8.923	**(2.654)**	6.698	**(2.049)**	11.485	**(2.815)**	11.725	**(2.284)**
18	20.998	**(6.094)**	19.282	**(4.279)**	9.371	**(2.618)**	6.672	**(1.835)**	11.627	**(2.694)**	12.609	**(2.217)**
19	21.782	**(6.076)**	20.016	**(4.232)**	10.288	**(3.079)**	6.221	(1.496)	11.494	**(2.824)**	13.795	**(2.183)**
20	22.831	**(6.289)**	20.324	**(4.057)**	11.18	**(3.359)**	6.214	(1.413)	11.651	**(2.874)**	14.11	**(2.075)**
21	23.653	**(6.482)**	21.2	**(4.063)**	12.041	**(3.553)**	6.489	(1.444)	11.612	**(2.902)**	14.711	**(2.082)**
22	24.026	**(6.619)**	21.919	**(4.174)**	13.439	**(3.905)**	6.462	(1.399)	10.587	**(2.744)**	15.457	**(2.152)**
23	24.675	**(6.638)**	22.986	**(4.289)**	14.493	**(4.572)**	6.771	(1.501)	10.182	**(2.813)**	16.215	**(2.257)**
24	25.47	**(6.774)**	23.791	**(4.401)**	15.158	**(5.050)**	7.321	(1.669)	10.313	**(3.117)**	16.469	**(2.313)**
Panel C: Returns for the Short Leg of the Momentum Portfolio (Losers) in the Whole Sample												
1	0.941	**(4.339)**	1.097	(1.214)	0.405	(1.627)	0.592	**(3.090)**	0.535	(1.566)	0.505	(0.551)
2	1.798	**(6.447)**	2.193	**(1.842)**	1.01	**(3.462)**	1.12	**(3.976)**	0.787	**(1.951)**	1.073	(0.877)
3	2.59	**(5.708)**	3.458	(1.695)	1.477	**(3.155)**	1.714	**(3.706)**	1.114	**(1.724)**	1.744	(0.846)
4	3.121	**(4.931)**	4.861	(1.551)	2.038	**(3.104)**	2.316	**(3.681)**	1.083	(1.234)	2.544	(0.808)
5	3.79	**(4.794)**	5.858	(1.358)	2.572	**(3.403)**	3.043	**(3.857)**	1.219	(1.169)	2.815	(0.651)
6	4.556	**(5.016)**	6.946	(1.264)	2.906	**(3.794)**	3.867	**(4.141)**	1.65	(1.455)	3.079	(0.560)
7	5.201	**(5.579)**	8.276	(1.234)	3.478	**(4.228)**	4.535	**(4.012)**	1.723	(1.467)	3.742	(0.558)

Holding	High TIV				Low TIV				High-Low TIV			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
8	5.817	**(6.030)**	9.881	(1.276)	3.929	**(4.516)**	5.213	**(4.063)**	1.888	(1.554)	4.669	(0.606)
9	6.467	**(6.574)**	11.41	(1.310)	4.269	**(4.661)**	5.984	**(4.292)**	2.198	**(1.721)**	5.427	(0.630)
10	7.025	**(6.837)**	13.396	(1.414)	4.738	**(4.802)**	6.524	**(3.967)**	2.287	(1.654)	6.872	(0.741)
11	7.597	**(7.259)**	15.875	(1.625)	5.291	**(4.779)**	6.837	**(3.328)**	2.307	(1.555)	9.039	(0.960)
12	8.246	**(7.526)**	18.084	**(1.828)**	5.825	**(4.873)**	7.061	**(2.954)**	2.42	(1.541)	11.023	(1.172)
13	8.88	**(7.554)**	20.247	**(2.038)**	6.356	**(4.802)**	7.302	**(2.826)**	2.524	(1.488)	12.945	(1.375)
14	9.401	**(7.662)**	22.421	**(2.264)**	6.871	**(4.861)**	7.553	**(2.691)**	2.53	(1.477)	14.868	(1.577)
15	10.178	**(7.708)**	24.736	**(2.578)**	7.329	**(5.014)**	7.683	**(2.494)**	2.849	(1.659)	17.053	**(1.846)**
16	10.826	**(7.984)**	27.135	**(2.920)**	7.538	**(4.238)**	8.008	**(2.574)**	3.288	(1.662)	19.127	**(2.098)**
17	11.396	**(8.339)**	29.089	**(3.160)**	8.249	**(4.286)**	8.772	**(3.123)**	3.147	(1.488)	20.317	**(2.218)**
18	12.009	**(8.572)**	30.92	**(3.386)**	9.339	**(4.942)**	9.119	**(3.278)**	2.67	(1.264)	21.801	**(2.370)**
19	12.709	**(8.754)**	32.717	**(3.593)**	10.048	**(5.456)**	9.422	**(3.436)**	2.661	(1.240)	23.294	**(2.502)**
20	13.401	**(9.184)**	34.542	**(3.757)**	10.469	**(5.321)**	10.155	**(4.276)**	2.932	(1.309)	24.386	**(2.583)**
21	13.792	**(9.143)**	37.22	**(4.029)**	10.92	**(5.194)**	10.753	**(5.447)**	2.872	(1.221)	26.467	**(2.802)**
22	14.129	**(9.402)**	38.941	**(4.155)**	11.465	**(5.277)**	11.266	**(6.556)**	2.665	(1.108)	27.675	**(2.918)**
23	14.516	**(9.640)**	41.766	**(4.455)**	11.84	**(5.747)**	11.469	**(6.575)**	2.676	(1.162)	30.297	**(3.200)**
24	15.251	**(9.499)**	43.484	**(4.629)**	12.39	**(6.561)**	11.564	**(6.349)**	2.861	(1.271)	31.92	**(3.378)**

Table IA.5: IG Momentum Portfolio Returns Conditional on Treasury Implied Volatility (TIV) and Market State

The table reports the stratified averages and associated t-statistic values of momentum returns, calculated conditional on the interaction of the HIGH and LOW TIV index with the state of the market UP and DOWN variables. These conditional averages are estimate by Equations A.2.1 and A.2.2. Panels A to C tabulate the stratified average returns and t-statistics conditional on the market state and TIV index, for the momentum strategies and corresponding winner and loser deciles, for holding periods ranging from 1 month to 2 years, in the investment grade subsample. The time period covered is from August 2002 to December 2014.

Holding	High TIV				Low TIV				High-Low TIV			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
Panel A: Momentum Profits (Winners minus Losers) in the Investment Grade Subsample												
1	0.327	(1.125)	−0.756	(−1.292)	−0.045	(−0.155)	−0.002	(−0.009)	0.372	(0.962)	−0.754	(−1.247)
2	0.727	**(2.104)**	−1.171	(−1.687)	−0.311	(−0.694)	0.136	(0.621)	1.038	**(1.834)**	−1.307	**(-1.796)**
3	0.835	(1.539)	−1.551	(−1.410)	−0.104	(−0.151)	0.122	(0.341)	0.939	(1.126)	−1.674	(−1.457)
4	1.165	(1.605)	−2.155	(−1.375)	0.44	(0.473)	0.075	(0.158)	0.725	(0.684)	−2.23	(−1.376)
5	1.335	(1.337)	−2.183	(−1.023)	0.541	(0.512)	−0.084	(−0.139)	0.794	(0.610)	−2.1	(−0.956)
6	1.341	(1.109)	−2.261	(−0.864)	0.803	(0.701)	−0.281	(−0.368)	0.538	(0.364)	−1.98	(−0.735)
7	1.652	(1.228)	−2.158	(−0.648)	0.575	(0.471)	−0.564	(−0.655)	1.076	(0.667)	−1.594	(−0.466)
8	1.809	(1.189)	−2.58	(−0.672)	0.733	(0.583)	−0.951	(−1.047)	1.076	(0.616)	−1.63	(−0.413)
9	2.391	(1.570)	−3.046	(−0.709)	0.598	(0.474)	−1.277	(−1.364)	1.793	(1.047)	−1.769	(−0.402)
10	2.978	**(1.996)**	−3.515	(−0.743)	0.378	(0.315)	−1.646	(−1.660)	2.6	(1.623)	−1.869	(−0.387)
11	3.602	**(2.506)**	−4.271	(−0.861)	0.358	(0.343)	−2.246	**(-2.021)**	3.244	**(2.320)**	−2.024	(−0.397)
12	3.915	**(2.723)**	−5.412	(−1.104)	0.058	(0.056)	−2.34	**(-1.923)**	3.857	**(2.983)**	−3.072	(−0.607)
13	4.12	**(2.687)**	−6.555	(−1.402)	0.25	(0.227)	−2.511	**(-2.283)**	3.869	**(2.888)**	−4.044	(−0.835)
14	4.485	**(2.691)**	−7.493	(−1.678)	0.474	(0.401)	−2.645	**(-3.173)**	4.011	**(2.802)**	−4.848	(−1.057)
15	4.451	**(2.351)**	−8.788	**(-2.155)**	0.392	(0.340)	−2.892	**(-4.393)**	4.059	**(2.463)**	−5.896	(−1.413)
16	4.439	**(2.185)**	−9.712	**(-2.547)**	0.427	(0.343)	−3.091	**(-4.487)**	4.011	**(2.162)**	−6.621	(−1.679)
17	4.242	**(1.910)**	−10.482	**(-2.867)**	0.034	(0.022)	−3.258	**(-4.122)**	4.208	**(1.869)**	−7.224	**(-1.897)**
18	4.139	**(1.750)**	−11.23	**(-3.163)**	−0.503	(−0.237)	−3.44	**(-3.419)**	4.642	(1.644)	−7.79	**(-2.108)**
19	4.024	(1.605)	−11.979	**(-3.404)**	−0.239	(−0.109)	−3.97	**(-2.938)**	4.263	(1.454)	−8.009	**(-2.174)**
20	4.246	(1.644)	−13.095	**(-3.723)**	0.158	(0.074)	−4.52	**(-2.925)**	4.088	(1.380)	−8.575	**(-2.343)**
21	4.669	**(1.795)**	−14.479	**(-4.177)**	0.756	(0.406)	−4.785	**(-2.671)**	3.913	(1.401)	−9.694	**(-2.668)**
22	4.765	**(1.836)**	−15.107	**(-4.151)**	1.389	(0.771)	−5.318	**(-2.384)**	3.376	(1.272)	−9.79	**(-2.561)**
23	5.101	**(2.042)**	−16.366	**(-4.429)**	1.824	(0.962)	−5.468	**(-2.363)**	3.277	(1.291)	−10.898	**(-2.911)**
24	5.194	**(2.151)**	−16.999	**(-4.518)**	2.015	(0.990)	−5.311	**(-2.361)**	3.179	(1.282)	−11.688	**(-3.220)**

Holding	High TIV				Low TIV				High-Low TIV			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
Panel B: Returns for the Long Leg of the Momentum Portfolio (Winners) in the Investment Grade Subsample												
1	1.438	**(3.144)**	0.596	(1.290)	0.343	(0.953)	0.52	**(2.840)**	1.096	**(1.899)**	0.076	(0.153)
2	2.798	**(5.192)**	1.379	**(1.776)**	0.741	**(1.804)**	0.998	**(3.465)**	2.057	**(3.036)**	0.381	(0.460)
3	3.837	**(4.242)**	2.116	**(1.859)**	1.391	**(2.055)**	1.524	**(3.275)**	2.447	**(2.198)**	0.592	(0.487)
4	4.781	**(4.273)**	2.906	**(1.886)**	2.379	**(2.507)**	1.951	**(3.379)**	2.402	**(1.701)**	0.955	(0.587)
5	5.789	**(4.612)**	3.895	**(2.084)**	2.994	**(2.569)**	2.352	**(3.388)**	2.795	**(1.721)**	1.543	(0.785)
6	6.63	**(5.177)**	5.072	**(2.207)**	3.482	**(2.397)**	2.779	**(3.374)**	3.148	**(1.725)**	2.294	(0.952)
7	7.634	**(5.732)**	6.405	**(2.517)**	3.705	**(2.186)**	3.131	**(3.284)**	3.929	**(1.943)**	3.274	(1.233)
8	8.527	**(5.932)**	7.574	**(2.665)**	4.129	**(2.190)**	3.36	**(3.079)**	4.398	**(1.982)**	4.215	(1.443)
9	9.92	**(6.572)**	8.387	**(2.705)**	4.079	**(2.004)**	3.897	**(3.477)**	5.841	**(2.453)**	4.49	(1.437)
10	11.178	**(7.603)**	9.657	**(3.096)**	4.216	**(2.031)**	4.164	**(3.334)**	6.961	**(2.953)**	5.493	**(1.774)**
11	12.468	**(8.109)**	11.142	**(3.819)**	4.501	**(2.215)**	4.021	**(2.420)**	7.967	**(3.415)**	7.121	**(2.415)**
12	13.536	**(8.119)**	12.128	**(4.145)**	4.666	**(2.314)**	4.193	**(2.202)**	8.87	**(3.747)**	7.935	**(2.614)**
13	14.363	**(8.058)**	12.614	**(3.895)**	5.369	**(2.484)**	4.425	**(2.260)**	8.994	**(3.562)**	8.189	**(2.483)**
14	15.302	**(8.173)**	13.448	**(3.967)**	6.067	**(2.689)**	4.533	**(2.165)**	9.235	**(3.522)**	8.914	**(2.527)**
15	16.115	**(8.232)**	14.365	**(4.046)**	6.315	**(2.836)**	4.405	**(1.837)**	9.8	**(3.770)**	9.96	**(2.564)**
16	16.567	**(8.117)**	15.545	**(4.220)**	6.404	**(2.471)**	4.673	**(1.876)**	10.163	**(3.526)**	10.872	**(2.622)**
17	16.864	**(7.551)**	16.352	**(4.147)**	6.67	**(2.321)**	5.157	**(2.143)**	10.194	**(3.287)**	11.195	**(2.522)**
18	17.248	**(6.761)**	17.06	**(4.075)**	7.364	**(2.646)**	5.231	**(1.933)**	9.884	**(3.220)**	11.829	**(2.384)**
19	17.727	**(5.973)**	17.719	**(4.023)**	8.405	**(3.371)**	4.955	(1.627)	9.323	**(3.138)**	12.764	**(2.341)**
20	18.612	**(5.858)**	17.952	**(3.814)**	9.114	**(3.486)**	5.338	**(1.815)**	9.498	**(3.027)**	12.614	**(2.207)**
21	19.383	**(5.918)**	18.749	**(3.793)**	10.094	**(3.774)**	5.912	**(2.009)**	9.289	**(2.975)**	12.837	**(2.174)**
22	19.722	**(5.803)**	19.377	**(3.884)**	11.412	**(4.229)**	6.135	**(1.988)**	8.31	**(2.730)**	13.242	**(2.208)**
23	20.259	**(5.745)**	20.458	**(4.070)**	12.464	**(4.759)**	6.321	**(2.023)**	7.795	**(2.638)**	14.138	**(2.347)**
24	20.934	**(5.708)**	21.159	**(4.197)**	13.2	**(5.108)**	6.833	**(2.249)**	7.734	**(2.709)**	14.326	**(2.409)**
Panel C: Returns for the Short Leg of the Momentum Portfolio (Lossers) in the Investment Grade Subsample												
1	1.111	**(4.275)**	1.351	(1.603)	0.387	(1.359)	0.521	**(2.364)**	0.724	**(1.859)**	0.83	(0.955)
2	2.071	**(5.833)**	2.55	**(2.169)**	1.052	**(2.972)**	0.862	**(2.553)**	1.019	**(2.033)**	1.688	(1.380)
3	3.002	**(5.137)**	3.667	**(1.953)**	1.495	**(2.371)**	1.402	**(2.569)**	1.507	**(1.805)**	2.265	(1.176)
4	3.616	**(4.985)**	5.062	**(1.819)**	1.939	**(2.054)**	1.877	**(2.721)**	1.677	(1.531)	3.185	(1.126)
5	4.454	**(5.265)**	6.078	(1.595)	2.453	**(2.271)**	2.435	**(2.882)**	2.001	(1.603)	3.643	(0.946)
6	5.289	**(5.548)**	7.333	(1.541)	2.679	**(2.534)**	3.06	**(2.966)**	2.61	**(2.049)**	4.274	(0.889)
7	5.983	**(6.201)**	8.562	(1.487)	3.129	**(2.913)**	3.695	**(3.042)**	2.853	**(2.216)**	4.868	(0.837)

Holding	High TIV				Low TIV				High-Low TIV			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
8	6.718	**(6.896)**	10.155	(1.547)	3.396	**(3.025)**	4.31	**(3.250)**	3.323	**(2.465)**	5.844	(0.887)
9	7.529	**(7.922)**	11.433	(1.569)	3.481	**(3.125)**	5.174	**(3.728)**	4.048	**(2.963)**	6.259	(0.859)
10	8.199	**(9.099)**	13.171	(1.694)	3.838	**(3.292)**	5.81	**(3.764)**	4.361	**(3.081)**	7.361	(0.958)
11	8.866	**(10.168)**	15.413	**(1.971)**	4.143	**(3.280)**	6.268	**(3.501)**	4.723	**(3.135)**	9.145	(1.202)
12	9.621	**(10.719)**	17.54	**(2.257)**	4.608	**(3.507)**	6.533	**(3.292)**	5.013	**(3.145)**	11.007	(1.470)
13	10.243	**(10.633)**	19.17	**(2.439)**	5.119	**(3.500)**	6.936	**(3.598)**	5.124	**(2.876)**	12.234	(1.611)
14	10.816	**(11.259)**	20.941	**(2.688)**	5.592	**(3.550)**	7.178	**(3.559)**	5.224	**(2.835)**	13.762	**(1.823)**
15	11.663	**(12.628)**	23.154	**(3.071)**	5.923	**(3.711)**	7.297	**(3.287)**	5.741	**(3.262)**	15.857	**(2.152)**
16	12.128	**(12.787)**	25.257	**(3.410)**	5.977	**(3.127)**	7.764	**(3.793)**	6.151	**(2.996)**	17.494	**(2.388)**
17	12.622	**(13.378)**	26.834	**(3.573)**	6.636	**(3.108)**	8.414	**(4.708)**	5.986	**(2.633)**	18.42	**(2.459)**
18	13.108	**(13.782)**	28.291	**(3.718)**	7.866	**(3.605)**	8.671	**(4.538)**	5.242	**(2.319)**	19.619	**(2.563)**
19	13.704	**(13.410)**	29.698	**(3.827)**	8.644	**(3.943)**	8.926	**(4.635)**	5.059	**(2.238)**	20.773	**(2.635)**
20	14.366	**(13.893)**	31.047	**(3.887)**	8.956	**(3.878)**	9.858	**(6.104)**	5.41	**(2.295)**	21.189	**(2.628)**
21	14.714	**(14.432)**	33.228	**(4.102)**	9.338	**(3.932)**	10.697	**(7.989)**	5.376	**(2.237)**	22.531	**(2.780)**
22	14.957	**(14.339)**	34.485	**(4.149)**	10.023	**(4.033)**	11.453	**(10.353)**	4.934	**(1.975)**	23.032	**(2.825)**
23	15.159	**(12.683)**	36.824	**(4.440)**	10.641	**(4.376)**	11.788	**(9.515)**	4.518	**(1.842)**	25.036	**(3.102)**
24	15.74	**(11.113)**	38.158	**(4.560)**	11.186	**(4.725)**	12.144	**(8.444)**	4.554	**(1.851)**	26.014	**(3.216)**

Table IA.6: NIG Momentum Portfolio Returns Conditional on Treasury Implied Volatility (TIV) and Market State

The table reports the stratified averages and associated t-statistic values of momentum returns, calculated conditional on the interaction of the HIGH and LOW TIV index with the state of the market UP and DOWN variables. These conditional averages are estimate by Equations A.2.1 and A.2.2. Panels A to C tabulate the stratified average returns and t-statistics conditional on the market state and TIV index, for the momentum strategies and corresponding winner and loser deciles, for holding periods ranging from 1 month to 2 years, in the non-investment grade subsample. The time period covered is from August 2002 to December 2014.

Holding	High TIV				Low TIV				High-Low TIV			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
Panel A: Momentum Profits (Winners minus Losers) in the Non-investment Grade Subsample												
1	1.242	**(3.227)**	−0.503	(−0.779)	0.421	(0.862)	0.56	**(2.795)**	0.82	(1.338)	−1.063	(−1.607)
2	2.762	**(4.527)**	−1.033	(−1.192)	0.68	(1.083)	0.926	**(3.459)**	2.081	**(2.378)**	−1.959	**(-2.160)**
3	3.815	**(3.875)**	−1.93	(−1.685)	1.377	(1.350)	1.218	**(2.503)**	2.438	**(1.750)**	−3.148	**(-2.599)**
4	4.193	**(3.053)**	−2.878	**(-2.095)**	2.789	**(2.043)**	1.235	**(1.748)**	1.403	(0.762)	−4.112	**(-2.834)**
5	4.38	**(2.418)**	−3.008	(−1.566)	3.939	**(2.427)**	1.177	(1.354)	0.441	(0.191)	−4.185	**(-2.095)**
6	4.539	**(2.122)**	−3.222	(−1.268)	4.846	**(2.541)**	1.342	(1.263)	−0.307	(−0.113)	−4.564	**(-1.723)**
7	4.49	**(1.861)**	−2.503	(−0.741)	5.597	**(2.726)**	1.494	(1.226)	−1.107	(−0.366)	−3.996	(−1.149)
8	4.859	**(1.831)**	−3.135	(−0.727)	5.988	**(2.820)**	1.509	(1.106)	−1.13	(−0.345)	−4.644	(−1.056)
9	5.352	**(2.091)**	−3.484	(−0.690)	6.383	**(3.082)**	1.317	(0.840)	−1.031	(−0.329)	−4.801	(−0.935)
10	5.477	**(2.206)**	−3.868	(−0.677)	6.903	**(3.735)**	1.18	(0.698)	−1.426	(−0.491)	−5.048	(−0.876)
11	5.933	**(2.364)**	−4.431	(−0.717)	6.993	**(3.689)**	1.31	(0.742)	−1.06	(−0.361)	−5.741	(−0.929)
12	6.492	**(2.671)**	−5.185	(−0.796)	6.809	**(3.709)**	1.623	(0.932)	−0.317	(−0.112)	−6.807	(−1.051)
13	6.854	**(2.683)**	−6.261	(−0.982)	6.435	**(3.608)**	1.939	(1.115)	0.419	(0.144)	−8.2	(−1.307)
14	7.53	**(2.838)**	−7.051	(−1.120)	5.993	**(3.519)**	1.901	(1.118)	1.538	(0.524)	−8.952	(−1.461)
15	7.538	**(2.940)**	−7.323	(−1.192)	5.483	**(3.323)**	2.269	(1.286)	2.055	(0.733)	−9.592	(−1.600)
16	7.484	**(3.021)**	−8.783	(−1.549)	4.792	**(2.941)**	2.368	(1.188)	2.692	(0.985)	−11.15	**(-2.013)**
17	7.376	**(3.241)**	−9.864	**(-1.777)**	4.003	**(2.394)**	1.865	(0.808)	3.372	(1.272)	−11.73	**(-2.088)**
18	7.662	**(3.403)**	−10.873	**(-2.044)**	3.344	**(1.823)**	1.305	(0.526)	4.318	(1.591)	−12.178	**(-2.198)**
19	7.562	**(3.898)**	−12.421	**(-2.481)**	3.644	**(1.889)**	0.958	(0.377)	3.918	(1.543)	−13.379	**(-2.497)**
20	8.507	**(4.832)**	−14.033	**(-2.909)**	3.442	**(1.714)**	−0.057	(−0.021)	5.065	**(2.097)**	−13.975	**(-2.594)**
21	9.471	**(5.337)**	−16.198	**(-3.612)**	4.268	**(2.145)**	−0.283	(−0.110)	5.203	**(2.222)**	−15.916	**(-3.132)**
22	9.647	**(5.172)**	−17.074	**(-3.787)**	4.867	**(2.436)**	−0.327	(−0.132)	4.78	**(2.026)**	−16.747	**(-3.314)**
23	10.219	**(5.279)**	−18.953	**(-4.140)**	5.88	**(2.984)**	−0.318	(−0.155)	4.339	**(1.863)**	−18.635	**(-3.835)**
24	11.07	**(5.554)**	−19.636	**(-4.275)**	6.297	**(3.114)**	0.542	(0.296)	4.773	**(2.105)**	−20.178	**(-4.367)**

Holding	High TIV				Low TIV				High-Low TIV			
Period	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$	*UP*	$t-stat$	*DOWN*	$t-stat$
Panel B: Returns for the Long Leg of the Momentum Portfolio (Winners) in the Non-investment Grade Subsample												
1	2.57	**(3.840)**	0.651	(0.760)	1.106	**(1.701)**	1.024	**(4.734)**	1.464	(1.609)	−0.373	(−0.433)
2	5.109	**(6.538)**	1.467	(1.429)	1.805	**(2.135)**	2.125	**(6.255)**	3.304	**(2.870)**	−0.658	(−0.609)
3	7.197	**(5.626)**	2.264	(1.285)	2.833	**(1.968)**	3.248	**(5.979)**	4.364	**(2.328)**	−0.984	(−0.533)
4	8.254	**(4.701)**	3.135	(1.206)	5.105	**(2.777)**	3.881	**(5.014)**	3.149	(1.327)	−0.746	(−0.275)
5	9.631	**(4.246)**	4.07	(1.231)	7.058	**(3.335)**	4.517	**(4.654)**	2.573	(0.907)	−0.447	(−0.130)
6	10.631	**(4.105)**	5.317	(1.368)	8.682	**(3.468)**	5.327	**(4.626)**	1.949	(0.594)	−0.01	(−0.002)
7	11.698	**(4.036)**	7.279	**(1.720)**	10.203	**(3.720)**	5.966	**(4.223)**	1.494	(0.409)	1.313	(0.298)
8	12.824	**(3.984)**	8.669	**(1.929)**	11.331	**(3.837)**	6.657	**(3.951)**	1.493	(0.365)	2.012	(0.431)
9	14.11	**(4.112)**	10.011	**(2.114)**	12.637	**(4.101)**	7.358	**(3.893)**	1.473	(0.341)	2.653	(0.541)
10	14.838	**(4.201)**	11.808	**(2.410)**	13.945	**(4.863)**	7.778	**(3.472)**	0.892	(0.213)	4.03	(0.793)
11	16.049	**(4.288)**	13.96	**(2.939)**	14.856	**(5.233)**	7.925	**(2.965)**	1.193	(0.277)	6.034	(1.215)
12	17.475	**(4.538)**	15.634	**(3.374)**	15.03	**(4.991)**	8.074	**(2.548)**	2.445	(0.549)	7.56	(1.546)
13	18.64	**(4.594)**	16.897	**(3.481)**	15.585	**(5.221)**	8.028	**(2.296)**	3.056	(0.662)	8.868	**(1.737)**
14	20.11	**(4.675)**	18.428	**(3.770)**	16.144	**(5.546)**	7.748	**(2.041)**	3.966	(0.815)	10.68	**(2.028)**
15	20.842	**(4.962)**	20.192	**(4.235)**	16.379	**(5.454)**	7.834	**(1.906)**	4.462	(0.920)	12.358	**(2.285)**
16	21.327	**(5.413)**	21.851	**(4.738)**	16.095	**(4.622)**	7.675	**(1.749)**	5.232	(1.033)	14.176	**(2.537)**
17	21.774	**(5.939)**	23.232	**(4.899)**	15.928	**(3.786)**	7.843	(1.688)	5.846	(1.063)	15.389	**(2.544)**
18	22.082	**(6.503)**	24.535	**(5.058)**	15.939	**(3.486)**	7.822	(1.592)	6.143	(1.081)	16.713	**(2.613)**
19	22.584	**(7.490)**	25.478	**(5.076)**	16.973	**(3.992)**	7.342	(1.361)	5.61	(1.077)	18.136	**(2.558)**
20	24.058	**(8.779)**	25.969	**(4.894)**	17.663	**(4.333)**	7.158	(1.280)	6.395	(1.286)	18.811	**(2.466)**
21	25.438	**(10.409)**	26.966	**(4.820)**	18.517	**(4.611)**	7.445	(1.369)	6.922	(1.424)	19.521	**(2.494)**
22	26.233	**(11.596)**	27.987	**(4.923)**	19.864	**(5.317)**	7.328	(1.354)	6.37	(1.373)	20.659	**(2.608)**
23	27.305	**(13.674)**	29.224	**(5.041)**	21.164	**(6.638)**	7.454	(1.447)	6.141	(1.526)	21.77	**(2.781)**
24	28.573	**(17.134)**	30.302	**(5.287)**	21.789	**(7.174)**	8.196	(1.637)	6.784	**(1.887)**	22.106	**(2.879)**
Panel C: Returns for the Short Leg of the Momentum Portfolio (Lossers) in the Noninvestment Grade Subsample												
1	1.328	**(3.125)**	1.154	(1.477)	0.685	**(2.175)**	0.464	(1.601)	0.643	(1.223)	0.69	(0.838)
2	2.348	**(4.893)**	2.5	**(2.088)**	1.125	**(2.336)**	1.199	**(3.000)**	1.223	**(1.800)**	1.301	(1.030)
3	3.382	**(4.692)**	4.194	**(2.108)**	1.456	**(2.210)**	2.03	**(3.206)**	1.927	**(1.996)**	2.164	(1.055)
4	4.061	**(4.759)**	6.013	**(1.920)**	2.316	**(2.819)**	2.647	**(2.939)**	1.745	(1.518)	3.366	(1.057)
5	5.252	**(4.982)**	7.078	(1.606)	3.119	**(3.038)**	3.34	**(3.060)**	2.133	(1.515)	3.738	(0.840)
6	6.092	**(5.346)**	8.54	(1.478)	3.836	**(3.206)**	3.985	**(3.145)**	2.256	(1.431)	4.554	(0.783)
7	7.208	**(5.355)**	9.781	(1.367)	4.606	**(3.430)**	4.472	**(3.156)**	2.602	(1.435)	5.309	(0.741)

Holding	High TIV				Low TIV				High-Low TIV			
Period	UP	$t-stat$	$DOWN$	$t-stat$	UP	$t-stat$	$DOWN$	$t-stat$	UP	$t-stat$	$DOWN$	$t-stat$
8	7.966	**(5.119)**	11.805	(1.401)	5.343	**(3.618)**	5.149	**(3.413)**	2.623	(1.281)	6.656	(0.794)
9	8.758	**(4.963)**	13.495	(1.425)	6.253	**(3.704)**	6.041	**(3.985)**	2.504	(1.058)	7.455	(0.798)
10	9.361	**(5.317)**	15.676	(1.517)	7.042	**(3.804)**	6.598	**(3.827)**	2.318	(0.951)	9.078	(0.900)
11	10.116	**(5.550)**	18.391	**(1.708)**	7.863	**(3.954)**	6.616	**(2.951)**	2.253	(0.884)	11.775	(1.139)
12	10.983	**(5.544)**	20.819	**(1.897)**	8.221	**(3.458)**	6.451	**(2.419)**	2.762	(0.946)	14.367	(1.391)
13	11.786	**(5.449)**	23.158	**(2.119)**	9.149	**(3.589)**	6.089	**(2.000)**	2.637	(0.840)	17.069	(1.676)
14	12.58	**(5.420)**	25.479	**(2.367)**	10.151	**(3.918)**	5.848	(1.676)	2.428	(0.733)	19.631	**(1.966)**
15	13.304	**(5.917)**	27.515	**(2.646)**	10.896	**(3.752)**	5.565	(1.485)	2.408	(0.685)	21.95	**(2.271)**
16	13.843	**(6.239)**	30.633	**(3.139)**	11.303	**(3.284)**	5.307	(1.334)	2.54	(0.640)	25.326	**(2.757)**
17	14.398	**(6.714)**	33.096	**(3.445)**	11.925	**(2.944)**	5.978	(1.599)	2.473	(0.554)	27.118	**(2.960)**
18	14.42	**(6.884)**	35.409	**(3.816)**	12.595	**(3.047)**	6.517	**(1.836)**	1.826	(0.401)	28.892	**(3.196)**
19	15.021	**(7.436)**	37.9	**(4.295)**	13.329	**(3.609)**	6.385	(1.696)	1.692	(0.412)	31.515	**(3.535)**
20	15.551	**(8.439)**	40.002	**(4.582)**	14.221	**(3.662)**	7.215	**(2.119)**	1.33	(0.317)	32.787	**(3.639)**
21	15.967	**(9.038)**	43.164	**(5.097)**	14.248	**(3.384)**	7.728	**(2.495)**	1.719	(0.384)	35.436	**(4.004)**
22	16.586	**(9.678)**	45.061	**(5.318)**	14.997	**(4.114)**	7.655	**(2.541)**	1.589	(0.400)	37.406	**(4.187)**
23	17.086	**(10.613)**	48.177	**(5.777)**	15.284	**(5.027)**	7.771	**(2.451)**	1.802	(0.531)	40.406	**(4.511)**
24	17.504	**(11.810)**	49.939	**(5.987)**	15.492	**(5.424)**	7.654	**(2.342)**	2.011	(0.651)	42.284	**(4.643)**

Appendix B: Market State for the Canadian Sample

In this paper, we show that momentum gains are strongly market-state dependent, a result that corroborates the conclusions of Cooper et al. (2004) and extends its validity from the equity to the corporate bond market. In this study, the market is in the UP (DOWN) state in month t when the average of the monthly returns of the bond market aggregate portfolio, over the year preceding month t, is above or equal (below) the sample average of EW market portfolio monthly returns.

In conducting our empirical analysis, we strived to foster consistency with the literature by focusing on commonly studied momentum strategies and examining their conditional performance according to the methodologies proposed in preceding studies. For a given month t, Cooper et al. (2004) define the UP and DOWN states on the basis of the average stock market return over the three-year preceding month t. The market is in the UP state if the three-year average is nonnegative, whereas the DOWN state occurs when the average is negative. They also show that using the one-year and the three-year market averages yield consistent results on the market state dependence of the momentum effect. We therefore examine whether momentum returns in corporate bonds also respond to stock market states.

Following Cooper et al. (2004), we define UP (DOWN) state in month t when the lagged Canadian stock market return is non-negative (negative). To do this, we evaluate the three-year (i.e. from $t-36$ to $t-1$) and one-year (i.e. from $t-12$ to $t-1$) moving averages of the TSX stock market Value Weighted (VW) Index, respectively. The results associated with the two stock market benchmarks defining the market states are tabulated in Table B.1, for both the pooled sample and the investment-grade subsample. As shown in the table, the UP and DOWN stock market states fail to predict distinctive patterns for momentum returns in corporate bonds, suggesting that the two markets are not highly integrated, which motivates the use of bond market states as the benchmark for our study.

Table B.1: Momentum Portfolio Returns Conditional on Stock Market States

The table reports conditional momentum returns in Canadian corporate bonds using lagged three-year and one-year returns of the Canadian stock market VW index as benchmarks in defining the UP and DOWN market states. Tabulated results are market-state stratified averages and their statistics, as estimated by Equation 2.2 for the pooled sample (Panels A1 and A2) and the investment-grade subsample (Panels B1 and B2). Each panel tabulates the conditional mean returns and their t-statistics for the winner and loser portfolios, as well as for the resulting momentum strategy in UP and DOWN markets. The portfolio holding periods are of 1, 3, 6, 12, 18 and 24 months. Each UP-DOWN column reports the t-statistics of the γ coefficient from Equation 2.3. This coefficient evaluates whether the stratified returns are statistically different across the market states. Panel B reports the analogous results for the investment-grade subsample. The time period covered is from August 1987 to December 2016.

Holding Period /	N (UP/DOWN)	WINNER *UP*	WINNER *DOWN*	WINNER UP-DOWN	LOSER *UP*	LOSER *DOWN*	LOSER UP-DOWN	WINNER-LOSER *UP*	WINNER-LOSER *DOWN*	WINNER-LOSER UP-DOWN
					Panel A1: Pooled Sample (3-year benckmark)					
1	314	0.933	1.26	(−1.200)	0.605	0.826	(−1.019)	0.328	0.434	(−0.442)
	38	**(10.243)**	**(4.900)**		**(8.334)**	**(4.033)**		**(4.108)**	**(1.924)**	
3	312	2.662	3.884	**(-2.349)**	1.779	2.756	(−1.638)	0.883	1.128	(−0.499)
	38	**(10.802)**	**(8.285)**		**(9.735)**	**(4.807)**		**(4.525)**	**(2.474)**	
6	309	5.335	7.571	**(-2.247)**	3.53	5.786	(−1.793)	1.805	1.785	(0.018)
	38	(8.962)	**(8.590)**		**(9.631)**	**(4.624)**		**(4.007)**	(1.780)	
12	303	10.678	14.184	(−1.580)	7.202	10.919	(−1.853)	3.477	3.265	(0.128)
	38	(7.315)	**(6.956)**		**(9.901)**	**(5.180)**		**(3.160)**	**(2.332)**	
18	297	16.459	19.363	(−1.085)	11.318	14.453	(−1.559)	5.141	4.91	(0.090)
	38	**(6.026)**	**(10.162)**		**(8.955)**	**(6.987)**		**(2.645)**	**(2.252)**	
24	291	21.869	25.972	(−1.051)	15.379	18.179	(−1.467)	6.49	7.792	(−0.391)
	38	**(5.152)**	**(8.313)**		**(8.488)**	**(9.045)**		**(2.134)**	**(2.621)**	
					Panel A2: Pooled Sample (1-year benchmark)					
1	256	0.88	1.215	(−1.732)	0.558	0.825	(−1.728)	0.321	0.39	(−0.405)
	96	**(8.796)**	**(7.329)**		**(7.010)**	**(6.247)**		**(3.657)**	**(2.679)**	
3	254	2.628	3.265	(−1.447)	1.676	2.468	**(-2.115)**	0.951	0.798	(0.407)
	96	**(9.547)**	**(9.089)**		**(8.200)**	**(7.694)**		(4.416)	**(2.514)**	
6	251	5.346	6.239	(−0.930)	3.282	5.14	**(-2.320)**	2.064	1.1	(1.217)
	96	**(8.399)**	**(7.395)**		**(8.320)**	**(7.054)**		**(4.276)**	(1.600)	

Holding Period /	N (UP/DOWN)	WINNER *UP*	WINNER *DOWN*	WINNER UP-DOWN	LOSER *UP*	LOSER *DOWN*	LOSER UP-DOWN	WINNER-LOSER *UP*	WINNER-LOSER *DOWN*	WINNER-LOSER UP-DOWN
12	251	10.907	11.588	(−0.298)	6.681	10.364	**(-2.363)**	4.226	1.223	**(1.944)**
	90	**(7.380)**	**(5.217)**		**(9.884)**	**(6.528)**		**(3.611)**	(0.962)	
18	251	16.808	16.774	(0.009)	10.748	14.594	(−1.669)	6.06	2.18	**(1.821)**
	84	**(6.245)**	**(4.558)**		**(9.977)**	**(5.930)**		**(3.015)**	(1.119)	
24	245	22.297	22.546	(−0.055)	14.795	18.492	(−1.402)	7.502	4.054	(1.175)
	84	**(5.181)**	**(4.817)**		**(9.100)**	**(6.394)**		**(2.371)**	(1.400)	
Panel B1: Investment Grade Subsample (3-year benckmark)										
1	314	0.683	1.047	(−1.344)	0.625	0.861	(−1.060)	0.058	0.186	(−0.531)
	38	**(7.468)**	**(4.103)**		**(8.294)**	**(4.098)**		(0.718)	(0.821)	
3	312	1.963	3.306	**(-2.277)**	1.843	2.701	(−1.373)	0.12	0.605	(−1.127)
	38	**(8.890)**	**(5.974)**		**(9.539)**	**(4.518)**		(0.676)	(1.531)	
6	309	3.886	6.385	**(-3.838)**	3.607	5.381	**(-1.950)**	0.279	1.005	(−0.953)
	38	**(8.223)**	**(13.374)**		**(8.904)**	**(6.115)**		(0.826)	(1.407)	
12	303	7.658	12.89	**(-4.714)**	6.9	12.581	**(-3.170)**	0.757	0.309	(0.360)
	38	**(8.725)**	**(16.491)**		**(8.380)**	**(7.164)**		(1.555)	(0.248)	
18	297	11.803	18.4	**(-3.878)**	11.06	**19.097**	**(-3.759)**	0.743	−0.697	(1.127)
	38	**(9.099)**	**(12.985)**		**(8.893)**	(8.634)		(0.995)	(−0.500)	
24	291	15.656	22.816	**(-4.098)**	15.269	22.017	**(-3.170)**	0.387	0.799	(−0.282)
	38	**(8.434)**	**(26.296)**		**(8.061)**	**(11.316)**		(0.390)	(0.419)	
Panel B2: Investment Grade Subsample(1-year benckmark)										
1	256	0.776	0.579	(1.000)	0.718	0.462	(1.586)	0.057	0.117	(−0.341)
	96	**(7.738)**	**(3.429)**		**(8.729)**	**(3.336)**		(0.645)	(0.779)	
3	254	2.305	1.589	(1.549)	2.024	1.708	(0.751)	0.281	−0.119	(1.173)
	96	**(9.562)**	**(3.967)**		**(9.782)**	**(4.524)**		(1.420)	(−0.424)	
6	251	4.216	4.063	(0.188)	3.565	4.499	(−1.200)	0.65	−0.436	(1.610)
	96	**(8.232)**	**(5.860)**		**(8.419)**	**(6.199)**		(1.767)	(−0.756)	
12	251	7.84	9.566	(−1.405)	6.655	10.297	**(-2.490)**	1.185	−0.731	**(2.081)**
	90	(8.316)	**(8.552)**		**(8.072)**	**(7.016)**		**(2.073)**	(−1.011)	
18	251	**12.005**	14.5	(−1.330)	10.459	17.055	**(-3.038)**	1.545	−2.554	**(3.086)**
	84	**(9.021)**	**(7.543)**		**(9.151)**	**(7.294)**		(1.862)	**(-2.369)**	
24	245	15.945	18.381	(−0.945)	14.257	21.846	**(-2.885)**	1.688	−3.465	**(3.244)**

Holding Period /	WINNER			LOSER			WINNER-LOSER		
N (UP/DOWN)	*UP*	*DOWN*	UP-DOWN	*UP*	*DOWN*	UP-DOWN	*UP*	*DOWN*	UP-DOWN
84	**(8.626)**	**(6.861)**		**(8.803)**	**(7.251)**		(1.428)	**(-2.743)**	

While the conditional evaluation of the momentum effect on the basis of stock market variables (e.g., sentiment and TSX VW Index) can be conducted deploying the methodologies used in preceding literature, the use of bond market conditioning variables requires some market-specific adjustments. In particular, the approach proposed by Cooper et al. (2004) to categorize market states turns out being not applicable in our 1987-2016 sample. As for the time period examined in this study, which covers almost three decades, there are very few periods in which the average return on the EW corporate bond market index is negative. Specifically, no month is categorized as a DOWN state if we use the sign of the lagged three-year bond market return to define UP and DOWN states, as done in Cooper et al. (2004) for stocks. When using the sign of the lagged one-year average, we would still get a very unbalanced sub-samples, with 336 and 5 UP and DOWN periods, respectively. Using the sign of the one-year or three-year median of the returns on the bond market EW index to separate the UP and DOWN states yield similarly unbalanced samples.

To evaluate the implications of this study's departure from the approach proposed in Cooper et al. (2004) to classify bond market states, we examine the state dependence of the benchmark equity momentum portfolio, which is available on Kenneth French's webpage.[59] Table B.2 reports the stratified averages of the stock market momentum factor according to four definitions of the UP and DOWN market states. What we find is that the methodology employed in this study makes harder to detect state dependence of the momentum factor. Presently, comparing the sample average of the return on the EW market index and the one-year average returns of the market portfolio to define the market states, as done in this study, yields a smaller spread between equity momentum in the UP vs. DOWN market states than the corresponding spread when the definition of UP and DOWN markets proposed in Cooper et al. (2004) is used. The annualized equity momentum gains stand at 10.43% and 1.41%, respectively in the UP and DOWN states, as defined in this study, over the 1987-2016 sample. These rates cor-

[59]We use the methodology of Stambaugh et al. (2012), and condition the returns on the momentum factor on the month preceding the holding period monthly return.

respond to a spread of 9.03%.[60] Over the same period, the corresponding returns for the UP and DOWN states, where these are defined as in Cooper et al. (2004), are 8.52% and -24.95%, with a spread equal to 33.47%, again in annualized percent terms.[61]

Further, we also find that the use of the one-year average market return to define the market state makes harder to detect state dependence, with respect to the use of the three-year average, employed in Cooper et al. (2004).[62] To illustrate, we consider the returns on the momentum equity factor in UP and DOWN states where the market states are defined comparing the sample average of the EW market index with the three-year versus the one-year average return on the same aggregate portfolio. Using the three-year average market return yields a spread between the average momentum gains in the UP vs. DOWN market states that is about 88% larger than the spread obtained using the one-year market return series, over the 1987-2016 sample.[63]

Summarizing, the use of the sample average of the return on the EW market index as a threshold for the one-year market return, to discriminate UP from DOWN markets, makes harder to provide evidence of state dependence for momentum than the sign of the (one or three-year) average of the EW market index return.

Turning our attention back to the corporate bond market, we note that defining the market states on the basis of the comparison of the lagged one-year average return with the sample average of returns on the EW portfolio of the bonds in our sample is both sample length dependent and ex-post. As the sample average is not in the information set of real-time investors. The use of an ex-post benchmark in defining the market states thus raises the concern that the robustness of our conclusions may be weakened by a look-ahead bias. In order to address this concern, we evaluate the market state effect using return cut-offs defined solely on the basis of information that

[60]Correspondingly, for 1929-2016 sample, equity momentum gains are 10.35% and 3.41% respectively using this study's definition of UP and DOWN states. The spread is 6.94%.

[61]The stratified momentum returns when the UP and DOWN states are defined as in Cooper et al. (2004) are 9.54% and -18.79% respectively, in the UP and DOWN states, over the 1929-2016 sample. The spread is 28.32%.

[62]As noted Cooper et al. (2004), the use of the market return average over longer vs. shorter time periods identifies market states that are more (less) extreme. However, using longer time periods also decrease the number of observations.

[63]For the 1929-2016 sample using the three-year average market returns yields a UP-minus-DOWN effect that is about 45% larger than that obtained relying on the one-year market average return.

Table B.2: State Dependence of the Stock Market Momentum Factor

	1-year		3-year	
Avg. ret. EW index	UP	DOWN	UP	DOWN
	10.43	1.41	13.63	-3.31
Sign ret. EW index	UP	DOWN	UP	DOWN
	12.84	-13.04	8.52	-24.95

Note: The table reports the stratified average returns on the equity market momentum factor, as obtained from Professor French's website. Stratification is according to the UP and DOWN market states that are defined, in the first row, by comparing the one-year average (first column) and three-year average (second column) return on the EW market portfolio with the sample average of the monthly returns on the same index. In the second row, the UP and DOWN market states are defined by the sign of the one-year average (first column) and three-year average (second column) of the monthly returns on the EW index. In this appendix, the monthly returns are gauged by the returns on the CRSP EW market portfolio for US equities.

is available to real-time investors, at the time of portfolio formation.

To begin with, we define the time-t threshold for the UP and DOWN states as the lagged average return on the EW portfolio of all bonds in our sample over the months spanning from August 1987 to $t-1$. Therefore, this benchmark is ex-ante. A portfolio formed in months t is deemed to be formed in an UP (DOWN) market if the lagged 12-month average return (from $t-12$ to $t-1$) of the EW bond portfolio is above (below) the average of the corresponding time-t return threshold. The results, reported in Table B.3, strongly support the significance of the market state effect on the profitability of the momentum strategy. Particularly, the use of the ex-ante benchmark improves the performance of the momentum strategy for investment-grade bonds in UP market states.

Table B.3: Momentum Portfolio Returns Conditional on Expanding Sample Market States

The table reports conditional momentum returns using as the benchmark in month t the lagged average return on the EW portfolio of all bonds in our sample over the months spanning from August 1987 to t-1, in defining the UP and DOWN market states. Tabulated results are market-state stratified averages and their statistics, as estimated by Equation 2.2 for the pooled sample (Panel A) and the investment-grade subsample (Panel B). Each panel tabulates the conditional mean returns and their t-statistics for the winner and loser portfolios, as well as for the resulting momentum strategy in UP and DOWN markets. The portfolio holding periods are of 1, 3, 6, 12, 18 and 24 months. Each UP-DOWN column reports the t-statistics of the γ coefficient from Equation 2.3. This coefficient evaluates whether the stratified returns are statistically different across the market states. Panel B reports the analogous results for the investment-grade subsample. The time period covered is from August 1987 to December 2016.

Holding Period /	N (UP/DOWN)	LONG UP	LONG DOWN	LONG UP-DOWN	SHORT UP	SHORT DOWN	SHORT UP-DOWN	LONG-SHORT UP	LONG-SHORT DOWN	LONG-SHORT UP-DOWN
					Panel A: Pooled Sample					
1	73	1.17	0.898	(1.310)	0.681	0.621	(0.357)	0.489	0.277	(1.185)
	267	**(6.368)**	**(9.352)**		**(4.599)**	**(8.025)**		**(3.088)**	**(3.348)**	
3	73	3.28	2.657	(1.027)	1.712	1.939	(-0.530)	1.567	0.718	**(2.122)**
	265	**(5.802)**	**(11.039)**		**(4.406)**	**(9.866)**		**(4.417)**	**(3.542)**	
6	73	6.923	5.217	(1.490)	3.417	3.9	(-0.611)	3.506	1.318	**(3.034)**
	262	**(6.297)**	**(9.064)**		**(4.776)**	**(9.233)**		**(5.348)**	**(2.953)**	
12	73	13.483	10.42	(1.493)	6.688	7.924	(-0.923)	6.795	2.497	**(3.158)**
	256	**(6.973)**	**(7.092)**		**(5.793)**	**(8.722)**		**(5.821)**	**(2.334)**	
18	73	20.264	15.835	(1.271)	10.812	11.985	(-0.499)	9.451	3.85	**(2.945)**
	250	**(6.055)**	**(5.965)**		**(5.007)**	**(8.559)**		**(5.609)**	**(2.042)**	
24	70	28.341	20.733	(1.630)	14.632	16.081	(-0.504)	13.71	4.652	**(3.343)**
	247	**(5.994)**	**(5.122)**		**(5.402)**	**(8.217)**		**(5.700)**	(1.605)	
					Panel B: Investment Grade Subsample					
1	73	1.275	0.584	**(3.279)**	1.034	0.554	**(2.750)**	0.242	0.03	(1.120)
	267	**(6.774)**	**(6.129)**		**(6.641)**	**(7.039)**		(1.430)	(0.346)	
3	73	4.148	1.594	**(6.003)**	3.28	1.596	**(3.535)**	0.868	-0.003	**(2.190)**
	265	**(10.996)**	**(7.330)**		**(7.405)**	**(8.458)**		**(2.415)**	(-0.015)	
6	73	7.841	3.22	**(7.841)**	6.048	3.23	(3.065)	1.793	-0.01	**(2.551)**
	262	**(16.992)**	**(7.395)**		**(6.654)**	**(9.041)**		**(2.718)**	(-0.029)	
12	73	12.088	7.256	**(3.607)**	9.996	6.921	(1.787)	2.092	0.335	**(1.911)**
	256	**(9.299)**	**(9.217)**		**(5.612)**	**(9.029)**		**(2.440)**	(0.663)	

18	73	16.601	11.497	**(2.438)**	14.556	11.334	(1.487)	2.045	0.163	**(2.024)**
	250	**(8.059)**	**(9.739)**		**(6.342)**	**(9.249)**		**(2.342)**	(0.203)	
24	70	22.33	14.993	**(2.373)**	19.619	15.161	(1.447)	2.711	-0.168	**(2.098)**
	247	**(7.651)**	**(9.296)**		**(6.174)**	**(8.597)**		**(2.301)**	(-0.148)	

It is conceivable that the time variation of the momentum returns, as shown in Figure 2.1, may be explained by factors outside the market being studied, such as a policy rate that reflects booms and busts of the business cycle. Therefore, as a robustness check, we define the UP (DOWN) state on the basis of the non-negative (negative) lagged three-year average monthly change of the yield spread between the 10-year and 1-year Bank of Canada Treasuries. The corresponding results, as reported in Table B.4, fail to separate the good and bad performance of the momentum strategy for corporate bonds. This finding is consistent with the conclusion in Griffin et al. (2003). The authors study the performance of the momentum strategy for equities in 40 countries (including Canada), and document that macroeconomic risk characterizing the business cycle does not account for the time variation of the momentum returns.

Table B.4: Momentum Portfolio Returns Conditional on the variable TERM

The table reports conditional momentum returns using as the benchmark in month t the lagged three-year average monthly change of the yield spread between the 10-year and 1-year Bank of Canada Treasuries, in defining the UP and DOWN market states. Tabulated results are market-state stratified averages and their statistics, as estimated by Equation 2.2 for the pooled sample (Panel A) and the investment-grade subsample (Panel B). Each panel tabulates the conditional mean returns and their t-statistics for the winner and loser portfolios, as well as for the resulting momentum strategy in UP and DOWN markets. The portfolio holding periods are of 1, 3, 6, 12, 18 and 24 months. Each UP-DOWN column reports the t-statistics of the γ coefficient from Equation 2.3. This coefficient evaluates whether the stratified returns are statistically different across the market states. Panel B reports the analogous results for the investment-grade subsample. The time period covered is from August 1987 to December 2016.

Holding Period /		LONG			SHORT			LONG-SHORT		
	N (UP/DOWN)	UP	DOWN	UP-DOWN	UP	DOWN	UP-DOWN	UP	DOWN	UP-DOWN
Panel A: Pooled Sample										
1	160	0.998	0.944	(0.313)	0.734	0.539	(1.426)	0.264	0.405	(-0.937)
	192	**(7.900)**	**(8.042)**		**(7.318)**	**(5.780)**		**(2.390)**	**(3.949)**	
3	160	3.124	2.515	(1.382)	2.404	1.439	**(2.809)**	0.72	1.076	(-1.028)
	190	**(11.028)**	**(7.324)**		**(9.537)**	**(6.061)**		**(3.435)**	**(3.826)**	
6	160	**6.194**	5.05	(1.121)	4.694	2.979	**(2.474)**	1.499	2.072	(-0.725)
	187	(11.220)	**(5.674)**		**(8.792)**	**(6.274)**		**(3.402)**	**(3.077)**	
12	158	12.309	9.982	(0.985)	9.181	6.24	**(2.228)**	3.128	3.743	(-0.345)
	183	**(11.681)**	**(4.401)**		**(10.335)**	**(5.759)**		**(3.295)**	**(2.312)**	
18	152	18.418	15.405	(0.734)	13.417	10.194	(1.644)	5.001	5.212	(-0.070)
	183	**(10.086)**	**(3.812)**		**(11.859)**	**(5.546)**		**(3.224)**	**(1.829)**	
24	150	24.355	20.621	(0.596)	16.942	14.644	(0.906)	7.413	5.978	(0.309)
	179	**(6.607)**	**(3.496)**		**(11.298)**	**(5.687)**		**(2.461)**	(1.449)	
Panel B: Investment Grade Subsample										
1	160	0.801	0.656	(0.837)	0.724	0.586	(0.973)	0.076	0.07	(0.041)
	192	**(6.385)**	**(5.522)**		**(7.026)**	**(6.000)**		(0.685)	(0.663)	
3	160	2.405	1.855	(1.352)	2.197	1.709	(1.361)	0.208	0.147	(0.190)
	190	**(7.519)**	**(7.070)**		**(8.109)**	**(6.964)**		(0.911)	(0.630)	
6	160	5.013	3.401	**(2.000)**	4.345	3.32	(1.407)	0.668	0.081	(0.992)
	187	**(8.139)**	**(6.175)**		**(7.576)**	**(6.792)**		(1.716)	(0.172)	
12	158	10.403	6.283	**(3.161)**	8.987	6.244	**(1.909)**	1.417	0.039	(1.585)
	183	**(10.992)**	**(6.234)**		**(8.467)**	**(5.785)**		**(2.000)**	(0.071)	

18	152	16	9.507	**(3.826)**	14.101	10.146	**(1.976)**	1.899	-0.639	**(2.048)**
	183	**(15.343)**	**(6.193)**		**(10.165)**	**(5.978)**		(1.632)	(-0.951)	
24	150	20.206	13.163	**(3.226)**	18.097	14.262	(1.547)	2.109	-1.099	**(2.116)**
	179	**(15.171)**	**(5.945)**		**(10.975)**	**(5.682)**		(1.444)	(-1.096)	

Table B.5: Conditional Momentum Portfolio Returns for the US and Canadian Corporate Bonds

The table reports market-state stratified averages, and their statistics, as estimated by Equation 2.2 for the TRACE sample (Panel A) and the Canadian corporate bond subsample (Panel B). Each panel tabulates the conditional mean returns and their t-statistics for the winner and loser portfolios, as well as for the resulting momentum strategy in UP and DOWN markets. The portfolio holding periods are of 1, 3, 6, 12, 18 and 24 months. Each UP-DOWN column reports the t-statistics of the γ coefficient from Equation 2.3. This coefficient evaluates whether the stratified returns are statistically different across the market states. Panel B reports the analogous results for the Canadian subsample. The time period covered is from August 2002 to December 2014.

Holding Period /	N (UP/DOWN)	LONG UP	LONG DOWN	LONG UP-DOWN	SHORT UP	SHORT DOWN	SHORT UP-DOWN	LONG-SHORT UP	LONG-SHORT DOWN	LONG-SHORT UP-DOWN
					Panel A: TRACE Sample 2002-2014					
1	58	1.429	0.716	(1.700)	0.71	0.786	(-0.213)	0.719	-0.07	**(2.014)**
	78	**(3.862)**	**(3.090)**		**(4.223)**	**(2.175)**		**(2.478)**	(-0.271)	
3	58	3.936	2.158	**(2.060)**	2.110	2.402	(-0.320)	1.825	-0.244	**(2.576)**
	76	**(5.490)**	**(4.056)**		**(6.183)**	**(2.745)**		**(2.980)**	(-0.456)	
6	57	7.334	4.252	**(1.941)**	3.861	5.115	(-0.540)	3.473	-0.864	**(2.273)**
	74	**(5.562)**	**(3.541)**		**(5.817)**	**(2.179)**		**(2.686)**	(-0.645)	
12	57	12.636	9.232	(1.220)	7.226	11.924	(-0.919)	5.409	-2.692	**(1.929)**
	68	**(5.053)**	**(3.815)**		**(7.599)**	**(2.211)**		**(2.478)**	(-0.839)	
18	57	16.103	12.774	(0.935)	10.885	19.668	(-1.282)	5.218	-6.894	**(2.236)**
	62	**(4.573)**	**(3.086)**		**(7.816)**	**(2.720)**		**(1.766)**	**(-1.964)**	
24	55	21.345	15.272	(1.228)	14.107	26.974	(-1.329)	7.239	-11.702	**(2.729)**
	58	**(5.713)**	**(2.665)**		**(9.573)**	**(2.705)**		**(2.596)**	**(-2.235)**	
					Panel B: Canadian 2002-2014 Subsample					
1	38	0.705	0.631	(0.267)	0.355	0.485	(-0.934)	0.35	0.146	(0.757)
	104	**(2.829)**	**(4.573)**		**(6.376)**	**(3.795)**		(1.502)	(1.134)	
3	38	2.178	1.827	(0.636)	1.02	1.535	(-1.411)	1.158	0.292	**(1.710)**
	104	**(4.620)**	**(5.765)**		**(7.100)**	**(4.523)**		**(2.797)**	(0.939)	
6	38	4.72	3.352	(1.529)	1.946	3.29	(-1.661)	2.774	0.063	**(3.077)**
	104	**(6.963)**	**(4.838)**		**(7.059)**	**(4.222)**		**(4.455)**	(0.098)	
12	38	8.314	6.971	(0.851)	3.817	7.09	**(-2.134)**	4.496	-0.118	**(2.836)**
	104	**(5.456)**	**(5.918)**		**(14.486)**	**(4.618)**		**(3.261)**	(-0.137)	
18	43	12.442	10.614	(0.594)	6.418	10.586	(-1.602)	6.023	0.028	**(2.430)**
	99	**(4.284)**	**(5.840)**		**(6.619)**	**(4.185)**		**(2.790)**	(0.021)	

24	45		17.373	13.422	(1.097)		8.993	14.886		(-1.658)	8.381	-1.464	**(2.949)**
	97		**(5.354)**	**(5.644)**			**(7.550)**	**(4.154)**			**(3.855)**	(-0.576)	

Appendix C: The Reversal Effect

Heston and Sadka (2008) document that returns on US stocks tend to follow a periodical pattern with the returns of a stock in each months being strongly correlated with its lagged returns in the same months over one or more preceding years. This periodic pattern suggests that if stock A performs better than stock B in any given month, then the same cross-sectional relationship over the same calendar month, which has been observed in the past, will be observed over the following years. This type of seasonality is called the cross-sectional seasonality because it describes a periodicity in the relative performance of stocks, at any given moment in time. In this appendix, I describe the methodology of the cross-sectional seasonality in Heston and Sadka (2008) in detail, an extension of which is employed in Section 3.4.1 to explore the explanatory power of two hypotheses. The examination of the cross-sectional seasonality for Canadian corporate bonds is also performed in this appendix.

Methodology

The methodological approach proposed in Heston and Sadka (2008) to examine the cross-sectional seasonality is inspired by the two-step procedure of the Fama and MacBeth regression (Fama and MacBeth, 1973). Presently, for the Canadian corporate bond sample in this paper, there are 353 months between August 1987 and December 2016. Let $t = 0, 1, \ldots, T$ be an index of time in the sample, with T equal to 352. For each given month t in the sample, and each given k lag, when $t \geq k$, I consider the following cross-sectional regression:

$$r_{b,t} = \alpha_{k,t} + \gamma_{k,t} r_{b,t-k} + e_{b,t} \text{ for } b = 1, 2.... \text{ given } t \text{ and } k, \qquad \text{(Model C1)}$$

where, $r_{b,t}$ is the excess return of bond b at time t, and $e_{b,t}$ are zero-mean disturbances.

For a given k, the same regression is evaluated $T - k + 1$ times, one for each months t in the sample with $t \geq k$. The $T - k + 1$ cross-sectional regressions yield a vector of estimated coefficients on lag-k returns,

$$\hat{\gamma}_k = (\hat{\gamma}_{k,k}, \hat{\gamma}_{k,k+1}, ..., \hat{\gamma}_{k,T}) \, .$$

The average, denoted by $\overline{\gamma_k}$, of the components of $\hat{\gamma}_k$ measures the average correlation between a given return and its k-lag. In particular,

$$\overline{\gamma_k} = \frac{1}{T-k+1} \sum_t \hat{\gamma}_{k,t}$$

is defined for $k = 1, 2, ..., 60$. Note that as the lag k increases, the number of components of the vector $\hat{\gamma}_k$ decreases.

To illustrate by providing an example, let $k = 1$. In this case, there are 352 cross-sectional regressions, defined as in Model C1, to be evaluated. Hence there are 352 components in the vector of estimated coefficients $\hat{\gamma}_1$, so that

$$\hat{\gamma}_1 = (\hat{\gamma}_{1,1}, \hat{\gamma}_{1,2}, ..., \hat{\gamma}_{1,352})$$

and

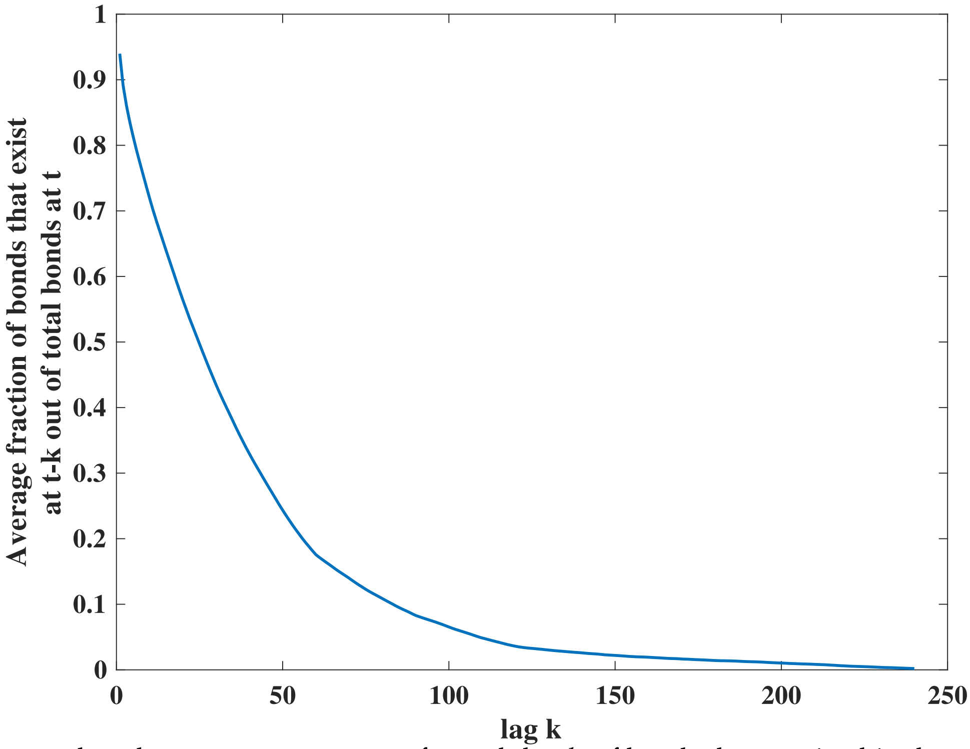
$$\overline{\gamma_1} = \frac{1}{352} \sum_{t=1}^{352} \hat{\gamma}_{1,t}.$$

In this example, the numbers of bonds included in each of the 352 lag-1 regressions are different. This difference is due to the rebalancing of bonds included in the regression for different months due to, say, the lack of lagged returns. That is the subset of bonds that have observations at time t and $t-1$ varies for each $t = 1, 2, \ldots, 352$.

Plot of Sample Size

For a given lag k and time $t \geq k$, I define two subsets of bonds, with subset B_t containing all bonds with observations at time t, and B_{t-k} containing all bonds with observa-

Figure C.1: Diagnostics of Sample Size



The figure plots the average percentage, for each lag k, of bonds that survived in the sample. The plot can be used for the inference of the cutting point of the number of lags to use for the cross-sectional seasonality regressions.

tions at time $t-k$. The percentage $p^k(t)$ is then defined by

$$p^k(t) = \frac{\cap(B_t, B_{t-k})}{B_t},$$

which is the ratio of the number of bonds in B_{t-k} that is also in B_t to the number of bonds in B_t. The average fraction for lag k is therefore $P^k = \frac{1}{T}\sum_{t=1}^{T} p^k(t)$. Figure C.1 plots the variation of the value P_k with the number of lags k.

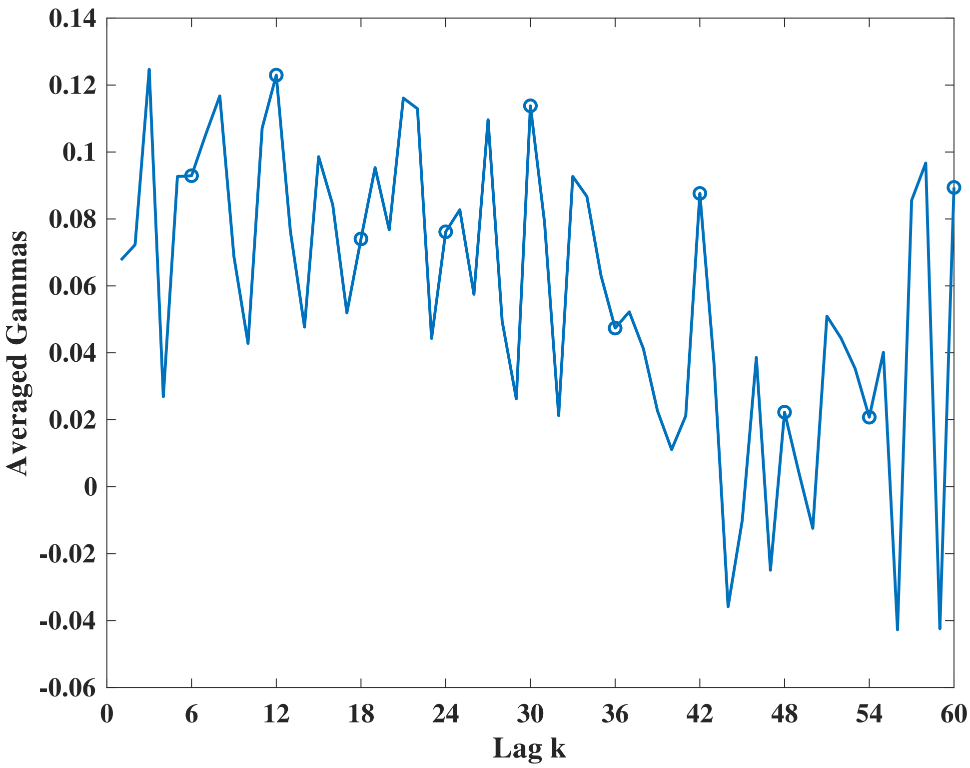
To illustrate, the value P^{100} is the average percentage of bonds included in the regressions of returns on their 100th-month lags. By necessity, these bonds maturity is of at least eight years. In the sample, the average fraction of bonds available in P^{100} is less than 10%, which is less than 240 bonds even considering the whole sample size of 2,317. In another special case, the value P^6 is the average fraction of bonds used in the regressions of returns on their 6th-month lags. Almost all bonds in the sample have at least six observations, so $p^6(t)$ should include most bonds in the sample, while P^6 being the averaged $p^6(t)$ is reasonably high.

In their evaluations, Heston and Sadka (2008) considered lags up to 20 years because most stocks in their sample are observable throughout the sample period. However, as shown in Figure C.1, as bonds drop off the sample naturally after reaching maturity, the cross-sectional seasonality analysis for Canadian corporate bonds in this study has to limit to a shorter number of lags. Therefore, in regressions specified in Model C1, I look at results for lags up to 60 (5 years) to foster the accuracy of the estimates of the coefficients on the lagged returns.

Cross-Sectional Seasonality

Figure C.2 below plots the average coefficient on the lagged returns of the univariate regressions of Model C1, across the bonds in the sample, for lags from one to sixty. Contrary to the findings documented in Heston and Sadka (2008) for the US stock market, no apparent cross-sectional periodic pattern can be detected for the Canadian corporate bond returns.

Figure C.2: Average Return Responses Over Different Lags



The figure plots, for each lag k, the averaged gammas obtained from Model C1.