Data Uncertainty in Corporate Bonds*

Gergana Jostova† Stanislava Nikolova‡ Alexander Philipov§

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ABSTRACT

We study the impact of data uncertainty in corporate bonds on decision making. We provide a taxonomy of data choices a researcher is compelled to make when constructing a sample of monthly corporate bond returns, and investigate the impact of these choices on the researcher's conclusions. Using momentum as a case study, we show that different but reasonable data choices may lead to conflicting findings about a strategy's profitability and thus result in data uncertainty. We propose a Bayesian decision-making framework for a researcher faced with data uncertainty.

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†George Washington University, Washington, DC 20052; email: jostova@gwu.edu.
‡University of Nebraska-Lincoln, Lincoln, NE 68588; email: snikolova2@unl.edu.
§George Mason University, Fairfax, VA 22030; email: aphilipo@gmu.edu.

Empirical studies make numerous choices about data sources, sample selection, and variable construction. The multitude of choices creates uncertainty about the extent to which samples reflect the true underlying data. This 'data uncertainty' has not been fully recognized in the literature. Rather, upon finalizing their sample, researchers usually proceed under the assumption that they are working with the 'true' data with probability one. Our paper takes a probabilistic approach to sample formation by explicitly recognizing the possibility that different studies may be analyzing different samples. Our approach is motivated by studies on 'model uncertainty' and 'estimation uncertainty' that adopt probabilistic views on the choice of an asset-pricing model and the veracity of the model's parameter estimates, respectively.[1]

Data uncertainty is especially salient for corporate bonds. For equities, returns calculated in a standard manner are readily available from the Center for Research in Security Prices (CRSP). This is not the case for corporate bonds for several reasons. Unlike equities, most corporate bonds trade in a fragmented over-the-counter market, complicating the consolidation of trading information. Dealers report their trades to the Trade Reporting and Compliance Engine (TRACE) since 2002, but having trades reported by an agglomeration of market participants instead of being recorded by a centralized exchange creates the potential for data entry errors and the need for researchers to decide how to filter these out.[2] Corporate bonds also trade at large bid-ask spreads, making bid-ask bounce and other microstructure issues a bigger concern than for equities; researchers then have to decide which noisy estimate of end-of-day price to choose. Unlike equities, corporate bonds trade infrequently, making it unlikely that a price is available on the last trading day of a month, forcing researchers to decide how to approximate a missing end-of-month price. While for equities delisting returns are readily available, default-month returns, viewed as their corporate bond counterpart, are

[1] Pástor and Stambaugh (2000) take a Bayesian approach to comparing asset pricing models, while Avramov (2002) proposes a Bayesian decision model for probability weighting candidate asset-pricing models. Kandel and Stambaugh (1996), Barberis (2000), and Lewellen and Shanken (2002) address parameter uncertainty by proposing a Bayesian model for investor portfolio allocation decisions. Tu and Zhou (2004) use Bayesian analysis to address the uncertainty that data is generated from a population model with a normal distribution.

[2] In 2023, 901 unique dealers reported secondary market trades in corporate securities to TRACE. See 2023 TRACE Fact Book, Participant Information, Table C9, www.finra.org/filing-reporting/trace/trace-fact-book.

often missing and researchers have to decide whether and how to estimate them and whether to include trading post default.[3] In sum, the decentralized and infrequent trading of corporate bonds compels researchers and third-party data providers to make numerous data choices, giving rise to data uncertainty.

In this paper, we study the implications of this data uncertainty for investors' trading strategies and decision making.[4] To do so, we use corporate bond data from TRACE from July 2002 through June 2023. While there are alternative data sources based on dealer quotes or proprietary model valuations (e.g., ICE BofA, Bloomberg, DataStream), we choose TRACE because unlike these sources it is freely accessible by researchers and investors, covers all traded bonds regardless of whether they are index constituents, and sources data from actual trades. Furthermore, constructing a monthly return from the raw trade prices in TRACE illustrates the many data choices a researcher is compelled to make; these data choices would be masked, but not eliminated, if we were to use quote- and valuation-based data sources where the data provider would have already made them.

We build a taxonomy of data choices by chronologically following the process of constructing a sample of monthly corporate bond returns and referencing existing bond studies. Our main takeaways are twofold. First, researchers make reasonable but often different data choices that may result in analyzing distributionally different data samples. To illustrate, with the 11 data choices in our taxonomy and 2 or 3 reasonable ways to make these choices, there would be between $2^{11} = 2,048$ to $3^{11} = 177,147$ different data samples, potentially leading to different conclusions. Second, since each data choice presents a tradeoff, there cannot be a single perfect way to construct a bond sample. This is what gives rise to data uncertainty.

We investigate the impact of data uncertainty on researchers' conclusions about the profitability of investment strategies. We focus on one such strategy, momentum, which makes for

[3] Jankowitsch, Nagler, and Subrahmanyam (2014) and Baumann et al. (2024) provide evidence of active trading after default, while most corporate bond studies, including all that use the TRACE-based Bond Returns Database constructed by the Wharton Research Data Services (WRDS), exclude returns after default.

[4] Bond investment strategy profitability is important given the size of the corporate bond market ($11 trillion, SIFMA 2Q2023 Corporate Bond Statistics sifma.org/resources/research/us-corporate-bonds-statistics).

a suitable case study for at least two reasons. First, a momentum strategy relies on extreme returns (winners and losers), which renders it particularly susceptible to data choices. Second, the empirical evidence on corporate bond momentum profitability is a subject of continued interest. Gebhardt, Hvidkjaer, and Swaminathan (2005b) find no momentum in investment grade [IG] bonds, while Jostova, Nikolova, Philipov, and Stahel (2013) [JNPS] find significant momentum among non-investment grade [NIG] bonds. Subsequent studies of momentum using different data sources, time periods, and sample construction approaches, largely confirm these findings, but some disagreement remains.[5]

We use our data-choice taxonomy to create more than 200 bond return samples and examine the distribution of returns and momentum profitability in these samples.[6] We focus on (3,3) and (6,6) momentum strategies in NIG bonds, since JNPS find that momentum is limited to NIG bonds and declines as the formation and holding periods increase.[7] Our analyses reveal that researchers' data choices can have a large impact on the distribution of returns. Across all samples, the mean monthly return varies between 0.35% and 0.54%, the standard deviation is between 3.32% and 5.12%, and the maximum return is between 8 and 80 standard deviations away from the mean. Momentum profits vary as well: they range between 0.37% and 1.64% with a mean of 0.80% for the (3,3) momentum strategies, and between 0.11% and 1.77% with a mean of 0.65% for the (6,6) momentum strategies.[8] Surprisingly, the conclusion on whether a momentum strategy is profitable or not could depend on the different treatment of as few as 0.012% of the more than 1.4 million available bond return observations.

We propose a decision-making framework for an investor faced with data uncertainty. We take a probabilistic approach to whether a sample and its momentum profits are the truth.

[5] Bali, Subrahmanyam, and Wen (2017), Houweling and Van Zundert (2017), Ho and Wang (2018), Israel, Palhares, and Richardson (2018), Li and Galvani (2018, 2021), Lee, Naranjo, and Sirmans (2021), and Liu, Wang, and Wu (2023) offer evidence on corporate bond momentum. Section II.A and Appendix A elaborate.

[6] The paper also references 400+ additional samples and 4,800+ profit estimates analyzed in Appendix B.

[7] Following Jegadeesh and Titman's (1993) notation, a (J,K) momentum strategy is based on a J-month formation and a K-month holding period. We skip a month between the formation and holding periods. We also report results for (9,9), (12,12), (3,1), (6,1), (9,1), and (12,1) momentum strategies among NIG bonds.

[8] While our focus is on NIG momentum, for comparison, we check for momentum in IG bonds—IG momentum is unprofitable in all 200+ samples, (3,3) momentum profits average −0.03% and range between −0.13% and 0.04%. For (6,6) IG momentum profits, the average is −0.09% and the range is from −0.18% to 0.004%.

Under Bayes rule, an investor can form a posterior probability-weighted estimate of momentum profits across many plausible data samples. The Bayesian approach naturally accounts for the uncertainty in the data as well as the uncertainty in the model parameters by providing a posterior distribution of momentum profits for each data sample and across samples after 'learning' from the data. The advantage of this approach over comparing mean profit estimates from multiple samples, is that by observing the joint posterior distribution of profits across samples, an investor can perform statistical inferences to evaluate the probability of observing a particular point estimate. The Bayesian approach also allows for imposing subjective priors that reflect the researcher's beliefs that some data choices are more reasonable than others.

To provide the parametric framework underlying the Bayesian approach, we propose a novel regression model to estimate momentum profitability from non-overlapping monthly cross-sections of returns that replicates the portfolio assignment from our (non-parametric) portfolio averaging analyses. Our regression setup offers additional insights into the relative contribution of each month of the holding period as well as the impact on momentum profits of the consistency with which a bond appears in consecutive momentum strategies.[9] The mean of the joint conditional posterior distribution of momentum profits is 0.57% (0.67%) [0.69%] when (3,3) strategies are implemented within dozens of individual (equally weighted firm-level) [value-weighted firm-level] bond samples. None of the draws in any of the samples produces negative profit estimates. Profit estimates tend to be smaller from the (6,6) strategies, at 0.55% (0.55%) [0.55%].[10] We interpret this as evidence that momentum strategies in NIG bonds are viable.

Our paper contributes to several strands of literature. First, it adds a new dimension—data uncertainty—to research of asset-pricing uncertainty. In the spirit of Avramov (2002), who studies 'model uncertainty', and Kandel and Stambaugh (1996) and Barberis (2000), who study 'estimation uncertainty', we offer a Bayesian decision-making framework to ad-

[9]We estimate our model using Markov Chain Monte Carlo [MCMC] simulations via the Gibbs sampler.

[10]In contrast, for IG bonds, our Bayesian model estimates average profits of 0.06% (0.03%) [0.02%] for (3,3) momentum (all indistinguishable from zero) and −0.03% (−0.03%) [−0.03%] for (6,6) momentum.

dress data uncertainty. Second, our paper contributes to studies examining replicability in asset pricing, and specifically in bond pricing. Several contemporaneous studies argue that conflicting results are in part due to variation in data choices and each proposes a unique clean dataset as the solution to the replicability problem.[11] Yet, when constructing such a dataset, the authors make various data choices that have reasonable alternatives. While we agree on the driver of the replicability problem in bond pricing, we differ in the proposed solution: we argue that a single perfect bond sample may be unattainable, and therefore an investment strategy's profitability should be assessed through the distribution of outcomes across a collection of plausible samples. This view is in the spirit of Menkveld et al. (2024), who show that researchers may take different paths to address the same research question and arrive at different answers. While their focus is on differences in methodologies applied to the same sample, our focus is on differences in samples while using the same methodology. Third, since we use corporate bond momentum as a case study for data uncertainty, we effectively present a spectrum of sensitivity analyses for the profitability of this anomaly. Surprisingly, data choices that affect a tiny fraction of observations may obfuscate potentially large strategy profits. We interpret this as confirmation that overlooking data uncertainty may lead to incomplete inferences and to suboptimal investment advice. While our framework for decision-making under data uncertainty is cast in an investment setting, the framework carries to other settings where corporate bond data is used. Finally, by presenting a taxonomy of data choices inherent to empirical corporate bond research and describing the tradeoffs that each choice presents, we hope to facilitate better informed data choices in future corporate bond work.

[11] For example, both Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2023) and Dickerson, Robotti, and Rossetti (2024) construct a sample of TRACE-based bond returns by making reasonable but different data choices, each believing their sample construction approach to be the best. Their respective samples seem to contain a vastly different number of observations over largely the same sample period (more than 25% difference) and lead to different asset-pricing conclusions. The latter study does not report descriptive statistics, so we infer the sample size from the October 2023 'full bond-level panel' data posted online.

I. Taxonomy of Corporate Bond Data Choices

In this section, we build a taxonomy of data choices facing a researcher when constructing a sample of monthly corporate bond returns. We draw from the literature on corporate bond asset pricing to illustrate the variation in these choices and highlight their tradeoffs.

I.A. Choice of Data Source

Corporate bond researchers use a variety of data sources for prices and returns. Some sources rely on information from trades, others on information from dealer quotes, and yet others combine trade and quote information into valuation estimates. Because corporate bond trades are infrequent and quotes are indicative, the choice of data source presents a tradeoff. Prices in trade-based sources reflect up-to-date market valuations but result in a smaller sample. While prices in quote and valuation-based sources may produce larger samples because they are available in the absence of trading, they may not represent true trading opportunities.[12]

TRACE is the most widely used trade-based data source. Since July 2002, dealers are required to report to TRACE all trades in eligible securities, but the public dissemination of trades was phased in to minimize market disruptions. Initially, only trades in large IG bonds were disseminated, then in smaller IG bonds, and finally in NIG bonds. *Standard TRACE* provides information about disseminated trades, but masks trade sizes larger than \$5m (\$1m) in IG (NIG) bonds. *Enhanced TRACE* provides information about both disseminated and non-disseminated trades with unmasked trade sizes, but with a 6-month lag.[13] Another trade-based data source is insurance company trades provided by the *National Association of Insurance Commissioners [NAIC]*. While *NAIC* covers a longer time period than TRACE, it represents only a fraction of total trading, so its usage has declined after TRACE's introduction.

[12] Goldstein, Hotchkiss, and Nikolova (2024) show that a year after issuance, less than half of bonds trade and among bonds that trade the median number of trades is 4. Harris (2015) and Hendershott et al. (2024) find that dealers execute more than a quarter of trades at a price worse than the last available quote.

[13] Two other versions of TRACE are *Academic TRACE*, which attaches an anonymized dealer identifier to *Enhanced TRACE*, and *Regulatory TRACE*, which attaches the actual dealer name.

Among quote and valuation-based data sources, we detect no clear preference among researchers. Early studies (e.g., Khang and King 2004 and Gebhardt, Hvidkjaer, and Swaminathan 2005a,b) use the *Lehman Brothers* database, later re-branded as the *Barclays* database, which provides month-end dealer bid quotes for bonds part of the Lehman Brothers (Barclays) indices. Recent studies (e.g., Kelly, Palhares, and Pruitt 2023, and Bektić et al. 2019) employ the *Bank of America* database, later referred to as the *Bank of America Merrill Lynch* and most recently *ICE BofA* database, which provides month-end valuations of Bank of America index constituents based on proprietary valuation models. Two other bond data sources, *Bloomberg* and *DataStream*, combine information from TRACE-reported trades, dealers, and proprietary valuation models to estimate month-end valuations (both used in JNPS and Ho and Wang 2018). Unlike *Barclays* and *ICE BofA*, *Bloomberg* and *DataStream* have wider market coverage, not limited to corporate bond index constituents. While researchers using quote and valuation-based sources do not need to decide how to aggregate intra-day prices into a daily price and which daily price to use as the month-end price, choices are still being made but by the data provider instead.

I.B. Choice of Bond Types and Characteristics

Unlike equities, bonds can be of various types and may have different characteristics. It is common for bond researchers, for various reasons, to implement filters based on bond types and/or characteristics. Some filters are ubiquitous—most researchers exclude convertible bonds and bonds with less than a year to maturity—while others vary across studies. For example, Chordia et al. (2017) limit their analyses to senior unsecured corporate bonds and mention no additional filters based on bond characteristics. In contrast, Ho and Wang (2018) eliminate a long list of bonds: bonds that are not U.S.-dollar denominated, bonds with a floating rate, bonds with Rule 144A restrictions, index-linked bonds, asset- or mortgage-backed bonds, convertible bonds, and bonds with warrants or embedded options, such as callable bonds. Similarly, Lin, Wang, and Wu (2011) exclude unrated bonds, bonds with less than 1 year to maturity, bonds with embedded options or sinking funds, floaters, bonds with a non-standard coupon payment frequency, among others. Notably, studies that use a data source linked to a corporate bond index (e.g., Barclays or ICE BofA), effectively filter out bonds whose characteristics make them ineligible for index inclusion.

I.C. Constructing a Daily Price

Researchers using a trade data source such as TRACE need to construct a daily price from intra-day prices. In equities, it is standard to use the closing price of the day. For corporate bonds, Bessembinder, Kahle, Maxwell, and Xu (2009) show that a daily price based on the trade-size weighted average of intra-day prices is less noisy than the last price of the day and helps minimize bid-ask bounce. Thus, the corporate bond literature typically uses a trade-size weighted average. A modification is to exclude small-size trades before taking the average, since such trades have large bid-ask spreads. For instance, Bali, Subrahmanyam, and Wen (2017) remove trades of less than $\$10,000$ par value, and Chung, Wang, and Wu (2019) and Chen and Choi (2024) remove trades smaller than $\$100,000$ par value.

I.D. Constructing a Month-End Price

A researcher using trade price data needs to decide which daily price would be an accurate representation of the month-end price. In the equity market where securities trade daily, the answer is clear—use the daily price on the last trading day of the month. In the corporate bond market, a small percentage of bonds trade in a given month, and from those that trade, only some trade on the last trading day of the month. Below we describe five alternative data choices in determining a month-end price that we have observed in the literature.

Like equity researchers, one can focus on daily prices on the last trading day of the month, utilizing the most up-to-date information, but this results in a smaller sample. To construct a larger sample, some researchers use the last daily price in a month as the month-end price regardless of the day of the month on which it takes place (e.g., October 8 or October 28; see Li and Galvani 2018, Galvani and Li 2023, and Liu, Wang, and Wu 2023). This approach omits information revealed after the last trade but before month-end and thus may misrepresent an investor's true monthly return. To compensate for this shortcoming, some interpolate the last price of the month and the first price of the following month (Lin, Wang, and Wu 2011, Lin, Wu, and Zhou 2018, and Chung, Wang, and Wu 2019), although using information past the month's end introduces look-ahead bias. A fourth alternative, employed by Bartram, Grinblatt, and Nozawa (2023), utilizes the martingale property to approximate beginning-of-month and end-of-month prices by extrapolating from middle-of-month prices. This approach avoids a look-ahead bias, but omits some information arriving between a month's last trade and next month's first trade. A fifth and most common approach is to use the last daily price within the last 5 trading days of the month (e.g., JNPS, Chordia et al. 2017, Lee, Naranjo, and Sirmans 2021, and Bredendiek, Ottonello, and Valkanov 2023). This approach is intended to strike a balance between sample size and up-to-date price information.

Figure I visualizes the tradeoff among alternative month-end price choices by displaying the time-series of the number of TRACE *price* observations over our sample period under each choice. Using the last price within the last 5 trading days (P_L5M) nearly doubles the sample size relative to using the price from the last trading day of the month (P_LDM), but more than halves it relative to using the last price of the month (P_EOM, Section II.C elaborates). Moreover, we notice a pronounced seasonality in the number of observations when requiring bond trades towards month-end: December end-of-month price observations display a visual drop (by 14%) relative to other months. Since a monthly return requires two consecutive monthly prices, December and January returns observations tend to be fewer (by 10%). This can be seen in Appendix B Figure B.I, which presents the time-series of the number of *return* observations under alternative end-of-month price choices.

I.E. Determining Trading Days

Most corporate bonds do not trade on exchanges with well-defined trading days. Hence a researcher needs to decide whether a day on which a corporate bond trades should be considered a trading day. While we are unaware of a study that discusses this decision, our conversations with researchers indicate that there are three approaches. One approach is to extract trading days from equity market data (CRSP) and assume that when stock markets are closed, corporate bonds should not trade either. A second approach, used by WRDS to construct its Bond Returns Database, is to rely on trading days extracted from Treasury market data, and again assume that Treasury bonds and corporate bonds share a trading calendar. A third approach is to treat every day with a reported trade in TRACE as a trading day. We find that doing so would include half of the Sundays from July 2002 through June 2023 in the analysis. Under this approach, the number of end-of-month return observations based on the last five trading days would drop sharply, because many of these Sundays would be included in the five 'trading' days, yet only a few bonds trade on Sundays.

With the first two approaches, researchers need to decide how to handle trades reported on a non-trading day. One choice is to exclude them from the sample—as does WRDS in the construction of its Bond Return Database—which results in loss of trading information. Another choice is to treat them as having taken place on the first trading day following the trade. Since corporate bonds do trade when stock or Treasury markets are closed this is another material choice that corporate bond researchers have to make.[14]

I.F. Choice of Price Filters

The next data choice facing a corporate bond researcher is whether and how to filter out price entry errors. Such errors might have a disproportionately large impact on returns because

[14] In 2022, 1.2% of TRACE trades were executed outside of regular business hours or on non-business days. See FINRA press release: www.finra.org/sites/default/files/2024-01/sr-finra-2024-004.pdf.

bonds are thinly traded, making the effect of a single incorrect price consequential.

Corporate bond researchers have taken a number of approaches to identify price entry errors. Some implement filters on intra-day prices, others on daily prices, and still others on monthly prices. Broadly speaking, price filters in existing studies are of two main types. The first and most common type is to identify large price reversals under the assumption that an incorrect high (low) price will result in a large price increase (decrease), followed by a large price decrease (increase) when the price is recorded back at its correct level. Researchers then either eliminate the two resultant incorrect returns or exclude a bond that experiences such a reversal. For instance, Gebhardt, Hvidkjaer, and Swaminathan (2005b) exclude all observations of a bond for which a return greater than 95% in one month is followed by a return less than −45% in the subsequent month, or vice versa. Ho and Wang (2018) use a symmetric threshold and remove instances where 20% or greater monthly returns are followed by 20% or greater monthly returns of the opposite sign. Chordia et al. (2017) delete a day-t return if $R_t R_{t-k} < -0.02$ for $k = 1, ..., 12$. Similarly, Bartram, Grinblatt, and Nozawa (2023) remove consecutive monthly returns if $R_t R_{t-1} < -0.04$.

The second approach to filtering out price entry errors is by detecting price outliers. Bali, Subrahmanyam, and Wen (2017) regard prices (expressed as a percent of par) outside the $(5, 1000)$ range as data entry errors and remove all observations for a bond that trades outside this range. Chordia et al. (2017) exclude corporate bond month-end prices that are higher than that of a matching Treasury bond but retain other observations for that bond.

One limitation of the above approaches to identifying price entry errors, is that they may incorrectly flag a correct price as incorrect and exclude the related returns. Another limitation is that, even after removing the incorrect price and related returns, a researcher is still missing the correct ones.

I.G. Calculating a Monthly Return

The next data decision a corporate bond researcher makes is how to calculate monthly returns. The most common approach is to define a return as:

$$R_t = \frac{P_t + AI_t + C_t}{P_{t-1} + AI_{t-1}} - 1 \tag{1}$$

where P_t is the price at month-end t, AI_t is accrued interest at month-end t, and C_t is the coupon paid between month-ends $t-1$ and t. While almost all studies use this approach, in an attempt to retain more monthly return observations, Bali, Subrahmanyam, and Wen (2017) identify three scenarios for a return to be realized at the month-end t: (1) from the end of month $t-1$ to the end of month t, (2) from the beginning of month t to the end of month t, and (3) from the beginning of month t to the beginning of month $t+1$.[15]

I.H. Choice of Return Filters

Since price filters eliminate some, but likely not all, data entry errors, the researcher has to decide whether and which return outliers to treat as erroneous. To err on the conservative side, some researchers assume that at least some return outliers result from data entry errors and winsorize or exclude them using various thresholds.[16] Galvani and Li (2023) explores how winsorizing or eliminating return outliers at 2 different thresholds affects momentum profits.

An alternative to winsorizing or eliminating returns outliers is to validate the data's accuracy. An easy-to-replicate outlier-validation method (proposed here) is to verify return outliers against an alternative commercially available database (*DataStream* in our case). Our

[15] Khang and King (2004), an early study of corporate bond momentum, does not account for accrued interest and defines a month-t return as "the difference between the bond price in month $t-1$ and t plus coupon payment (if any) divided by the price in month $t-1$." Notably, when accounting for accrued interest, researchers should recognize that on a given day either accrued interest or a coupon is received but not both.

[16] Momentum studies that implement return outlier winsorization or trimming include Pospisil and Zhang (2010), JNPS, Lee, Naranjo, and Sirmans (2021), and Li and Galvani (2021). Other corporate-bond asset-pricing studies that also follow this approach include Kelly, Pruitt, and Su (2023), Bali, Beckmeyer, Goyal, and Wen (2023), Bai, Bali, and Wen (2023), and every study that uses the WRDS Bond Return Database.

approach excludes monthly return outliers that are either more than two standard deviations away or missing in the alternative data source. Instead, Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2023) propose a manual validation of the 5,000 largest returns in absolute value in their sample. They employ a team of research assistants to independently determine if an outlier is erroneous based on factors such as the price pattern, price volatility, unusual volume, prices of other bonds of the same firm, etc. Their validation process results in eliminating as data entry errors only 5.84% (292 returns) of the examined suspect data.

It is important to recognize the tradeoff of these approaches. Winsorizing does not eliminate data entry errors but aims to reduce their impact, while retaining more data points. Excluding outliers eliminates large entry errors at the cost of reducing sample size. Both approaches share a notable limitation: they may unnecessarily treat a correct return, which could have been influential given its magnitude. Manual validation is commendable given the effort it requires, but may be difficult for a researcher to implement and replicate. Finally, none of these approaches replaces an incorrect return with a correct one, hence none of them produces a sample that is both complete and error-free.

I.I. Treatment of Default-Month Returns

Default has a large effect on corporate bond returns—Davydenko, Strebulaev, and Zhao (2012) find default-month returns average -16.2%. Because default-month returns may be missing (we find about 40% of them are) or impacted by data entry errors, deciding how to handle them is an important data choice.

The treatment of default-month returns varies across studies. One approach is to use default-month returns that can be calculated and leave the rest as missing.[17] The drawback is that this approach may overestimate the return to a strategy that is long bonds, which subsequently default, since their returns are on average negative. A second approach, is to

[17] Many corporate bond papers do not discuss how defaulted bonds are treated, which implies that they only include default-month returns that can be calculated (JNPS, Chordia et al. 2017, Bai, Bali, and Wen 2021).

compute the average (or median) default-month return for all IG (NIG) bonds with available price data and replace missing default-month returns for all IG (NIG) bonds with this average (or median) (Chen and Choi, 2024). A third approach, adopted by WRDS when constructing its Bond Return Database and Bali, Subrahmanyam, and Wen (2021), is to replace both missing and non-missing default-month returns with this average (or median). The drawback of the last two approaches is that the average (or median) default-month return could be based on a few observations, some possibly data entry errors, and then be assigned to many bonds.

In addition to which default-month return to use, the return calculation itself requires a choice: include or exclude accrued interest. It is common industry practice that bonds begin to trade "flat" (i.e., without the inclusion of accrued interest) when there is significant uncertainty about the issuer's ability to continue making scheduled payments on time and in full. Default would likely create such uncertainty, hence equation (1) would change to:

$$R_t^{DM} = \frac{P_t}{P_{t-1} + AI_{t-1}} - 1 \tag{2}$$

Indeed, Bartram, Grinblatt, and Nozawa (2023) and Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2023) account for flat trading when calculating default-month returns. Nonetheless, the Bond Market Association clarifies that default is neither a necessary nor a sufficient trigger for a bond to trade flat: events other than default can be triggers and default is not an automatic trigger.[18] Credit enhancements, sinking funds, and other bond features may allow an issuer to continue to make payments even after an event that would typically trigger flat trading occurs. Thus, unless a researchers knows the precise circumstances of a trade, they cannot know with certainty whether a default-month return should be calculated as in equation (1) or (2), making it challenging to construct an entirely error-free return sample.

[18] www.sifma.org/wp-content/uploads/2017/08/Corporate-Credit-and-Money-Markets_Practice-Guidelines-for-Trading-in-Distressed-Bonds.pdf.

I.J. Treatment of Trading after Default

Since many corporate bonds continue to trade post default, a researcher needs to decide how to handle post-default-month returns.[19] The most common approach is to exclude such returns, which parallels the treatment of equities post exchange delisting, using the default date in Mergent's Fixed Income Securities Database (FISD) as the default marker. Since some studies do not explicitly state that trades after default are excluded, it seems that at least some researchers retain returns post default in their sample. Another approach is the one used by Bartram, Grinblatt, and Nozawa (2023), who exclude defaulted bonds when forming their trading strategy but retain their returns when bonds default during the holding period.

I.K. Bond-Level versus Firm-Level Returns

Because many firms have multiple bonds outstanding, unlike equity researchers, corporate bond researchers need to decide whether to analyze bond or firm-level returns. Some studies use individual bond returns (Chordia et al. 2017[20], Gebhardt, Hvidkjaer, and Swaminathan 2005b), others use firm returns constructed by equally or value-weighting individual bond returns (Gebhardt, Hvidkjaer, and Swaminathan 2005a, Choi and Kim 2018), and still others use both (JNPS). This choice represents a tradeoff between sample size and the potential to reduce data errors and noise through aggregation. If data errors and noise are randomly distributed across firms, averaging individual bond returns at the firm level may reduce their effect and produce a cleaner sample. Conversely, if data errors are more likely for firms with few bonds, then these errors will be over-represented at the firm level. Notably, the choice between individual and firm-level samples depends on the researcher's question: individual bond analyses describe the typical bond (thus overweighting the impact of firms with many, sometimes hundreds of, bonds) while results based on firm-level samples describe the typical

[19] Jankowitsch, Nagler, and Subrahmanyam (2014) and Baumann et al. (2024) analyze trading post default.

[20] For robustness, the study also reports results using one randomly selected bond per firm.

firm (giving more weight to firms with fewer bonds relative to individual bond samples).

In sum, the discussion above underscores the many data choices a corporate bond researcher is compelled to make when constructing a sample of returns. These data choices could produce thousands of data samples. But are these samples distributionally different? Do they result in different investment advice? We attempt to answer these questions next.

II. The Impact of Data Uncertainty

This section examines the impact of data uncertainty in corporate bonds. We construct more than 200 samples motivated by our data choice taxonomy and investigate the return distribution and momentum profitability in these samples.

II.A. Existing Evidence on Bond Momentum

Early studies, using mostly IG price quotes from the *Lehman Brothers* database, find no evidence of momentum in corporate bonds (Khang and King 2004 and Gebhardt, Hvidkjaer, and Swaminathan 2005b). In contrast, with samples spanning all credit risk categories, Pospisil and Zhang (2010) and JNPS show that momentum strategies are profitable but only among NIG bonds.[21] While most subsequent studies corroborate the profitability of momentum strategies, there is recent disagreement that seems to be related to data choices.[22] Appendix A summarizes the existing evidence on corporate bond momentum, as well as the choices of data source, sample period, month-end price, and outlier treatment.

[21] Pospisil and Zhang (2010) use Bloomberg data on constituents of the Merrill Lynch US Board Corporate Index and US High Yield Index. JNPS combine data from five sources: (1) *Lehman*, (2) *DataStream*, (3) *Bloomberg*, (4) *NAIC*, and (5) *Standard TRACE* (TRACE comprises 13% of their full sample).

[22] Using only Enhanced TRACE as the data source, Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2023) confirm positive momentum under JNPS' other data choices but not under some alternatives. Dickerson, Robotti, and Rossetti (2024) find no evidence of (6,6) momentum under a set of data choices they make.

II.B. Momentum Strategy

To assess the impact of data uncertainty, we calculate profits from a Jegadeesh and Titman (1993) (J, K) momentum strategy, where J is the formation period and K is the holding period. We focus on NIG bonds as the drivers for momentum profitability and on (3,3) and (6,6) strategies where profits are strongest (JNPS), although studies of momentum vary in the strategies they analyze.

At the end of month $t-1$, we sort bonds with a $t-1$ NIG rating into decile portfolios based on their cumulative returns over months $t-J$ to $t-1$ (formation period). NIG status is based on a bond's S&P rating.[23] Because a bond may be downgraded from IG before the end of the formation period or upgraded post-formation, we do not exclude IG bonds from our sample altogether. The momentum strategy involves buying the highest decile (winner) and shorting the lowest decile (loser) portfolio at the end of month t. The portfolios are held over months $t+1$ to $t+K$ (holding period). To be included in a momentum portfolio, a bond needs to have non-missing returns for the entire formation period. To avoid look-ahead bias, we do not exclude bonds that do not have returns for the entire holding period. Portfolio returns are either equally weighted (EW) across their constituent bonds or value weighted (VW) using a bond's month-t par value outstanding as the weight. The momentum strategy's month $t+1$ return is the equally weighted average month-$t+1$ return of strategies implemented in the prior month and strategies formed up to K months earlier. This allows for standard statistical inference using non-overlapping returns.

We skip a month (month t) between the formation and holding periods for two reasons. First, this is common practice in the equity momentum literature as a way of minimizing biases from bid-ask bounce and short-term price reversal. These biases are likely more pronounced for corporate bonds since their bid-ask spreads are much larger (Edwards, Harris, and Piwowar, 2007). Second, most corporate bonds trade in a fragmented over-the-counter market, in which

[23] We later examine samples where NIG status is based on a combined S&P, Moody's and Fitch rating.

trades can take days or weeks to execute (Wu, 2022). Thus, implementing a momentum strategy immediately at the end of the formation period (month $t-1$) may be unfeasible.

II.C. Data and Sample Construction

We collect prices from *Standard TRACE* and *Enhanced TRACE* for their full period of coverage. Because *Enhanced TRACE* provides more detailed trade-size information but is available with a 6-month lag, we use it as our base data source from July 2002 to December 2022, then supplement it with *Standard TRACE* over January 2023–June 2023. To highlight accessibility and replicability, we use the available WRDS SAS programs for pre-cleaning the two versions of TRACE.[24] The programs implement trade corrections, cancelations, and reversals reported by dealers, and delete duplicates for interdealer trades—Appendix C provides details.

We use the resulting TRACE data to construct 204 different samples of monthly returns by making various combinations of data choices. Because the treatment of return outliers masks the effect of other data choices, we begin by constructing three *starting samples* that treat the most extreme return outliers differently. For each starting sample, we then vary other data choices one at a time.

We construct our first starting sample using the WRDS SAS program that constructs monthly returns.[25] The program estimates a daily price as a trade-size-weighted average of all intra-day prices after excluding commission and negative-price trades. The program produces 3 alternative month-end prices: P_LDM (the price on month's last trading day), P_L5M (the last daily price within the month's last 5 trading days), and P_EOM (the last daily price of the month). Figure I displays the number of price observations under the alternative choices.

[24]See wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/wrds-bond-return/cleaning-trace-data/wrds-clean-trace-enhanced-file/ and wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/wrds-bond-return/cleaning-trace-data/wrds-clean-standard-trace-file/, dated October 2017.

[25]The program, wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/wrds-bond-return/sas-code-behind-the-scene/sas-code-behind-the-scene/, combines *Standard TRACE* and *Enhanced TRACE*, matches it to FISD, and uses FISD data to remove convertible, non-U.S., Rule 144A bonds, etc. Appendix C provides details.

Trading days are based on the Treasury market holiday schedule and trades on non-trading days are excluded (0.19% of trades).[26] Using the 3 alternative month-end prices, 3 alternative returns, RET_LDM, RET_L5M, and RET_EOM, are calculated as in equation (1). We use RET_L5M as our baseline return but present results for the other return measures as well. To minimize the effect of data entry errors, the WRDS program winsorizes returns at 100%. Finally, the program calculates the cumulative monthly return of defaulted IG (NIG) bonds with available price data, aggregating the return during the month before, of, and after default. It then replaces the default-month return of IG and NIG/unrated bonds with these averages, −20.779% and −22.488% respectively, for our sample period. The calculation of default-month returns is not adjusted for "flat trading" and post-default month returns are excluded from the sample. The WRDS program produces a sample of 1,427,056 bond-month return observations over July 2002–June 2023. This is the Bond Return Database constructed by WRDS and made available to WRDS subscribers.[27] We refer to this sample as the **"WRDS sample"** and present descriptive statistics for it in the first row of Table I Panel A. Its mean monthly return and standard deviation are 0.43% and 4.29%.

Because some have argued that the TRACE data should be minimally treated, we examine how removing the winsorization at 100% affects the return distribution. The second row of Table I Panel A shows that there are obvious data entry errors among the winsorized data as the mean jumps from 0.43% to 60.95% and the standard deviation from 4.29% to $72,251.21\%$. The maximum monthly return is now $86,310,900\%$, and there are 10 returns greater than $1,000\%$ per month and 26 more in the 300%–$1,000\%$ range. To get a sense of these outliers, Appendix B Table B.1 presents the month-end prices from 3 months prior to 3 months after the outlier return. The pattern of month-end prices suggests that the 36 returns greater than 300% may be due to data entry errors, most likely a misplaced decimal point. For example, 7 of the 10 outliers in Panel A are caused by prices at or below 1.00, surrounded by much larger

[26]The WRDS program extracts Treasury trading days from the CRSP Treasury daily rates database. Because we have no access to it, we rely on the Federal Reserve Economic Data (FRED) at fred.stlouisfed.org. We consider a trading day a day on which a 10-year Treasury market yield (DGS10 series) is available.

[27]This database is used by Bali, Beckmeyer, Goyal, and Wen (2023), Bai, Bali, and Wen (2023), and others.

prices. Conversely, 2 of the 10 outliers are due to prices of $3,348$ and $1,325$ surrounded by prices around 100. The table also demonstrates that an incorrect price in month m results in incorrect returns in two consecutive months. Having established that the 36 returns greater than 300% are likely the result of price entry errors, we remove them from the sample along with the adjacent returns impacted by the incorrectly recorded price. We refer to this sample of 1,426,993 bond-month return observations as the **"Raw WRDS sample"** and present its descriptive statistics in the third row of Table I Panel A. While filtering out returns impacted by the 36 price entry errors has a minimal effect on the sample size, it substantially affects the distribution of returns. The mean is 0.43% per month and the standard deviation is 4.47%. Nonetheless, the highest return of 295% is still 66 standard deviations away from the mean, which has a normal distribution tail probability of 0 up to the 946^{th} decimal point.

To visualize the distribution of returns in the Raw WRDS sample, in Figure II we present histograms that progressively zoom into the range of returns where the mass of observations lie. Plot A shows that the sample still includes outliers so extreme that the mass of return observations is barely visible. Zooming into monthly returns between -100% and 100% in Plot B shows that even in this subsample there are returns that appear extreme, which remains the case even when we zoom into monthly returns between -30% and 30% in Plot C and between -10% and 10% in Plot D. The percentage of bond returns that fall into the $\pm 100\%$, $\pm 30\%$, and $\pm 10\%$ intervals are 99.99%, 99.73%, and 97.65%, respectively. In comparison, for monthly *stock returns* these percentage are 99.7%, 94%, and 65%, respectively. Figure II suggests that the Raw WRDS sample may still include data errors.

As an alternative to the winsorization, we attempt to identify data errors by cross-checking return outliers in the Raw WRDS sample against returns from an alternative, commercially available data source. By doing so, we implicitly assume that a return outlier is more likely to be the result of a data entry error if it cannot be confirmed through another data source. Unlike manual verification, our approach of validating return outliers through a commercially available data source should be easier for researchers to implement and replicate. While any such data source would do, we choose to verify return outliers using *DataStream* [*DS*] since this is the source available to us.[28] We focus on the 3,887 returns in the Raw WRDS sample that are outside the ±30% range. For 586 bond-months, *DS* has no return data and for 1541 bond-months the *DS* return is more than 2 standard deviations (i.e., $2 \times 4.35\% = 8.70\%$) away from the TRACE return. We exclude these return outliers from the Raw WRDS sample as likely data errors, to form what we refer to as the **"DS Confirmed sample"**. The DS Confirmed sample includes all Raw WRDS sample returns in the ±30% range and the 1,760 Raw WRDS returns outside the ±30% range for which the corresponding DS return is within 2 standard deviations of the TRACE return.

Table I Panel A reports descriptive statistics for the Raw WRDS and DS Confirmed samples of monthly corporate bond returns, revealing several noteworthy points. First, while the DS Confirmed sample has only 2,127 fewer observations (0.15%) than the Raw WRDS sample, the distributional moments of the two samples are quite different. The Raw WRDS sample monthly mean and standard deviation are 0.43% and 4.47%, while the DS Confirmed sample has a mean of 0.40% and a standard deviation of 3.73%. Strikingly, the skewness and kurtosis are 8 and 406 in the Raw WRDS sample, but 1 and 98 in the DS Confirmed sample. Second, the DS Confirmed sample still contains monthly returns of 265% that are 71 standard deviations away from the mean. Notably, the 25th and 75th percentiles of the monthly bond return distribution are −0.5% and 1.4%, suggesting that 50% of the observations fall within a 2% range, yet the kurtosis is 98.

Table I Panel B shows that using the last-trade-of-the-month return (RET_EOM) increases the number of observations relative to our WRDS sample from 1.4 to 3.3 million, while using the last-day-of-month return (RET_LDM) reduces it from 1.4 to 0.79 million. Figure B.I visualizes this sample size impact. The choice of month-end price also affects the return distribution. The mean and standard deviation are 0.50% and 4.94% for RET_EOM and 0.34% and 4.11% for RET_LDM. In Appendix B, we replicate our main analyses using

[28] *DataStream* provides a month-end total return index (RI), from which we calculate monthly bond returns.

RET_EOM and RET_LDM.

II.D. Data Choices and Momentum in Individual Bond Returns

We next investigate the profitability of the (3,3) and (6,6) momentum strategies in our three starting samples: WRDS, Raw WRDS, and DS Confirmed samples. The portfolio analyses, presented in Table I Panel C, show that the WRDS sample generates equally weighted [EW] and value-weighted [VW] (3,3) momentum profits of 0.63% and 0.71% (t-statistics of 2.02 and 2.22), while the (6,6) strategy is unprofitable. In the Raw WRDS sample, (3,3) momentum is significant at the 10% level, while (6,6) momentum remains insignificant. Results are similar when we exclude return outliers (outside the ±30% range) for which we do not find data in *DS*, suggesting that *DS* coverage is not a source of momentum bias. However, results change when we also eliminate outliers for which returns from *TRACE* and *DS* differ significantly. EW and VW (3,3) momentum profits are now 0.68% and 0.75% (t-statistics of 2.66 and 2.81), while (6,6) profits are 0.85% and 0.88% (t-statistics of 2.59 and 2.71), respectively. This change is driven by the removal of 2,127 of 1,426,993 observations (or 0.15%) in the Raw WRDS sample and underscores that a data choice affecting a tiny fraction of the sample can result in markedly different asset-pricing conclusions.

For each base sample, we next explore how making a particular data choice impacts momentum profits, one data choice at a time. Results are presented in Table II Panel A (B) [C] for the WRDS (Raw WRDS) [DS Confirmed] sample. Each panel's first row repeats momentum profits from Table I Panel C. Data choices are grouped in blocks by category.

The first data choice category is the treatment of default-month returns. There are 1,062 default bond-months in the Raw WRDS sample but returns are often missing—there are 696 (692) [533] non-missing default-month returns in the WRDS (Raw WRDS) [DS Confirmed] sample. Our baseline is the approach taken in the WRDS SAS program to calculate default-month returns inclusive of accrued interest (as in equation (1)) and to replace all default-month returns with the cumulative return over the month before, of, and after default. As a first alternative, we calculate default-month returns assuming that default triggers flat trading (as in equation (2)) and do not replace missing observations. We use P_EOM in the default month, since default may not happen in the last five trading days of a month. Figure III presents histograms of these alternative default-month returns in our three starting samples. We find that there are large positive outliers in the Raw WRDS sample, some over 200%, many of which we cannot confirm in DS. A second (third) data choice is to replace all (only missing) default-month returns with our sample's average default-month return, −17.82%.

The first block of Table II Panel A shows that the treatment of default-month returns significantly impacts momentum, even though it affects only a handful of observations. The three alternative default-month return treatments decrease momentum profits relative to the baseline. Profits are lowest when missing default-month returns are left as such, increase when they are replaced with the sample average, and increase further when the sample average is used in place of both missing and non-missing default-month returns.

The next two blocks of Panel A examine two categories of data choices aimed at detecting incorrect month-end prices—through price reversals and price outliers. Our first price reversal filter is motivated by Gebhardt, Hvidkjaer, and Swaminathan (2005b), who eliminate returns greater than 95% followed by next-month returns less than −45% or vice versa; it has a negligible impact on momentum. The next three price reversal filters are motivated by Ho and Wang (2018), who remove observations where 20% or greater return is followed by 20% or greater next-month return of the opposite sign, though we experiment with additional cutoffs. A cutoff of ±60% has no impact on momentum, while more restrictive cutoffs do. For example, a cutoff of ±30% (±20%), which removes 0.07% (0.17%) of observations, increases VW (3,3) momentum profits from 0.71% to 0.84% (0.95%), and makes VW (6,6) momentum significant at the 10% level or higher with profits of 0.69% (0.73%) [t-statistics=1.88 (2.06)]. Bartram, Grinblatt, and Nozawa's (2023) price reversal filter, $R_t R_{t-1} < -0.04$, affects 0.27% of observations and has the largest impact on momentum. After implementing it, all four strategies generate significant monthly profits in the 0.81% to 1.09% range (t-statistics between 2.47 and 4.29). The $R_t R_{t-1} < -0.02$ filter has a similar impact. Unlike price reversal filters, price outlier filters, motivated by Bali, Subrahmanyam, and Wen (2017), have little impact on momentum profits. The profitability of the (3,3) momentum strategies persists, while that of the (6,6) momentum strategies remains insignificant.

We find that common filters based on bond characteristics have little impact on momentum even though some eliminate a large fraction of bonds. Restricting bonds to those with over a year to maturity eliminates 8% of observations and changes momentum profits by 1-5 basis points. Extending our strategy to include bonds rated NIG by Moody's (when S&P rating is missing) and by Fitch (when S&P and Moody's ratings are missing) has virtually no impact on momentum profits. Eliminating bonds with $10 par value, which tend to be equity-linked notes (ELNs), does not affect the profitability of the momentum strategies we study, since the ELNs in our sample are IG rated.[29] Finally, limiting the sample to corporate debentures (bond type CDEB, 87.5% of the WRDS sample) has little impact on momentum.

Choices for filtering out return outliers, whether symmetric or focusing on only positive outliers, have a big impact on return and momentum statistics even though they affect a tiny fraction of observations.[30] In the last block of Panel A, we show that as progressively more outliers are excluded, the monthly mean return decreases from 0.43% to 0.35% and the standard deviation from 4.29% to 3.32%. This parallels the increase in profitability for all momentum strategies with the symmetric ±30% filter the only exception. In particular, when we eliminate monthly returns of 100% (the winsorized value), which comprise 0.015% of observations and are 24 standard deviations away from the mean, the VW (6,6) monthly momentum profits become significant at 0.76% and the VW (3,3) momentum profits increase from 0.71% to 0.91%. All four momentum strategies are profitable (0.82% to 0.95%) when we

[29] TRACE defines an ELN as "a debt instrument whose return on investment is tied to the equity markets. It may be tied to a single stock, a basket of stocks, or an index." We identify ELNs by searching for (equity+link) or (index+link) in the issue_name field in FISD.

[30] Prior research argues that these are likely the result of data entry errors and removes them from the sample—e.g., JNPS, Ho and Wang (2018), Lee, Naranjo, and Sirmans (2021), and Galvani and Li (2023).

exclude returns of 90% or higher (0.018% of observations). A symmetric ±90% return filter produces virtually identical results and excludes 0.019% of observations. As the return filter becomes more restrictive, the symmetry of the exclusion starts to matter. A symmetric ±60% filter, affecting 0.05% of observations, results in monthly momentum profits in the 0.87% to 1.01% range, while an asymmetric 60% filter, affecting 0.04% of observations, results in profits in the 1.08% to 1.17% range. The difference between the symmetric and asymmetric filters is even more pronounced at the 30% cutoff.

In Table II Panel B, we repeat the analyses in Panel A but using the Raw WRDS sample as our starting sample. Likely because momentum is unprofitable in the starting sample, many additional data choices leave momentum unprofitable. Out of the reported 100 profit estimates (25 data choices × 4 momentum profit estimates each), 46 (25) have t-statistics greater than 1.96 (3.0). These estimates range from 0.12% to 1.77% per month. Different default-month return treatments and filters based on bond characteristics or price levels have a minimal impact on the return distribution and momentum profits even when removing a big portion of observations. This is in contrast to price reversal and return outlier filters. All but one of the (3,3) momentum profit estimates are significant after applying any of the price reversal filters. The (6,6) momentum profit estimates are significant with both the $R_t R_{t-1} < -0.04$ and $R_t R_{t-1} < -0.02$ filters, while the sample still includes 77- and 80-sigma returns. After excluding returns outside the ±90% range, both (3,3) and (6,6) momentum strategies become significant, with profits ranging from 0.82% to 0.95% per month. Results in the last block of Panel B are almost identical to those in the last block of Panel A since, after trimming returns at 100%, the two samples only differ by the returns affected by the 36 price entry errors described in Appendix B Table B.1.

Table II Panel C repeats the analyses in Panels A and B but starting with the DS Confirmed sample. There are two main takeaways. First, when starting with this sample, alternative data choices have a smaller impact on the return distribution, likely because the process of confirming returns in *DS* already eliminates about half of extreme (±30%) returns. Second, regardless of the alternative data choices made, all momentum strategies are always profitable. Profits range from 0.55% to 1.42% with a mean of 0.82%, and all but one of 100 momentum t-statistics are greater than 1.96 and 35 are greater than 3.0. As in the WRDS sample, alternative default-month return treatments in the DS Confirmed sample decrease momentum profits, while eliminating large prices reversals increases them. Price-level or characteristics-based filters have a negligible effect on the return distribution and momentum profits. Momentum profits increase monotonically with more restrictive asymmetric return outlier filters, while they peak at ±60% with symmetric filters and then decrease with the ±30% filter.

In Appendix B Table B.2, we repeat the analyses in Table II but use returns calculated from last-day-of-month prices (RET_LDM) or end-of-month prices (RET_EOM) rather than our baseline of last-5-days-of-month prices (RET_L5M). We find that with RET_LDM, momentum is profitable in almost all samples and consistently larger in magnitude even though the samples are half the size of those analyzed in Table II. For comparison (Table B.2 versus Table II), in the starting WRDS sample of individual bonds (Panels A), EW (3,3) momentum profits based on RET_LDM are 1.06%, while they are 0.63% in our baseline. Moreover, EW (6,6) momentum profits in the starting WRDS samples are significant at 1.07% with RET_LDM and insignificant in the baseline. Momentum profits are smaller and their statistical significance is reduced when using RET_EOM, but (3,3) momentum profits tend to be consistently significant in the DS Confirmed samples for individual bond returns and in the WRDS and DS Confirmed samples for firm-level returns.

In sum, our analyses in Table II and Table B.2 demonstrate that the data choices a researcher makes when constructing a sample of monthly bond returns affect asset-pricing conclusions, even when impacting a tiny fraction of observations.

II.E. Data Choices and Momentum in Firm-Level Bond Returns

We next study the impact of data choices when analyzing returns at the firm level instead of individual bond level. We first compute firm-level variables as the equally weighted average of the corresponding individual bond variables, and then investigate the return distribution and momentum profits of firm-level returns in Table III.[31] Panel A (B) [C] uses the WRDS (Raw WRDS) [DS Confirmed] sample. In all panels, we find that the mean and standard deviation of returns are higher at the firm level than at the individual bond level. The difference is most pronounced in the Raw WRDS sample, in which the mean and standard deviation of monthly returns are 0.53% and 5.03% at the firm level but 0.43% and 4.47% at the individual bond level (Table II Panel B). This may indicate that firms with fewer bonds have higher returns, consistent with the intuition that firms with high credit risk have limited borrowing capacity. It may also indicate that firms with fewer bonds are more likely to have outlier returns.

Our (3,3) momentum strategies are profitable at the firm level in all 3 starting samples, and profits are larger. Our (6,6) momentum is only profitable, as before, in the DS Confirmed sample. Overall, the firm-level momentum impact of data choices mirrors the impact documented at the individual bond level. Alternative default-month treatments reduce momentum profits but these remain significant for the EW (3,3) strategy in all three samples. Price reversal filters strengthen momentum, while price level and bond characteristic filters have a minimal impact. Momentum profits increase monotonically with more restrictive positive return outlier filters, are similar with the symmetric ±90% and ±60% filters, and are lowest with the symmetric ±30% filter. For perspective, the ±90% (±60%) [±30%] filters affect 0.004% to 0.02% (0.02% to 0.06%) [0.16% to 0.32%] of firm-level observations.

Table IV repeats these analyses using firm-level variables constructed as a weighted average of individual bond variables, using a bond's prior-month par value outstanding as the weight.[32] The mean and standard deviation of returns are virtually identical to those in Table III.

[31] We identify all bonds of an issuer using issuer_id in FISD.

[32] Appendix B Table B.3 and Table B.4 replicate Table III and Table IV using RET_EOM and RET_LDM.

Momentum profits are slightly larger, especially from the (3,3) strategy.

Figure IV displays the time series of momentum profits. Plot A (B) compares individual bond momentum profits in the Raw WRDS sample to those in the WRDS (DS Confirmed) sample. A few large negative spikes in the monthly momentum profits in the Raw WRDS sample appear more subdued in the WRDS sample and even more so in the DS Confirmed sample. Surprisingly, just one of these spikes is responsible for the insignificant momentum in the Raw WRDS sample (without it, momentum profits are significantly positive). In March 2016 when the bond market rebound from a January-February bottom, bonds in our momentum loser portfolio produce average returns of 47%, resulting in an extraordinary monthly momentum loss of 40%.[33] Equities experience similar momentum crashes when the market rebounds from a bottom (Daniel and Moskowitz, 2016). Firm-level averaging alleviates momentum crashes (Plot C), but it is less impactful in the DS Confirmed sample (Plot D).

Overall, firm-level averaging does not help reduce the impact of outliers on the return distribution, but tends to increase momentum profitability.

II.F. Momentum Profits Across 204 Data Samples

Given the data uncertainty we document, we argue that it is suboptimal to rely on a single data sample and a single profit estimate when assessing the viability of trading strategies. Instead, an investor would benefit from examining the distribution of profits across data samples.

Figure V summarizes the distribution the 408 momentum profit estimates across the 204 data samples examined in Tables II, III, and IV. Combined, the 3 tables present results from $3 \times 25 \times 3 = 225$ data samples. However, in each table, the last 7 samples in Panel B are almost identical (except for the returns impacted by the 36 price entry errors in Appendix B Table B.1) to the last 7 samples in Panel A. To err on the conservative side, we exclude them from the plots in Figure V. Specifically, Plot A displays the frequency distribution of the 408

[33] Coined by S&P as the 'great bond rebound of 2016': spglobal.com/marketintelligence/en/mi/research-analysis/15032017-Credit-The-great-bond-rebound-of-2016.html.

EW and VW (3,3) momentum profit estimates across the other 204 rows of Tables II, III, and IV. These estimates range between 0.37% to 1.64% per month, averaging 0.80% per month (marked as a vertical red line) with a standard deviation of 0.17%. Importantly, none of the samples produces negative momentum profits. For 370 (145) or 91% (36%) of the 408 (3,3) momentum profits estimates, t-statistics are above 1.96 (3.00).

Figure V Plot B repeats this analysis but for the 408 EW and VW (6,6) momentum profit estimates in Tables II, III, and IV. Across all samples, these estimates range between 0.11% and 1.77%, with a mean of 0.65% and a standard deviation of 0.27%. Just as in Plot A, no sample produces negative momentum profits. For 177 (56) of the 408 (6,6) momentum profit estimates or 43% (14%), t-statistics are above 1.96 (3).

While in Figure V we focus on the momentum profit estimates from the samples in the main paper, in Appendix B Figure B.II we add to these the profit estimates generated from the 204 samples using last-day-of-month returns (R_LDM) and the 204 samples using end-of-month returns (R_EOM) for a total of 1,224 EW and VW profit estimates. In Plot A, (3,3) monthly momentum profits average 0.84% compared to 0.80% with R_L5M alone. In Plot B, (6,6) monthly momentum profits average 0.69% compared to 0.65% with only R_L5M.

Although we view momentum as merely a case study and thus believe that examining the profitability of all possible momentum strategies is outside the scope of the paper, in Appendix B Figure B.III we nonetheless summarize the profitability of some. In each plot, we present the distribution of the 408 momentum profit estimates from EW and VW strategies using data from our 204 samples from Tables II, III, and IV. In Plots A and B, where we study (9,9) and (12,12) strategies, we find that the distribution is dispersed, shifted to the left, and includes a significant proportion of negative values. In contrast, the distribution of profits estimates from (3,1), (6,1), (9,1), and (12,1) strategies in Plots C through F is tighter, to the right of 0, and the estimates average 0.92%, 1.04%, 0.92%, and 0.81%. Momentum profitability diminishing as the formation and holding periods increase is consistent with the findings of JNPS. Under an underreaction view of momentum, these results suggest that while investors may underreact to bond-level information, that underreaction is short-lived.

II.G. Individual Bond Momentum with Random Sampling

Corporate bonds are notoriously illiquid. The number of observations for *RET_L5M* and *RET_EOM* in Table I suggests that 57% (= 1 − 1427056/3307118) of the bonds traded in a month have no trades in the last 5 trading days of that month, and 76% (= 1−788393/3307118) have no trades on the last trading day. We next assess momentum profits' sensitivity to the fraction ψ of the bonds an investor can trade.

We draw 1000 random samples of 30% (or 50% or 90%) of the bonds in the WRDS sample and estimate momentum profits from each sample. Table V reports sample statistics for the (3,3) and (6,6) EW and VW momentum strategy profits for the 1000 random draws. For comparison, the first row presents momentum profits from the full WRDS sample (first row in Table II Panel A). In Panel A, where we randomly draw 30% of bonds, EW (3,3) momentum profits average 0.63% across the 1000 draws, with a standard deviation of 0.16%, and range between 0.16% and 1.11%. EW (6,6) momentum profits average 0.48%, with a standard deviation of 0.16%. For all strategies, average profits across the 1000 30% samples are almost identical to those from the full sample. In Panels B and C, when we randomly draw 50% and 90% of the WRDS sample, respectively, average EW (3,3) profits remain 0.63%, while their standard deviations decrease to 0.11% and 0.03%.

Figure VI visualizes the frequency distribution of the EW (3,3) and (6,6) momentum profits for the 1000 random draws of 30% (50%) [90%] of the WRDS sample. The mass of profit estimates lies above zero and their distribution is more dispersed when a smaller fraction of bonds is drawn.

In sum, while the simulation results indicate that working with a fraction of the outstanding bonds does not bias momentum profit estimates, they also underscore that relying on a *single* random sample may result in an estimate away from the true full-sample momentum profit, especially if the fraction is small.

III. A Model of Learning under Uncertainty

The cross-sample analysis of average momentum profits in the previous section illustrates the effect of data uncertainty on the point estimates. However, it only compares sample means and lacks information about the distributions from which they come, preventing an investor from performing statistical inference across samples. Bayesian analysis lends itself to such inference, because it can produce the posterior distributions of the estimates within each sample and, even more useful, the joint posterior distribution of the estimates across samples.

Bayesian analysis requires a parametric model that portfolio sorts do not provide. Hence, we propose a novel regression model for momentum that offers several advantages. First, the model can be estimated with Bayesian sampling techniques to better account for within-sample parameter-estimation uncertainty. Second, the model can be estimated across multiple data samples to account for both data and estimation uncertainty. Third the model uses the same momentum portfolio assignment criteria as in our portfolio analyses, allowing direct momentum profits comparison between the two methods. Finally, the regression model setup captures not only overall momentum profits but also the contribution of each month of the formation and holding periods to these profits—thus providing a finer mesh of information to better understand the dynamics of momentum profitability.

III.A. A Regression Model for Momentum

Let there be S researchers who make data choices independently, each producing a unique data sample. Each researcher s estimates momentum profits using the following model:

$$r^s_{i,t+1} = \alpha^s + \boldsymbol{W}^s_{i,t}\boldsymbol{\beta}^s_W + \boldsymbol{L}^s_{i,t}\boldsymbol{\beta}^s_L + \sigma^s\varepsilon_{i,t+1} \qquad \varepsilon_{i,t+1} \sim N(0,1) \tag{3}$$

Equation (3) represents a regression of monthly non-overlapping holding-period returns, $r_{i,t+1}$, on a set of variables, $\boldsymbol{W}_{i,t}$ and $\boldsymbol{L}_{i,t}$, each indicating the preceding months in which a bond was in a winner or loser portfolio. The bond returns' standard deviation, σ, is set as a constant (a constraint that is easily relaxed). Specifically, dropping subscripts, $\boldsymbol{W}$ is a $1 \times H$ vector:

$$\boldsymbol{W} = [W_1, W_2, \ldots, W_H] \text{ where } H = \sum_{k=1}^{K} \binom{K}{k}$$

where K is the number of holding periods and the construct $\binom{K}{k} = \frac{K!}{k!(K-k!)}$ means 'K choose k' and counts the number of ways to choose k out of a total of K elements. To illustrate, consider a three-month holding period, $K = 3$. Then let $I_{W,k}$ take the value 1 if a bond is included in the winner portfolio based on a preceding J-month formation period computed in month $t-k$, $(k = 1, 2, 3)$, zero otherwise:

$$I_{W,k} = \begin{cases} 1 & \text{if } R^J_{i,t-k} \in \text{ top decile} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where $R^J_{i,t-k}$ is bond i's cumulative return over J formation period months computed in month $t-k$. Then each winner-inclusion indicator W_h in $\boldsymbol{W}$ will reflect the realization of the triplet $\{I_{W,1}, I_{W,2}, I_{W,3}\}$. The first indicator in $\boldsymbol{W}$, W_1, represents the triplet $\{1, 0, 0\}$, i.e. $W_1 = 1$ if the bond was in the holding period in month $t+1$, based on formation period return computed in month $t-1$, R_{t-1}, but was not selected for addition to the winner portfolio based on R_{t-2} and R_{t-3}. For a three-month holding period, $K = 3$, there are seven such winner indicator variables, $H = \binom{3}{1} + \binom{3}{2} + \binom{3}{3} = 7$. Then:

$$\boldsymbol{W} = [W_1, W_2, W_3, W_4, W_5, W_6, W_7] = [W_{\{1,0,0\}}, W_{\{0,1,0\}}, W_{\{0,0,1\}}, W_{\{1,1,0\}}, W_{\{1,0,1\}}, W_{\{0,1,1\}}, W_{\{1,1,1\}}]$$

The W_h are mutually exclusive. That is, in any given month, if a bond is in the winner portfolio, only one of the W_h takes the value 1; the others equal 0. If a bond is not in the winner portfolio, they are all zeros. For $K = 6$, the number of winner indicator variables, W_h, increases from 7 to 63.

Likewise, $\boldsymbol{L} = [L_1, \ldots, L_H]$ is an $1 \times H$ vector of indicator variables which track when a bond is included in the loser portfolio using the same construct as with $\boldsymbol{W}$:

$$I_{L,k} = \begin{cases} 1 & \text{if } R^J_{t-k} \in \text{ bottom decile} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

However, each L_h takes the value 0 or -1, where the negative sign reflects a short position. For example, for $K = 3$ $L_{\{0,1,0\}}$ will take the value -1 if a bond is included in the loser portfolio based on R^J_{t-2} but not included based on R^J_{t-1} and R^J_{t-3}, while $L_{\{1,1,0\}}$ will take the value -1 to reflect that a bond was added to the holding period based on R^J_{t-1} and R^J_{t-2} but not on R^J_{t-3}. The estimated coefficient on each indicator variable $[W_1, \ldots, W_H, L_1, \ldots, L_H]$ measures the incremental effect to momentum profits of each of the holding period inclusion scenarios. Momentum profits are measured as a weighted average of the indicator variables' coefficients, where the weights reflect the frequency of each scenario. That is,

$$\pi^s = [\omega_{W,1}, \ldots, \omega_{W,H}] \times [\beta_{W,1}, \ldots, \beta_{W,H}] + [\omega_{L,1}, \ldots, \omega_{L,H}] \times [\beta_{L,1}, \ldots, \beta_{L,H}] \tag{6}$$

where

$$\omega_{W,h} = \frac{\text{number of inclusions as winner based on } W_h}{\text{total number of inclusions as winner}}$$
$$\omega_{L,h} = \frac{\text{number of inclusions as loser based on } L_h}{\text{total number of inclusions as loser}}$$

In the case of $K = 3$, the first weight, $\omega_{W,1} = \omega_{W_{\{1,0,0\}}}$ divides the number of times a bond was added to the winner portfolio based on R^J_{t-1} but not R^J_{t-2} and R^J_{t-3} by the total additions of any bond to the winner portfolio.

III.B. Model Fitting

Generalizing the model across time, for each data sample equation (3) becomes:

$$\mathbf{R}^s = \mathbf{X}^s \mathbf{b}^s + \sigma^s \boldsymbol{\mathcal{E}} \tag{7}$$

where $\mathbf{R}^s = [\mathbf{r}'_1, \ldots, \mathbf{r}'_T]'$ is a $NT \times 1$ vector of 'stacked' monthly cross sections of returns, $\mathbf{X}^s = [[\mathbf{W}, \mathbf{L}]'_1, \ldots, [\mathbf{W}, \mathbf{L}]'_T]'$ is a $NT \times (2H + 1)$ matrix of 'stacked' monthly cross-sections of winner and loser portfolio indicators; $\boldsymbol{\mathcal{E}} = [\boldsymbol{\varepsilon}'_1, \boldsymbol{\varepsilon}'_2, \ldots, \boldsymbol{\varepsilon}'_T]'$, is a $NT \times 1$ vector of 'stacked' error terms. Individual error terms follow a normal distribution as described in equation (3).

The coefficient vector $\mathbf{b}$ has a dimension of $(2H + 1) \times 1$ and equals:

$$\mathbf{b} = \begin{bmatrix} \alpha \\ \boldsymbol{\beta}_W \\ \boldsymbol{\beta}_L \end{bmatrix}$$

We estimate the model parameters using MCMC methods via the Gibbs sampler. We draw the parameter set $\boldsymbol{\theta}^s = [\boldsymbol{\alpha}^s, \boldsymbol{\beta}^s_W, \boldsymbol{\beta}^s_L, \sigma^s]$ from their joint posterior distribution. In the case of one data sample s, the joint posterior distribution is proportional, by Bayes Theorem, to the product of the joint prior and the likelihood function (Zellner, 1971):

$$p(\boldsymbol{\theta}^s \mid \mathbf{Y}^s) \propto p(\boldsymbol{\theta}^s) L(\boldsymbol{\theta}^s \mid \mathbf{Y}^s) \tag{8}$$

where $\mathbf{Y}^s$=$[\mathbf{r}^s, \mathbf{W}^s, \mathbf{L}^s]$. Having S independently obtained samples yields a joint posterior distribution of the parameters equal to:

$$p(\boldsymbol{\theta} \mid \mathbf{Y}^1, ..., \mathbf{Y}^S) \propto p(\boldsymbol{\theta}) \prod_{s=1}^{S} L(\boldsymbol{\theta} \mid \mathbf{Y}^s) \tag{9}$$

In a restricted parameter case, we may estimate the same set, $[\boldsymbol{\alpha}, \boldsymbol{\beta}_W, \boldsymbol{\beta}_L, \sigma]$, across all data samples. In an unrestricted case (as in this study), we estimate a different parameter set for each sample,[34]

$$\boldsymbol{\theta} = [\boldsymbol{\theta}^1, \ldots, \boldsymbol{\theta}^S] = [\boldsymbol{\alpha}^1, \boldsymbol{\beta}_W^1, \boldsymbol{\beta}_L^1, \sigma^1, \ldots, \boldsymbol{\alpha}^S, \boldsymbol{\beta}_W^S, \boldsymbol{\beta}_L^S, \sigma^S]$$

The Bayesian estimation approach would allow us to summarize the combined distributional properties of the parameters. That is, we could estimate a probability of a parameter set coming from a particular sample, or perform cross-sample inference. We could also test hypotheses using Bayes factor ratios.

The Bayes factor approach corresponds to traditional Likelihood Ratio tests. We test the null hypothesis (no momentum, in our case) versus the alternative hypothesis (momentum, represented by the full set of indicators). Since our samples have millions of observations, the choice of prior is not as important as with small samples.[35] When computing the Bayesian factor for this hypothesis test, we use JZS priors (based on contributions by Jeffreys 1961 and Zellner and Siow 1980). Due to the very large sample size, we obtain extremely large Bayesian factors. For example, using the WRDS sample, the alternative versus null hypothesis Bayes factor is 5.935382e+93, rejecting the null of no momentum with probability one. As a more illustrative approach, we summarize the conditional posterior draws of momentum profits across samples via plots of their joint posterior distributions.

III.C. Estimation results: learning from our 3 starting samples

Figure VII present the Gibbs sampler's posterior estimates of momentum profitability. Plot A uses returns from the DS Confirmed sample for r^s_{it+1} (Appendix B Figure B.IV provides the same for the WRDS and Raw WRDS samples). Each subplot presents 10,000 draws (1,000 burn-in iterations) from the marginal posterior of each parameter in equation (3) for $J = 3$ and $K = 3$: the intercept (α^s), the winners' contributions to momentum profits ($\boldsymbol{\beta}^s_W$), and the losers' contributions to momentum profits ($\boldsymbol{\beta}^s_L$).

[34]This approach could also employ a hierarchical Bayesian model with additional parameters that span the spectrum between the most restricted and the most unrestricted specifications.

[35]See, for example, Rouder et al. (2009) or George and McCulloch (1993).

Figure VII Plot A reveals that a bond's contribution to momentum profits depends on how many and which momentum strategies it enters. For example, in the DS Confirmed sample, the highest contribution to momentum profits comes from bonds that are in the loser portfolio for three consecutive months ($L_{\{1,1,1\}}$), the last subplot. The same is true for the WRDS and Raw WRDS samples (see Appendix B Figure B.IV). In contrast, bonds that enter the loser portfolio in the latest month but not in the other two, $L_{\{1,0,0\}}$, or a month prior but not in the other months, $L_{\{0,1,0\}}$, do not contribute to momentum profits. On the winner side, the biggest contribution to momentum profits comes from bonds that are in the winner portfolio in all three months, $W_{\{1,1,1\}}$, or in the last two, $W_{\{1,1,0\}}$, or just in the last one $W_{\{1,0,0\}}$. Panel C of Appendix B Table B.5, which mirrors Plot A of Figure VII in a table format, shows that in the DS Confirmed sample, 5 of the 7 selection subsets of winner bonds and 5 of the 7 subsets of loser bonds in a (3,3) momentum strategy significantly contribute to momentum profits.

Focusing on the Raw WRDS sample, Appendix B Figure B.IV Plot B highlights that a small difference in observations (0.11%) makes a big difference in conclusions. Here, only two types of loser bonds (mainly $L_{\{1,1,1\}}$ and only marginally $L_{\{0,0,1\}}$) and all but one type of winner bonds contribute to momentum (see also Panel B of Appendix B Table B.5, which mirrors Figure VII Plot B).

Figure VII Plot B visualizes data and estimation uncertainty for a bond momentum investor. It presents the posterior density of the resulting momentum strategy profits, calculated from the parameters in Figure VII Plot A as in equation (6). Each histogram reflects the estimation uncertainty in the particular data sample. Comparing the three histograms reveals the extent of data uncertainty: the first (second) [third] histogram, based on the WRDS (Raw WRDS) [DS Confirmed] sample, is centered around 0.56% (0.47%) [0.56%] monthly (3,3) momentum strategy profits. The latter three momentum profit estimates differ somewhat from the portfolio-sort-based estimates in Table II, which reports monthly EW (3,3) momentum profits of 0.63% (0.54%) [0.68%]. This is because the portfolio-sorts methodology weighs each month equally (regardless of how many bonds enter the momentum strategy), while the regression model above weighs each bond-month observation equally (regardless of which month it comes from). Notably, while the frequentist approach in Table II produces an insignificant at the 5% level momentum profit estimate of 0.54% (t-statistic=1.67) in the starting Raw WRDS sample, the 10,000 Gibbs sampler estimates in Figure VII are all positive and their mass is far above zero.

III.D. Estimation results: learning from 204 data samples

Whereas Figure VII presents the posterior distribution of momentum profits in our 3 starting samples one at a time, Figure VIII illustrates the 'cumulative' probability density of momentum profits from the multiple samples examined in Table II, Table III, and Table IV. Specifically, for each of the 204 data samples, we produce 10,000 draws from the marginal posterior densities of the (3,3) momentum strategy parameters (from equation 6) using the Gibbs sampler.[36] We then aggregate these draws across many samples and present the resulting cumulative posterior distribution. Plot A aggregates across the 68 ($=26 \times 3 - 10$) individual bond samples in Table II, with each sample represented by a different shade of blue. The resulting color scheme of the cumulative plot illustrates that some momentum profit estimates tend to be supported by many samples while others seem to be supported by only a few. The monthly momentum profits across the $680,000$ (=10,000 draws$\times$68 samples) Gibbs sampler draws average 0.57% and range between 0.20% and 1.32%. Plot B (C) paints a similar picture coming from the 68 equally (value-) weighted firm-level samples in Table III (IV). Here the average momentum profits from the $680,000$ Gibbs sampler draws are 0.67% (0.69%). Notably, none of the 680,000 Gibbs sampler draws in Plots A, B and C results in a negative (3,3) bond momentum profit.

Plots D-F present the cumulative probability density of the (6,6) momentum profit estimates. Compared to Plots A-C, the mass of the distribution here is shifted to the left

[36] As in Figure V, we combine the $3 \times 26 \times 3 = 234$ data samples from Tables II, III, and IV, but exclude the last 10 samples in each Panel B as they are almost exact replicas of the last 10 samples in each Panel A.

consistent with the portfolio analyses and prior evidence that momentum weakens as the formation and holding periods increase. In Plot D, monthly momentum profits from the $680,000$ Gibbs sampler draws are in the 0.12%–1.37% range and average 0.55%. In Plot E (F), where the $680,000$ draws are from the 68 equally (value-) weighted firm-level samples, average momentum profits are 0.55% (0.55%) per month and Gibbs sampler momentum draws range between 0.13% and 1.37% (0.13% and 1.35%).

In sum, our Bayesian setup offers a more comprehensive decision making framework than the frequentist approach of relying on a single point estimate from a single (or a few) data samples. Moreover, this setup puts a single point estimate in context and allows an investor to estimate the likelihood of observing such a point estimate. While in our estimation, we are agnostic about how well each sample reflects the true population, the Bayesian setup would allow an investor to impose subjective priors that reflect their beliefs that some data choices may be more reasonable than others.

IV. Momentum Profitability among Investment Grade Bonds

Our analyses thus far reveal that data choices impact NIG momentum profitability: while always positive, profits are significant in some samples but insignificant in others. To understand whether the lack of momentum profitability among IG bonds may be driven by data choices as well, we repeat our analyses in bonds/firms rated IG at the end of the formation period. As before, we retain all bonds in each data sample to avoid look-ahead bias from excluding bonds that may be downgraded during the holding period. Appendix B Tables B.6, B.7, and B.8 report the results from our analysis of IG momentum profitability in 204 samples, replicating the analyses for NIG bonds in Tables II, III, and IV.

Momentum profits among IG bonds are insignificant in every single sample we analyze. Figure IX summarizes the EW and VW (3,3) and (6,6) IG momentum profit estimates across the 204 samples using the same X-axis scale for comparison with the NIG results in Figure V.

Monthly (3,3) momentum profits range between -0.13% and 0.04% and average -0.03%. Monthly (6,6) momentum profits range between -0.18% and 0.004% and average -0.09%.

A similar picture emerges from Figure X, which summarizes the Bayesian Gibbs sampling estimates of momentum profits, as in Figure VIII, but for IG bonds. For both (3,3) and (6,6) momentum strategies, and for individual and firm-level returns, the mass of IG momentum profit estimates is concentrated around zero. The Gibbs sampler draws of momentum profits here average 0.06% (0.03%) [0.02%] for (3,3) strategies and -0.03% (-0.03%) [-0.03%] for (6,6) strategies.

The distribution of IG momentum profits across data samples reveals that momentum is absent from the cross-section of IG corporate bond returns, consistent with previous findings in the literature (see Appendix A). The analysis of IG bonds underscores the paper's message that it is important to examine the distribution of point estimates across samples, rather than focusing on a single point estimate.

V. Conclusion

Data uncertainty is pervasive throughout empirical research yet there is limited appreciation for its importance in finance studies. In this paper, we address data uncertainty in corporate bonds. Specifically, we describe the source of data uncertainty and account for its impact when interpreting the findings of asset-pricing studies. To do so, we provide a taxonomy of data choices researchers are bound to make in the course of constructing a sample of corporate bond returns. These data choices lead to hundreds of plausible samples which we show have different distributional properties and may lead to different asset-pricing conclusions. We propose and fit a stylized model of an investor's rational response when faced with data and estimation uncertainty. Instead of focusing on a single point estimate from a single sample, we argue that the investor should consider the distribution of profit estimates within and across samples. While this framework for decision-making under data uncertainty is cast in an asset-pricing setting, the framework carries to other settings where data choices have to be made.

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Table I

Descriptive statistics and momentum in starting samples

The table presents descriptive statistics for different samples of bonds traded from July 2002 to June 2023. The first row of Panel A describes the WRDS sample obtained using WRDS SAS programs for pre-cleaning TRACE and computing returns, based on prices from the last 5 trading days of the month. The WRDS program winsorizes returns at 100% per month and assigns default-month returns of -20.779% to IG bonds and -22.488% to NIG/unrated bonds over our sample period. The 'WRDS sample w/o winsorization' removes the winsorization but retains the WRDS-implied default-month returns. The 'Raw WRDS sample' is the same as the 'WRDS sample w/o winsorization' but excludes returns based on the 36 prices examined in Appendix B Table B.1. The 'DS Confirmed sample' starts with the 'Raw WRDS sample' but excludes return outliers (defined as those larger than 30% per month in absolute value) that are missing in DS or are further than 2 standard deviations ($2 \times 4.35\%$) away from the DS return. Column '% of total obs' displays percentages relative to the WRDS sample. Column 'n-sigma of max' displays the number of standard deviations the maximum value is from the mean of the sample. Panel A uses returns calculated from trading prices within the last 5 trading days of the month (RET_L5M). Panel B report statistics for the WRDS sample for alternative ways of calculating monthly returns: using the last price of the month (RET_EOM) or the price on the last trading day of the month (RET_LDM). Panel C uses RET_L5M returns and presents descriptive and NIG momentum profitability statistics for our starting samples. The last four columns display, for each sample, profits from the (3,3) and (6,6) momentum strategies described in Section II.B for NIG bonds.

Sample	Total obs	% of total obs	Bond return statistics											
			Mean (%)	SD (%)	Skewness	Kurtosis	Min (%)	1st (%)	25th (%)	50th (%)	75th (%)	99th (%)	Max (%)	n-sigma of max
Panel A: Using returns based on last price within last 5 trading days of month (RET_L5M)														
WRDS sample	1427056	100.000	0.43	4.29	2	110	-100.0	-10.7	-0.5	0.3	1.4	11.1	100	23
WRDS sample w/o winsorization	1427056	100.000	60.95	72251.21	1195	1427054	-100.0	-10.7	-0.5	0.3	1.4	11.1	86310900	1195
Raw WRDS sample	1426993	99.996	0.43	4.47	8	406	-98.5	-10.6	-0.5	0.3	1.4	11.1	295	66
DS Confirmed sample	1424866	99.847	0.40	3.73	1	98	-95.0	-10.4	-0.5	0.3	1.4	10.6	265	71
Panel B: Using returns based on last price of the month (RET_EOM) or price on the last trading day of the month (RET_LDM)														
WRDS sample (RET_EOM)	3307118	231.744	0.50	4.94	3	99	-100.0	-12.1	0.0	0.0	0.9	15.3	100	20
WRDS sample (RET_LDM)	788393	55.246	0.34	4.11	2	108	-98.5	-10.6	-0.5	0.3	1.3	10.2	100	24

Panel C: Bond momentum in starting samples

Sample	Total obs	% of total obs.	Number of return outliers		NIG momentum profits (%)			
					Equally weighted		Value-weighted	
			$\leq -30\%$	$\geq 30\%$	$\pi_{3,3}$	$\pi_{6,6}$	$\pi_{3,3}$	$\pi_{6,6}$
WRDS sample	1427056	100.000	1715	2232	0.63 (**2.02**)	0.47 (1.11)	0.71 (**2.22**)	0.48 (1.14)
Raw WRDS sample	1426993	99.996	1693	2194	0.54 (1.67)	0.33 (0.74)	0.64 (1.95)	0.37 (0.83)
Raw WRDS excl missing DS returns	1426407	99.955	1482	1819	0.54 (1.67)	0.38 (0.85)	0.65 (**2.01**)	0.42 (0.97)
DS Confirmed sample	1424866	99.847	911	849	0.68 (**2.66**)	0.85 (**2.59**)	0.75 (**2.81**)	0.88 (**2.71**)

Table II

Bond momentum in samples of individual NIG bond returns

The table presents descriptive and momentum profitability statistics for samples of bonds traded from July 2002 to June 2023. The last four columns display profits from the (3,3) and (6,6) momentum strategies described in Section II.B for NIG bonds. Panel A (B) [C] starts with the WRDS (Raw WRDS) [DS Confirmed] sample. Additional samples differ by one data choice at a time. Row '$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$' replaces the WRDS program's assumed default-month return of −20.779% for IG and −22.488% for NIG/unrated bonds with each bond's actual default-month return assuming flat trading post-default (missing returns are left missing). Row '$R(def) = ave(R(def))$' replaces all default-month returns (missing or not) with our sample's average default-month return of −17.82%, calculated assuming flat trading. Row '$missR(def) = ave(R(def))$' replaces only missing default-month returns with our sample average default-month return of −17.82%. Row 'Exclude +95%/−45%' removes returns of 95% followed by returns of −45%, or vice versa. Other price reversal filters are similarly defined. Row '$P < 1,000$' excludes bonds priced above 1000% of par at the end of the prior month, with other price level filters similarly defined. Row 'Maturity>1 year' excludes bonds with less than a year to maturity. Row 'Rated by any agency' includes in the momentum strategy bonds that are rated NIG by S&P, or Moody's, or Fitch, in that sequence, not just by S&P. Row 'Exclude face=$10' includes only bonds with $1,000 par value. Row 'Corp debentures only' includes only US corporate debentures (CDEB in FISD). Row '$R < 90\%$' ('$|R| < 90\%$') includes only returns below 90% (in absolute value), with other return outlier filters similarly defined.

Panel A: WRDS sample as starting sample

Sample	Total obs.	% of total obs.	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	1427056	100.000	0.43	4.29	100	23	0.63	0.47	0.71	0.48
							(**2.02**)	(1.11)	(**2.22**)	(1.14)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	1426644	99.971	0.43	4.35	100	23	0.49	0.29	0.55	0.24
							(1.54)	(0.67)	(1.71)	(0.56)
$R(def) = ave(R(def))$	1427056	100.000	0.43	4.27	100	23	0.57	0.39	0.65	0.40
							(1.84)	(0.92)	(**2.06**)	(0.95)
$missR(def) = ave(R(def))$	1427056	100.000	0.43	4.36	100	23	0.52	0.34	0.56	0.26
							(1.64)	(0.78)	(1.76)	(0.62)
Exclude $+95\%/-45\%$	1426885	99.988	0.42	4.19	100	24	0.65	0.54	0.71	0.54
							(**2.18**)	(1.36)	(**2.29**)	(1.36)
Exclude $+60\%/-60\%$	1426936	99.992	0.42	4.22	100	24	0.63	0.51	0.70	0.51
							(**2.05**)	(1.24)	(**2.17**)	(1.24)
Exclude $+30\%/-30\%$	1426095	99.933	0.42	4.01	100	25	0.74	0.65	0.84	0.69
							(**2.58**)	(1.73)	(**2.86**)	(1.88)
Exclude $+20\%/-20\%$	1424610	99.829	0.42	3.86	100	26	0.82	0.68	0.95	0.73
							(**2.96**)	(1.83)	(**3.38**)	(**2.06**)
Exclude $R_t R_{t-1} < -0.04$	1423125	99.725	0.41	3.72	100	27	0.93	0.81	1.09	0.91
							(**3.82**)	(**2.47**)	(**4.29**)	(**2.82**)
Exclude $R_t R_{t-1} < -0.02$	1419227	99.451	0.41	3.57	100	28	0.87	0.68	1.06	0.78
							(**3.78**)	(**2.17**)	(**4.38**)	(**2.59**)
$P < 1,000$	1426872	99.987	0.43	4.29	100	23	0.63	0.47	0.71	0.48
							(**2.02**)	(1.11)	(**2.22**)	(1.14)
$P < 200$	1426617	99.969	0.43	4.28	100	23	0.63	0.48	0.71	0.48
							(**2.01**)	(1.12)	(**2.21**)	(1.15)
$P > 1$	1426945	99.992	0.42	4.26	100	23	0.65	0.53	0.73	0.54
							(**2.09**)	(1.24)	(**2.28**)	(1.29)
$P > 5$	1426500	99.961	0.42	4.22	100	24	0.63	0.55	0.73	0.58
							(**2.06**)	(1.34)	(**2.40**)	(1.47)
Maturity > 1 year	1315895	92.210	0.43	4.31	100	23	0.58	0.44	0.68	0.47
							(1.85)	(1.02)	(**2.10**)	(1.13)
Rated by any agency	1427056	100.000	0.43	4.29	100	23	0.64	0.43	0.70	0.43
							(**2.16**)	(1.10)	(**2.29**)	(1.10)
Exclude face=$10	1394216	97.699	0.41	4.19	100	24	0.63	0.47	0.71	0.48
							(**2.02**)	(1.11)	(**2.22**)	(1.14)
Corp debentures only	1249095	87.530	0.41	4.22	100	24	0.68	0.48	0.72	0.45
							(**2.16**)	(1.12)	(**2.23**)	(1.07)
$\|R\| < 100\%$	1426848	99.985	0.41	4.12	100	24	0.84	0.74	0.91	0.76
							(**2.88**)	(1.90)	(**3.00**)	(**1.96**)
$\|R\| < 90\%$	1426785	99.981	0.41	4.07	90	22	0.87	0.82	0.95	0.82
							(**3.05**)	(**2.12**)	(**3.18**)	(**2.17**)
$R < 90\%$	1426800	99.982	0.41	4.08	90	22	0.88	0.82	0.95	0.82
							(**3.07**)	(**2.11**)	(**3.18**)	(**2.17**)
$\|R\| < 60\%$	1426281	99.946	0.40	3.84	60	15	0.87	1.01	0.91	0.99
							(**3.43**)	(**3.25**)	(**3.37**)	(**3.07**)
$R < 60\%$	1426480	99.960	0.39	3.94	60	15	1.10	1.17	1.08	1.10
							(**4.15**)	(**3.39**)	(**3.90**)	(**3.19**)
$\|R\| < 30\%$	1423109	99.723	0.40	3.32	30	9	0.55	0.74	0.65	0.75
							(**3.25**)	(**3.73**)	(**3.29**)	(**3.46**)
$R < 30\%$	1424824	99.844	0.35	3.69	30	8	1.56	1.77	1.50	1.61
							(**6.26**)	(**5.57**)	(**5.64**)	(**5.11**)

Table II (continued)

Panel B: Raw WRDS sample as starting sample

Sample	Total obs.	% of total obs.	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	1426993	100.000	0.43	4.47	295	66	0.54	0.33	0.64	0.37
							(1.67)	(0.74)	(1.95)	(0.83)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	1426577	99.971	0.44	4.54	295	65	0.37	0.14	0.46	0.12
							(1.12)	(0.30)	(1.40)	(0.26)
$R(def) = ave(R(def))$	1426993	100.000	0.44	4.46	295	66	0.47	0.24	0.58	0.27
							(1.45)	(0.53)	(1.76)	(0.62)
$missR(def) = ave(R(def))$	1426993	100.000	0.44	4.54	295	65	0.41	0.18	0.48	0.14
							(1.23)	(0.40)	(1.47)	(0.32)
Exclude $+95\%/-45\%$	1426873	99.992	0.43	4.33	295	68	0.61	0.48	0.67	0.49
							(**1.99**)	(1.17)	(**2.11**)	(1.22)
Exclude $+60\%/-60\%$	1426924	99.995	0.43	4.38	295	67	0.58	0.43	0.66	0.44
							(1.83)	(1.00)	(**1.99**)	(1.04)
Exclude $+30\%/-30\%$	1426083	99.936	0.42	4.14	295	71	0.71	0.61	0.82	0.66
							(**2.43**)	(1.58)	(**2.78**)	(1.79)
Exclude $+20\%/-20\%$	1424598	99.832	0.42	3.99	295	74	0.80	0.65	0.94	0.71
							(**2.85**)	(1.74)	(**3.31**)	(**2.00**)
Exclude $R_tR_{t-1} < -0.04$	1423116	99.728	0.42	3.81	294	77	0.92	0.80	1.09	0.90
							(**3.79**)	(**2.44**)	(**4.27**)	(**2.79**)
Exclude $R_tR_{t-1} < -0.02$	1419225	99.456	0.42	3.67	294	80	0.86	0.68	1.05	0.77
							(**3.73**)	(**2.14**)	(**4.35**)	(**2.57**)
$P < 1,000$	1426812	99.987	0.43	4.47	295	66	0.54	0.33	0.64	0.37
							(1.67)	(0.74)	(1.95)	(0.83)
$P < 200$	1426564	99.970	0.43	4.47	295	66	0.54	0.33	0.64	0.37
							(1.66)	(0.74)	(1.95)	(0.83)
$P > 1$	1426896	99.993	0.43	4.39	295	67	0.57	0.43	0.68	0.47
							(1.79)	(0.96)	(**2.07**)	(1.08)
$P > 5$	1426453	99.962	0.43	4.34	295	68	0.56	0.46	0.69	0.51
							(1.79)	(1.07)	(**2.19**)	(1.25)
Maturity > 1 year	1315836	92.210	0.44	4.49	295	66	0.49	0.30	0.61	0.36
							(1.53)	(0.66)	(1.86)	(0.82)
Rated by any agency	1426993	100.000	0.43	4.47	295	66	0.55	0.31	0.63	0.33
							(1.79)	(0.74)	(**2.02**)	(0.80)
Exclude face=$10	1394155	97.699	0.42	4.38	295	67	0.54	0.33	0.64	0.37
							(1.67)	(0.74)	(1.95)	(0.83)
Corp debentures only	1249041	87.530	0.42	4.40	295	67	0.58	0.34	0.64	0.34
							(1.78)	(0.75)	(1.95)	(0.77)
$\|R\| < 100\%$	1426822	99.988	0.41	4.11	100	24	0.83	0.74	0.91	0.76
							(**2.85**)	(1.90)	(**2.99**)	(**1.98**)
$\|R\| < 90\%$	1426765	99.984	0.41	4.06	90	22	0.87	0.82	0.94	0.83
							(**3.02**)	(**2.13**)	(**3.16**)	(**2.18**)
$R < 90\%$	1426774	99.985	0.41	4.07	90	22	0.87	0.82	0.95	0.83
							(**3.04**)	(**2.12**)	(**3.17**)	(**2.18**)
$\|R\| < 60\%$	1426278	99.950	0.40	3.84	60	15	0.87	1.01	0.91	0.99
							(**3.43**)	(**3.25**)	(**3.37**)	(**3.07**)
$R < 60\%$	1426455	99.962	0.39	3.93	60	15	1.09	1.17	1.07	1.10
							(**4.12**)	(**3.40**)	(**3.89**)	(**3.21**)
$\|R\| < 30\%$	1423106	99.728	0.40	3.32	30	9	0.55	0.74	0.65	0.75
							(**3.25**)	(**3.73**)	(**3.29**)	(**3.46**)
$R < 30\%$	1424799	99.846	0.35	3.67	30	8	1.55	1.77	1.50	1.62
							(**6.24**)	(**5.58**)	(**5.63**)	(**5.14**)

Table II (continued)

Panel C: DS Confirmed sample as starting sample

Sample	Total obs.	% of total obs.	Bond return statistics				NIG momentum profits (%)			
			Mean (%)	SD (%)	Max (%)	n-sigma of max	Equally weighted		Value-weighted	
							$\pi_{3,3}$	$\pi_{6,6}$	$\pi_{3,3}$	$\pi_{6,6}$
Starting sample	1424860	100.000	0.40	3.73	265	71	0.68	0.85	0.75	0.87
							(2.65)	**(2.58)**	**(2.80)**	**(2.69)**
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	1424285	99.960	0.41	3.74	265	71	0.57	0.67	0.61	0.62
							(2.22)	**(2.03)**	**(2.31)**	(1.91)
$R(def) = ave(R(def))$	1424860	100.000	0.40	3.71	265	71	0.64	0.77	0.71	0.79
							(2.49)	**(2.35)**	**(2.67)**	**(2.47)**
$missR(def) = ave(R(def))$	1424860	100.000	0.40	3.76	265	70	0.63	0.75	0.67	0.72
							(2.45)	**(2.30)**	**(2.53)**	**(2.24)**
Exclude $+95\%/-45\%$	1424848	99.999	0.40	3.72	265	71	0.69	0.87	0.76	0.89
							(2.70)	**(2.66)**	**(2.84)**	**(2.75)**
Exclude $+60\%/-60\%$	1424858	100.000	0.40	3.73	265	71	0.68	0.85	0.75	0.87
							(2.66)	**(2.58)**	**(2.82)**	**(2.69)**
Exclude $+30\%/-30\%$	1424614	99.983	0.40	3.67	265	72	0.72	0.88	0.80	0.89
							(2.86)	**(2.75)**	**(3.04)**	**(2.78)**
Exclude $+20\%/-20\%$	1423652	99.915	0.40	3.58	265	74	0.79	0.91	0.91	0.93
							(3.31)	**(2.84)**	**(3.59)**	**(2.96)**
Exclude $R_tR_{t-1} < -0.04$	1422719	99.850	0.40	3.49	206	59	0.85	0.95	1.01	0.97
							(3.84)	**(3.16)**	**(4.22)**	**(3.22)**
Exclude $R_tR_{t-1} < -0.02$	1419101	99.596	0.40	3.36	206	61	0.79	0.86	0.97	0.90
							(3.77)	**(3.03)**	**(4.33)**	**(3.30)**
$P < 1,000$	1424683	99.988	0.40	3.73	265	71	0.68	0.85	0.75	0.87
							(2.65)	**(2.58)**	**(2.80)**	**(2.69)**
$P < 200$	1424445	99.971	0.40	3.73	265	71	0.68	0.85	0.75	0.87
							(2.65)	**(2.58)**	**(2.80)**	**(2.69)**
$P > 1$	1424800	99.996	0.40	3.73	265	71	0.68	0.85	0.75	0.87
							(2.65)	**(2.58)**	**(2.80)**	**(2.70)**
$P > 5$	1424422	99.969	0.40	3.72	265	71	0.64	0.80	0.72	0.83
							(2.47)	**(2.43)**	**(2.71)**	**(2.57)**
Maturity $>$ 1 year	1313965	92.217	0.41	3.78	265	70	0.63	0.83	0.72	0.87
							(2.44)	**(2.52)**	**(2.66)**	**(2.67)**
Rated by any agency	1424860	100.000	0.40	3.73	265	71	0.67	0.77	0.72	0.78
							(2.74)	**(2.49)**	**(2.81)**	**(2.56)**
Exclude face=$10	1392287	97.714	0.39	3.66	265	72	0.68	0.85	0.75	0.87
							(2.65)	**(2.58)**	**(2.80)**	**(2.69)**
Corp debentures only	1247426	87.547	0.39	3.72	265	71	0.70	0.84	0.77	0.85
							(2.70)	**(2.56)**	**(2.84)**	**(2.63)**
$\lvert R\rvert < 100\%$	1424835	99.998	0.40	3.69	100	27	0.73	0.94	0.79	0.95
							(2.92)	**(3.01)**	**(3.00)**	**(3.05)**
$\lvert R\rvert < 90\%$	1424821	99.997	0.40	3.68	90	24	0.74	0.96	0.80	0.97
							(2.96)	**(3.07)**	**(3.05)**	**(3.10)**
$R < 90\%$	1424823	99.997	0.40	3.68	90	24	0.74	0.96	0.80	0.97
							(2.98)	**(3.07)**	**(3.06)**	**(3.10)**
$\lvert R\rvert < 60\%$	1424622	99.983	0.39	3.58	60	17	0.76	1.02	0.82	1.01
							(3.30)	**(3.72)**	**(3.26)**	**(3.53)**
$R < 60\%$	1424705	99.989	0.39	3.62	60	16	0.89	1.13	0.91	1.09
							(3.77)	**(3.78)**	**(3.57)**	**(3.61)**
$\lvert R\rvert < 30\%$	1423106	99.877	0.40	3.32	30	9	0.55	0.74	0.65	0.75
							(3.25)	**(3.73)**	**(3.29)**	**(3.46)**
$R < 30\%$	1424012	99.940	0.37	3.51	30	8	1.15	1.42	1.16	1.35
							(5.15)	**(5.05)**	**(4.77)**	**(4.78)**

Table III
Bond momentum in samples of NIG firm returns - equally weighted

The table presents descriptive and momentum profitability statistics for different samples of firms with bonds traded from July 2002 to June 2023. The statistics are constructed as in Table II, but now the level of observation is a firm-month instead of bond-month. Firm variables in month t are equally weighted averages of individual bond variables in month t across all bonds of the firm. A firm-level rating of BB+ or worse at time $t-1$ qualifies the firm as NIG for our momentum strategy. We use a firm's $t-1$ total par value outstanding across all its bonds in TRACE when computing value-weighted momentum profits. All samples are as defined in Table II.

Panel A: WRDS sample as starting sample

Sample	Total obs.	% of total obs.	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	370384	100.000	0.52	4.70	100	21	0.80	0.52	0.77	0.51
							(2.69)	(1.32)	**(2.28)**	(1.22)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	370239	99.961	0.53	4.78	100	21	0.76	0.39	0.62	0.23
							(2.47)	(0.94)	(1.84)	(0.54)
$R(def) = ave(R(def))$	370384	100.000	0.52	4.67	100	21	0.74	0.43	0.73	0.42
							(2.50)	(1.09)	**(2.21)**	(1.00)
$missR(def) = ave(R(def))$	370384	100.000	0.53	4.77	100	21	0.78	0.41	0.63	0.23
							(2.54)	(1.00)	(1.88)	(0.54)
Exclude $+95\%/-45\%$	370336	99.987	0.52	4.57	100	22	0.81	0.55	0.75	0.53
							(2.75)	(1.45)	**(2.27)**	(1.29)
Exclude $+60\%/-60\%$	370340	99.988	0.52	4.59	100	22	0.80	0.54	0.75	0.53
							(2.69)	(1.40)	**(2.24)**	(1.27)
Exclude $+30\%/-30\%$	370167	99.941	0.51	4.40	100	23	0.89	0.64	0.83	0.68
							(3.11)	(1.75)	**(2.65)**	(1.84)
Exclude $+20\%/-20\%$	369793	99.840	0.51	4.25	100	23	0.92	0.60	0.92	0.64
							(3.41)	(1.79)	**(3.13)**	(1.83)
Exclude $R_tR_{t-1} < -0.04$	369422	99.740	0.50	4.08	100	24	0.95	0.63	0.94	0.69
							(3.78)	**(2.05)**	**(3.37)**	**(2.08)**
Exclude $R_tR_{t-1} < -0.02$	368566	99.509	0.50	3.94	100	25	1.01	0.55	1.13	0.59
							(3.82)	(1.80)	**(3.93)**	(1.84)
$P < 1,000$	370383	100.000	0.52	4.70	100	21	0.80	0.52	0.77	0.51
							(2.68)	(1.32)	**(2.29)**	(1.22)
$P < 200$	370355	99.992	0.52	4.69	100	21	0.80	0.52	0.76	0.51
							(2.67)	(1.33)	**(2.28)**	(1.22)
$P > 1$	370321	99.983	0.51	4.61	100	22	0.81	0.54	0.78	0.54
							(2.73)	(1.38)	**(2.34)**	(1.31)
$P > 5$	370260	99.967	0.51	4.58	100	22	0.79	0.56	0.85	0.63
							(2.67)	(1.46)	**(2.59)**	(1.57)
Maturity > 1 year	361263	97.537	0.53	4.74	100	21	0.73	0.47	0.74	0.46
							(2.44)	(1.16)	**(2.16)**	(1.07)
Rated by any agency	370384	100.000	0.52	4.70	100	21	0.78	0.51	0.75	0.48
							(2.71)	(1.38)	**(2.29)**	(1.22)
Exclude face=$10	370207	99.952	0.52	4.70	100	21	0.78	0.51	0.75	0.48
							(2.71)	(1.38)	**(2.29)**	(1.22)
Corp debentures only	358188	96.707	0.52	4.74	100	21	0.78	0.51	0.70	0.50
							(2.70)	(1.40)	**(2.14)**	(1.29)
$\|R\| < 100\%$	370305	99.979	0.49	4.44	97	22	0.92	0.73	0.84	0.68
							(3.25)	**(2.01)**	**(2.62)**	(1.71)
$\|R\| < 90\%$	370292	99.975	0.49	4.39	90	20	0.91	0.76	0.85	0.71
							(3.30)	**(2.13)**	**(2.65)**	(1.80)
$R < 90\%$	370297	99.977	0.49	4.41	90	20	0.93	0.77	0.87	0.73
							(3.36)	**(2.16)**	**(2.71)**	(1.85)
$\|R\| < 60\%$	370145	99.935	0.48	4.09	60	15	0.98	0.96	0.94	0.99
							(3.94)	**(3.23)**	**(3.27)**	**(2.92)**
$R < 60\%$	370208	99.952	0.47	4.23	60	14	1.14	1.05	1.06	1.03
							(4.41)	**(3.25)**	**(3.57)**	**(2.86)**
$\|R\| < 30\%$	369188	99.677	0.48	3.38	30	9	0.57	0.65	0.59	0.73
							(3.45)	**(3.68)**	**(2.85)**	**(3.43)**
$R < 30\%$	369723	99.822	0.40	3.90	30	8	1.61	1.72	1.46	1.60
							(6.56)	**(5.90)**	**(5.28)**	**(4.98)**

Table III (continued)

Panel B: Raw WRDS sample as starting sample

Sample	Total obs.	% of total obs.	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	370352	100.000	0.53	5.03	295	59	0.71	0.33	0.69	0.39
							(**2.23**)	(0.75)	(**1.98**)	(0.88)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	370206	99.961	0.54	5.11	295	58	0.66	0.20	0.55	0.11
							(**2.03**)	(0.43)	(1.57)	(0.26)
$R(def) = ave(R(def))$	370352	100.000	0.54	5.00	295	59	0.64	0.23	0.65	0.28
							(**2.05**)	(0.51)	(1.91)	(0.64)
$missR(def) = ave(R(def))$	370352	100.000	0.54	5.10	295	58	0.68	0.21	0.56	0.11
							(**2.09**)	(0.47)	(1.61)	(0.25)
Exclude $+95\%/-45\%$	370327	99.993	0.52	4.88	295	60	0.76	0.44	0.70	0.45
							(**2.52**)	(1.08)	(**2.06**)	(1.04)
Exclude $+60\%/-60\%$	370331	99.994	0.52	4.91	295	60	0.75	0.40	0.71	0.42
							(**2.42**)	(0.96)	(**2.06**)	(0.97)
Exclude $+30\%/-30\%$	370159	99.948	0.52	4.71	295	62	0.85	0.56	0.77	0.63
							(**2.89**)	(1.44)	(**2.37**)	(1.63)
Exclude $+20\%/-20\%$	369785	99.847	0.51	4.56	295	65	0.89	0.55	0.89	0.59
							(**3.25**)	(1.58)	(**2.97**)	(1.63)
Exclude $R_tR_{t-1} < -0.04$	369415	99.747	0.51	4.34	294	68	0.94	0.63	0.93	0.69
							(**3.74**)	(**2.03**)	(**3.33**)	(**2.06**)
Exclude $R_tR_{t-1} < -0.02$	368563	99.517	0.51	4.22	294	70	1.00	0.55	1.12	0.60
							(**3.75**)	(1.78)	(**3.87**)	(1.85)
$P < 1,000$	370352	100.000	0.53	5.03	295	59	0.71	0.33	0.69	0.39
							(**2.23**)	(0.75)	(**1.98**)	(0.88)
$P < 200$	370328	99.994	0.53	5.02	295	59	0.71	0.33	0.69	0.39
							(**2.23**)	(0.75)	(**1.98**)	(0.88)
$P > 1$	370301	99.986	0.52	4.77	295	62	0.72	0.37	0.72	0.45
							(**2.28**)	(0.85)	(**2.08**)	(1.03)
$P > 5$	370240	99.970	0.51	4.74	295	62	0.71	0.40	0.80	0.54
							(**2.27**)	(0.94)	(**2.37**)	(1.28)
Maturity > 1 year	361234	97.538	0.54	5.05	295	58	0.63	0.30	0.64	0.36
							(**1.99**)	(0.68)	(1.80)	(0.81)
Rated by any agency	370352	100.000	0.53	5.03	295	59	0.71	0.35	0.69	0.39
							(**2.32**)	(0.86)	(**2.06**)	(0.95)
Exclude face=$10	370175	99.952	0.53	5.02	295	59	0.71	0.35	0.69	0.39
							(**2.32**)	(0.86)	(**2.06**)	(0.95)
Corp debentures only	358155	96.707	0.53	5.05	295	58	0.71	0.36	0.66	0.40
							(**2.33**)	(0.88)	(**1.98**)	(0.99)
$\|R\| < 100\%$	370292	99.984	0.50	4.41	97	22	0.90	0.73	0.83	0.68
							(**3.19**)	(**2.04**)	(**2.57**)	(1.71)
$\|R\| < 90\%$	370282	99.981	0.49	4.37	90	20	0.90	0.77	0.84	0.71
							(**3.25**)	(**2.16**)	(**2.62**)	(1.81)
$R < 90\%$	370284	99.982	0.49	4.38	90	20	0.92	0.78	0.85	0.73
							(**3.31**)	(**2.19**)	(**2.67**)	(1.86)
$\|R\| < 60\%$	370144	99.944	0.48	4.09	60	15	0.99	0.96	0.95	1.00
							(**3.95**)	(**3.23**)	(**3.29**)	(**2.92**)
$R < 60\%$	370196	99.958	0.47	4.20	60	14	1.13	1.06	1.06	1.04
							(**4.39**)	(**3.30**)	(**3.56**)	(**2.87**)
$\|R\| < 30\%$	369187	99.685	0.48	3.38	30	9	0.57	0.65	0.59	0.73
							(**3.45**)	(**3.68**)	(**2.86**)	(**3.44**)
$R < 30\%$	369711	99.827	0.40	3.87	30	8	1.61	1.73	1.46	1.60
							(**6.53**)	(**5.95**)	(**5.26**)	(**5.00**)

Table III (continued)

Panel C: DS Confirmed sample as starting sample

Sample	Total obs.	% of total obs.	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	369787	100.000	0.48	4.03	265	66	0.81	0.79	0.76	0.65
							(**3.02**)	(**2.41**)	(**2.39**)	(1.68)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	369584	99.945	0.50	4.05	265	65	0.74	0.66	0.62	0.47
							(**2.63**)	(1.94)	(1.92)	(1.19)
$R(def) = ave(R(def))$	369787	100.000	0.49	4.00	265	66	0.74	0.70	0.69	0.56
							(**2.77**)	(**2.14**)	(**2.18**)	(1.45)
$missR(def) = ave(R(def))$	369787	100.000	0.49	4.04	265	65	0.79	0.72	0.67	0.50
							(**2.88**)	(**2.17**)	(**2.11**)	(1.28)
Exclude $+95\%/-45\%$	369787	100.000	0.48	4.03	265	66	0.81	0.80	0.76	0.67
							(**3.02**)	(**2.43**)	(**2.35**)	(1.74)
Exclude $+60\%/-60\%$	369785	99.999	0.48	4.03	265	66	0.81	0.79	0.76	0.65
							(**3.02**)	(**2.41**)	(**2.39**)	(1.68)
Exclude $+30\%/-30\%$	369739	99.987	0.48	3.97	265	67	0.82	0.83	0.81	0.77
							(**3.08**)	(**2.64**)	(**2.67**)	(**2.20**)
Exclude $+20\%/-20\%$	369501	99.923	0.48	3.87	265	68	0.87	0.82	0.88	0.82
							(**3.52**)	(**2.76**)	(**3.16**)	(**2.48**)
Exclude $R_tR_{t-1} < -0.04$	369291	99.866	0.47	3.76	206	55	0.94	0.84	0.97	0.85
							(**3.94**)	(**2.92**)	(**3.59**)	(**2.67**)
Exclude $R_tR_{t-1} < -0.02$	368511	99.655	0.47	3.64	206	56	0.92	0.80	1.02	0.82
							(**3.74**)	(**2.84**)	(**3.69**)	(**2.72**)
$P < 1,000$	369787	100.000	0.48	4.03	265	66	0.81	0.79	0.76	0.65
							(**3.01**)	(**2.41**)	(**2.39**)	(1.68)
$P < 200$	369764	99.994	0.48	4.03	265	66	0.81	0.79	0.76	0.65
							(**3.01**)	(**2.41**)	(**2.39**)	(1.68)
$P > 1$	369763	99.994	0.48	4.03	265	66	0.81	0.80	0.76	0.66
							(**3.02**)	(**2.43**)	(**2.39**)	(1.70)
$P > 5$	369717	99.981	0.48	4.02	265	66	0.78	0.76	0.77	0.68
							(**2.99**)	(**2.36**)	(**2.56**)	(1.85)
Maturity > 1 year	360694	97.541	0.49	4.10	265	64	0.74	0.78	0.72	0.67
							(**2.85**)	(**2.40**)	(**2.23**)	(1.73)
Rated by any agency	369787	100.000	0.48	4.03	265	66	0.78	0.74	0.72	0.61
							(**3.01**)	(**2.40**)	(**2.35**)	(1.66)
Exclude face=$10	369610	99.952	0.48	4.03	265	66	0.78	0.74	0.72	0.61
							(**3.01**)	(**2.40**)	(**2.35**)	(1.66)
Corp debentures only	357604	96.705	0.48	4.08	265	65	0.77	0.76	0.71	0.61
							(**3.03**)	(**2.45**)	(**2.34**)	(1.68)
$\lvert R\rvert < 100\%$	369776	99.997	0.48	3.94	100	25	0.88	0.93	0.85	0.83
							(**3.56**)	(**3.15**)	(**2.89**)	(**2.44**)
$\lvert R\rvert < 90\%$	369772	99.996	0.48	3.92	87	22	0.89	0.95	0.87	0.86
							(**3.63**)	(**3.22**)	(**2.95**)	(**2.49**)
$R < 90\%$	369773	99.996	0.48	3.93	87	22	0.90	0.95	0.87	0.86
							(**3.67**)	(**3.22**)	(**2.96**)	(**2.49**)
$\lvert R\rvert < 60\%$	369702	99.977	0.47	3.77	60	16	0.87	0.93	0.79	0.85
							(**3.85**)	(**3.55**)	(**2.95**)	(**2.80**)
$R < 60\%$	369737	99.986	0.47	3.85	60	15	1.03	1.06	0.97	0.98
							(**4.38**)	(**3.70**)	(**3.42**)	(**2.98**)
$\lvert R\rvert < 30\%$	369187	99.838	0.48	3.38	30	9	0.57	0.65	0.59	0.73
							(**3.45**)	(**3.68**)	(**2.86**)	(**3.44**)
$R < 30\%$	369500	99.922	0.44	3.68	30	8	1.28	1.41	1.23	1.37
							(**5.75**)	(**5.32**)	(**4.72**)	(**4.59**)

Table IV
Bond momentum in samples of NIG firm returns - value weighted

The table presents descriptive and momentum profitability statistics for different samples of firms with bonds traded from July 2002 to June 2023. The statistics are constructed as in Table II, but now the level of observation is a firm-month instead of bond-month. Firm variables in month t are value-weighted averages of individual bond variables in month t across all bonds of the firm, using each bond's $t-1$ par value outstanding as the weight. A firm-level rating of BB+ or worse at time $t-1$ qualifies the firm as NIG for our momentum strategy. We use a firm's $t-1$ total par value outstanding across all its bonds in TRACE when computing value-weighted momentum profits. All samples are as defined in Table II.

Panel A: WRDS sample as starting sample

Sample	Total obs.	% of total obs.	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	370094	100.000	0.52	4.71	100	21	0.84	0.53	0.79	0.56
							(**2.85**)	(1.31)	(**2.34**)	(1.32)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	369961	99.964	0.53	4.79	100	21	0.83	0.41	0.70	0.29
							(**2.72**)	(0.98)	(**2.05**)	(0.68)
$R(def) = ave(R(def))$	370094	100.000	0.52	4.69	100	21	0.78	0.43	0.76	0.47
							(**2.68**)	(1.08)	(**2.28**)	(1.11)
$missR(def) = ave(R(def))$	370094	100.000	0.52	4.79	100	21	0.84	0.42	0.69	0.28
							(**2.77**)	(1.02)	(**2.03**)	(0.65)
Exclude $+95\%/-45\%$	370046	99.987	0.51	4.58	100	22	0.85	0.56	0.79	0.58
							(**2.93**)	(1.44)	(**2.37**)	(1.38)
$Exclude + 60\%/-60\%$	370050	99.988	0.51	4.60	100	22	0.85	0.54	0.79	0.57
							(**2.91**)	(1.39)	(**2.34**)	(1.37)
$Exclude + 30\%/-30\%$	369875	99.941	0.51	4.41	100	23	0.93	0.63	0.92	0.68
							(**3.31**)	(1.68)	(**2.99**)	(1.76)
Exclude $+20\%/-20\%$	369500	99.840	0.51	4.26	100	23	0.96	0.61	0.99	0.71
							(**3.55**)	(1.74)	(**3.33**)	(**1.97**)
Exclude $R_tR_{t-1} < -0.04$	369130	99.740	0.50	4.09	100	24	0.99	0.65	1.08	0.77
							(**3.97**)	(**2.07**)	(**3.85**)	(**2.28**)
Exclude $R_tR_{t-1} < -0.02$	368275	99.509	0.50	3.95	100	25	1.02	0.63	1.13	0.73
							(**3.93**)	(**2.01**)	(**3.98**)	(**2.24**)
$P < 1,000$	370093	100.000	0.52	4.71	100	21	0.84	0.53	0.79	0.56
							(**2.85**)	(1.31)	(**2.35**)	(1.32)
$P < 200$	370065	99.992	0.52	4.70	100	21	0.83	0.53	0.79	0.56
							(**2.84**)	(1.32)	(**2.34**)	(1.32)
$P > 1$	370032	99.983	0.51	4.62	100	22	0.85	0.54	0.81	0.60
							(**2.90**)	(1.37)	(**2.41**)	(1.41)
$P > 5$	369971	99.967	0.51	4.59	100	22	0.85	0.57	0.90	0.68
							(**2.89**)	(1.43)	(**2.72**)	(1.65)
Maturity > 1 year	360984	97.538	0.53	4.74	100	21	0.75	0.47	0.73	0.50
							(**2.54**)	(1.14)	(**2.14**)	(1.15)
Rated by any agency	370094	100.000	0.52	4.71	100	21	0.83	0.53	0.74	0.53
							(**2.91**)	(1.41)	(**2.22**)	(1.33)
Exclude face=$10	369917	99.952	0.52	4.71	100	21	0.83	0.53	0.74	0.53
							(**2.91**)	(1.41)	(**2.22**)	(1.33)
Corp debentures only	357900	96.705	0.52	4.75	100	21	0.84	0.54	0.74	0.53
							(**2.95**)	(1.42)	(**2.24**)	(1.33)
$\|R\| < 100\%$	370016	99.979	0.49	4.45	97	22	0.97	0.72	0.93	0.71
							(**3.48**)	(**1.97**)	(**2.88**)	(1.77)
$\|R\| < 90\%$	370003	99.975	0.49	4.41	90	20	0.98	0.76	0.95	0.76
							(**3.57**)	(**2.10**)	(**2.95**)	(1.91)
$R < 90\%$	370008	99.977	0.49	4.42	90	20	0.99	0.77	0.96	0.77
							(**3.62**)	(**2.12**)	(**2.99**)	(1.94)
$\|R\| < 60\%$	369856	99.936	0.48	4.10	60	14	1.03	0.96	1.02	1.02
							(**4.17**)	(**3.19**)	(**3.56**)	(**2.98**)
$R < 60\%$	369919	99.953	0.47	4.24	60	14	1.19	1.05	1.13	1.04
							(**4.66**)	(**3.21**)	(**3.82**)	(**2.86**)
$\|R\| < 30\%$	368898	99.677	0.48	3.40	30	9	0.63	0.68	0.66	0.81
							(**3.82**)	(**3.76**)	(**3.10**)	(**3.67**)
$R < 30\%$	369434	99.822	0.40	3.91	30	8	1.64	1.73	1.49	1.61
							(**6.67**)	(**5.79**)	(**5.37**)	(**4.99**)

Table IV (continued)

Panel B: Raw WRDS sample as starting sample

Sample	Total obs.	% of total obs.	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	370063	100.000	0.53	5.04	295	58	0.74	0.35	0.72	0.45
							(**2.38**)	(0.80)	(**2.08**)	(1.01)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	369929	99.964	0.54	5.12	295	57	0.72	0.21	0.63	0.16
							(**2.24**)	(0.46)	(1.80)	(0.35)
$R(def) = ave(R(def))$	370063	100.000	0.53	5.01	295	59	0.67	0.24	0.68	0.34
							(**2.18**)	(0.55)	(**1.99**)	(0.77)
$missR(def) = ave(R(def))$	370063	100.000	0.53	5.12	295	58	0.73	0.22	0.62	0.15
							(**2.28**)	(0.49)	(1.79)	(0.32)
Exclude $+95\%/-45\%$	370038	99.993	0.52	4.89	295	60	0.80	0.46	0.74	0.51
							(**2.68**)	(1.15)	(**2.18**)	(1.20)
$Exclude + 60\%/-60\%$	370042	99.994	0.52	4.92	295	60	0.78	0.42	0.74	0.49
							(**2.58**)	(1.00)	(**2.14**)	(1.13)
$Exclude + 30\%/-30\%$	369868	99.947	0.52	4.72	295	62	0.89	0.55	0.89	0.65
							(**3.06**)	(1.39)	(**2.86**)	(1.65)
Exclude $+20\%/-20\%$	369493	99.846	0.51	4.57	295	64	0.93	0.56	0.97	0.68
							(**3.35**)	(1.54)	(**3.20**)	(1.83)
Exclude $R_tR_{t-1} < -0.04$	369124	99.746	0.51	4.36	294	67	0.99	0.65	1.08	0.76
							(**3.93**)	(**2.04**)	(**3.80**)	(**2.26**)
Exclude $R_tR_{t-1} < -0.02$	368273	99.516	0.50	4.23	294	69	1.01	0.62	1.14	0.73
							(**3.87**)	(**1.96**)	(**3.95**)	(**2.21**)
$P < 1,000$	370063	100.000	0.53	5.04	295	58	0.74	0.35	0.72	0.45
							(**2.38**)	(0.80)	(**2.08**)	(1.01)
$P < 200$	370039	99.994	0.53	5.03	295	58	0.74	0.35	0.72	0.45
							(**2.38**)	(0.80)	(**2.08**)	(1.01)
$P > 1$	370013	99.986	0.51	4.78	295	62	0.76	0.39	0.76	0.52
							(**2.45**)	(0.89)	(**2.20**)	(1.18)
$P > 5$	369952	99.970	0.51	4.74	295	62	0.76	0.43	0.85	0.61
							(**2.47**)	(0.98)	(**2.51**)	(1.43)
Maturity > 1 year	360956	97.539	0.54	5.05	295	58	0.65	0.31	0.65	0.43
							(**2.07**)	(0.69)	(1.86)	(0.95)
Rated by any agency	370063	100.000	0.53	5.04	295	58	0.74	0.37	0.67	0.42
							(**2.47**)	(0.89)	(**1.96**)	(1.01)
Exclude face=$10	369886	99.952	0.53	5.04	295	58	0.74	0.37	0.67	0.42
							(**2.47**)	(0.89)	(**1.96**)	(1.01)
Corp debentures only	357868	96.705	0.53	5.07	295	58	0.75	0.37	0.67	0.43
							(**2.51**)	(0.90)	(**1.96**)	(1.02)
$\|R\| < 100\%$	370003	99.984	0.49	4.42	97	22	0.97	0.73	0.93	0.71
							(**3.47**)	(**2.00**)	(**2.87**)	(1.78)
$\|R\| < 90\%$	369993	99.981	0.49	4.39	90	20	0.97	0.78	0.95	0.76
							(**3.55**)	(**2.14**)	(**2.94**)	(1.91)
$R < 90\%$	369995	99.982	0.49	4.39	90	20	0.99	0.78	0.96	0.77
							(**3.60**)	(**2.15**)	(**2.97**)	(1.94)
$\|R\| < 60\%$	369855	99.944	0.48	4.10	60	14	1.03	0.96	1.03	1.02
							(**4.18**)	(**3.19**)	(**3.57**)	(**2.98**)
$R < 60\%$	369907	99.958	0.47	4.21	60	14	1.19	1.07	1.13	1.05
							(**4.64**)	(**3.26**)	(**3.81**)	(**2.88**)
$\|R\| < 30\%$	368897	99.685	0.48	3.40	30	9	0.63	0.68	0.66	0.81
							(**3.82**)	(**3.76**)	(**3.10**)	(**3.67**)
$R < 30\%$	369422	99.827	0.40	3.88	30	8	1.64	1.74	1.49	1.62
							(**6.64**)	(**5.83**)	(**5.35**)	(**5.01**)

Table IV (continued))

Panel C: DS Confirmed sample as starting sample

Sample	Total obs.	% of total obs.	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	369497	100.000	0.48	4.06	265	65	0.86	0.77	0.88	0.67
							(**3.24**)	(**2.26**)	(**2.76**)	(1.65)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	369306	99.948	0.50	4.07	265	65	0.79	0.64	0.73	0.45
							(**2.83**)	(1.80)	(**2.27**)	(1.07)
$R(def) = ave(R(def))$	369497	100.000	0.49	4.03	265	66	0.80	0.68	0.81	0.58
							(**3.01**)	(**2.00**)	(**2.59**)	(1.44)
$missR(def) = ave(R(def))$	369497	100.000	0.49	4.07	265	65	0.83	0.71	0.77	0.51
							(**3.05**)	(**2.04**)	(**2.44**)	(1.24)
Exclude $+95\%/-45\%$	369497	100.000	0.48	4.05	265	65	0.86	0.78	0.88	0.69
							(**3.24**)	(**2.29**)	(**2.75**)	(1.72)
$Exclude + 60\%/-60\%$	369495	99.999	0.48	4.05	265	65	0.86	0.77	0.88	0.67
							(**3.24**)	(**2.26**)	(**2.76**)	(1.66)
$Exclude + 30\%/-30\%$	369449	99.987	0.48	4.00	265	66	0.87	0.81	0.89	0.79
							(**3.25**)	(**2.45**)	(**2.95**)	(**2.12**)
Exclude $+20\%/-20\%$	369210	99.922	0.48	3.89	265	68	0.90	0.83	0.96	0.86
							(**3.61**)	(**2.68**)	(**3.35**)	(**2.53**)
Exclude $R_tR_{t-1} < -0.04$	369000	99.865	0.47	3.78	206	54	0.97	0.87	1.05	0.91
							(**4.02**)	(**2.93**)	(**3.77**)	(**2.75**)
Exclude $R_tR_{t-1} < -0.02$	368221	99.655	0.47	3.66	206	56	0.96	0.85	1.11	0.92
							(**3.95**)	(**2.94**)	(**3.96**)	(**2.93**)
$P < 1,000$	369497	100.000	0.48	4.06	265	65	0.86	0.77	0.87	0.67
							(**3.24**)	(**2.26**)	(**2.76**)	(1.65)
$P < 200$	369474	99.994	0.48	4.05	265	65	0.86	0.77	0.87	0.67
							(**3.24**)	(**2.26**)	(**2.76**)	(1.65)
$P > 1$	369474	99.994	0.48	4.05	265	65	0.86	0.78	0.88	0.67
							(**3.24**)	(**2.28**)	(**2.78**)	(1.67)
$P > 5$	369428	99.981	0.48	4.04	265	65	0.83	0.74	0.88	0.69
							(**3.15**)	(**2.20**)	(**2.88**)	(1.78)
Maturity $>$ 1 year	360414	97.542	0.49	4.12	265	64	0.77	0.76	0.73	0.68
							(**2.98**)	(**2.26**)	(**2.30**)	(1.70)
Rated by any agency	369497	100.000	0.48	4.06	265	65	0.80	0.75	0.77	0.65
							(**3.09**)	(**2.34**)	(**2.50**)	(1.72)
Exclude face=$10	369320	99.952	0.48	4.05	265	65	0.80	0.75	0.77	0.65
							(**3.09**)	(**2.34**)	(**2.50**)	(1.72)
Corp debentures only	357316	96.703	0.48	4.10	265	65	0.79	0.77	0.76	0.66
							(**3.10**)	(**2.37**)	(**2.50**)	(1.74)
$\|R\| < 100\%$	369486	99.997	0.48	3.96	100	25	0.94	0.93	0.96	0.85
							(**3.76**)	(**3.02**)	(**3.22**)	(**2.37**)
$\|R\| < 90\%$	369482	99.996	0.48	3.94	87	22	0.95	0.95	0.98	0.87
							(**3.82**)	(**3.07**)	(**3.26**)	(**2.41**)
$R < 90\%$	369483	99.996	0.48	3.95	87	22	0.96	0.95	0.98	0.87
							(**3.86**)	(**3.06**)	(**3.27**)	(**2.41**)
$\|R\| < 60\%$	369412	99.977	0.47	3.80	60	16	0.93	0.95	0.91	0.90
							(**4.07**)	(**3.56**)	(**3.30**)	(**2.88**)
$R < 60\%$	369447	99.986	0.47	3.87	60	15	1.08	1.07	1.07	1.01
							(**4.57**)	(**3.65**)	(**3.69**)	(**2.95**)
$\|R\| < 30\%$	368897	99.838	0.48	3.40	30	9	0.63	0.68	0.66	0.81
							(**3.82**)	(**3.76**)	(**3.10**)	(**3.67**)
$R < 30\%$	369210	99.922	0.44	3.70	30	8	1.32	1.44	1.28	1.42
							(**5.87**)	(**5.27**)	(**4.84**)	(**4.65**)

Table V
NIG bond momentum with random sampling

The table presents descriptive and momentum profitability statistics for randomly drawn subsamples of bonds traded from July 2002 to June 2023. We draw 1000 random samples of ψ fraction of bonds from the WRDS sample. We use these 1000 random subsamples to calculate profits from the (3,3) and (6,6) momentum strategies described in Section II.B for non-investment grade (NIG) bonds in each subsample. We reports statistics for the 1000 randomly drawn sample of bonds when $\psi = 30\%$ in Panel A, $\psi = 50\%$ in Panel B, and $\psi = 90\%$ in Panel C. For comparison, the table's top row displays the momentum profit estimates from the full sample, also reported in the first row of Table II Panel A.

	NIG momentum profits - EW		NIG momentum profits - VW	
	$\pi_{3,3}$	$\pi_{6,6}$	$\pi_{3,3}$	$\pi_{6,6}$
Full sample π (%)	0.63	0.47	0.71	0.48
	(**2.02**)	(1.11)	(**2.22**)	(1.14)
Panel A: Sampling 30% of bonds in each iteration				
Average π (%) across 1,000 draws	0.63	0.48	0.70	0.50
St. deviation of π (%)	0.16	0.16	0.19	0.21
Minimum	0.16	0.00	0.06	-0.07
5th percentile	0.35	0.22	0.39	0.15
25th percentile	0.53	0.37	0.57	0.37
75th percentile	0.74	0.59	0.83	0.64
95th percentile	0.90	0.75	1.01	0.84
Maximum	1.11	1.06	1.22	1.13
Panel B: Sampling 50% of bonds in each iteration				
Average π (%) across 1,000 draws	0.63	0.48	0.70	0.48
St. deviation of π (%)	0.11	0.11	0.13	0.14
Minimum	0.24	0.13	0.23	-0.04
5th percentile	0.44	0.30	0.49	0.25
25th percentile	0.56	0.40	0.61	0.39
75th percentile	0.70	0.55	0.78	0.57
95th percentile	0.80	0.65	0.91	0.70
Maximum	0.92	0.85	1.12	0.94
Panel C: Sampling 90% of bonds in each iteration				
Average π (%) across 1,000 draws	0.63	0.48	0.71	0.48
St. deviation of π (%)	0.03	0.04	0.04	0.05
Minimum	0.52	0.35	0.57	0.26
5th percentile	0.57	0.42	0.63	0.39
25th percentile	0.61	0.45	0.68	0.45
75th percentile	0.65	0.50	0.74	0.51
95th percentile	0.69	0.54	0.77	0.56
Maximum	0.74	0.58	0.82	0.64

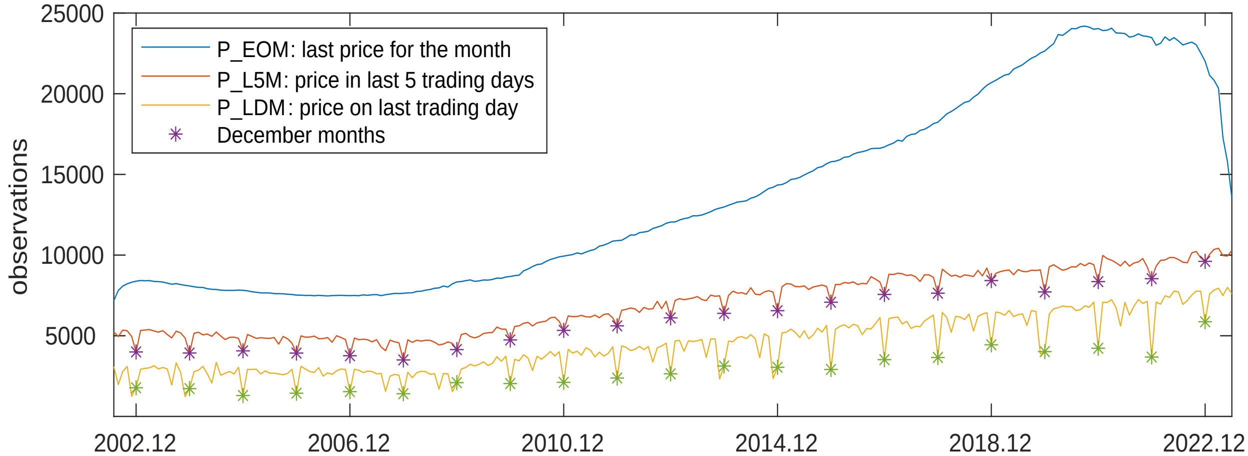


Figure I. Time series of month-end price observations. The figure presents the time series of the number of month-end price observations in the WRDS sample under three alternative month-end price choices: (1) last daily price of the month (P_EOM), (2) last daily price within the last 5 trading days of the month (P_L5M), or (3) daily price on the last trading day of the month (P_LDM).

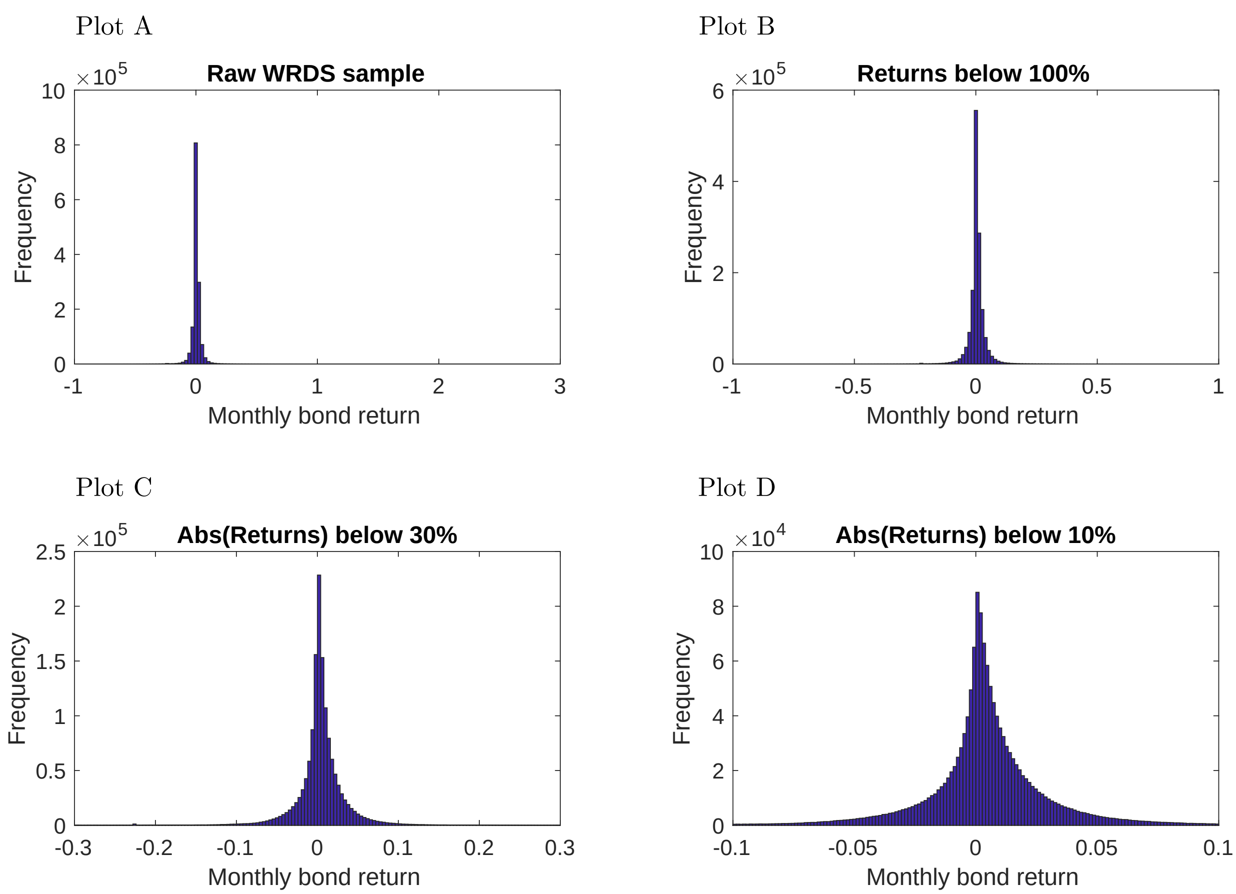
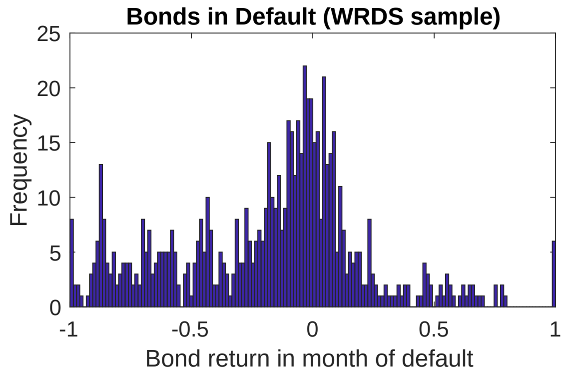
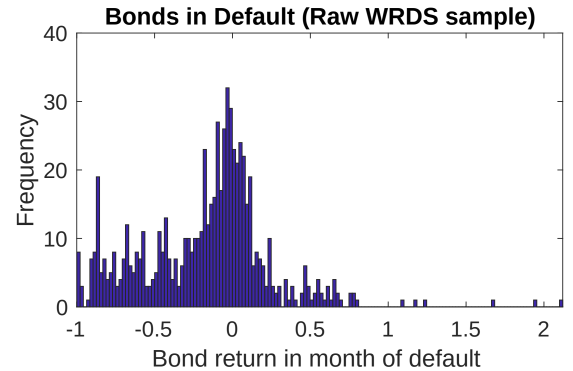


Figure II. Frequency distribution of monthly corporate bond returns. The figure presents the frequency distribution of monthly corporate bond returns for bonds traded from July 2002 to June 2023. We start with the Raw WRDS sample in Plot A, and then zoom into progressively smaller ranges of returns in that sample. Returns are calculated from prices within the last 5 trading days of the month (RET_L5M).

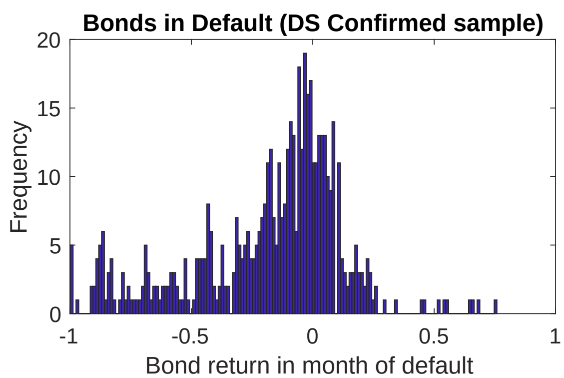
Plot A



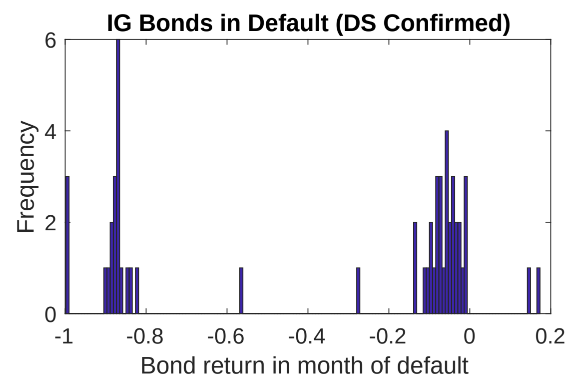
Plot B



Plot C



Plot D



Plot E

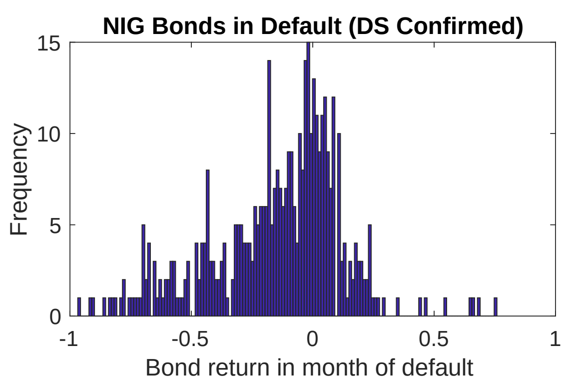


Figure III. Frequency distribution of default-month bond returns. The figure presents the frequency distribution of default-month return observations. Plot A (B) [C] focuses on the 696 (692) [533] such observations in the WRDS (Raw WRDS) [DS Confirmed] sample. Plot D (E) displays the default-month returns in the DS Confirmed sample for the 55 (478) defaulted bonds that were rated IG (NIG/unrated) at the end of the month prior to default. Returns are calculated from prices within the last 5 trading days of the month and assume flat trading in the month of default.

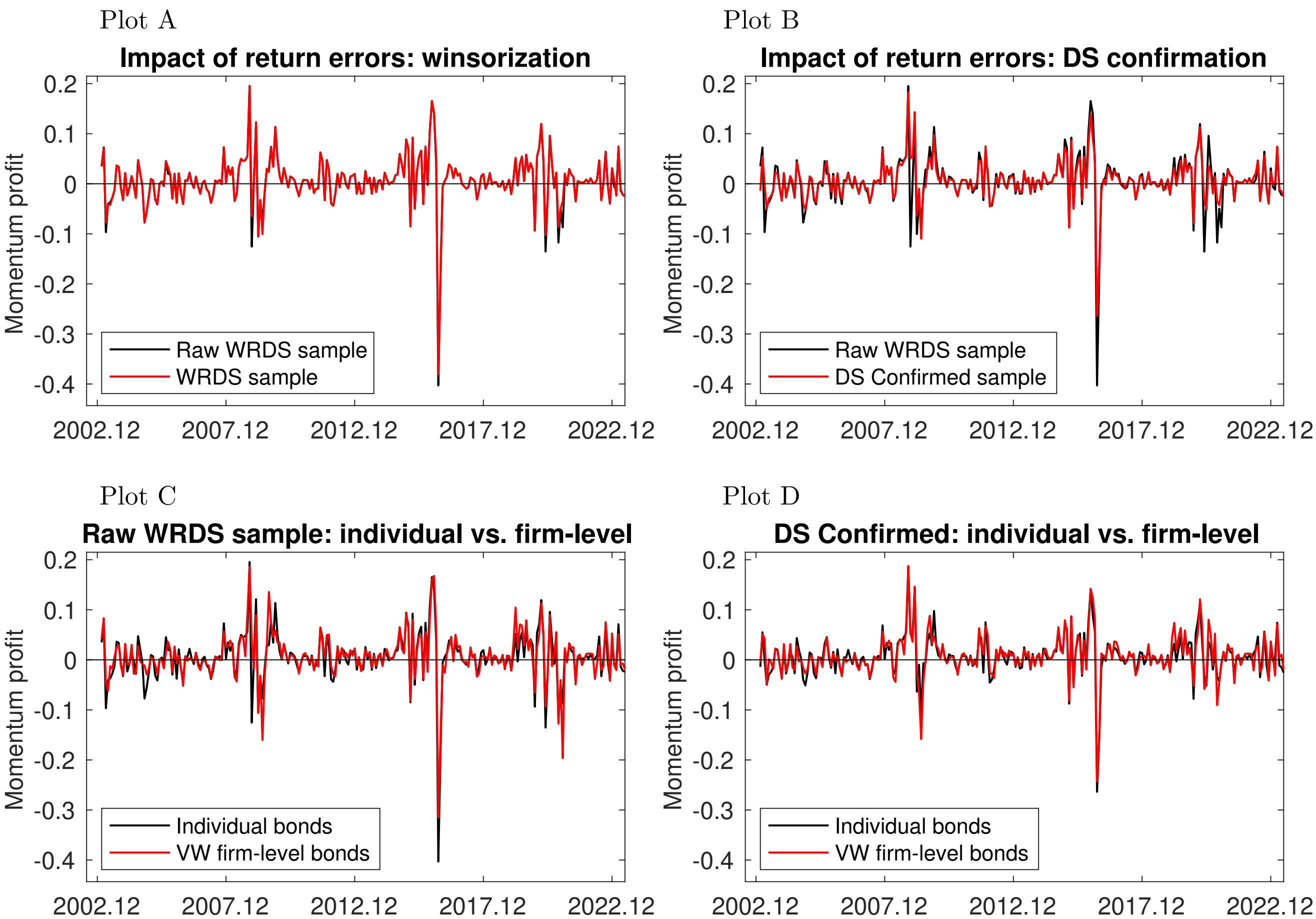
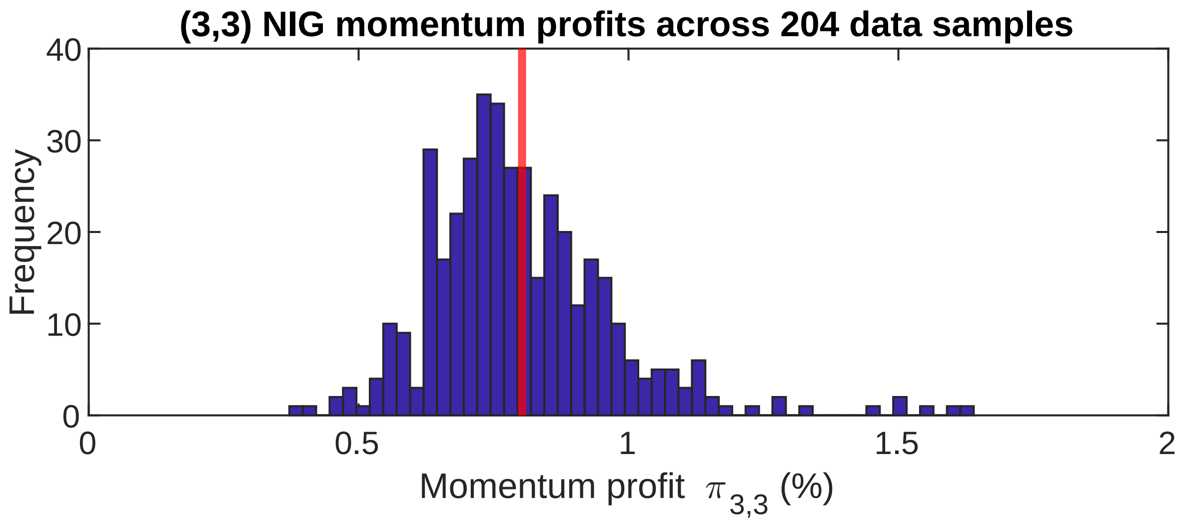


Figure IV. Time-series of NIG momentum profits. The figure displays the time-series of monthly profits from a (3,3) equally weighted momentum strategy. Plot A (B) compares the time-series of NIG momentum profits using individual bond returns from the Raw WRDS sample to that from the WRDS (DS Confirmed) sample. Plot C (D) compares the time-series of momentum profits based on individual bond returns to those based on value-weighted firm-level bond returns from the Raw WRDS (DS Confirmed) sample.

Plot A



Plot B

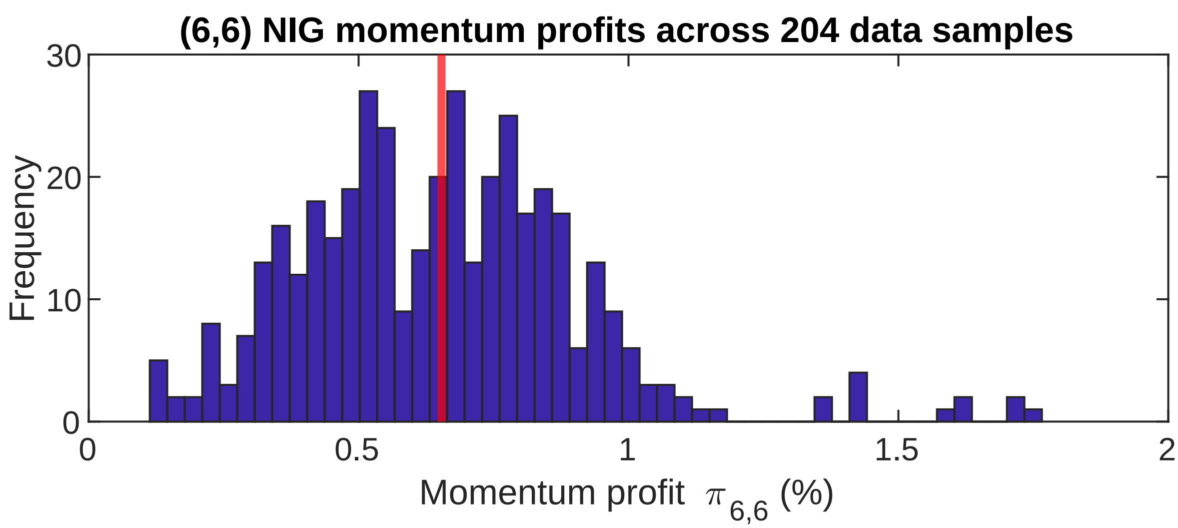


Figure V. Frequency distribution of NIG momentum profit estimates across 204 samples. Plots A and B present the frequency distribution of (3,3) and (6,6) monthly NIG momentum profits across the 204 data samples described in Tables II, III, and IV (excluding the last 10 rows in all Panels B). Both equally and value-weighted profits are included for a total of 408 $\pi_{3,3}$ and 408 $\pi_{6,6}$. The red line represents the average of the 408 sample momentum profit estimates in each plot.

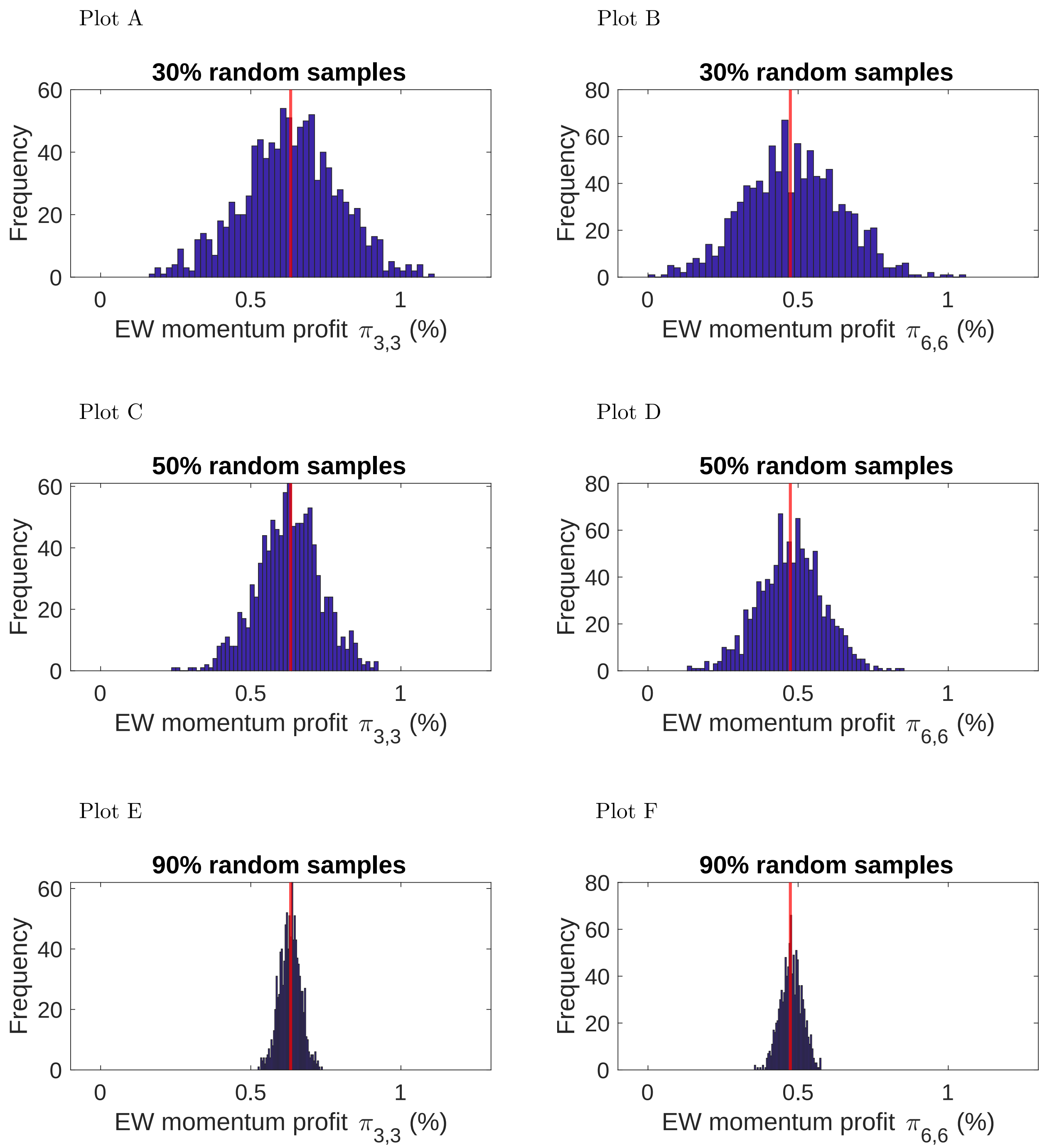
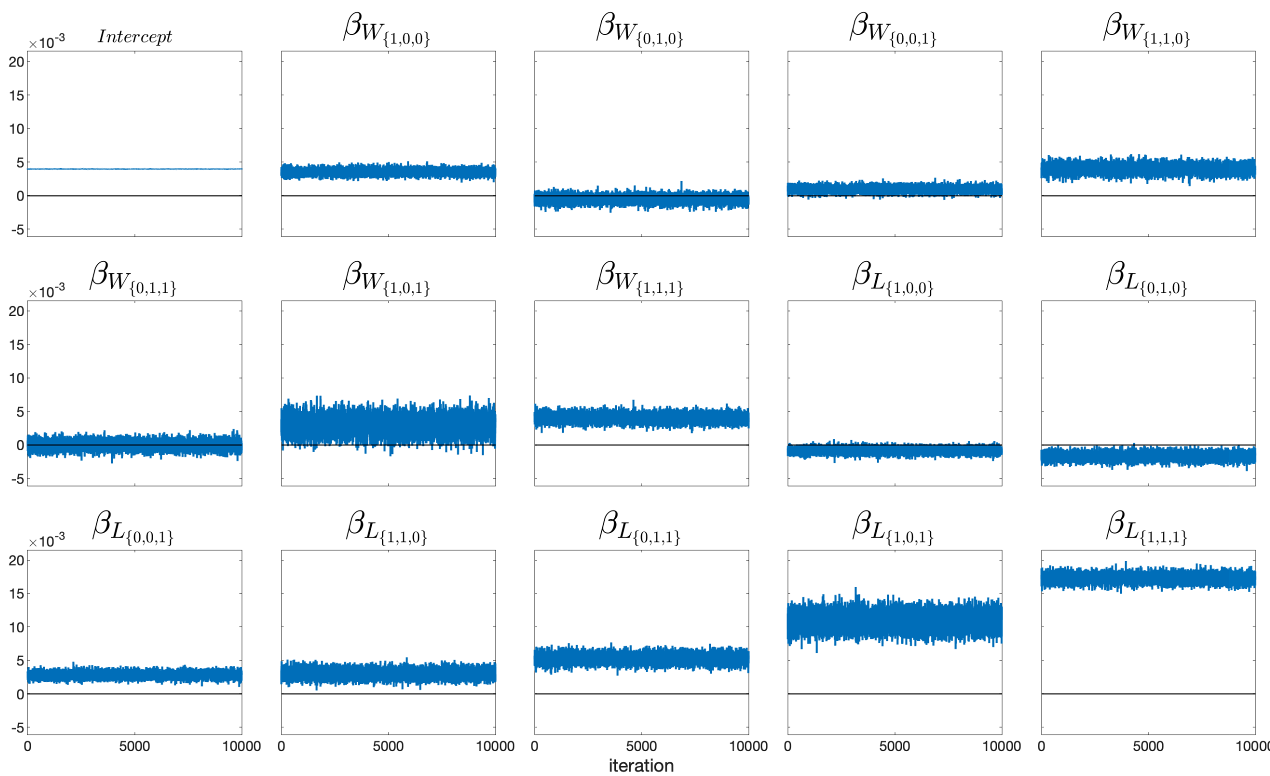


Figure VI. Frequency distribution of NIG momentum profits with random sampling. The figure presents the frequency distribution of monthly NIG momentum profits with random sampling. We draw 1000 random samples of ψ fraction of bonds from the WRDS sample. For each randomly drawn sample, we calculate profits from (3,3) and (6,6) equally weighted momentum strategies in bonds rated NIG in month $t-1$. ψ is 30% in Plots A and B, 50% in Plots C and D, and 90% in Plots E and F. The red line represents the average momentum profits in the full WRDS sample (from Table II).

Plot A: Momentum regression model Gibbs sampler parameter draws for DS Confirmed sample



Plot B: Distribution of momentum profits from 10,000 parameter draws

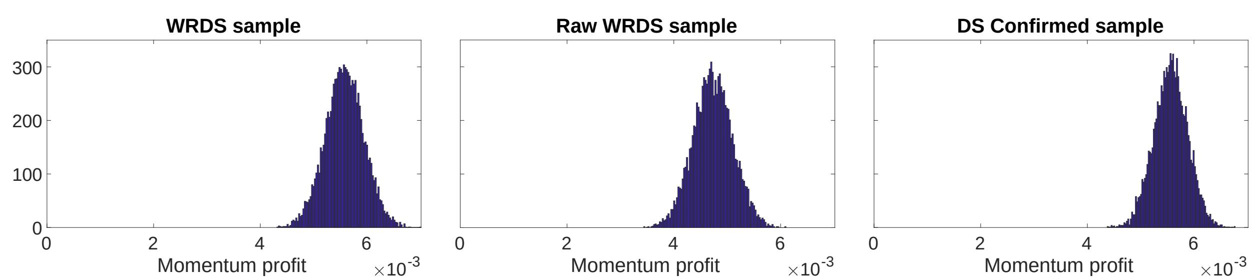


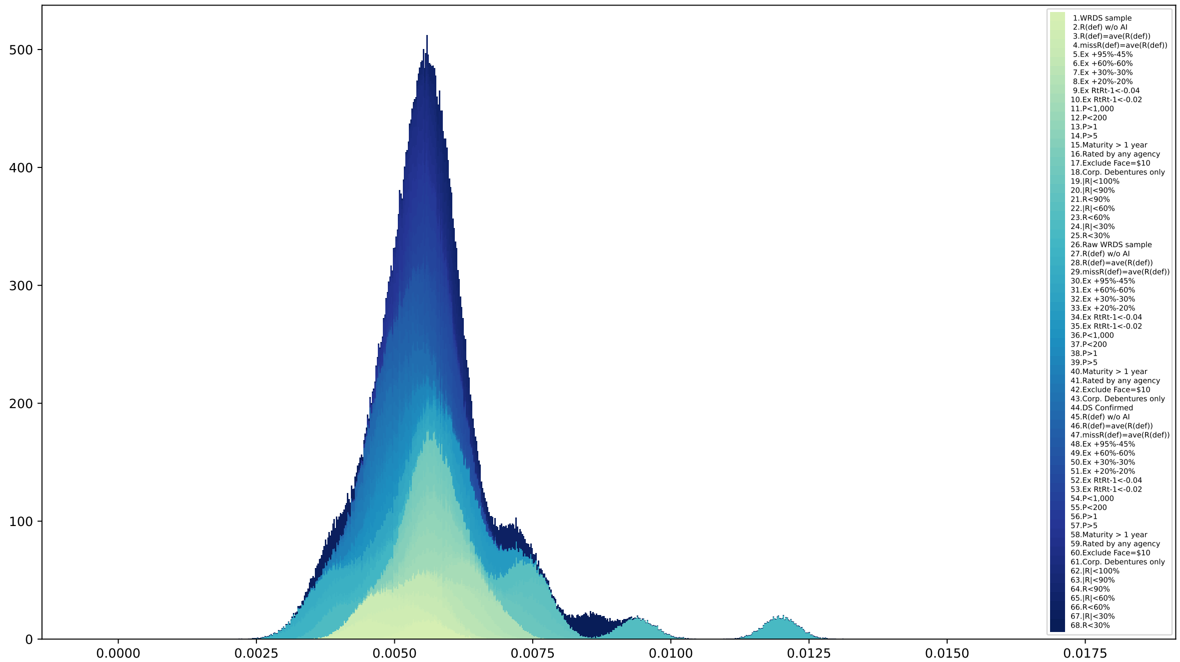
Figure VII. Gibbs sampler posterior estimates of NIG momentum profits. The figure presents estimation results for the regression model (equation 3):

$$r^s_{i,t+1} = \alpha^s + \boldsymbol{W}^s_{i,t}\boldsymbol{\beta}^s_W + \boldsymbol{L}^s_{i,t}\boldsymbol{\beta}^s_L + \sigma^s \varepsilon_{i,t+1} \qquad \varepsilon_{i,t+1} \sim N(0,1)$$

for $K = 3$, using 10,000 draws of the Gibbs sampler (1000 burn-in iterations). Plot A uses DS Confirmed sample returns for $r^s_{i,t+1}$; Appendix B Figure B.IV presents results with WRDS and Raw WRDS sample returns. Each subplot presents the marginal posterior draws for each parameter of the model: the intercept (α^s), the winners' contributions ($\boldsymbol{\beta}^s_W$), and the losers' contributions ($\boldsymbol{\beta}^s_L$) to momentum profits. The histograms in Plot B present the resulting momentum profits estimates for all three starting samples, calculated as

$$\pi^s = [\omega_{W,1}, \ldots, \omega_{W,H}] \times [\beta_{W,1}, \ldots, \beta_{W,H}] + [\omega_{L,1}, \ldots, \omega_{L,H}] \times [\beta_{L,1}, \ldots, \beta_{L,H}].$$

Plot A: (3,3) NIG momentum profits in 68 samples of individual bond returns



Plot B: (3,3) NIG momentum profits in 68 samples of equally weighted firm returns

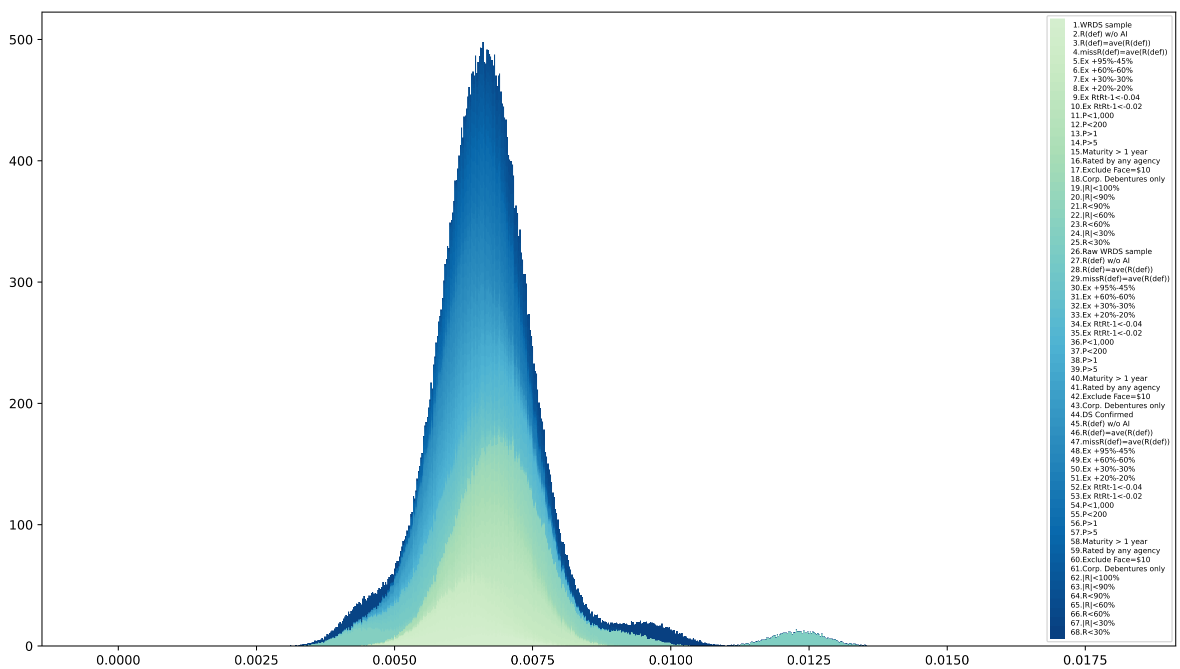
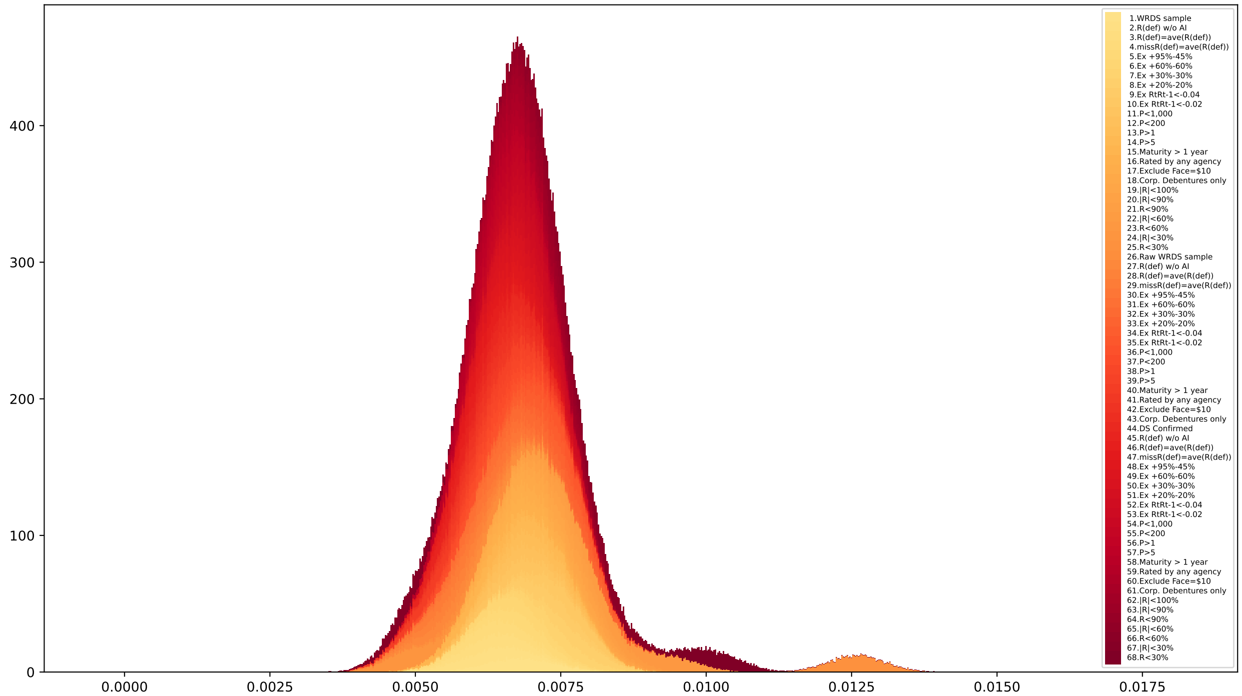


Figure VIII. Gibbs sampler posterior estimates of NIG momentum profits across samples. We estimate the regression model (equation 3) for $K = 3$ and $K = 6$, using 10,000 draws of the Gibbs sampler (1000 burn-in iterations) for the samples in Tables II, III, and IV. For each parameter draw, we calculate the corresponding momentum profit, π^{si} (equation 6), where s identifies the sample and i identifies the posterior draw of the parameters. Plot A (B) [C] presents the 'cumulative' posterior density for (3,3) NIG momentum profits across the 68 individual (68 equally weighted firm-level) [68 value-weighted firm-level] bond samples. Plot D (E) [F] presents the same for (6,6) NIG momentum profits.

Plot C: (3,3) NIG momentum profits in 68 samples of value-weighted firm returns



Plot D: (6,6) NIG momentum profits in 68 samples of individual bond returns

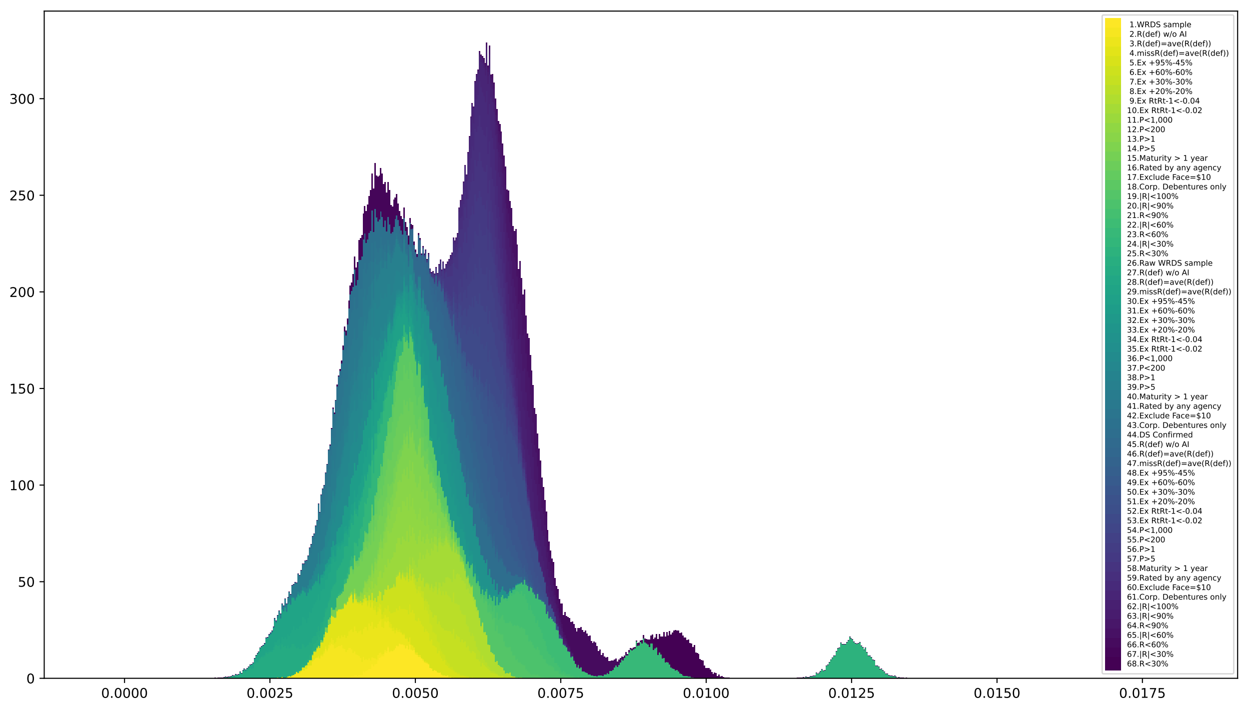
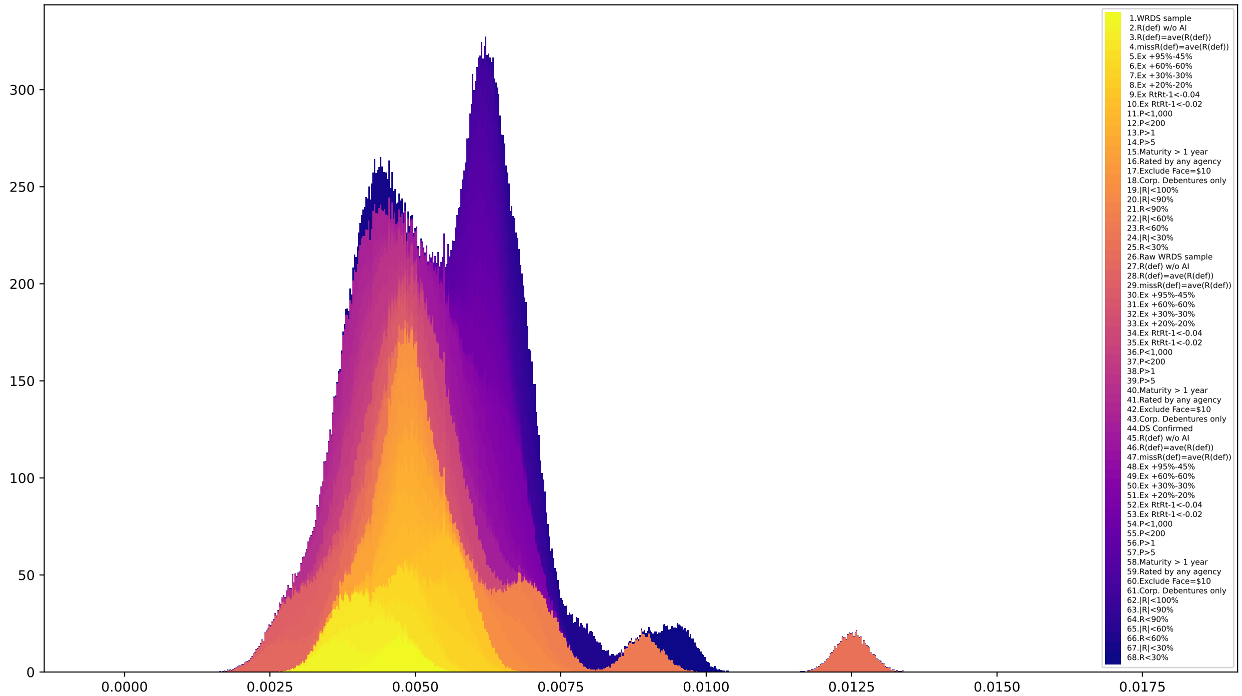


Figure VIII. Gibbs sampler posterior estimates of NIG momentum profits across samples. (continued)

Plot E: (6,6) NIG momentum profits in 68 samples of equally weighted firm returns



Plot F: (6,6) NIG momentum profits in 68 samples of value-weighted firm returns

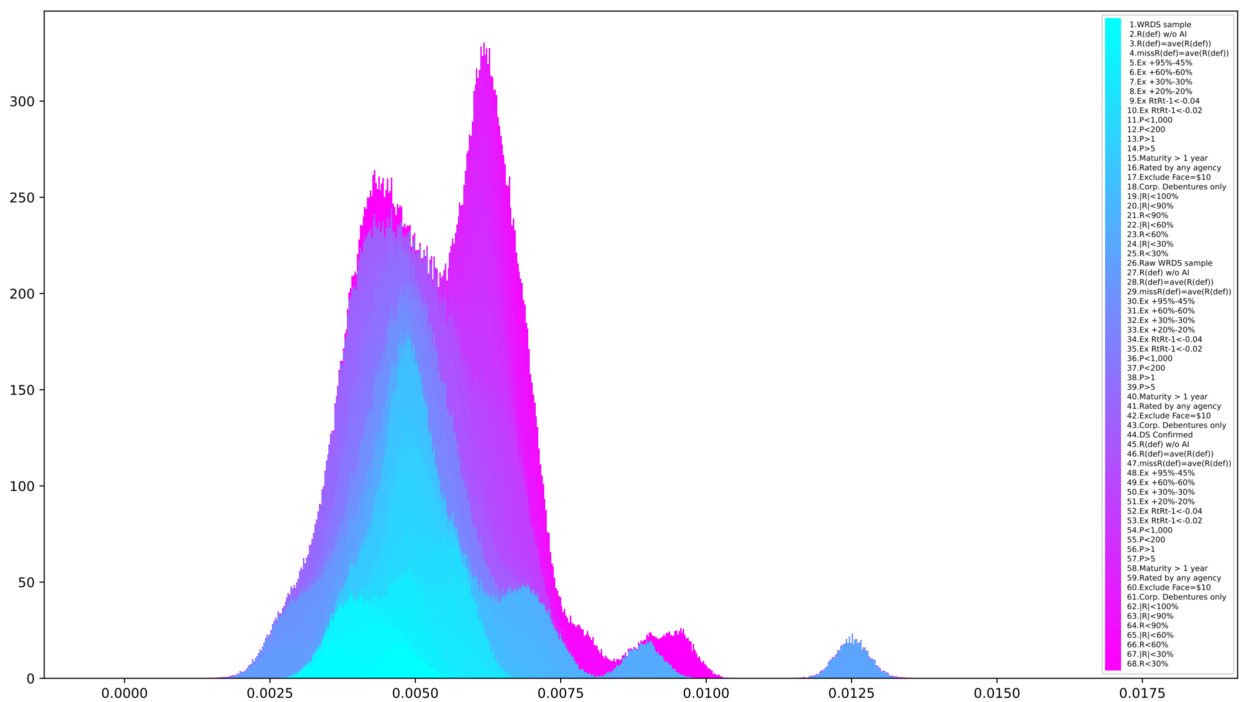


Figure VIII. Gibbs sampler posterior estimates of NIG momentum profits across samples. (continued)

Plot A Plot B

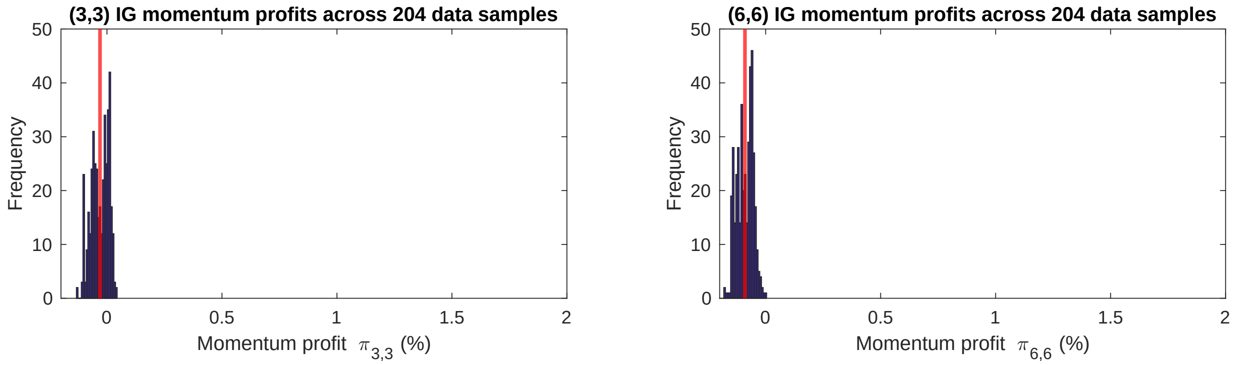


Figure IX. Frequency distribution of IG momentum profit estimates across 204 samples. We repeat the analyses in Figure V but for IG bonds. Plots A and B present the frequency distribution of (3,3) and (6,6) monthly momentum profits across the 204 samples described in Appendix B Tables B.6, B.7, and B.8 (excluding the last 10 rows in all Panels B). Both equally and value-weighted profits are included for a total of 408 $\pi_{3,3}$ and 408 $\pi_{6,6}$. The red line represents the average of the 408 sample momentum profit estimates in each plot.

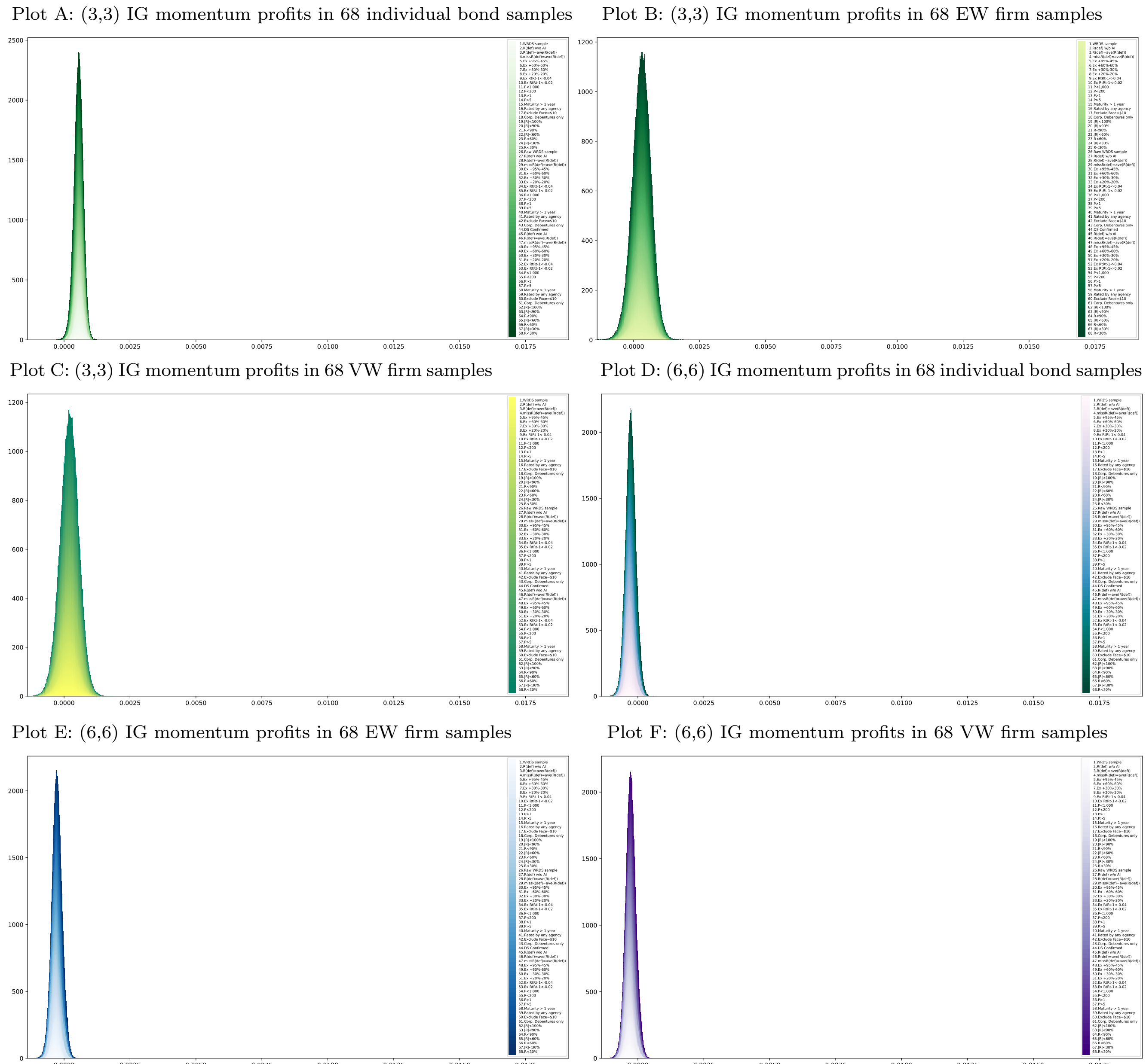


Figure X. Gibbs sampler posterior estimates of IG momentum profits across samples. The figure repeats the analyses in Figure VIII but for IG bonds. We estimate the regression model (equation 3) for $K = 3$ and $K = 6$ using 10,000 draws of the Gibbs sampler (1000 burn-in iterations) for the samples in Appendix B Tables B.6, B.7, and B.8. For each parameter draw, we calculate the corresponding momentum profit, π^{si} (equation 6). Plot A (B) [C] presents the 'cumulative' posterior density for (3,3) IG momentum profits across the 68 individual (68 equally weighted firm-level) [68 value-weighted firm-level] bond samples. Plot D (E) [F] presents the same for (6,6) IG momentum profits.

Internet Appendix

Appendix A

Studies of corporate bond momentum and data choices made by the authors

Paper	Momentum profits	Data source	Sample period	Monthly price	Data error treatment
Khang and King (2004)	Insignificant or negative	Lehman	1978-1998	Last day quote	None described
Gebhardt, Hvidkjaer, and Swaminathan (2005b)	Negative or insignificant for IG	Lehman	1973-1996	Last day quote	Exclude returns greater than 95% in month t followed by less than 45% in month $t+1$ or vice versa.
Pospisil and Zhang (2010)	Positive for HY	Bloomberg	1996-2009	Last day quote	At formation, exclude bonds with the 10% option-adjusted spread, and bottom 1% of return observations.
Jostova, Nikolova, Philipov, and Stahel (2013)	Positive for HY	Lehman, NAIC, Datastream, TRACE Standard, Bloomberg	1973-2011	Last in the last 5 days	Eliminate monthly returns above the 99.5th percentile ($>30\%$)
Bali, Subrahmanyam, and Wen (2017)	Positive	TRACE Enhanced	2002-2015	Last (first) in the last (first) 5 days	Prices in 5-1000 range
Chordia et al. (2017)	Negative, positive or insignificant	Lehman, NAIC, Datastream, TRACE Standard	1973-2014	Last in the last 5 days	Exclude prices lower than Treasury or stale; exclude daily prices with extreme bounce: if $R_t R_{t-k} < -0.02$ for k=1, ...,12; exclude prices constant for 3 months.
Houweling and Van Zundert (2017)	Positive for HY, insignificant for IG	Barclays constituents	1994-2015	Last day quote	None described
Choi and Kim (2018)	Positive	Reuters, Lehman	1979-2012	Last day quote	None described
Ho and Wang (2018)	Positive or insignificant	Datastream, Bloomberg	1994-2014	Last day quote	Exclude large monthly price reversals: 20% or greater returns followed by 20% or greater returns of the opposite sign; exclude returns $>30\%$
Israel, Palhares, and Richardson (2018)	Positive	BAML constituents	1997-2015	Last day quote	None described
Li and Galvani (2018)	Positive or insignificant	TRACE Enhanced	2002-2014	Last available	None described
Lee, Naranjo, and Sirmans (2021)	Positive or insignificant	TRACE Standard	2003-2015	Last in the last 5 days	Exclude returns above the 99.5th percentile
Li and Galvani (2021)	Positive or insignificant	TRACE Enhanced	2002-2017	Last available	Winsorize returns at the 1% level (0.5% for each tail)
Galvani and Li (2023)	Positive or insignificant	TRACE Enhanced	2002-2021	Last available	Winsorize or trim at various thresholds
Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2023)	Positive or insignificant	TRACE Enhanced	2002-2021 & 1985-2021	Last in the last 5 days	Manual check
Dickerson, Robotti, and Rossetti (2024)	Insignificant	TRACE Enhanced, Standard	2002-2022	Last in the last 5 days	No treatment (returns not winsorized)
Liu, Wang, and Wu (2023)	Positive	NAIC, TRACE Enhanced	2000-2020	Last available	None described

Appendix B

Table B.1
Return outliers

We extract corporate bond return data from TRACE from July 2002 to June 2023 using the official WRDS TRACE cleaning and return calculation programs (see Section II.C) without removing outliers and replacing default-month returns. Panel A presents price data for the 10 (26) return outliers with a return of over 1000% (between 300% and 1,000%) per month. The first column reports the bond CUSIP. The second column presents the month of the return outlier, m. The last 7 columns report the month-end prices, $PRICE\_L5M$, in the window from 3 months prior to 3 months after the outlier return. Panel B presents the return and price history of CUSIP 15200EAA3, a bond issued by Centerplate Inc. Age and time-to-maturity [TTM] are in months. The default indicator variable, based on information from FISD, shows the months counting down to a declared default and indicates that this bond never defaults.

Panel A: Return outliers due to incorrect price

		Price around outlier entry								
Cusip	Month m	$m-4$	$m-3$	$m-2$	$m-1$	m	$m+1$	$m+2$	$m+3$	$m-4$
Return outliers above 1,000% per month (10 observations)										
967446AA3	2004.01	61.50		54.50	1.00	16.50				
51769RAA2	2014.01		18.00		0.01	20.00		9.93	10.00	10.00
48123M6K3	2009.01	84.46	49.10	26.03	0.49	44.69	44.85	45.16	46.00	49.25
05873KAL2	2008.03	100.35		75.13	1.00	59.00			49.00	
82670CAA8	2011.03	92.03	87.50	93.02	0.00	86.31	88.74	88.56	89.93	87.20
48123LE67	2009.03				0.91	93.18			101.36	101.38
293562AE4	2002.11		86.75	95.19	0.13	96.50	95.00	103.50	89.29	109.31
857689AZ6	2009.03			2.50	3.00	100.00	3.76	3.00	2.00	2.25
775101AC2	2004.06			116.00	112.33	1325.00	113.09	116.00	112.50	115.90
27746QAE4	2004.09	93.87	95.21	95.73	97.80	3348.00	98.11	97.27	98.29	97.46
Return outliers between 300% and 1,000% per month (26 observations)										
15200EAA3	2011.07	0.01	0.34	0.01	0.02	0.05	0.06		0.05	0.06
15200EAA3	2011.04	0.75	0.53	0.40	0.01	0.34	0.01	0.02	0.05	0.06
15200EAA3	2010.09	1.33	1.39	1.00	0.00	1.00	1.00	0.47	0.75	0.53
452729AG1	2005.05	0.06	0.02		0.01	15.17	0.01			
075896AA8	2023.06	20.95	30.83	22.11	5.28	31.15	11.67	2.87	2.57	2.32
866930AB6	2009.08		63.63		15.02	75.56		77.84	80.16	90.09
17313G431	2009.05			9.26	9.37	92.50	19.46	9.20	9.15	
835415AG5	2004.12		87.75	91.59	13.29	93.33	97.72	99.38	100.94	101.73
737662AX4	2004.01	100.92		96.03	10.00	99.50	100.13	103.00		
84610FAE2	2004.06	100.63	94.75		10.00	101.50	99.25	103.00	103.50	
026375AE5	2003.10	93.97	97.00	98.16	16.69	102.00		97.00	101.00	101.44
124845AF5	2003.07	107.13	100.73	108.97	19.44	104.75	112.23	120.70	116.46	112.52
493267AA6	2004.10	108.82	109.00	106.95	24.15	105.60	105.74	105.83		
00209TAB1	2003.03				13.13	110.99	116.52	120.82	126.12	126.57
695112AE2	2005.02	114.50	113.50	116.00	15.00	113.28	115.00	112.51	113.31	112.90
22539T308	2014.12				14.80	148.33				
292505AB0	2004.06	98.27	98.27	96.91	99.15	403.21	101.25	94.60	94.18	94.63
194832AD3	2005.02	101.09	101.79	103.49	100.29	431.73	101.53	102.75	99.42	95.76
889479AH4	2004.10		104.00	103.88	103.00	553.25	104.33			104.27
29245UAC1	2007.01	109.82	108.00	109.50	110.02	605.30	110.38	109.82		109.09
12201PAB2	2003.07	110.71		113.61	117.63	627.14	119.60	126.03		111.72
364760AG3	2002.12				100.37	700.00	98.31	101.50	108.00	
767754BD5	2004.05	113.22	112.63	112.50	115.25	950.58	112.25	112.26	112.50	108.83
143658AG7	2003.02		104.08	104.08	106.70	1021.40	106.10	106.36		104.45
001814AV4	2005.03	110.63	113.50	112.50	112.50	1112.60		110.96	110.83	108.75
90261KBV1	2008.02	132.58	133.25	129.75	136.00	1391.70				

Table B.2

Bond momentum in individual NIG bond returns - RET_LDM **and** RET_EOM

This table replicates the results in Table II with returns using the price on the last trading day of the month, RET_EOM, or the last trade of the month, RET_EOM, instead of the last price from the last five trading days of the month, RET_L5D, which is our base case. All other data choices are as described in Table II, except that price filters are based on $PRICE\_LDM$ and $PRICE\_EOM$, respectively, instead of $PRICE\_L5D$.

Panel A: Using RET_LDM and $PRICE\_LDM$

Starting with the equivalent of WRDS sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	788393	100.000	0.34	4.11	100	24	1.06	1.07	1.13	1.10
							(2.75)	**(2.21)**	**(2.80)**	**(2.32)**
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	787697	99.912	0.36	4.14	100	24	0.77	0.75	0.85	0.66
							(1.96)	(1.53)	**(2.10)**	(1.40)
$R(def) = ave(R(def))$	788393	100.000	0.35	4.07	100	24	0.91	0.92	1.00	0.94
							(2.40)	(1.91)	**(2.53)**	**(2.03)**
$missR(def) = ave(R(def))$	788393	100.000	0.35	4.16	100	24	0.80	0.78	0.86	0.67
							(2.06)	(1.60)	**(2.13)**	(1.43)
Exclude $+95\%/-45\%$	788334	99.993	0.34	4.05	100	25	1.02	1.10	1.08	1.14
							(2.67)	**(2.36)**	**(2.69)**	**(2.50)**
Exclude $+60\%/-60\%$	788358	99.996	0.34	4.08	100	24	1.04	1.09	1.11	1.13
							(2.69)	**(2.25)**	**(2.73)**	**(2.37)**
Exclude $+30\%/-30\%$	787996	99.950	0.34	3.90	100	26	1.13	1.08	1.29	1.16
							(2.98)	**(2.40)**	**(3.22)**	**(2.70)**
Exclude $+20\%/-20\%$	787317	99.864	0.33	3.77	100	26	1.15	0.98	1.23	1.11
							(3.12)	**(2.18)**	**(3.21)**	**(2.58)**
Exclude $R_tR_{t-1} < -0.04$	786726	99.789	0.33	3.66	100	27	1.29	1.06	1.40	1.18
							(4.04)	**(2.67)**	**(4.00)**	**(2.96)**
Exclude $R_tR_{t-1} < -0.02$	785153	99.589	0.33	3.55	100	28	1.08	0.81	1.18	0.88
							(3.99)	**(2.33)**	**(4.01)**	**(2.56)**
$P < 1,000$	788386	99.999	0.34	4.11	100	24	1.06	1.07	1.13	1.10
							(2.75)	**(2.21)**	**(2.80)**	**(2.32)**
$P < 200$	788364	99.996	0.34	4.11	100	24	1.05	1.07	1.12	1.09
							(2.72)	**(2.20)**	**(2.76)**	**(2.32)**
$P > 1$	788360	99.996	0.34	4.10	100	24	1.08	1.14	1.15	1.16
							(2.80)	**(2.31)**	**(2.83)**	**(2.42)**
$P > 5$	788223	99.978	0.34	4.07	100	24	0.99	1.16	1.12	1.22
							(2.58)	**(2.47)**	**(2.84)**	**(2.73)**
Maturity > 1 year	735667	93.312	0.35	4.17	100	24	1.09	0.98	1.17	1.04
							(2.82)	**(2.04)**	**(2.92)**	**(2.21)**
Rated by any agency	788393	100.000	0.34	4.11	100	24	0.84	1.00	0.92	1.05
							(2.37)	**(2.19)**	**(2.53)**	**(2.38)**
Exclude Face=$10	784303	99.481	0.33	4.09	100	24	1.06	1.07	1.13	1.10
							(2.75)	**(2.21)**	**(2.80)**	**(2.32)**
Corp. Debentures only	707508	89.741	0.34	4.18	100	24	1.06	0.92	1.13	0.94
							(2.74)	(1.92)	**(2.78)**	**(2.02)**
$\|R\| < 100\%$	788315	99.990	0.33	3.99	100	25	1.26	1.38	1.34	1.38
							(3.47)	**(3.06)**	**(3.46)**	**(3.06)**
$\|R\| < 90\%$	788284	99.986	0.33	3.95	89	23	1.29	1.42	1.37	1.42
							(3.63)	**(3.18)**	**(3.63)**	**(3.22)**
$R < 90\%$	788289	99.987	0.33	3.96	89	23	1.29	1.42	1.37	1.42
							(3.63)	**(3.18)**	**(3.63)**	**(3.22)**
$\|R\| < 60\%$	788016	99.952	0.32	3.73	60	16	1.15	1.43	1.19	1.44
							(3.46)	**(3.72)**	**(3.42)**	**(3.68)**
$R < 60\%$	788133	99.967	0.31	3.83	60	16	1.36	1.59	1.36	1.55
							(4.03)	**(3.90)**	**(3.82)**	**(3.78)**
$\|R\| < 30\%$	786477	99.757	0.32	3.25	30	9	0.83	0.96	0.82	0.98
							(3.68)	**(3.50)**	**(3.23)**	**(3.33)**
$R < 30\%$	787352	99.868	0.27	3.60	30	8	1.80	1.99	1.77	1.89
							(6.08)	**(5.45)**	**(5.32)**	**(5.03)**

Table B.2 (continued)

Panel B: Using RET_LDM and $PRICE\_LDM$
Starting with the equivalent of Raw WRDS sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	788381	100.000	0.34	4.26	295	69	0.97	0.94	1.06	1.02
							(2.44)	(1.85)	**(2.57)**	**(2.11)**
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	787685	99.912	0.37	4.29	295	69	0.66	0.61	0.75	0.57
							(1.63)	(1.19)	(1.81)	(1.17)
$R(def) = ave(R(def))$	788381	100.000	0.35	4.22	295	70	0.82	0.79	0.93	0.87
							(2.10)	(1.56)	**(2.29)**	(1.81)
$missR(def) = ave(R(def))$	788381	100.000	0.35	4.31	295	68	0.69	0.64	0.76	0.58
							(1.71)	(1.25)	(1.84)	(1.20)
Exclude $+95\%/-45\%$	788331	99.994	0.34	4.15	295	71	0.99	1.05	1.05	1.13
							(2.51)	**(2.18)**	**(2.57)**	**(2.43)**
Exclude $+60\%/-60\%$	788355	99.997	0.34	4.19	295	70	1.01	1.01	1.08	1.09
							(2.52)	**(1.99)**	**(2.60)**	**(2.22)**
Exclude $+30\%/-30\%$	787993	99.951	0.34	3.99	295	74	1.10	1.02	1.28	1.13
							(2.84)	**(2.19)**	**(3.14)**	**(2.59)**
Exclude $+20\%/-20\%$	787314	99.865	0.33	3.84	295	77	1.12	0.93	1.21	1.08
							(2.98)	**(2.02)**	**(3.13)**	**(2.47)**
Exclude $R_tR_{t-1} < -0.04$	786723	99.790	0.33	3.70	288	78	1.28	1.04	1.39	1.16
							(4.00)	**(2.59)**	**(3.98)**	**(2.91)**
Exclude $R_tR_{t-1} < -0.02$	785152	99.590	0.33	3.60	288	80	1.08	0.79	1.17	0.86
							(3.96)	**(2.27)**	**(3.99)**	**(2.52)**
$P < 1,000$	788374	99.999	0.34	4.26	295	69	0.97	0.94	1.06	1.02
							(2.44)	(1.85)	**(2.57)**	**(2.11)**
$P < 200$	788354	99.997	0.34	4.26	295	69	0.97	0.94	1.06	1.02
							(2.45)	(1.85)	**(2.57)**	**(2.11)**
$P > 1$	788350	99.996	0.34	4.20	295	70	1.01	1.04	1.09	1.12
							(2.54)	**(2.00)**	**(2.64)**	**(2.25)**
$P > 5$	788213	99.979	0.34	4.17	295	71	0.92	1.07	1.06	1.19
							(2.31)	**(2.17)**	**(2.65)**	**(2.59)**
Maturity > 1 year	735655	93.312	0.35	4.32	295	68	1.01	0.86	1.10	0.97
							(2.56)	(1.70)	**(2.71)**	**(2.00)**
Rated by any agency	788381	100.000	0.34	4.26	295	69	0.76	0.89	0.85	0.99
							(2.06)	(1.85)	**(2.29)**	**(2.18)**
Exclude Face=$10	784291	99.481	0.34	4.24	295	70	0.97	0.94	1.06	1.02
							(2.44)	(1.85)	**(2.57)**	**(2.11)**
Corp. Debentures only	707498	89.741	0.34	4.34	295	68	0.97	0.79	1.05	0.86
							(2.43)	(1.56)	**(2.55)**	(1.80)
$\lvert R\rvert < 100\%$	788311	99.991	0.33	3.99	100	25	1.24	1.37	1.32	1.37
							(3.42)	**(3.04)**	**(3.42)**	**(3.05)**
$\lvert R\rvert < 90\%$	788280	99.987	0.33	3.95	89	23	1.27	1.41	1.35	1.42
							(3.58)	**(3.16)**	**(3.59)**	**(3.21)**
$R < 90\%$	788285	99.988	0.33	3.95	89	23	1.27	1.41	1.35	1.42
							(3.58)	**(3.16)**	**(3.59)**	**(3.21)**
$\lvert R\rvert < 60\%$	788016	99.954	0.32	3.73	60	16	1.15	1.43	1.19	1.44
							(3.46)	**(3.72)**	**(3.42)**	**(3.68)**
$R < 60\%$	788129	99.968	0.31	3.82	60	16	1.34	1.58	1.34	1.55
							(3.97)	**(3.88)**	**(3.77)**	**(3.77)**
$\lvert R\rvert < 30\%$	786477	99.758	0.32	3.25	30	9	0.83	0.96	0.82	0.98
							(3.68)	**(3.50)**	**(3.23)**	**(3.33)**
$R < 30\%$	787348	99.869	0.27	3.60	30	8	1.79	1.98	1.75	1.89
							(6.02)	**(5.43)**	**(5.27)**	**(5.02)**

Table B.2 (continued)

Panel C: Using RET_LDM and $PRICE\_LDM$
Starting with the equivalent of DS Confirmed sample

Sample	Total obs	% of total obs	Mean (%)	SD (%)	Max (%)	n-sigma of Max	Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
			Bond return statistics				NIG momentum profits (%)			
Starting sample	787609	100.000	0.32	3.75	265	71	0.93 **(2.74)**	1.20 **(2.92)**	0.96 **(2.64)**	1.25 **(3.12)**
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	786814	99.899	0.35	3.71	265	71	0.71 **(2.17)**	0.91 **(2.24)**	0.77 **(2.26)**	0.91 **(2.29)**
$R(def) = ave(R(def))$	787609	100.000	0.33	3.69	265	72	0.82 **(2.45)**	1.06 **(2.63)**	0.86 **(2.40)**	1.11 **(2.83)**
$missR(def) = ave(R(def))$	787609	100.000	0.33	3.74	265	71	0.73 **(2.19)**	0.98 **(2.45)**	0.75 **(2.13)**	0.97 **(2.47)**
Exclude $+95\%/-45\%$	787603	99.999	0.32	3.74	265	71	0.93 **(2.74)**	1.20 **(2.92)**	0.96 **(2.64)**	1.25 **(3.12)**
Exclude $+60\%/-60\%$	787607	100.000	0.32	3.74	265	71	0.93 **(2.74)**	1.20 **(2.92)**	0.96 **(2.64)**	1.25 **(3.12)**
Exclude $+30\%/-30\%$	787433	99.978	0.32	3.66	265	72	1.05 **(3.06)**	1.19 **(2.97)**	1.16 **(3.13)**	1.23 **(3.13)**
Exclude $+20\%/-20\%$	786936	99.915	0.32	3.57	265	74	1.17 **(3.44)**	1.22 **(3.00)**	1.24 **(3.44)**	1.28 **(3.23)**
Exclude $R_tR_{t-1} < -0.04$	786515	99.861	0.32	3.50	265	76	1.34 **(4.31)**	1.25 **(3.35)**	1.43 **(4.21)**	1.32 **(3.54)**
Exclude $R_tR_{t-1} < -0.02$	785021	99.671	0.32	3.40	265	78	1.32 **(4.54)**	1.11 **(3.18)**	1.37 **(4.42)**	1.15 **(3.34)**
$P < 1,000$	787604	99.999	0.32	3.75	265	71	0.93 **(2.74)**	1.20 **(2.92)**	0.96 **(2.64)**	1.25 **(3.12)**
$P < 200$	787589	99.997	0.32	3.75	265	71	0.93 **(2.74)**	1.20 **(2.92)**	0.96 **(2.64)**	1.25 **(3.12)**
$P > 1$	787590	99.998	0.32	3.74	265	71	0.93 **(2.75)**	1.20 **(2.93)**	0.96 **(2.65)**	1.25 **(3.12)**
$P > 5$	787478	99.983	0.32	3.74	265	71	0.84 **(2.35)**	1.19 **(2.95)**	0.91 **(2.48)**	1.25 **(3.17)**
Maturity > 1 year	734949	93.314	0.33	3.81	265	70	0.88 **(2.65)**	1.14 **(2.79)**	0.92 **(2.66)**	1.20 **(2.96)**
Rated by any agency	787609	100.000	0.32	3.75	265	71	0.83 **(2.59)**	1.20 **(3.05)**	0.86 **(2.51)**	1.28 **(3.32)**
Exclude Face=$10	783554	99.485	0.32	3.73	265	71	0.93 **(2.74)**	1.20 **(2.92)**	0.96 **(2.64)**	1.25 **(3.12)**
Corp. Debentures only	706815	89.742	0.33	3.82	265	69	0.95 **(2.77)**	1.00 **(2.51)**	0.97 **(2.66)**	1.04 **(2.67)**
$\|R\| < 100\%$	787594	99.998	0.32	3.70	100	27	1.07 **(3.22)**	1.25 **(3.24)**	1.15 **(3.18)**	1.29 **(3.40)**
$\|R\| < 90\%$	787583	99.997	0.32	3.68	87	24	1.08 **(3.30)**	1.27 **(3.30)**	1.16 **(3.27)**	1.31 **(3.46)**
$R < 90\%$	787584	99.997	0.32	3.68	87	24	1.08 **(3.30)**	1.27 **(3.30)**	1.16 **(3.27)**	1.31 **(3.46)**
$\|R\| < 60\%$	787439	99.978	0.32	3.55	60	17	1.10 **(3.51)**	1.38 **(3.97)**	1.16 **(3.37)**	1.40 **(3.95)**
$R < 60\%$	787505	99.987	0.31	3.61	60	16	1.20 **(3.76)**	1.47 **(4.04)**	1.23 **(3.56)**	1.47 **(3.97)**
$\|R\| < 30\%$	786477	99.856	0.32	3.25	30	9	0.83 **(3.68)**	0.96 **(3.50)**	0.82 **(3.23)**	0.98 **(3.33)**
$R < 30\%$	787054	99.930	0.29	3.48	30	9	1.48 **(5.32)**	1.68 **(5.00)**	1.50 **(4.85)**	1.64 **(4.74)**

Table B.2 (continued)

Panel D: Using RET_EOM and $PRICE\_EOM$
Starting with the equivalent of WRDS sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	3307118	100.000	0.50	4.94	100	20	0.46 (1.60)	0.17 (0.45)	0.58 (1.88)	0.28 (0.70)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	3307076	99.999	0.51	4.98	100	20	0.42 (1.42)	0.08 (0.20)	0.48 (1.53)	0.08 (0.20)
$R(def) = ave(R(def))$	3307118	100.000	0.51	4.94	100	20	0.43 (1.49)	0.12 (0.32)	0.55 (1.77)	0.22 (0.56)
$missR(def) = ave(R(def))$	3307118	100.000	0.51	4.99	100	20	0.42 (1.42)	0.08 (0.20)	0.48 (1.53)	0.08 (0.20)
Exclude $+95\%/-45\%$	3306633	99.985	0.50	4.83	100	21	0.49 (1.79)	0.25 (0.68)	0.59 (**1.98**)	0.33 (0.88)
Exclude $+60\%/-60\%$	3306766	99.989	0.50	4.86	100	20	0.48 (1.69)	0.23 (0.61)	0.58 (1.88)	0.31 (0.80)
Exclude $+30\%/-30\%$	3304706	99.927	0.50	4.67	100	21	0.56 (**2.15**)	0.36 (1.06)	0.71 (**2.63**)	0.48 (1.38)
Exclude $+20\%/-20\%$	3301135	99.819	0.50	4.54	100	22	0.57 (**2.28**)	0.38 (1.13)	0.75 (**2.89**)	0.51 (1.51)
Exclude $R_tR_{t-1} < -0.04$	3297585	99.712	0.49	4.42	100	23	0.63 (**2.86**)	0.46 (1.52)	0.88 (**3.77**)	0.65 (**2.15**)
Exclude $R_tR_{t-1} < -0.02$	3288705	99.443	0.49	4.30	100	23	0.59 (**2.83**)	0.38 (1.31)	0.81 (**3.75**)	0.55 (**1.96**)
$P < 1,000$	3290486	99.497	0.50	4.93	100	20	0.47 (1.61)	0.18 (0.46)	0.59 (1.88)	0.28 (0.70)
$P < 200$	3280227	99.187	0.51	4.92	100	20	0.46 (1.61)	0.18 (0.46)	0.58 (1.88)	0.28 (0.71)
$P > 1$	3306289	99.975	0.50	4.87	100	20	0.47 (1.65)	0.24 (0.63)	0.60 (**1.96**)	0.34 (0.85)
$P > 5$	3304408	99.918	0.49	4.83	100	21	0.47 (1.67)	0.27 (0.73)	0.60 (**2.03**)	0.39 (1.02)
Maturity > 1 year	2874878	86.930	0.47	4.72	100	21	0.40 (1.38)	0.14 (0.36)	0.58 (1.83)	0.27 (0.67)
Rated by any agency	3307118	100.000	0.50	4.94	100	20	0.42 (1.56)	0.10 (0.29)	0.54 (1.84)	0.24 (0.65)
Exclude Face=$10	2973042	89.898	0.47	4.69	100	21	0.46 (1.60)	0.17 (0.45)	0.58 (1.88)	0.28 (0.70)
Corp. Debentures only	1757655	53.148	0.47	4.53	100	22	0.50 (1.72)	0.19 (0.50)	0.59 (1.89)	0.27 (0.67)
$\lvert R\rvert < 100\%$	3306379	99.978	0.48	4.71	100	21	0.65 (**2.46**)	0.50 (1.45)	0.78 (**2.71**)	0.58 (1.62)
$\lvert R\rvert < 90\%$	3306094	99.969	0.48	4.63	90	19	0.68 (**2.65**)	0.58 (1.67)	0.81 (**2.91**)	0.64 (1.82)
$R < 90\%$	3306213	99.973	0.48	4.67	90	19	0.68 (**2.64**)	0.57 (1.66)	0.82 (**2.92**)	0.64 (1.81)
$\lvert R\rvert < 60\%$	3304210	99.912	0.47	4.31	60	14	0.72 (**3.25**)	0.74 (**2.71**)	0.83 (**3.35**)	0.86 (**2.98**)
$R < 60\%$	3304941	99.934	0.45	4.45	60	13	0.90 (**3.90**)	0.91 (**2.96**)	0.98 (**3.81**)	0.96 (**3.06**)
$\lvert R\rvert < 30\%$	3292150	99.547	0.43	3.55	30	8	0.41 (**2.85**)	0.49 (**2.94**)	0.54 (**3.04**)	0.59 (**3.03**)
$R < 30\%$	3297346	99.705	0.36	4.02	30	7	1.32 (**6.10**)	1.48 (**5.23**)	1.38 (**5.66**)	1.47 (**5.03**)

Table B.2 (continued)

Panel E: Using RET_EOM and $PRICE\_EOM$
Starting with the equivalent of Raw WRDS sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	$\pi_{6,6}$	Value-weighted $\pi_{3,3}$	$\pi_{6,6}$
Starting sample	3306751	100.000	0.51	5.12	299	58	0.33	0.01	0.49	0.14
							(1.07)	(0.02)	(1.51)	(0.33)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	3306692	99.998	0.51	5.16	299	58	0.26	-0.10	0.35	-0.08
							(0.84)	(-0.24)	(1.08)	(-0.18)
$R(def) = ave(R(def))$	3306751	100.000	0.51	5.11	299	59	0.28	-0.06	0.44	0.06
							(0.92)	(-0.15)	(1.36)	(0.15)
$missR(def) = ave(R(def))$	3306751	100.000	0.51	5.16	299	58	0.26	-0.10	0.35	-0.08
							(0.84)	(-0.24)	(1.08)	(-0.18)
Exclude $+95\%/-45\%$	3306446	99.991	0.50	4.99	299	60	0.43	0.16	0.55	0.26
							(1.53)	(0.42)	(1.79)	(0.68)
Exclude $+60\%/-60\%$	3306576	99.995	0.51	5.04	299	59	0.39	0.12	0.52	0.22
							(1.33)	(0.30)	(1.62)	(0.54)
Exclude $+30\%/-30\%$	3304520	99.933	0.50	4.82	299	62	0.51	0.30	0.68	0.44
							(1.90)	(0.86)	(**2.50**)	(1.25)
Exclude $+20\%/-20\%$	3300962	99.825	0.50	4.69	299	64	0.54	0.35	0.73	0.49
							(**2.10**)	(1.04)	(**2.80**)	(1.45)
Exclude $R_tR_{t-1} < -0.04$	3297445	99.719	0.50	4.56	299	66	0.62	0.44	0.87	0.64
							(**2.77**)	(1.48)	(**3.73**)	(**2.12**)
Exclude $R_tR_{t-1} < -0.02$	3288582	99.451	0.50	4.44	299	67	0.59	0.38	0.82	0.55
							(**2.83**)	(1.32)	(**3.78**)	(**1.96**)
$P < 1,000$	3290137	99.498	0.51	5.11	299	59	0.33	0.01	0.49	0.14
							(1.07)	(0.02)	(1.51)	(0.33)
$P < 200$	3279893	99.188	0.51	5.09	299	59	0.33	0.01	0.49	0.14
							(1.07)	(0.02)	(1.51)	(0.33)
$P > 1$	3306034	99.978	0.50	5.00	299	60	0.36	0.11	0.52	0.24
							(1.19)	(0.28)	(1.64)	(0.59)
$P > 5$	3304194	99.923	0.50	4.94	299	60	0.37	0.16	0.54	0.31
							(1.26)	(0.40)	(1.77)	(0.79)
Maturity > 1 year	2874586	86.931	0.48	4.90	299	61	0.28	-0.02	0.48	0.14
							(0.90)	(-0.05)	(1.47)	(0.33)
Rated by any agency	3306751	100.000	0.51	5.12	299	58	0.32	-0.04	0.46	0.12
							(1.11)	(-0.11)	(1.52)	(0.30)
Exclude Face=$10	2972708	89.898	0.48	4.88	299	61	0.33	0.01	0.49	0.14
							(1.07)	(0.02)	(1.51)	(0.33)
Corp. Debentures only	1757434	53.147	0.47	4.81	298	62	0.36	0.03	0.48	0.13
							(1.17)	(0.08)	(1.49)	(0.30)
$\lvert R\rvert < 100\%$	3306203	99.983	0.48	4.69	100	21	0.63	0.50	0.77	0.59
							(**2.40**)	(1.45)	(**2.67**)	(1.63)
$\lvert R\rvert < 90\%$	3305955	99.976	0.48	4.62	90	19	0.66	0.57	0.80	0.64
							(**2.57**)	(1.66)	(**2.86**)	(1.82)
$R < 90\%$	3306037	99.978	0.48	4.65	90	19	0.66	0.57	0.80	0.65
							(**2.57**)	(1.66)	(**2.86**)	(1.82)
$\lvert R\rvert < 60\%$	3304117	99.920	0.47	4.30	60	14	0.71	0.73	0.83	0.86
							(**3.24**)	(**2.70**)	(**3.34**)	(**2.98**)
$R < 60\%$	3304772	99.940	0.45	4.43	60	13	0.89	0.91	0.97	0.96
							(**3.83**)	(**2.95**)	(**3.75**)	(**3.06**)
$\lvert R\rvert < 30\%$	3292065	99.556	0.43	3.55	30	8	0.41	0.49	0.54	0.59
							(**2.83**)	(**2.94**)	(**3.04**)	(**3.03**)
$R < 30\%$	3297183	99.711	0.36	3.99	30	7	1.30	1.48	1.36	1.47
							(**6.02**)	(**5.22**)	(**5.60**)	(**5.04**)

Table B.2 (continued)

Panel F: Using RET_EOM and $PRICE\_EOM$
Starting with the equivalent of DS Confirmed sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	3294288	100.000	0.43	3.77	265	70	0.53	0.57	0.64	0.68
							(2.32)	(1.95)	**(2.54)**	**(2.22)**
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	3293959	99.990	0.43	3.77	265	70	0.38	0.33	0.47	0.37
							(1.62)	(1.09)	(1.86)	(1.20)
$R(def) = ave(R(def))$	3294288	100.000	0.43	3.75	265	71	0.45	0.42	0.55	0.51
							(1.95)	(1.43)	**(2.19)**	(1.67)
$missR(def) = ave(R(def))$	3294288	100.000	0.43	3.77	265	70	0.42	0.38	0.51	0.43
							(1.83)	(1.30)	**(2.02)**	(1.39)
Exclude $+95\%/-45\%$	3294272	100.000	0.43	3.76	265	70	0.53	0.58	0.64	0.68
							(2.33)	**(1.98)**	**(2.55)**	**(2.25)**
Exclude $+60\%/-60\%$	3294286	100.000	0.43	3.77	265	70	0.53	0.57	0.64	0.68
							(2.32)	(1.95)	**(2.55)**	**(2.22)**
Exclude $+30\%/-30\%$	3293975	99.990	0.43	3.73	265	71	0.56	0.58	0.67	0.69
							(2.47)	**(2.02)**	**(2.69)**	**(2.27)**
Exclude $+20\%/-20\%$	3292173	99.936	0.43	3.67	265	72	0.60	0.59	0.75	0.71
							(2.80)	**(2.07)**	**(3.13)**	**(2.36)**
Exclude $R_t R_{t-1} < -0.04$	3290292	99.879	0.43	3.61	178	49	0.68	0.65	0.85	0.77
							(3.41)	**(2.43)**	**(3.75)**	**(2.77)**
Exclude $R_t R_{t-1} < -0.02$	3282418	99.640	0.43	3.50	178	51	0.61	0.57	0.77	0.68
							(3.26)	**(2.21)**	**(3.66)**	**(2.63)**
$P < 1,000$	3277799	99.499	0.43	3.77	265	70	0.53	0.57	0.64	0.68
							(2.32)	(1.95)	**(2.54)**	**(2.22)**
$P < 200$	3267687	99.193	0.43	3.76	265	70	0.53	0.57	0.64	0.68
							(2.32)	(1.95)	**(2.54)**	**(2.22)**
$P > 1$	3293814	99.986	0.43	3.76	265	70	0.53	0.57	0.64	0.68
							(2.32)	(1.94)	**(2.53)**	**(2.21)**
$P > 5$	3292192	99.936	0.43	3.75	265	71	0.51	0.54	0.63	0.65
							(2.20)	(1.82)	**(2.48)**	**(2.11)**
Maturity $>$ 1 year	2865500	86.984	0.41	3.69	265	72	0.50	0.54	0.63	0.67
							(2.14)	(1.84)	**(2.45)**	**(2.18)**
Rated by any agency	3294288	100.000	0.43	3.77	265	70	0.51	0.49	0.60	0.58
							(2.36)	(1.78)	**(2.47)**	**(2.00)**
Exclude Face=$10	2963207	89.950	0.41	3.60	265	74	0.53	0.57	0.64	0.68
							(2.32)	(1.95)	**(2.54)**	**(2.22)**
Corp. Debentures only	1753945	53.242	0.43	3.69	265	72	0.55	0.58	0.65	0.67
							(2.36)	**(1.97)**	**(2.55)**	**(2.18)**
$\|R\| < 100\%$	3294253	99.999	0.43	3.74	100	26	0.59	0.67	0.69	0.77
							(2.67)	**(2.41)**	**(2.80)**	**(2.64)**
$\|R\| < 90\%$	3294234	99.998	0.43	3.73	90	24	0.60	0.68	0.71	0.79
							(2.74)	**(2.45)**	**(2.87)**	**(2.69)**
$R < 90\%$	3294240	99.999	0.43	3.74	90	24	0.60	0.68	0.71	0.79
							(2.75)	**(2.46)**	**(2.87)**	**(2.69)**
$\|R\| < 60\%$	3293995	99.991	0.43	3.69	60	16	0.59	0.71	0.70	0.84
							(3.00)	**(3.01)**	**(3.04)**	**(3.20)**
$R < 60\%$	3294103	99.994	0.42	3.71	60	16	0.72	0.82	0.80	0.91
							(3.51)	**(3.14)**	**(3.40)**	**(3.29)**
$\|R\| < 30\%$	3292065	99.933	0.43	3.55	30	8	0.41	0.49	0.54	0.59
							(2.83)	**(2.94)**	**(3.04)**	**(3.03)**
$R < 30\%$	3293222	99.968	0.41	3.65	30	8	0.93	1.09	1.03	1.17
							(4.87)	**(4.43)**	**(4.60)**	**(4.49)**

Table B.3

Bond momentum in samples of NIG firm returns - equally weighted RET_LDM **and** RET_EOM

This table replicates the results in Table III with returns using the price on the last trading day of the month, RET_EOM, or the last trade of the month, RET_EOM, instead of the last price from the last five trading days of the month, RET_L5D, which is our base case. All other data choices are as described in Table II, except that price filters are based on $PRICE\_LDM$ and $PRICE\_EOM$, respectively, instead of $PRICE\_L5D$.

Panel A: Using RET_LDM and $PRICE\_LDM$
Starting with the equivalent of WRDS sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	230411	100.000	0.43	4.52	100	22	0.93	0.93	1.13	1.00
							(2.64)	**(2.01)**	**(2.78)**	**(2.10)**
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	230139	99.882	0.46	4.54	100	22	0.79	0.65	0.84	0.53
							(2.15)	(1.38)	**(2.04)**	(1.12)
$R(def) = ave(R(def))$	230411	100.000	0.44	4.46	100	22	0.80	0.77	1.01	0.80
							(2.28)	(1.71)	**(2.51)**	(1.73)
$missR(def) = ave(R(def))$	230411	100.000	0.44	4.54	100	22	0.77	0.66	0.83	0.57
							(2.11)	(1.44)	**(2.03)**	(1.21)
Exclude $+95\%/-45\%$	230402	99.996	0.43	4.47	100	22	0.92	0.94	1.11	1.06
							(2.62)	**(2.15)**	**(2.73)**	**(2.32)**
Exclude $+60\%/-60\%$	230402	99.996	0.43	4.48	100	22	0.94	0.89	1.12	0.98
							(2.65)	**(2.00)**	**(2.76)**	**(2.09)**
Exclude $+30\%/-30\%$	230325	99.963	0.43	4.35	100	23	0.92	0.91	1.17	1.11
							(2.59)	**(2.03)**	**(3.04)**	**(2.55)**
Exclude $+20\%/-20\%$	230122	99.875	0.42	4.22	100	24	1.12	1.01	1.32	1.17
							(3.33)	**(2.51)**	**(3.44)**	**(2.79)**
Exclude $R_tR_{t-1} < -0.04$	229955	99.802	0.42	4.10	100	24	1.19	0.99	1.37	1.17
							(3.66)	**(2.54)**	**(3.62)**	**(2.88)**
Exclude $R_tR_{t-1} < -0.02$	229534	99.619	0.42	4.00	100	25	1.14	0.92	1.39	1.08
							(3.73)	**(2.44)**	**(3.94)**	**(2.78)**
$P < 1,000$	230411	100.000	0.43	4.52	100	22	0.93	0.93	1.13	1.00
							(2.64)	**(2.01)**	**(2.78)**	**(2.10)**
$P < 200$	230400	99.995	0.43	4.51	100	22	0.92	0.94	1.12	1.01
							(2.61)	**(2.05)**	**(2.76)**	**(2.13)**
$P > 1$	230400	99.995	0.43	4.50	100	22	0.96	0.96	1.16	1.06
							(2.72)	**(2.09)**	**(2.86)**	**(2.24)**
$P > 5$	230373	99.984	0.43	4.48	100	22	0.91	0.99	1.17	1.16
							(2.58)	**(2.17)**	**(2.97)**	**(2.46)**
Maturity $>$ 1 year	224629	97.491	0.44	4.56	100	22	0.79	0.70	0.88	0.71
							(2.16)	(1.49)	**(2.14)**	(1.48)
Rated by any agency	230411	100.000	0.43	4.52	100	22	0.92	0.80	1.11	0.88
							(2.80)	(1.76)	**(2.89)**	(1.86)
Exclude Face=$10	230235	99.924	0.43	4.51	100	22	0.92	0.80	1.11	0.88
							(2.80)	(1.76)	**(2.89)**	(1.86)
Corp. Debentures only	221994	96.347	0.43	4.58	100	22	0.93	0.78	1.10	0.83
							(2.83)	(1.73)	**(2.86)**	(1.74)
$\|R\| < 100\%$	230383	99.988	0.42	4.36	97	22	1.16	1.13	1.33	1.17
							(3.36)	**(2.65)**	**(3.36)**	**(2.63)**
$\|R\| < 90\%$	230379	99.986	0.41	4.33	89	21	1.17	1.15	1.34	1.20
							(3.42)	**(2.68)**	**(3.41)**	**(2.68)**
$R < 90\%$	230380	99.987	0.41	4.34	89	20	1.17	1.15	1.34	1.20
							(3.42)	**(2.68)**	**(3.41)**	**(2.68)**
$\|R\| < 60\%$	230291	99.948	0.41	4.06	60	15	1.11	1.08	1.31	1.19
							(3.47)	**(2.79)**	**(3.59)**	**(2.86)**
$R < 60\%$	230328	99.964	0.39	4.18	60	14	1.23	1.35	1.39	1.47
							(3.78)	**(3.31)**	**(3.78)**	**(3.49)**
$\|R\| < 30\%$	229720	99.700	0.40	3.40	30	9	0.79	0.95	0.85	1.05
							(3.61)	**(3.71)**	**(3.23)**	**(3.58)**
$R < 30\%$	230040	99.839	0.33	3.87	30	8	1.73	1.92	1.78	1.91
							(5.79)	**(5.17)**	**(5.39)**	**(4.99)**

Table B.3 (continued)

Panel B: Using RET_LDM and $PRICE\_LDM$
Starting with the equivalent of Raw WRDS sample

Sample	Total obs	% of total obs	Bond return statistics Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%) Equally weighted $\pi_{3,3}$	$\pi_{6,6}$	Value-weighted $\pi_{3,3}$	$\pi_{6,6}$
Starting sample	230406	100.000	0.44	4.72	295	62	0.82	0.67	1.04	0.81
							(**2.23**)	(1.32)	(**2.48**)	(1.61)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	230134	99.882	0.47	4.76	295	62	0.67	0.37	0.74	0.33
							(1.78)	(0.72)	(1.76)	(0.64)
$R(def) = ave(R(def))$	230406	100.000	0.45	4.67	295	63	0.69	0.51	0.93	0.62
							(1.87)	(1.02)	(**2.22**)	(1.26)
$missR(def) = ave(R(def))$	230406	100.000	0.45	4.76	295	62	0.65	0.38	0.74	0.36
							(1.73)	(0.76)	(1.75)	(0.72)
Exclude $+95\%/-45\%$	230401	99.998	0.43	4.66	295	63	0.86	0.83	1.06	0.99
							(**2.38**)	(1.81)	(**2.53**)	(**2.12**)
Exclude $+60\%/-60\%$	230401	99.998	0.43	4.68	295	63	0.88	0.75	1.07	0.87
							(**2.39**)	(1.59)	(**2.53**)	(1.76)
Exclude $+30\%/-30\%$	230325	99.965	0.43	4.54	295	65	0.87	0.80	1.14	1.05
							(**2.40**)	(1.65)	(**2.95**)	(**2.29**)
Exclude $+20\%/-20\%$	230122	99.877	0.43	4.41	295	67	1.09	0.92	1.29	1.12
							(**3.17**)	(**2.15**)	(**3.33**)	(**2.60**)
Exclude $R_tR_{t-1} < -0.04$	229955	99.804	0.42	4.25	288	68	1.18	0.97	1.36	1.17
							(**3.59**)	(**2.45**)	(**3.58**)	(**2.84**)
Exclude $R_tR_{t-1} < -0.02$	229535	99.622	0.42	4.15	288	69	1.11	0.89	1.38	1.08
							(**3.62**)	(**2.33**)	(**3.88**)	(**2.73**)
$P < 1,000$	230406	100.000	0.44	4.72	295	62	0.82	0.67	1.04	0.81
							(**2.23**)	(1.32)	(**2.48**)	(1.61)
$P < 200$	230396	99.996	0.44	4.72	295	62	0.82	0.67	1.04	0.81
							(**2.23**)	(1.32)	(**2.47**)	(1.61)
$P > 1$	230395	99.995	0.43	4.63	295	64	0.86	0.73	1.11	0.93
							(**2.35**)	(1.44)	(**2.65**)	(1.86)
$P > 5$	230368	99.984	0.43	4.60	295	64	0.82	0.76	1.11	1.03
							(**2.24**)	(1.51)	(**2.76**)	(**2.09**)
Maturity > 1 year	224624	97.491	0.45	4.78	295	62	0.68	0.43	0.78	0.53
							(1.77)	(0.83)	(1.84)	(1.04)
Rated by any agency	230406	100.000	0.44	4.72	295	62	0.83	0.55	1.04	0.72
							(**2.44**)	(1.13)	(**2.62**)	(1.44)
Exclude Face=$10	230230	99.924	0.44	4.72	295	62	0.83	0.55	1.04	0.72
							(**2.44**)	(1.13)	(**2.62**)	(1.44)
Corp. Debentures only	221989	96.347	0.44	4.82	295	61	0.82	0.54	1.01	0.67
							(**2.41**)	(1.10)	(**2.56**)	(1.34)
$\lvert R\rvert < 100\%$	230381	99.989	0.42	4.36	97	22	1.14	1.18	1.32	1.21
							(**3.33**)	(**2.80**)	(**3.35**)	(**2.74**)
$\lvert R\rvert < 90\%$	230377	99.987	0.41	4.33	89	21	1.16	1.20	1.33	1.24
							(**3.38**)	(**2.83**)	(**3.40**)	(**2.80**)
$R < 90\%$	230378	99.988	0.41	4.33	89	21	1.16	1.20	1.33	1.24
							(**3.38**)	(**2.83**)	(**3.40**)	(**2.80**)
$\lvert R\rvert < 60\%$	230291	99.950	0.41	4.06	60	15	1.11	1.08	1.31	1.19
							(**3.47**)	(**2.79**)	(**3.59**)	(**2.86**)
$R < 60\%$	230326	99.965	0.40	4.17	60	14	1.22	1.40	1.39	1.51
							(**3.75**)	(**3.48**)	(**3.77**)	(**3.62**)
$\lvert R\rvert < 30\%$	229720	99.702	0.40	3.40	30	9	0.79	0.95	0.85	1.05
							(**3.61**)	(**3.71**)	(**3.23**)	(**3.58**)
$R < 30\%$	230038	99.840	0.33	3.86	30	8	1.72	1.97	1.78	1.95
							(**5.76**)	(**5.40**)	(**5.38**)	(**5.17**)

Table B.3 (continued)

Panel C: Using *RET_LDM* and *PRICE_LDM*
Starting with the equivalent of DS Confirmed sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	230147	100.000	0.41	4.13	265	64	0.84	0.82	1.07	0.93
							(2.36)	**(1.97)**	**(2.82)**	**(2.07)**
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	229843	99.868	0.44	4.10	265	65	0.69	0.58	0.91	0.63
							(1.91)	(1.37)	**(2.36)**	(1.37)
$R(def) = ave(R(def))$	230147	100.000	0.42	4.07	265	65	0.71	0.64	0.96	0.74
							(2.04)	(1.57)	**(2.55)**	(1.66)
$missR(def) = ave(R(def))$	230147	100.000	0.42	4.10	265	65	0.72	0.63	0.92	0.68
							(2.05)	(1.53)	**(2.45)**	(1.53)
Exclude $+95\%/-45\%$	230147	100.000	0.41	4.13	265	64	0.84	0.82	1.07	0.93
							(2.36)	**(1.97)**	**(2.82)**	**(2.07)**
Exclude $+60\%/-60\%$	230145	99.999	0.41	4.13	265	64	0.85	0.83	1.08	0.94
							(2.40)	**(1.99)**	**(2.84)**	**(2.08)**
Exclude $+30\%/-30\%$	230120	99.988	0.41	4.07	265	65	0.88	0.89	1.13	1.06
							(2.56)	**(2.22)**	**(3.06)**	**(2.54)**
Exclude $+20\%/-20\%$	229977	99.926	0.40	3.97	265	67	1.03	0.98	1.24	1.10
							(3.08)	**(2.68)**	**(3.34)**	**(2.74)**
Exclude $R_tR_{t-1} < -0.04$	229857	99.874	0.40	3.90	265	68	1.15	1.01	1.35	1.22
							(3.57)	**(2.79)**	**(3.70)**	**(3.15)**
Exclude $R_tR_{t-1} < -0.02$	229465	99.704	0.40	3.80	265	70	1.04	1.03	1.31	1.22
							(3.31)	**(2.99)**	**(3.90)**	**(3.30)**
$P < 1,000$	230147	100.000	0.41	4.13	265	64	0.84	0.82	1.07	0.93
							(2.36)	**(1.97)**	**(2.82)**	**(2.07)**
$P < 200$	230138	99.996	0.41	4.13	265	64	0.84	0.82	1.07	0.93
							(2.36)	**(1.97)**	**(2.82)**	**(2.07)**
$P > 1$	230140	99.997	0.41	4.13	265	64	0.84	0.82	1.08	0.94
							(2.37)	**(1.97)**	**(2.82)**	**(2.09)**
$P > 5$	230119	99.988	0.41	4.12	265	64	0.81	0.84	1.08	1.02
							(2.32)	**(2.08)**	**(2.89)**	**(2.43)**
Maturity > 1 year	224380	97.494	0.42	4.19	265	63	0.66	0.75	0.83	0.88
							(1.96)	(1.85)	**(2.18)**	**(2.00)**
Rated by any agency	230147	100.000	0.41	4.13	265	64	0.82	0.86	1.02	1.01
							(2.42)	**(2.18)**	**(2.75)**	**(2.41)**
Exclude Face=$10	229973	99.924	0.41	4.13	265	64	0.82	0.86	1.02	1.01
							(2.42)	**(2.18)**	**(2.75)**	**(2.41)**
Corp. Debentures only	221732	96.344	0.41	4.19	265	63	0.81	0.87	1.02	0.98
							(2.42)	**(2.19)**	**(2.77)**	**(2.31)**
$\|R\| < 100\%$	230139	99.997	0.40	4.03	100	25	0.92	0.96	1.15	1.11
							(2.73)	**(2.52)**	**(3.18)**	**(2.83)**
$\|R\| < 90\%$	230138	99.996	0.40	4.02	87	22	0.94	0.99	1.17	1.14
							(2.79)	**(2.59)**	**(3.23)**	**(2.88)**
$R < 90\%$	230138	99.996	0.40	4.02	87	22	0.94	0.99	1.17	1.14
							(2.79)	**(2.59)**	**(3.23)**	**(2.88)**
$\|R\| < 60\%$	230075	99.969	0.40	3.83	60	16	0.98	1.04	1.09	1.16
							(3.29)	**(3.28)**	**(3.21)**	**(3.35)**
$R < 60\%$	230104	99.981	0.39	3.92	60	15	1.12	1.18	1.28	1.32
							(3.60)	**(3.38)**	**(3.57)**	**(3.46)**
$\|R\| < 30\%$	229720	99.814	0.40	3.40	30	9	0.79	0.95	0.85	1.05
							(3.61)	**(3.71)**	**(3.23)**	**(3.58)**
$R < 30\%$	229936	99.908	0.36	3.73	30	8	1.45	1.55	1.54	1.64
							(5.02)	**(4.71)**	**(4.66)**	**(4.55)**

Table B.3 (continued)

Panel D: Using RET_EOM and $PRICE\_EOM$
Starting with the equivalent of WRDS sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	$\pi_{6,6}$	Value-weighted $\pi_{3,3}$	$\pi_{6,6}$
Starting sample	517169	100.000	0.59	5.12	100	19	0.71 (**2.58**)	0.31 (0.86)	0.76 (**2.44**)	0.36 (0.93)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	517158	99.998	0.59	5.22	100	19	0.71 (**2.49**)	0.25 (0.68)	0.62 (**1.97**)	0.10 (0.25)
$R(def) = ave(R(def))$	517169	100.000	0.60	5.10	100	19	0.66 (**2.43**)	0.25 (0.71)	0.72 (**2.31**)	0.30 (0.77)
$missR(def) = ave(R(def))$	517169	100.000	0.59	5.22	100	19	0.71 (**2.49**)	0.25 (0.68)	0.62 (**1.97**)	0.10 (0.25)
Exclude $+95\%/-45\%$	517049	99.977	0.59	4.91	100	20	0.72 (**2.68**)	0.34 (0.98)	0.75 (**2.42**)	0.42 (1.12)
Exclude $+60\%/-60\%$	517058	99.979	0.59	4.92	100	20	0.71 (**2.63**)	0.33 (0.95)	0.75 (**2.42**)	0.40 (1.05)
Exclude $+30\%/-30\%$	516725	99.914	0.58	4.68	100	21	0.76 (**2.90**)	0.41 (1.24)	0.80 (**2.78**)	0.52 (1.46)
Exclude $+20\%/-20\%$	516139	99.801	0.58	4.51	100	22	0.79 (**3.18**)	0.38 (1.21)	0.83 (**2.99**)	0.52 (1.53)
Exclude $R_tR_{t-1} < -0.04$	515455	99.669	0.58	4.28	100	23	0.81 (**3.51**)	0.44 (1.52)	0.85 (**3.19**)	0.55 (1.75)
Exclude $R_tR_{t-1} < -0.02$	514110	99.409	0.58	4.12	100	24	0.90 (**3.94**)	0.42 (1.49)	0.97 (**3.70**)	0.53 (1.77)
$P < 1,000$	517166	99.999	0.59	5.11	100	19	0.71 (**2.60**)	0.31 (0.87)	0.76 (**2.44**)	0.37 (0.93)
$P < 200$	517118	99.990	0.60	5.10	100	20	0.71 (**2.61**)	0.32 (0.90)	0.76 (**2.43**)	0.37 (0.94)
$P > 1$	516657	99.901	0.55	4.81	100	21	0.69 (**2.55**)	0.34 (0.96)	0.77 (**2.47**)	0.45 (1.16)
$P > 5$	516399	99.851	0.54	4.75	100	21	0.67 (**2.48**)	0.38 (1.07)	0.79 (**2.58**)	0.54 (1.44)
Maturity > 1 year	504065	97.466	0.60	5.10	100	20	0.61 (**2.18**)	0.24 (0.65)	0.69 (**2.12**)	0.35 (0.86)
Rated by any agency	517169	100.000	0.59	5.12	100	19	0.62 (**2.38**)	0.24 (0.70)	0.70 (**2.30**)	0.37 (1.00)
Exclude Face=$10	517032	99.974	0.59	5.11	100	19	0.62 (**2.38**)	0.24 (0.70)	0.70 (**2.30**)	0.37 (1.00)
Corp. Debentures only	495250	95.762	0.60	5.21	100	19	0.61 (**2.33**)	0.24 (0.70)	0.69 (**2.25**)	0.39 (1.05)
$\vert R\vert < 100\%$	516947	99.957	0.54	4.63	100	21	0.82 (**3.22**)	0.55 (1.73)	0.84 (**2.73**)	0.57 (1.56)
$\vert R\vert < 90\%$	516895	99.947	0.54	4.52	89	20	0.82 (**3.22**)	0.58 (1.83)	0.84 (**2.76**)	0.60 (1.66)
$R < 90\%$	516923	99.952	0.54	4.58	89	19	0.82 (**3.19**)	0.58 (1.83)	0.85 (**2.78**)	0.61 (1.70)
$\vert R\vert < 60\%$	516580	99.886	0.53	4.08	60	15	0.84 (**3.75**)	0.68 (**2.61**)	0.93 (**3.50**)	0.86 (**2.81**)
$R < 60\%$	516736	99.916	0.50	4.34	60	14	0.98 (**4.24**)	0.85 (**2.94**)	1.05 (**3.80**)	0.94 (**2.85**)
$\vert R\vert < 30\%$	515061	99.592	0.52	3.26	30	9	0.53 (**3.71**)	0.46 (**3.05**)	0.58 (**3.15**)	0.61 (**3.19**)
$R < 30\%$	515942	99.763	0.42	3.97	30	7	1.45 (**6.75**)	1.46 (**5.69**)	1.46 (**5.61**)	1.49 (**5.06**)

Table B.3 (continued)

Panel E: Using RET_EOM and $PRICE\_EOM$
Starting with the equivalent of Raw WRDS sample

Sample	Total obs	% of total obs	Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%) Equally weighted $\pi_{3,3}$	$\pi_{6,6}$	Value-weighted $\pi_{3,3}$	$\pi_{6,6}$
Starting sample	517041	100.000	0.61	5.66	298	53	0.56 (1.90)	0.10 (0.24)	0.67 (**2.06**)	0.25 (0.59)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	517021	99.996	0.61	5.76	298	52	0.53 (1.74)	0.01 (0.02)	0.51 (1.57)	-0.03 (-0.07)
$R(def) = ave(R(def))$	517041	100.000	0.61	5.65	298	53	0.49 (1.68)	0.02 (0.05)	0.59 (1.84)	0.16 (0.38)
$missR(def) = ave(R(def))$	517041	100.000	0.61	5.77	298	52	0.54 (1.75)	0.02 (0.04)	0.51 (1.58)	-0.03 (-0.07)
Exclude $+95\%/-45\%$	516981	99.988	0.60	5.44	298	55	0.66 (**2.35**)	0.20 (0.54)	0.71 (**2.23**)	0.37 (0.94)
Exclude $+60\%/-60\%$	516988	99.990	0.60	5.48	298	54	0.62 (**2.18**)	0.17 (0.45)	0.70 (**2.16**)	0.33 (0.82)
Exclude $+30\%/-30\%$	516657	99.926	0.59	5.22	298	57	0.69 (**2.56**)	0.30 (0.84)	0.78 (**2.64**)	0.51 (1.40)
Exclude $+20\%/-20\%$	516076	99.813	0.59	5.06	298	59	0.72 (**2.79**)	0.28 (0.85)	0.80 (**2.78**)	0.47 (1.35)
Exclude $R_tR_{t-1} < -0.04$	515405	99.684	0.59	4.81	298	62	0.77 (**3.26**)	0.39 (1.35)	0.84 (**3.11**)	0.54 (1.70)
Exclude $R_tR_{t-1} < -0.02$	514068	99.425	0.59	4.67	298	64	0.87 (**3.74**)	0.38 (1.34)	0.96 (**3.64**)	0.51 (1.71)
$P < 1,000$	517041	100.000	0.61	5.66	298	53	0.56 (1.90)	0.10 (0.24)	0.67 (**2.06**)	0.25 (0.59)
$P < 200$	516999	99.992	0.61	5.66	298	53	0.56 (1.90)	0.10 (0.25)	0.67 (**2.06**)	0.25 (0.60)
$P > 1$	516586	99.912	0.56	5.08	295	58	0.54 (1.88)	0.15 (0.37)	0.68 (**2.12**)	0.34 (0.84)
$P > 5$	516344	99.865	0.56	4.97	295	59	0.55 (1.92)	0.20 (0.51)	0.72 (**2.30**)	0.44 (1.11)
Maturity > 1 year	503953	97.469	0.61	5.64	298	53	0.47 (1.57)	0.04 (0.09)	0.59 (1.75)	0.25 (0.61)
Rated by any agency	517041	100.000	0.61	5.66	298	53	0.51 (1.83)	0.06 (0.16)	0.62 (**1.99**)	0.28 (0.73)
Exclude Face=$10	516904	99.974	0.61	5.66	298	53	0.51 (1.83)	0.06 (0.16)	0.62 (**1.99**)	0.28 (0.73)
Corp. Debentures only	495122	95.761	0.61	5.76	298	52	0.50 (1.79)	0.06 (0.16)	0.62 (1.95)	0.28 (0.73)
$\|R\| < 100\%$	516885	99.970	0.55	4.58	100	22	0.79 (**3.10**)	0.56 (1.74)	0.82 (**2.67**)	0.57 (1.56)
$\|R\| < 90\%$	516845	99.962	0.54	4.49	89	20	0.79 (**3.09**)	0.58 (1.83)	0.83 (**2.69**)	0.61 (1.68)
$R < 90\%$	516861	99.965	0.54	4.53	89	20	0.78 (**3.07**)	0.58 (1.83)	0.83 (**2.72**)	0.62 (1.71)
$\|R\| < 60\%$	516548	99.905	0.53	4.08	60	15	0.83 (**3.72**)	0.68 (**2.60**)	0.93 (**3.49**)	0.87 (**2.83**)
$R < 60\%$	516677	99.930	0.51	4.28	60	14	0.96 (**4.11**)	0.85 (**2.95**)	1.04 (**3.73**)	0.94 (**2.87**)
$\|R\| < 30\%$	515032	99.611	0.52	3.26	30	9	0.52 (**3.67**)	0.46 (**3.04**)	0.58 (**3.14**)	0.61 (**3.18**)
$R < 30\%$	515885	99.776	0.42	3.91	30	8	1.43 (**6.64**)	1.45 (**5.68**)	1.45 (**5.56**)	1.49 (**5.07**)

Table B.3 (continued)

Panel F: Using RET_EOM and $PRICE\_EOM$
Starting with the equivalent of DS Confirmed sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	515740	100.000	0.52	3.84	265	69	0.64	0.52	0.69	0.52
							(**2.66**)	(1.79)	(**2.33**)	(1.48)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	515623	99.977	0.53	3.85	265	69	0.49	0.31	0.50	0.21
							(**1.99**)	(1.03)	(1.67)	(0.60)
$R(def) = ave(R(def))$	515740	100.000	0.53	3.79	265	70	0.53	0.34	0.57	0.31
							(**2.24**)	(1.19)	(1.95)	(0.86)
$missR(def) = ave(R(def))$	515740	100.000	0.53	3.84	265	69	0.53	0.35	0.54	0.23
							(**2.18**)	(1.17)	(1.84)	(0.64)
Exclude $+95\%/-45\%$	515740	100.000	0.52	3.84	265	69	0.64	0.52	0.69	0.53
							(**2.67**)	(1.80)	(**2.31**)	(1.50)
Exclude $+60\%/-60\%$	515738	100.000	0.52	3.84	265	69	0.64	0.52	0.69	0.52
							(**2.67**)	(1.79)	(**2.33**)	(1.48)
Exclude $+30\%/-30\%$	515689	99.990	0.52	3.79	265	70	0.69	0.57	0.75	0.62
							(**3.00**)	(**2.05**)	(**2.66**)	(1.89)
Exclude $+20\%/-20\%$	515367	99.928	0.52	3.69	265	72	0.74	0.57	0.83	0.65
							(**3.43**)	(**2.14**)	(**3.18**)	(**2.05**)
Exclude $R_tR_{t-1} < -0.04$	515055	99.867	0.52	3.57	178	50	0.84	0.63	0.92	0.70
							(**3.96**)	(**2.46**)	(**3.61**)	(**2.29**)
Exclude $R_tR_{t-1} < -0.02$	513881	99.640	0.52	3.43	178	52	0.83	0.60	0.96	0.75
							(**3.98**)	(**2.39**)	(**3.86**)	(**2.58**)
$P < 1,000$	515740	100.000	0.52	3.84	265	69	0.64	0.52	0.69	0.52
							(**2.67**)	(1.79)	(**2.33**)	(1.48)
$P < 200$	515702	99.993	0.52	3.84	265	69	0.64	0.52	0.69	0.52
							(**2.66**)	(1.79)	(**2.33**)	(1.48)
$P > 1$	515470	99.948	0.51	3.81	265	69	0.63	0.52	0.69	0.53
							(**2.66**)	(1.80)	(**2.32**)	(1.49)
$P > 5$	515273	99.909	0.51	3.79	265	70	0.64	0.51	0.74	0.57
							(**2.74**)	(1.79)	(**2.63**)	(1.70)
Maturity > 1 year	502738	97.479	0.53	3.91	265	68	0.59	0.50	0.66	0.51
							(**2.49**)	(1.73)	(**2.18**)	(1.44)
Rated by any agency	515740	100.000	0.52	3.84	265	69	0.62	0.47	0.66	0.47
							(**2.70**)	(1.72)	(**2.36**)	(1.40)
Exclude Face=$10	515603	99.973	0.52	3.84	265	69	0.62	0.47	0.66	0.47
							(**2.70**)	(1.72)	(**2.36**)	(1.40)
Corp. Debentures only	493827	95.751	0.52	3.93	265	67	0.61	0.47	0.68	0.49
							(**2.63**)	(1.73)	(**2.39**)	(1.45)
$\|R\| < 100\%$	515725	99.997	0.52	3.75	100	26	0.77	0.70	0.84	0.73
							(**3.50**)	(**2.68**)	(**3.03**)	(**2.31**)
$\|R\| < 90\%$	515720	99.996	0.52	3.74	87	23	0.78	0.71	0.85	0.75
							(**3.57**)	(**2.72**)	(**3.08**)	(**2.36**)
$R < 90\%$	515723	99.997	0.52	3.75	87	23	0.79	0.71	0.85	0.75
							(**3.56**)	(**2.73**)	(**3.09**)	(**2.36**)
$\|R\| < 60\%$	515636	99.980	0.52	3.61	60	16	0.75	0.68	0.77	0.75
							(**3.82**)	(**3.06**)	(**3.20**)	(**2.77**)
$R < 60\%$	515682	99.989	0.51	3.68	60	16	0.89	0.82	0.97	0.90
							(**4.34**)	(**3.31**)	(**3.70**)	(**3.00**)
$\|R\| < 30\%$	515032	99.863	0.52	3.26	30	9	0.52	0.46	0.58	0.61
							(**3.67**)	(**3.04**)	(**3.14**)	(**3.18**)
$R < 30\%$	515408	99.936	0.48	3.53	30	8	1.08	1.10	1.19	1.23
							(**5.68**)	(**4.85**)	(**4.88**)	(**4.51**)

Table B.4

Bond momentum in samples of NIG firm returns - value weighted RET_LDM and RET_EOM

This table replicates the results in Table IV with returns using the price on the last trading day of the month, RET_EOM, or the last trade of the month, RET_EOM, instead of the last price from the last five trading days of the month, RET_L5D, which is our base case. All other data choices are as described in Table II, except that price filters are based on $PRICE\_LDM$ and $PRICE\_EOM$, respectively, instead of $PRICE\_L5D$.

Panel A: Using RET_LDM and $PRICE\_LDM$
Starting with the equivalent of WRDS sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	230267	100.000	0.43	4.53	100	22	0.99 (**2.73**)	0.91 (1.95)	1.17 (**2.74**)	1.03 (**2.13**)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	230008	99.888	0.46	4.56	100	22	0.84 (**2.24**)	0.63 (1.33)	0.87 (**2.09**)	0.60 (1.23)
$R(def) = ave(R(def))$	230267	100.000	0.44	4.48	100	22	0.83 (**2.27**)	0.76 (1.66)	1.02 (**2.44**)	0.87 (1.83)
$missR(def) = ave(R(def))$	230267	100.000	0.44	4.57	100	22	0.85 (**2.27**)	0.64 (1.37)	0.93 (**2.17**)	0.60 (1.24)
Exclude $+95\%/-45\%$	230258	99.996	0.43	4.49	100	22	0.99 (**2.73**)	0.93 (**2.10**)	1.16 (**2.74**)	1.09 (**2.35**)
$Exclude + 60\%/-60\%$	230258	99.996	0.43	4.49	100	22	0.99 (**2.73**)	0.88 (**1.96**)	1.16 (**2.73**)	1.03 (**2.15**)
$Exclude + 30\%/-30\%$	230181	99.963	0.43	4.36	100	23	0.99 (**2.77**)	0.90 (**2.00**)	1.26 (**3.29**)	1.20 (**2.77**)
Exclude $+20\%/-20\%$	229977	99.874	0.42	4.23	100	24	1.19 (**3.58**)	0.97 (**2.37**)	1.37 (**3.71**)	1.24 (**2.88**)
Exclude $R_tR_{t-1} < -0.04$	229810	99.802	0.42	4.11	100	24	1.24 (**3.85**)	0.99 (**2.51**)	1.45 (**3.98**)	1.30 (**3.13**)
Exclude $R_tR_{t-1} < -0.02$	229389	99.619	0.42	4.01	100	25	1.19 (**3.91**)	0.90 (**2.31**)	1.45 (**4.17**)	1.15 (**2.89**)
$P < 1,000$	230267	100.000	0.43	4.53	100	22	0.99 (**2.73**)	0.91 (1.95)	1.17 (**2.74**)	1.03 (**2.13**)
$P < 200$	230256	99.995	0.43	4.53	100	22	0.98 (**2.70**)	0.92 (**2.01**)	1.16 (**2.73**)	1.04 (**2.16**)
$P > 1$	230256	99.995	0.43	4.51	100	22	1.02 (**2.80**)	0.95 (**2.06**)	1.20 (**2.81**)	1.12 (**2.32**)
$P > 5$	230229	99.983	0.43	4.49	100	22	0.99 (**2.74**)	0.99 (**2.14**)	1.18 (**2.87**)	1.25 (**2.62**)
Maturity > 1 year	224488	97.490	0.44	4.57	100	22	0.83 (**2.22**)	0.76 (1.59)	0.90 (**2.06**)	0.77 (1.59)
Rated by any agency	230267	100.000	0.43	4.53	100	22	0.91 (**2.77**)	0.69 (1.51)	1.06 (**2.69**)	0.77 (1.60)
Exclude Face=$10	230091	99.924	0.43	4.53	100	22	0.91 (**2.77**)	0.69 (1.51)	1.06 (**2.69**)	0.77 (1.60)
Corp. Debentures only	221852	96.346	0.43	4.60	100	22	0.93 (**2.80**)	0.71 (1.53)	1.06 (**2.68**)	0.74 (1.53)
$\lvert R\rvert < 100\%$	230239	99.988	0.42	4.37	97	22	1.24 (**3.56**)	1.12 (**2.62**)	1.41 (**3.54**)	1.24 (**2.74**)
$\lvert R\rvert < 90\%$	230235	99.986	0.41	4.35	89	20	1.25 (**3.58**)	1.14 (**2.66**)	1.40 (**3.54**)	1.26 (**2.81**)
$R < 90\%$	230236	99.987	0.41	4.35	89	20	1.25 (**3.58**)	1.14 (**2.66**)	1.40 (**3.54**)	1.26 (**2.81**)
$\lvert R\rvert < 60\%$	230147	99.948	0.41	4.07	60	15	1.13 (**3.48**)	1.08 (**2.79**)	1.36 (**3.70**)	1.28 (**3.03**)
$R < 60\%$	230184	99.964	0.39	4.19	60	14	1.29 (**3.91**)	1.35 (**3.29**)	1.48 (**3.97**)	1.55 (**3.63**)
$\lvert R\rvert < 30\%$	229576	99.700	0.40	3.42	30	9	0.77 (**3.44**)	0.92 (**3.71**)	0.87 (**3.27**)	1.08 (**3.73**)
$R < 30\%$	229896	99.839	0.33	3.88	30	8	1.75 (**5.77**)	1.88 (**5.07**)	1.77 (**5.37**)	1.96 (**5.03**)

Table B.4 (continued)

Panel B: Using RET_LDM and $PRICE\_LDM$
Starting with the equivalent of Raw WRDS sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	230262	100.000	0.44	4.74	295	62	0.88	0.65	1.08	0.83
							(**2.31**)	(1.26)	(**2.45**)	(1.59)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	230003	99.888	0.47	4.77	295	62	0.71	0.34	0.78	0.37
							(1.82)	(0.66)	(1.81)	(0.71)
$R(def) = ave(R(def))$	230262	100.000	0.45	4.68	295	63	0.71	0.50	0.94	0.67
							(1.85)	(0.99)	(**2.17**)	(1.30)
$missR(def) = ave(R(def))$	230262	100.000	0.45	4.78	295	62	0.73	0.36	0.84	0.39
							(1.87)	(0.70)	(1.90)	(0.74)
Exclude $+95\%/-45\%$	230257	99.998	0.43	4.67	295	63	0.92	0.81	1.10	1.01
							(**2.46**)	(1.76)	(**2.51**)	(**2.11**)
$Exclude + 60\%/-60\%$	230257	99.998	0.44	4.69	295	63	0.93	0.73	1.10	0.90
							(**2.46**)	(1.52)	(**2.49**)	(1.78)
$Exclude + 30\%/-30\%$	230181	99.965	0.43	4.55	295	65	0.93	0.80	1.23	1.18
							(**2.56**)	(1.69)	(**3.17**)	(**2.65**)
Exclude $+20\%/-20\%$	229977	99.876	0.43	4.42	295	67	1.15	0.87	1.34	1.18
							(**3.38**)	(**1.99**)	(**3.58**)	(**2.65**)
Exclude $R_tR_{t-1} < -0.04$	229810	99.804	0.42	4.26	288	68	1.22	0.97	1.42	1.29
							(**3.75**)	(**2.42**)	(**3.89**)	(**3.07**)
Exclude $R_tR_{t-1} < -0.02$	229390	99.621	0.42	4.16	288	69	1.15	0.87	1.42	1.14
							(**3.77**)	(**2.19**)	(**4.07**)	(**2.83**)
$P < 1,000$	230262	100.000	0.44	4.74	295	62	0.88	0.65	1.08	0.83
							(**2.31**)	(1.26)	(**2.45**)	(1.59)
$P < 200$	230252	99.996	0.44	4.73	295	62	0.88	0.65	1.08	0.83
							(**2.30**)	(1.26)	(**2.45**)	(1.59)
$P > 1$	230251	99.995	0.43	4.64	295	64	0.92	0.72	1.14	0.99
							(**2.42**)	(1.41)	(**2.60**)	(1.94)
$P > 5$	230224	99.983	0.43	4.61	295	64	0.88	0.76	1.13	1.12
							(**2.35**)	(1.48)	(**2.65**)	(**2.23**)
Maturity > 1 year	224483	97.490	0.45	4.78	295	62	0.73	0.48	0.81	0.57
							(1.86)	(0.91)	(1.79)	(1.09)
Rated by any agency	230262	100.000	0.44	4.74	295	62	0.80	0.44	0.97	0.59
							(**2.35**)	(0.90)	(**2.37**)	(1.17)
Exclude Face=$10	230086	99.924	0.44	4.73	295	62	0.80	0.44	0.97	0.59
							(**2.35**)	(0.90)	(**2.37**)	(1.17)
Corp. Debentures only	221847	96.345	0.44	4.84	295	61	0.82	0.46	0.97	0.56
							(**2.38**)	(0.91)	(**2.36**)	(1.09)
$\|R\| < 100\%$	230237	99.989	0.42	4.37	97	22	1.23	1.17	1.40	1.27
							(**3.53**)	(**2.76**)	(**3.53**)	(**2.84**)
$\|R\| < 90\%$	230233	99.987	0.42	4.34	89	20	1.23	1.19	1.39	1.30
							(**3.55**)	(**2.81**)	(**3.54**)	(**2.91**)
$R < 90\%$	230234	99.988	0.41	4.35	89	20	1.23	1.19	1.39	1.30
							(**3.55**)	(**2.81**)	(**3.54**)	(**2.91**)
$\|R\| < 60\%$	230147	99.950	0.41	4.07	60	15	1.13	1.08	1.36	1.28
							(**3.48**)	(**2.79**)	(**3.70**)	(**3.03**)
$R < 60\%$	230182	99.965	0.40	4.18	60	14	1.28	1.39	1.47	1.58
							(**3.88**)	(**3.45**)	(**3.96**)	(**3.75**)
$\|R\| < 30\%$	229576	99.702	0.40	3.42	30	9	0.77	0.92	0.87	1.08
							(**3.44**)	(**3.71**)	(**3.27**)	(**3.73**)
$R < 30\%$	229894	99.840	0.34	3.87	30	8	1.73	1.92	1.77	1.99
							(**5.75**)	(**5.30**)	(**5.37**)	(**5.19**)

Table B.4 (continued)

Panel C: Using RET_LDM and $PRICE\_LDM$
Starting with the equivalent of DS Confirmed sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	230003	100.000	0.41	4.15	265	64	0.85	0.78	1.12	0.98
							(**2.46**)	(1.88)	(**2.97**)	(**2.18**)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	229712	99.873	0.44	4.13	265	64	0.68	0.58	0.87	0.69
							(**1.97**)	(1.35)	(**2.29**)	(1.51)
$R(def) = ave(R(def))$	230003	100.000	0.42	4.09	265	65	0.69	0.64	0.92	0.82
							(**2.05**)	(1.56)	(**2.45**)	(1.87)
$missR(def) = ave(R(def))$	230003	100.000	0.42	4.13	265	64	0.70	0.63	0.88	0.73
							(**2.07**)	(1.50)	(**2.34**)	(1.65)
Exclude $+95\%/-45\%$	230003	100.000	0.41	4.15	265	64	0.85	0.78	1.12	0.98
							(**2.46**)	(1.88)	(**2.97**)	(**2.18**)
$Exclude + 60\%/-60\%$	230001	99.999	0.41	4.15	265	64	0.86	0.79	1.12	0.98
							(**2.48**)	(1.90)	(**2.99**)	(**2.18**)
$Exclude + 30\%/-30\%$	229976	99.988	0.41	4.09	265	65	0.89	0.87	1.16	1.10
							(**2.63**)	(**2.14**)	(**3.20**)	(**2.64**)
Exclude $+20\%/-20\%$	229832	99.926	0.40	3.99	265	66	1.00	0.96	1.22	1.19
							(**3.18**)	(**2.58**)	(**3.45**)	(**2.96**)
Exclude $R_tR_{t-1} < -0.04$	229712	99.873	0.40	3.92	265	68	1.14	0.98	1.38	1.28
							(**3.67**)	(**2.68**)	(**4.03**)	(**3.29**)
Exclude $R_tR_{t-1} < -0.02$	229320	99.703	0.40	3.82	265	69	1.08	1.03	1.37	1.28
							(**3.54**)	(**2.94**)	(**4.11**)	(**3.51**)
$P < 1,000$	230003	100.000	0.41	4.15	265	64	0.85	0.78	1.12	0.98
							(**2.46**)	(1.88)	(**2.97**)	(**2.18**)
$P < 200$	229994	99.996	0.41	4.15	265	64	0.85	0.78	1.12	0.98
							(**2.46**)	(1.88)	(**2.97**)	(**2.18**)
$P > 1$	229996	99.997	0.41	4.15	265	64	0.86	0.78	1.12	0.98
							(**2.50**)	(1.88)	(**3.00**)	(**2.18**)
$P > 5$	229975	99.988	0.41	4.14	265	64	0.86	0.81	1.14	1.05
							(**2.53**)	(**1.98**)	(**3.12**)	(**2.50**)
Maturity > 1 year	224239	97.494	0.42	4.21	265	63	0.59	0.71	0.70	0.86
							(1.75)	(1.72)	(1.68)	(1.95)
Rated by any agency	230003	100.000	0.41	4.15	265	64	0.83	0.82	1.00	1.01
							(**2.49**)	(**2.09**)	(**2.73**)	(**2.42**)
Exclude Face=$10	229829	99.924	0.41	4.15	265	64	0.83	0.82	1.00	1.01
							(**2.49**)	(**2.09**)	(**2.73**)	(**2.42**)
Corp. Debentures only	221590	96.342	0.41	4.21	265	63	0.83	0.84	1.00	1.00
							(**2.45**)	(**2.13**)	(**2.71**)	(**2.37**)
$\|R\| < 100\%$	229995	99.997	0.40	4.05	100	24	0.93	0.95	1.19	1.18
							(**2.81**)	(**2.53**)	(**3.34**)	(**3.02**)
$\|R\| < 90\%$	229994	99.996	0.40	4.03	87	22	0.95	0.98	1.21	1.21
							(**2.87**)	(**2.59**)	(**3.39**)	(**3.07**)
$R < 90\%$	229994	99.996	0.40	4.04	87	22	0.95	0.98	1.21	1.21
							(**2.87**)	(**2.59**)	(**3.39**)	(**3.07**)
$\|R\| < 60\%$	229931	99.969	0.40	3.85	60	15	0.99	1.02	1.11	1.21
							(**3.35**)	(**3.23**)	(**3.31**)	(**3.50**)
$R < 60\%$	229960	99.981	0.39	3.93	60	15	1.13	1.16	1.30	1.37
							(**3.66**)	(**3.34**)	(**3.69**)	(**3.61**)
$\|R\| < 30\%$	229576	99.814	0.40	3.42	30	9	0.77	0.92	0.87	1.08
							(**3.44**)	(**3.71**)	(**3.27**)	(**3.73**)
$R < 30\%$	229792	99.908	0.36	3.74	30	8	1.45	1.51	1.58	1.65
							(**5.07**)	(**4.62**)	(**4.81**)	(**4.60**)

Table B.4 (continued)

Panel D: Using RET_EOM and $PRICE\_EOM$
Starting with the equivalent of WRDS sample

Sample	Total obs	% of total obs	Mean (%)	SD (%)	Max (%)	n-sigma of Max	Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
			Bond return statistics				NIG momentum profits (%)			
Starting sample	515261	100.000	0.59	5.14	100	19	0.70	0.29	0.76	0.43
							(**2.60**)	(0.79)	(**2.40**)	(1.08)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	515261	100.000	0.59	5.24	100	19	0.72	0.23	0.64	0.16
							(**2.57**)	(0.61)	(**2.02**)	(0.40)
$R(def) = ave(R(def))$	515261	100.000	0.59	5.12	100	19	0.66	0.23	0.72	0.37
							(**2.45**)	(0.64)	(**2.27**)	(0.94)
$missR(def) = ave(R(def))$	515261	100.000	0.59	5.24	100	19	0.72	0.23	0.64	0.16
							(**2.57**)	(0.61)	(**2.02**)	(0.40)
Exclude $+95\%/-45\%$	515141	99.977	0.58	4.93	100	20	0.72	0.32	0.77	0.46
							(**2.70**)	(0.90)	(**2.44**)	(1.18)
$Exclude+60\%/-60\%$	515150	99.978	0.59	4.94	100	20	0.70	0.31	0.76	0.44
							(**2.61**)	(0.87)	(**2.39**)	(1.12)
$Exclude+30\%/-30\%$	514820	99.914	0.58	4.70	100	21	0.74	0.41	0.80	0.53
							(**2.89**)	(1.20)	(**2.80**)	(1.45)
Exclude $+20\%/-20\%$	514239	99.802	0.58	4.53	100	22	0.78	0.37	0.85	0.48
							(**3.24**)	(1.14)	(**3.13**)	(1.35)
Exclude $R_tR_{t-1} < -0.04$	513558	99.669	0.57	4.30	100	23	0.83	0.43	0.89	0.55
							(**3.70**)	(1.50)	(**3.43**)	(1.71)
Exclude $R_tR_{t-1} < -0.02$	512213	99.408	0.58	4.14	100	24	0.90	0.42	0.99	0.51
							(**4.06**)	(1.48)	(**3.90**)	(1.63)
$P < 1,000$	515258	99.999	0.59	5.13	100	19	0.71	0.29	0.76	0.43
							(**2.62**)	(0.81)	(**2.41**)	(1.08)
$P < 200$	515210	99.990	0.59	5.12	100	19	0.71	0.30	0.76	0.43
							(**2.63**)	(0.83)	(**2.40**)	(1.09)
$P > 1$	514786	99.908	0.55	4.86	100	20	0.67	0.31	0.75	0.46
							(**2.53**)	(0.85)	(**2.41**)	(1.18)
$P > 5$	514534	99.859	0.54	4.79	100	21	0.67	0.34	0.78	0.55
							(**2.49**)	(0.96)	(**2.55**)	(1.43)
Maturity > 1 year	502218	97.469	0.60	5.12	100	19	0.61	0.24	0.71	0.39
							(**2.23**)	(0.65)	(**2.20**)	(0.95)
Rated by any agency	515261	100.000	0.59	5.14	100	19	0.59	0.20	0.66	0.37
							(**2.26**)	(0.58)	(**2.15**)	(0.99)
Exclude Face=$10	515124	99.973	0.59	5.13	100	19	0.59	0.20	0.66	0.37
							(**2.26**)	(0.58)	(**2.15**)	(0.99)
Corp. Debentures only	493731	95.822	0.59	5.22	100	19	0.59	0.20	0.65	0.38
							(**2.23**)	(0.59)	(**2.10**)	(1.02)
$\|R\| < 100\%$	515045	99.958	0.54	4.67	100	21	0.81	0.54	0.87	0.60
							(**3.22**)	(1.64)	(**2.86**)	(1.63)
$\|R\| < 90\%$	514997	99.949	0.54	4.56	89	19	0.81	0.57	0.89	0.65
							(**3.24**)	(1.77)	(**2.93**)	(1.80)
$R < 90\%$	515023	99.954	0.53	4.62	89	19	0.80	0.57	0.89	0.66
							(**3.21**)	(1.76)	(**2.94**)	(1.80)
$\|R\| < 60\%$	514687	99.889	0.53	4.14	60	14	0.84	0.67	0.97	0.85
							(**3.77**)	(**2.51**)	(**3.57**)	(**2.71**)
$R < 60\%$	514839	99.918	0.50	4.38	60	14	0.99	0.84	1.04	0.93
							(**4.31**)	(**2.87**)	(**3.74**)	(**2.78**)
$\|R\| < 30\%$	513177	99.596	0.52	3.32	30	9	0.54	0.47	0.66	0.64
							(**3.78**)	(**3.10**)	(**3.37**)	(**3.24**)
$R < 30\%$	514055	99.766	0.42	4.01	30	7	1.43	1.46	1.44	1.43
							(**6.79**)	(**5.61**)	(**5.59**)	(**4.79**)

Table B.4 (continued)

Panel E: Using RET_EOM and $PRICE\_EOM$
Starting with the equivalent of Raw WRDS sample

Sample	Total obs	% of total obs	Bond return statistics Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%) Equally weighted $\pi_{3,3}$	$\pi_{6,6}$	Value-weighted $\pi_{3,3}$	$\pi_{6,6}$
Starting sample	515136	100.000	0.60	5.67	298	52	0.56	0.08	0.67	0.28
							(1.92)	(0.20)	(**2.07**)	(0.68)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	515127	99.998	0.61	5.78	298	51	0.55	-0.03	0.54	-0.03
							(1.83)	(-0.06)	(1.67)	(-0.06)
$R(def) = ave(R(def))$	515136	100.000	0.61	5.66	298	53	0.50	-0.00	0.61	0.18
							(1.71)	(-0.00)	(1.89)	(0.44)
$missR(def) = ave(R(def))$	515136	100.000	0.61	5.78	298	51	0.55	-0.02	0.54	-0.02
							(1.85)	(-0.04)	(1.67)	(-0.05)
Exclude $+95\%/-45\%$	515076	99.988	0.60	5.45	298	55	0.65	0.17	0.71	0.36
							(**2.37**)	(0.46)	(**2.22**)	(0.91)
$Exclude + 60\%/-60\%$	515083	99.990	0.60	5.49	298	54	0.61	0.14	0.70	0.32
							(**2.19**)	(0.36)	(**2.18**)	(0.78)
$Exclude + 30\%/-30\%$	514755	99.926	0.59	5.23	298	57	0.68	0.29	0.77	0.48
							(**2.57**)	(0.80)	(**2.66**)	(1.27)
Exclude $+20\%/-20\%$	514178	99.814	0.59	5.06	298	59	0.72	0.27	0.82	0.43
							(**2.87**)	(0.81)	(**2.93**)	(1.18)
Exclude $R_tR_{t-1} < -0.04$	513509	99.684	0.58	4.82	298	62	0.80	0.39	0.88	0.54
							(**3.48**)	(1.34)	(**3.36**)	(1.67)
Exclude $R_tR_{t-1} < -0.02$	512171	99.424	0.58	4.67	298	64	0.88	0.39	0.98	0.50
							(**3.89**)	(1.34)	(**3.84**)	(1.57)
$P < 1,000$	515136	100.000	0.60	5.67	298	52	0.56	0.08	0.67	0.28
							(1.92)	(0.20)	(**2.07**)	(0.68)
$P < 200$	515094	99.992	0.61	5.67	298	52	0.56	0.09	0.67	0.28
							(1.93)	(0.21)	(**2.08**)	(0.68)
$P > 1$	514715	99.918	0.56	5.12	295	58	0.54	0.12	0.69	0.35
							(1.91)	(0.30)	(**2.15**)	(0.84)
$P > 5$	514478	99.872	0.55	5.01	295	59	0.56	0.18	0.73	0.45
							(**1.96**)	(0.45)	(**2.33**)	(1.13)
Maturity > 1 year	502109	97.471	0.61	5.66	298	53	0.47	0.03	0.63	0.24
							(1.63)	(0.08)	(1.91)	(0.56)
Rated by any agency	515136	100.000	0.60	5.67	298	52	0.48	0.02	0.59	0.25
							(1.72)	(0.06)	(1.88)	(0.64)
Exclude Face=$10	514999	99.973	0.60	5.67	298	52	0.48	0.02	0.59	0.25
							(1.72)	(0.06)	(1.88)	(0.64)
Corp. Debentures only	493606	95.821	0.61	5.77	298	52	0.48	0.02	0.58	0.24
							(1.72)	(0.06)	(1.83)	(0.60)
$\lvert R\rvert < 100\%$	514984	99.970	0.54	4.61	100	21	0.78	0.54	0.86	0.60
							(**3.10**)	(1.64)	(**2.82**)	(1.63)
$\lvert R\rvert < 90\%$	514948	99.964	0.54	4.53	89	20	0.78	0.57	0.88	0.66
							(**3.12**)	(1.76)	(**2.90**)	(1.81)
$R < 90\%$	514962	99.966	0.54	4.56	89	19	0.78	0.57	0.88	0.66
							(**3.10**)	(1.77)	(**2.90**)	(1.82)
$\lvert R\rvert < 60\%$	514656	99.907	0.53	4.13	60	14	0.83	0.67	0.97	0.86
							(**3.74**)	(**2.50**)	(**3.58**)	(**2.73**)
$R < 60\%$	514781	99.931	0.51	4.32	60	14	0.96	0.85	1.03	0.94
							(**4.19**)	(**2.89**)	(**3.71**)	(**2.81**)
$\lvert R\rvert < 30\%$	513149	99.614	0.52	3.32	30	9	0.54	0.47	0.66	0.64
							(**3.74**)	(**3.10**)	(**3.36**)	(**3.27**)
$R < 30\%$	513999	99.779	0.43	3.95	30	7	1.41	1.45	1.43	1.43
							(**6.68**)	(**5.59**)	(**5.57**)	(**4.81**)

Table B.4 (continued)

Panel F: Using RET_EOM and $PRICE\_EOM$
Starting with the equivalent of DS Confirmed sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	NIG momentum profits (%): Equally weighted $\pi_{3,3}$	$\pi_{6,6}$	Value-weighted $\pi_{3,3}$	$\pi_{6,6}$
Starting sample	513855	100.000	0.52	3.91	265	68	0.63	0.50	0.78	0.50
							(**2.61**)	(1.66)	(**2.61**)	(1.35)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	513748	99.979	0.53	3.92	265	67	0.48	0.28	0.55	0.19
							(1.90)	(0.88)	(1.84)	(0.49)
$R(def) = ave(R(def))$	513855	100.000	0.53	3.87	265	68	0.51	0.33	0.63	0.31
							(**2.14**)	(1.10)	(**2.15**)	(0.84)
$missR(def) = ave(R(def))$	513855	100.000	0.53	3.92	265	68	0.50	0.33	0.58	0.22
							(**2.03**)	(1.05)	(**1.97**)	(0.57)
Exclude $+95\%/-45\%$	513855	100.000	0.52	3.91	265	68	0.63	0.50	0.77	0.52
							(**2.60**)	(1.67)	(**2.58**)	(1.39)
$Exclude+60\%/-60\%$	513853	100.000	0.52	3.91	265	68	0.63	0.50	0.78	0.50
							(**2.61**)	(1.66)	(**2.61**)	(1.35)
$Exclude+30\%/-30\%$	513804	99.990	0.52	3.86	265	69	0.68	0.56	0.82	0.62
							(**2.92**)	(1.91)	(**2.89**)	(1.75)
Exclude $+20\%/-20\%$	513484	99.928	0.52	3.76	265	70	0.73	0.58	0.89	0.68
							(**3.32**)	(**2.08**)	(**3.28**)	(**2.05**)
Exclude $R_tR_{t-1} < -0.04$	513172	99.867	0.52	3.64	178	49	0.84	0.64	0.97	0.76
							(**3.93**)	(**2.43**)	(**3.68**)	(**2.41**)
Exclude $R_tR_{t-1} < -0.02$	511998	99.639	0.52	3.50	178	51	0.85	0.63	1.04	0.79
							(**4.06**)	(**2.38**)	(**4.01**)	(**2.58**)
$P < 1,000$	513855	100.000	0.52	3.91	265	68	0.63	0.50	0.78	0.50
							(**2.61**)	(1.66)	(**2.61**)	(1.35)
$P < 200$	513817	99.993	0.52	3.91	265	68	0.63	0.50	0.78	0.50
							(**2.61**)	(1.66)	(**2.61**)	(1.35)
$P > 1$	513603	99.951	0.52	3.88	265	68	0.63	0.50	0.77	0.51
							(**2.63**)	(1.66)	(**2.60**)	(1.35)
$P > 5$	513410	99.913	0.51	3.87	265	68	0.63	0.50	0.81	0.54
							(**2.63**)	(1.65)	(**2.84**)	(1.51)
Maturity > 1 year	500909	97.481	0.53	3.98	265	67	0.58	0.47	0.71	0.46
							(**2.42**)	(1.57)	(**2.36**)	(1.23)
Rated by any agency	513855	100.000	0.52	3.91	265	68	0.60	0.46	0.68	0.47
							(**2.58**)	(1.63)	(**2.35**)	(1.37)
Exclude Face=$10	513718	99.973	0.52	3.91	265	68	0.60	0.46	0.68	0.47
							(**2.58**)	(1.63)	(**2.35**)	(1.37)
Corp. Debentures only	492331	95.811	0.53	3.99	265	66	0.60	0.47	0.67	0.49
							(**2.56**)	(1.66)	(**2.34**)	(1.40)
$\|R\| < 100\%$	513840	99.997	0.52	3.82	100	26	0.76	0.70	0.90	0.73
							(**3.42**)	(**2.57**)	(**3.23**)	(**2.20**)
$\|R\| < 90\%$	513835	99.996	0.52	3.80	87	23	0.78	0.72	0.91	0.75
							(**3.51**)	(**2.64**)	(**3.28**)	(**2.26**)
$R < 90\%$	513838	99.997	0.52	3.81	87	23	0.78	0.72	0.92	0.75
							(**3.50**)	(**2.65**)	(**3.28**)	(**2.26**)
$\|R\| < 60\%$	513751	99.980	0.52	3.67	60	16	0.75	0.69	0.83	0.77
							(**3.78**)	(**3.02**)	(**3.36**)	(**2.75**)
$R < 60\%$	513797	99.989	0.51	3.75	60	16	0.89	0.83	1.01	0.90
							(**4.32**)	(**3.22**)	(**3.80**)	(**2.90**)
$\|R\| < 30\%$	513149	99.863	0.52	3.32	30	9	0.54	0.47	0.66	0.64
							(**3.74**)	(**3.10**)	(**3.36**)	(**3.27**)
$R < 30\%$	513525	99.936	0.48	3.60	30	8	1.09	1.11	1.26	1.24
							(**5.76**)	(**4.77**)	(**5.08**)	(**4.39**)

Table B.5
Posterior distribution of NIG momentum profits

The table presents estimation results for the regression model, Equation 3:

$$r^s_{i,t+1} = \alpha^s + \boldsymbol{W}^s_{i,t}\boldsymbol{\beta}^s_W + \boldsymbol{L}^s_{i,t}\boldsymbol{\beta}^s_L + \sigma^s\varepsilon_{i,t+1} \qquad \varepsilon_{i,t+1} \sim N(0,1)$$

for $K = 3$, using 10,000 draws of the Gibbs sampler (1000 burn-in iterations). Panel A (B) [C] uses returns in the WRDS (Raw WRDS) [DS Confirmed] sample for r^s_{it+1}. Each row of the table summarizes the Gibbs sampler posterior draws for $\boldsymbol{\beta}^s_W$ and $\boldsymbol{\beta}^s_L$, the winner and loser portfolio contribution to momentum, emanating from month k of the holding period. The resulting momentum strategy profits use these posterior estimates following Equation 6.

	Mean	SD	95% confidence bounds		Prob($estimate > 0$)
			Panel A: WRDS sample		
Intercept	0.0042	0.0000	0.004	0.004	1.000
$W_{\{1,0,0\}}$	0.0043	0.0005	0.003	0.005	1.000
$W_{\{0,1,0\}}$	0.0024	0.0006	0.001	0.004	1.000
$W_{\{0,0,1\}}$	0.0023	0.0005	0.001	0.003	1.000
$W_{\{1,1,0\}}$	0.0062	0.0007	0.005	0.008	1.000
$W_{\{0,1,1\}}$	-0.0014	0.0007	-0.003	0.000	0.029
$W_{\{1,0,1\}}$	0.0053	0.0013	0.003	0.008	1.000
$W_{\{1,1,1\}}$	0.0060	0.0007	0.005	0.007	1.000
$L_{\{1,0,0\}}$	-0.0017	0.0005	-0.003	-0.001	0.000
$L_{\{0,1,0\}}$	-0.0016	0.0006	-0.003	-0.000	0.004
$L_{\{0,0,1\}}$	0.0014	0.0005	0.000	0.002	0.997
$L_{\{1,1,0\}}$	-0.0023	0.0007	-0.004	-0.001	0.001
$L_{\{0,1,1\}}$	0.0019	0.0008	0.000	0.003	0.995
$L_{\{1,0,1\}}$	0.0014	0.0013	-0.001	0.004	0.856
$L_{\{1,1,1\}}$	0.0193	0.0007	0.018	0.021	1.000
			Panel B: Raw WRDS sample		
Intercept	0.0042	0.0000	0.004	0.004	1.000
$W_{\{1,0,0\}}$	0.0040	0.0005	0.003	0.005	1.000
$W_{\{0,1,0\}}$	0.0031	0.0006	0.002	0.004	1.000
$W_{\{0,0,1\}}$	0.0022	0.0005	0.001	0.003	1.000
$W_{\{1,1,0\}}$	0.0062	0.0007	0.005	0.008	1.000
$W_{\{0,1,1\}}$	-0.0012	0.0007	-0.003	0.000	0.049
$W_{\{1,0,1\}}$	0.0047	0.0014	0.002	0.007	1.000
$W_{\{1,1,1\}}$	0.0064	0.0007	0.005	0.008	1.000
$L_{\{1,0,0\}}$	-0.0028	0.0005	-0.004	-0.002	0.000
$L_{\{0,1,0\}}$	-0.0017	0.0006	-0.003	-0.000	0.005
$L_{\{0,0,1\}}$	0.0010	0.0005	-0.000	0.002	0.964
$L_{\{1,1,0\}}$	-0.0032	0.0008	-0.005	-0.002	0.000
$L_{\{0,1,1\}}$	0.0007	0.0008	-0.001	0.002	0.807
$L_{\{1,0,1\}}$	0.0012	0.0014	-0.002	0.004	0.798
$L_{\{1,1,1\}}$	0.0173	0.0007	0.016	0.019	1.000
			Panel C: DS Confirmed sample		
Intercept	0.0040	0.0000	0.004	0.004	1.000
$W_{\{1,0,0\}}$	0.0035	0.0004	0.003	0.004	1.000
$W_{\{0,1,0\}}$	-0.0005	0.0005	-0.002	0.001	0.163
$W_{\{0,0,1\}}$	0.0009	0.0004	0.000	0.002	0.987
$W_{\{1,1,0\}}$	0.0040	0.0006	0.003	0.005	1.000
$W_{\{0,1,1\}}$	-0.0000	0.0006	-0.001	0.001	0.482
$W_{\{1,0,1\}}$	0.0029	0.0012	0.001	0.005	0.994
$W_{\{1,1,1\}}$	0.0040	0.0006	0.003	0.005	1.000
$L_{\{1,0,0\}}$	-0.0008	0.0004	-0.002	0.000	0.026
$L_{\{0,1,0\}}$	-0.0017	0.0005	-0.003	-0.001	0.001
$L_{\{0,0,1\}}$	0.0028	0.0004	0.002	0.004	1.000
$L_{\{1,1,0\}}$	0.0030	0.0006	0.002	0.004	1.000
$L_{\{0,1,1\}}$	0.0053	0.0006	0.004	0.007	1.000
$L_{\{1,0,1\}}$	0.0109	0.0012	0.009	0.013	1.000
$L_{\{1,1,1\}}$	0.0173	0.0006	0.016	0.018	1.000

Table B.6
Bond momentum in samples of individual IG bond returns

The table repeats the analyses in Table II, except that the momentum strategy includes only bonds rated IG, instead of NIG, at month-end $t-1$. All other data choices are as described in Table II.

Panel A: WRDS sample as starting sample

Sample	Total obs	% of total obs	Bond return statistics				IG momentum profits (%)			
			Mean (%)	SD (%)	Max (%)	n-sigma of Max	Equally weighted		Value-weighted	
							$\pi_{3,3}$	$\pi_{6,6}$	$\pi_{3,3}$	$\pi_{6,6}$
Starting sample	1427056	100.000	0.43	4.29	100	23	-0.06	-0.14	-0.10	-0.15
							(-0.47)	(-0.92)	(-0.78)	(-0.97)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	1426644	99.971	0.43	4.35	100	23	-0.05	-0.13	-0.09	-0.14
							(-0.40)	(-0.85)	(-0.65)	(-0.89)
$R(def) = ave(R(def))$	1427056	100.000	0.43	4.27	100	23	-0.06	-0.14	-0.10	-0.15
							(-0.48)	(-0.93)	(-0.79)	(-0.99)
$missR(def) = ave(R(def))$	1427056	100.000	0.43	4.36	100	23	-0.05	-0.13	-0.09	-0.14
							(-0.40)	(-0.85)	(-0.65)	(-0.89)
Exclude $+95\%/-45\%$	1426885	99.988	0.42	4.19	100	24	-0.06	-0.14	-0.10	-0.15
							(-0.47)	(-0.91)	(-0.78)	(-0.97)
Exclude $+60\%/-60\%$	1426936	99.992	0.42	4.22	100	24	-0.06	-0.14	-0.10	-0.15
							(-0.46)	(-0.92)	(-0.78)	(-0.97)
Exclude $+30\%/-30\%$	1426095	99.933	0.42	4.01	100	25	-0.05	-0.13	-0.10	-0.14
							(-0.43)	(-0.84)	(-0.75)	(-0.91)
Exclude $+20\%/-20\%$	1424610	99.829	0.42	3.86	100	26	-0.04	-0.11	-0.08	-0.12
							(-0.33)	(-0.73)	(-0.62)	(-0.80)
Exclude $R_tR_{t-1} < -0.04$	1423125	99.725	0.41	3.72	100	27	-0.03	-0.09	-0.07	-0.11
							(-0.26)	(-0.64)	(-0.58)	(-0.73)
Exclude $R_tR_{t-1} < -0.02$	1419227	99.451	0.41	3.57	100	28	-0.02	-0.08	-0.06	-0.10
							(-0.20)	(-0.59)	(-0.47)	(-0.69)
$P < 1,000$	1426872	99.987	0.43	4.29	100	23	-0.06	-0.14	-0.10	-0.15
							(-0.48)	(-0.91)	(-0.78)	(-0.97)
$P < 200$	1426617	99.969	0.43	4.28	100	23	-0.06	-0.14	-0.10	-0.15
							(-0.48)	(-0.91)	(-0.79)	(-0.97)
$P > 1$	1426945	99.992	0.42	4.26	100	23	-0.06	-0.14	-0.10	-0.15
							(-0.47)	(-0.92)	(-0.78)	(-0.97)
$P > 5$	1426500	99.961	0.42	4.22	100	24	-0.06	-0.14	-0.10	-0.15
							(-0.48)	(-0.92)	(-0.79)	(-0.97)
Maturity > 1 year	1315895	92.210	0.43	4.31	100	23	-0.09	-0.17	-0.13	-0.18
							(-0.71)	(-1.13)	(-1.03)	(-1.21)
Rated by any agency	1427056	100.000	0.43	4.29	100	23	-0.05	-0.14	-0.09	-0.14
							(-0.39)	(-0.93)	(-0.68)	(-0.93)
Exclude Face=$10	1394216	97.699	0.41	4.19	100	24	-0.06	-0.14	-0.10	-0.15
							(-0.48)	(-0.92)	(-0.79)	(-0.97)
Corp. Debentures only	1249095	87.530	0.41	4.22	100	24	-0.07	-0.12	-0.11	-0.14
							(-0.54)	(-0.83)	(-0.84)	(-0.97)
$\|R\| < 100\%$	1426848	99.985	0.41	4.12	100	24	-0.05	-0.14	-0.10	-0.15
							(-0.44)	(-0.92)	(-0.77)	(-0.98)
$\|R\| < 90\%$	1426785	99.981	0.41	4.07	90	22	-0.06	-0.13	-0.10	-0.14
							(-0.46)	(-0.85)	(-0.78)	(-0.94)
$R < 90\%$	1426800	99.982	0.41	4.08	90	22	-0.06	-0.13	-0.10	-0.14
							(-0.46)	(-0.86)	(-0.78)	(-0.94)
$\|R\| < 60\%$	1426281	99.946	0.40	3.84	60	15	-0.05	-0.13	-0.10	-0.14
							(-0.43)	(-0.84)	(-0.77)	(-0.94)
$R < 60\%$	1426480	99.960	0.39	3.94	60	15	-0.05	-0.13	-0.10	-0.14
							(-0.43)	(-0.84)	(-0.76)	(-0.94)
$\|R\| < 30\%$	1423109	99.723	0.40	3.32	30	9	-0.02	-0.08	-0.06	-0.10
							(-0.15)	(-0.61)	(-0.45)	(-0.72)
$R < 30\%$	1424824	99.844	0.35	3.69	30	8	-0.01	-0.06	-0.05	-0.09
							(-0.10)	(-0.41)	(-0.42)	(-0.58)

Table B.6 (continued)

Panel B: Raw WRDS sample as starting sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	IG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	1426993	100.000	0.43	4.47	295	66	-0.06	-0.14	-0.10	-0.15
							(-0.46)	(-0.93)	(-0.78)	(-0.98)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	1426577	99.971	0.44	4.54	295	65	-0.05	-0.13	-0.09	-0.14
							(-0.39)	(-0.88)	(-0.66)	(-0.91)
$R(def) = ave(R(def))$	1426993	100.000	0.44	4.46	295	66	-0.06	-0.14	-0.10	-0.15
							(-0.47)	(-0.94)	(-0.79)	(-0.99)
$missR(def) = ave(R(def))$	1426993	100.000	0.44	4.54	295	65	-0.05	-0.13	-0.09	-0.14
							(-0.39)	(-0.88)	(-0.67)	(-0.92)
Exclude $+95\%/-45\%$	1426873	99.992	0.43	4.33	295	68	-0.06	-0.14	-0.10	-0.15
							(-0.47)	(-0.91)	(-0.78)	(-0.97)
Exclude $+60\%/-60\%$	1426924	99.995	0.43	4.38	295	67	-0.06	-0.14	-0.10	-0.15
							(-0.46)	(-0.92)	(-0.78)	(-0.97)
Exclude $+30\%/-30\%$	1426083	99.936	0.42	4.14	295	71	-0.05	-0.13	-0.10	-0.14
							(-0.43)	(-0.84)	(-0.75)	(-0.91)
Exclude $+20\%/-20\%$	1424598	99.832	0.42	3.99	295	74	-0.04	-0.11	-0.08	-0.12
							(-0.33)	(-0.73)	(-0.62)	(-0.80)
Exclude $R_tR_{t-1} < -0.04$	1423116	99.728	0.42	3.81	294	77	-0.03	-0.09	-0.07	-0.11
							(-0.26)	(-0.64)	(-0.58)	(-0.73)
Exclude $R_tR_{t-1} < -0.02$	1419225	99.456	0.42	3.67	294	80	-0.02	-0.08	-0.06	-0.10
							(-0.20)	(-0.59)	(-0.47)	(-0.69)
$P < 1,000$	1426812	99.987	0.43	4.47	295	66	-0.06	-0.14	-0.10	-0.15
							(-0.46)	(-0.93)	(-0.78)	(-0.98)
$P < 200$	1426564	99.970	0.43	4.47	295	66	-0.06	-0.14	-0.10	-0.15
							(-0.46)	(-0.93)	(-0.78)	(-0.98)
$P > 1$	1426896	99.993	0.43	4.39	295	67	-0.06	-0.14	-0.10	-0.15
							(-0.46)	(-0.93)	(-0.78)	(-0.98)
$P > 5$	1426453	99.962	0.43	4.34	295	68	-0.06	-0.14	-0.10	-0.15
							(-0.46)	(-0.93)	(-0.78)	(-0.98)
Maturity $>$ 1 year	1315836	92.210	0.44	4.49	295	66	-0.09	-0.17	-0.13	-0.18
							(-0.70)	(-1.14)	(-1.02)	(-1.21)
Rated by any agency	1426993	100.000	0.43	4.47	295	66	-0.05	-0.14	-0.09	-0.14
							(-0.38)	(-0.94)	(-0.68)	(-0.93)
Exclude Face=$10	1394155	97.699	0.42	4.38	295	67	-0.06	-0.14	-0.10	-0.15
							(-0.47)	(-0.93)	(-0.79)	(-0.97)
Corp. Debentures only	1249041	87.530	0.42	4.40	295	67	-0.07	-0.12	-0.11	-0.14
							(-0.55)	(-0.85)	(-0.84)	(-0.97)
$\|R\| < 100\%$	1426822	99.988	0.41	4.11	100	24	-0.06	-0.14	-0.10	-0.15
							(-0.45)	(-0.91)	(-0.78)	(-0.97)
$\|R\| < 90\%$	1426765	99.984	0.41	4.06	90	22	-0.06	-0.13	-0.10	-0.14
							(-0.46)	(-0.85)	(-0.79)	(-0.94)
$R < 90\%$	1426774	99.985	0.41	4.07	90	22	-0.06	-0.13	-0.10	-0.14
							(-0.46)	(-0.85)	(-0.79)	(-0.94)
$\|R\| < 60\%$	1426278	99.950	0.40	3.84	60	15	-0.05	-0.13	-0.10	-0.14
							(-0.43)	(-0.84)	(-0.77)	(-0.94)
$R < 60\%$	1426455	99.962	0.39	3.93	60	15	-0.05	-0.12	-0.10	-0.14
							(-0.44)	(-0.83)	(-0.77)	(-0.93)
$\|R\| < 30\%$	1423106	99.728	0.40	3.32	30	9	-0.02	-0.08	-0.06	-0.10
							(-0.15)	(-0.61)	(-0.45)	(-0.72)
$R < 30\%$	1424799	99.846	0.35	3.67	30	8	-0.01	-0.06	-0.05	-0.08
							(-0.11)	(-0.40)	(-0.42)	(-0.58)

Table B.6 (continued)

Panel C: DS Confirmed sample as starting sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	IG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	1424860	100.000	0.40	3.73	265	71	-0.04 (-0.34)	-0.11 (-0.77)	-0.08 (-0.65)	-0.12 (-0.85)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	1424285	99.960	0.41	3.74	265	71	-0.04 (-0.29)	-0.11 (-0.75)	-0.07 (-0.59)	-0.12 (-0.82)
$R(def) = ave(R(def))$	1424860	100.000	0.40	3.71	265	71	-0.04 (-0.35)	-0.11 (-0.78)	-0.08 (-0.66)	-0.13 (-0.87)
$missR(def) = ave(R(def))$	1424860	100.000	0.40	3.76	265	70	-0.03 (-0.29)	-0.11 (-0.75)	-0.07 (-0.59)	-0.12 (-0.82)
Exclude $+95\%/-45\%$	1424848	99.999	0.40	3.72	265	71	-0.04 (-0.35)	-0.11 (-0.76)	-0.08 (-0.65)	-0.12 (-0.85)
Exclude $+60\%/-60\%$	1424858	100.000	0.40	3.73	265	71	-0.04 (-0.34)	-0.11 (-0.77)	-0.08 (-0.65)	-0.12 (-0.85)
Exclude $+30\%/-30\%$	1424614	99.983	0.40	3.67	265	72	-0.04 (-0.33)	-0.10 (-0.71)	-0.08 (-0.63)	-0.12 (-0.81)
Exclude $+20\%/-20\%$	1423652	99.915	0.40	3.58	265	74	-0.03 (-0.26)	-0.09 (-0.64)	-0.07 (-0.54)	-0.10 (-0.72)
Exclude $R_tR_{t-1} < -0.04$	1422719	99.850	0.40	3.49	206	59	-0.02 (-0.20)	-0.08 (-0.59)	-0.06 (-0.48)	-0.10 (-0.68)
Exclude $R_tR_{t-1} < -0.02$	1419101	99.596	0.40	3.36	206	61	-0.02 (-0.15)	-0.07 (-0.53)	-0.05 (-0.39)	-0.09 (-0.63)
$P < 1,000$	1424683	99.988	0.40	3.73	265	71	-0.04 (-0.34)	-0.11 (-0.77)	-0.08 (-0.65)	-0.12 (-0.85)
$P < 200$	1424445	99.971	0.40	3.73	265	71	-0.04 (-0.34)	-0.11 (-0.76)	-0.08 (-0.65)	-0.12 (-0.85)
$P > 1$	1424800	99.996	0.40	3.73	265	71	-0.04 (-0.34)	-0.11 (-0.77)	-0.08 (-0.65)	-0.12 (-0.85)
$P > 5$	1424422	99.969	0.40	3.72	265	71	-0.04 (-0.34)	-0.11 (-0.77)	-0.08 (-0.66)	-0.12 (-0.86)
Maturity > 1 year	1313965	92.217	0.41	3.78	265	70	-0.07 (-0.58)	-0.13 (-0.98)	-0.11 (-0.87)	-0.15 (-1.09)
Rated by any agency	1424860	100.000	0.40	3.73	265	71	-0.03 (-0.24)	-0.11 (-0.76)	-0.07 (-0.53)	-0.12 (-0.80)
Exclude Face=$10	1392287	97.714	0.39	3.66	265	72	-0.04 (-0.34)	-0.11 (-0.77)	-0.08 (-0.65)	-0.12 (-0.85)
Corp. Debentures only	1247426	87.547	0.39	3.72	265	71	-0.06 (-0.48)	-0.09 (-0.69)	-0.10 (-0.77)	-0.12 (-0.84)
$\|R\| < 100\%$	1424835	99.998	0.40	3.69	100	27	-0.04 (-0.34)	-0.11 (-0.77)	-0.08 (-0.65)	-0.12 (-0.85)
$\|R\| < 90\%$	1424821	99.997	0.40	3.68	90	24	-0.04 (-0.35)	-0.10 (-0.71)	-0.08 (-0.66)	-0.12 (-0.83)
$R < 90\%$	1424823	99.997	0.40	3.68	90	24	-0.04 (-0.35)	-0.10 (-0.71)	-0.08 (-0.66)	-0.12 (-0.83)
$\|R\| < 60\%$	1424622	99.983	0.39	3.58	60	17	-0.04 (-0.35)	-0.10 (-0.69)	-0.08 (-0.66)	-0.12 (-0.82)
$R < 60\%$	1424705	99.989	0.39	3.62	60	16	-0.04 (-0.35)	-0.10 (-0.69)	-0.08 (-0.66)	-0.12 (-0.82)
$\|R\| < 30\%$	1423106	99.877	0.40	3.32	30	9	-0.02 (-0.15)	-0.08 (-0.61)	-0.06 (-0.45)	-0.10 (-0.72)
$R < 30\%$	1424012	99.940	0.37	3.51	30	8	-0.02 (-0.17)	-0.07 (-0.51)	-0.06 (-0.46)	-0.09 (-0.65)

Table B.7
Bond momentum in samples of IG firm returns - equally weighted

The table repeats the analyses in Table III, except that the momentum strategy includes only firms rated IG, instead of NIG, at month-end $t-1$. All other data choices are as described in Table II.

Panel A: WRDS sample as starting sample

Sample	Total obs	% of total obs	Mean (%)	SD (%)	Max (%)	n-sigma of Max	IG momentum profits (%) Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	370384	100.000	0.52	4.70	100	21	-0.01 (-0.06)	-0.07 (-0.65)	0.01 (0.11)	-0.06 (-0.61)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	370239	99.961	0.53	4.78	100	21	-0.00 (-0.04)	-0.06 (-0.62)	0.03 (0.27)	-0.04 (-0.35)
$R(def) = ave(R(def))$	370384	100.000	0.52	4.67	100	21	-0.01 (-0.06)	-0.07 (-0.66)	0.01 (0.10)	-0.07 (-0.64)
$missR(def) = ave(R(def))$	370384	100.000	0.53	4.77	100	21	-0.01 (-0.06)	-0.07 (-0.65)	0.01 (0.14)	-0.06 (-0.57)
Exclude $+95\%/-45\%$	370336	99.987	0.52	4.57	100	22	-0.00 (-0.05)	-0.06 (-0.60)	0.01 (0.14)	-0.06 (-0.59)
Exclude $+60\%/-60\%$	370340	99.988	0.52	4.59	100	22	-0.00 (-0.04)	-0.06 (-0.59)	0.01 (0.13)	-0.06 (-0.57)
Exclude $+30\%/-30\%$	370167	99.941	0.51	4.40	100	23	-0.00 (-0.00)	-0.05 (-0.52)	0.01 (0.12)	-0.06 (-0.57)
Exclude $+20\%/-20\%$	369793	99.840	0.51	4.25	100	23	0.00 (0.02)	-0.04 (-0.44)	0.02 (0.20)	-0.05 (-0.55)
Exclude $R_tR_{t-1} < -0.04$	369422	99.740	0.50	4.08	100	24	0.01 (0.13)	-0.04 (-0.38)	0.02 (0.27)	-0.05 (-0.55)
Exclude $R_tR_{t-1} < -0.02$	368566	99.509	0.50	3.94	100	25	0.01 (0.16)	-0.03 (-0.36)	0.02 (0.24)	-0.05 (-0.56)
$P < 1,000$	370383	100.000	0.52	4.70	100	21	-0.01 (-0.06)	-0.06 (-0.63)	0.01 (0.11)	-0.06 (-0.59)
$P < 200$	370355	99.992	0.52	4.69	100	21	-0.01 (-0.06)	-0.07 (-0.65)	0.01 (0.13)	-0.06 (-0.58)
$P > 1$	370321	99.983	0.51	4.61	100	22	-0.01 (-0.06)	-0.07 (-0.65)	0.01 (0.15)	-0.06 (-0.58)
$P > 5$	370260	99.967	0.51	4.58	100	22	-0.01 (-0.06)	-0.07 (-0.65)	0.02 (0.19)	-0.06 (-0.57)
Maturity > 1 year	361263	97.537	0.53	4.74	100	21	-0.03 (-0.30)	-0.08 (-0.75)	-0.02 (-0.22)	-0.08 (-0.77)
Rated by any agency	370384	100.000	0.52	4.70	100	21	0.01 (0.13)	-0.07 (-0.64)	0.03 (0.34)	-0.06 (-0.56)
Exclude Face=$10	370207	99.952	0.52	4.70	100	21	0.01 (0.09)	-0.07 (-0.69)	0.00 (0.01)	-0.09 (-0.91)
Corp. Debentures only	358188	96.707	0.52	4.74	100	21	-0.00 (-0.04)	-0.08 (-0.75)	-0.07 (-0.66)	-0.08 (-0.77)
$\lvert R\rvert < 100\%$	370305	99.979	0.49	4.44	97	22	0.01 (0.06)	-0.05 (-0.51)	0.02 (0.23)	-0.06 (-0.54)
$\lvert R\rvert < 90\%$	370292	99.975	0.49	4.39	90	20	0.01 (0.06)	-0.05 (-0.50)	0.02 (0.19)	-0.06 (-0.55)
$R < 90\%$	370297	99.977	0.49	4.41	90	20	0.01 (0.07)	-0.05 (-0.48)	0.02 (0.26)	-0.05 (-0.49)
$\lvert R\rvert < 60\%$	370145	99.935	0.48	4.09	60	15	-0.00 (-0.00)	-0.05 (-0.53)	0.01 (0.09)	-0.06 (-0.61)
$R < 60\%$	370208	99.952	0.47	4.23	60	14	0.01 (0.11)	-0.04 (-0.43)	0.02 (0.18)	-0.05 (-0.53)
$\lvert R\rvert < 30\%$	369188	99.677	0.48	3.38	30	9	0.02 (0.25)	-0.02 (-0.26)	0.02 (0.26)	-0.05 (-0.49)
$R < 30\%$	369723	99.822	0.40	3.90	30	8	0.04 (0.49)	0.00 (0.04)	0.04 (0.49)	-0.02 (-0.18)

Table B.7 (continued)

Panel B: Raw WRDS sample as starting sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	IG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	370352	100.000	0.53	5.03	295	59	-0.01	-0.08	0.00	-0.07
							(-0.06)	(-0.74)	(0.05)	(-0.65)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	370206	99.961	0.54	5.11	295	58	-0.00	-0.07	0.02	-0.04
							(-0.05)	(-0.72)	(0.21)	(-0.40)
$R(def) = ave(R(def))$	370352	100.000	0.54	5.00	295	59	-0.01	-0.08	0.00	-0.07
							(-0.06)	(-0.75)	(0.03)	(-0.68)
$missR(def) = ave(R(def))$	370352	100.000	0.54	5.10	295	58	-0.01	-0.08	0.01	-0.07
							(-0.06)	(-0.75)	(0.08)	(-0.62)
Exclude $+95\%/-45\%$	370327	99.993	0.52	4.88	295	60	-0.00	-0.06	0.01	-0.06
							(-0.05)	(-0.60)	(0.15)	(-0.62)
Exclude $+60\%/-60\%$	370331	99.994	0.52	4.91	295	60	-0.00	-0.06	0.01	-0.06
							(-0.03)	(-0.59)	(0.15)	(-0.58)
Exclude $+30\%/-30\%$	370159	99.948	0.52	4.71	295	62	-0.00	-0.05	0.01	-0.06
							(-0.00)	(-0.53)	(0.12)	(-0.60)
Exclude $+20\%/-20\%$	369785	99.847	0.51	4.56	295	65	0.00	-0.04	0.02	-0.06
							(0.02)	(-0.45)	(0.20)	(-0.60)
Exclude $R_t R_{t-1} < -0.04$	369415	99.747	0.51	4.34	294	68	0.01	-0.04	0.02	-0.06
							(0.13)	(-0.38)	(0.27)	(-0.60)
Exclude $R_t R_{t-1} < -0.02$	368563	99.517	0.51	4.22	294	70	0.01	-0.04	0.02	-0.06
							(0.15)	(-0.37)	(0.24)	(-0.62)
$P < 1,000$	370352	100.000	0.53	5.03	295	59	-0.01	-0.08	0.01	-0.07
							(-0.06)	(-0.74)	(0.06)	(-0.66)
$P < 200$	370328	99.994	0.53	5.02	295	59	-0.00	-0.08	0.01	-0.07
							(-0.05)	(-0.77)	(0.07)	(-0.65)
$P > 1$	370301	99.986	0.52	4.77	295	62	-0.01	-0.08	0.00	-0.07
							(-0.06)	(-0.74)	(0.05)	(-0.65)
$P > 5$	370240	99.970	0.51	4.74	295	62	-0.01	-0.08	0.01	-0.07
							(-0.06)	(-0.74)	(0.08)	(-0.65)
Maturity $>$ 1 year	361234	97.538	0.54	5.05	295	58	-0.03	-0.09	-0.03	-0.09
							(-0.31)	(-0.87)	(-0.28)	(-0.81)
Rated by any agency	370352	100.000	0.53	5.03	295	59	0.01	-0.07	0.03	-0.06
							(0.14)	(-0.73)	(0.28)	(-0.61)
Exclude Face=$10	370175	99.952	0.53	5.02	295	59	0.01	-0.08	-0.00	-0.10
							(0.09)	(-0.77)	(-0.03)	(-0.98)
Corp. Debentures only	358155	96.707	0.53	5.05	295	58	-0.01	-0.09	-0.07	-0.09
							(-0.14)	(-0.87)	(-0.73)	(-0.81)
$\|R\| < 100\%$	370292	99.984	0.50	4.41	97	22	0.00	-0.06	0.02	-0.06
							(0.03)	(-0.55)	(0.17)	(-0.59)
$\|R\| < 90\%$	370282	99.981	0.49	4.37	90	20	0.00	-0.05	0.02	-0.06
							(0.04)	(-0.51)	(0.17)	(-0.57)
$R < 90\%$	370284	99.982	0.49	4.38	90	20	0.00	-0.05	0.02	-0.06
							(0.03)	(-0.52)	(0.17)	(-0.58)
$\|R\| < 60\%$	370144	99.944	0.48	4.09	60	15	-0.00	-0.05	0.01	-0.06
							(-0.00)	(-0.53)	(0.09)	(-0.61)
$R < 60\%$	370196	99.958	0.47	4.20	60	14	0.01	-0.05	0.01	-0.07
							(0.08)	(-0.47)	(0.09)	(-0.62)
$\|R\| < 30\%$	369187	99.685	0.48	3.38	30	9	0.02	-0.02	0.02	-0.05
							(0.25)	(-0.26)	(0.26)	(-0.49)
$R < 30\%$	369711	99.827	0.40	3.87	30	8	0.04	0.00	0.04	-0.03
							(0.46)	(0.00)	(0.42)	(-0.29)

Table B.7 (continued)

Panel C: DS Confirmed sample as starting sample

Sample	Total obs	% of total obs	Bond return statistics				IG momentum profits (%)			
			Mean (%)	SD (%)	Max (%)	n-sigma of Max	Equally weighted		Value-weighted	
							$\pi_{3,3}$	$\pi_{6,6}$	$\pi_{3,3}$	$\pi_{6,6}$
Starting sample	369787	100.000	0.48	4.03	265	66	0.01	-0.05	0.01	-0.07
							(0.07)	(-0.52)	(0.11)	(-0.66)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	369584	99.945	0.50	4.05	265	65	0.01	-0.05	0.03	-0.04
							(0.08)	(-0.50)	(0.28)	(-0.40)
$R(def) = ave(R(def))$	369787	100.000	0.49	4.00	265	66	0.01	-0.05	0.01	-0.07
							(0.06)	(-0.53)	(0.10)	(-0.69)
$missR(def) = ave(R(def))$	369787	100.000	0.49	4.04	265	65	0.01	-0.05	0.01	-0.07
							(0.07)	(-0.53)	(0.13)	(-0.67)
Exclude $+95\%/-45\%$	369787	100.000	0.48	4.03	265	66	0.01	-0.05	0.01	-0.07
							(0.07)	(-0.52)	(0.11)	(-0.66)
Exclude $+60\%/-60\%$	369785	99.999	0.48	4.03	265	66	0.01	-0.05	0.01	-0.07
							(0.07)	(-0.52)	(0.11)	(-0.66)
Exclude $+30\%/-30\%$	369739	99.987	0.48	3.97	265	67	0.01	-0.03	0.01	-0.05
							(0.09)	(-0.35)	(0.15)	(-0.55)
Exclude $+20\%/-20\%$	369501	99.923	0.48	3.87	265	68	0.01	-0.03	0.02	-0.05
							(0.12)	(-0.30)	(0.25)	(-0.54)
Exclude $R_tR_{t-1} < -0.04$	369291	99.866	0.47	3.76	206	55	0.02	-0.03	0.03	-0.05
							(0.21)	(-0.28)	(0.32)	(-0.53)
Exclude $R_tR_{t-1} < -0.02$	368511	99.655	0.47	3.64	206	56	0.02	-0.02	0.03	-0.04
							(0.25)	(-0.22)	(0.31)	(-0.45)
$P < 1,000$	369787	100.000	0.48	4.03	265	66	0.01	-0.05	0.01	-0.07
							(0.07)	(-0.52)	(0.11)	(-0.66)
$P < 200$	369764	99.994	0.48	4.03	265	66	0.01	-0.05	0.01	-0.06
							(0.07)	(-0.53)	(0.13)	(-0.65)
$P > 1$	369763	99.994	0.48	4.03	265	66	0.01	-0.05	0.01	-0.07
							(0.07)	(-0.52)	(0.12)	(-0.66)
$P > 5$	369717	99.981	0.48	4.02	265	66	0.01	-0.05	0.01	-0.06
							(0.08)	(-0.52)	(0.16)	(-0.62)
Maturity > 1 year	360694	97.541	0.49	4.10	265	64	-0.02	-0.06	-0.03	-0.08
							(-0.21)	(-0.62)	(-0.29)	(-0.74)
Rated by any agency	369787	100.000	0.48	4.03	265	66	0.02	-0.05	0.03	-0.06
							(0.21)	(-0.54)	(0.34)	(-0.62)
Exclude Face=$10	369610	99.952	0.48	4.03	265	66	0.02	-0.05	0.01	-0.08
							(0.20)	(-0.56)	(0.16)	(-0.86)
Corp. Debentures only	357604	96.705	0.48	4.08	265	65	0.01	-0.06	-0.06	-0.07
							(0.13)	(-0.57)	(-0.57)	(-0.67)
$\lvert R\rvert < 100\%$	369776	99.997	0.48	3.94	100	25	0.01	-0.05	0.01	-0.07
							(0.07)	(-0.52)	(0.11)	(-0.66)
$\lvert R\rvert < 90\%$	369772	99.996	0.48	3.92	87	22	0.01	-0.05	0.01	-0.06
							(0.07)	(-0.49)	(0.11)	(-0.64)
$R < 90\%$	369773	99.996	0.48	3.93	87	22	0.01	-0.05	0.01	-0.06
							(0.07)	(-0.49)	(0.11)	(-0.64)
$\lvert R\rvert < 60\%$	369702	99.977	0.47	3.77	60	16	0.01	-0.04	0.01	-0.06
							(0.09)	(-0.46)	(0.11)	(-0.63)
$R < 60\%$	369737	99.986	0.47	3.85	60	15	0.01	-0.04	0.01	-0.06
							(0.09)	(-0.46)	(0.11)	(-0.62)
$\lvert R\rvert < 30\%$	369187	99.838	0.48	3.38	30	9	0.02	-0.02	0.02	-0.05
							(0.25)	(-0.26)	(0.26)	(-0.49)
$R < 30\%$	369500	99.922	0.44	3.68	30	8	0.03	-0.02	0.03	-0.03
							(0.30)	(-0.18)	(0.33)	(-0.33)

Table B.8
Bond momentum in samples of IG firm returns - value weighted

The table repeats the analyses in Table IV, except that the momentum strategy includes only firms rated IG, instead of NIG, at month-end $t-1$. All other data choices are as described in Table II.

Panel A: WRDS sample as starting sample

Sample	Total obs	% of total obs	Mean (%)	SD (%)	Max (%)	n-sigma of Max	IG momentum profits (%) Equally weighted $\pi_{3,3}$	$\pi_{6,6}$	Value-weighted $\pi_{3,3}$	$\pi_{6,6}$
Starting sample	370094	100.000	0.52	4.71	100	21	-0.02 (-0.22)	-0.08 (-0.73)	-0.07 (-0.66)	-0.12 (-1.10)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	369961	99.964	0.53	4.79	100	21	-0.02 (-0.18)	-0.08 (-0.73)	-0.03 (-0.27)	-0.11 (-1.00)
$R(def) = ave(R(def))$	370094	100.000	0.52	4.69	100	21	-0.02 (-0.22)	-0.08 (-0.74)	-0.07 (-0.68)	-0.12 (-1.12)
$missR(def) = ave(R(def))$	370094	100.000	0.52	4.79	100	21	-0.02 (-0.18)	-0.08 (-0.72)	-0.03 (-0.28)	-0.11 (-1.01)
Exclude $+95\%/-45\%$	370046	99.987	0.51	4.58	100	22	-0.02 (-0.20)	-0.07 (-0.70)	-0.07 (-0.64)	-0.12 (-1.08)
$Exclude+60\%/-60\%$	370050	99.988	0.51	4.60	100	22	-0.02 (-0.19)	-0.07 (-0.69)	-0.07 (-0.64)	-0.12 (-1.08)
$Exclude+30\%/-30\%$	369875	99.941	0.51	4.41	100	23	-0.01 (-0.09)	-0.07 (-0.62)	-0.06 (-0.53)	-0.11 (-1.04)
Exclude $+20\%/-20\%$	369500	99.840	0.51	4.26	100	23	-0.00 (-0.04)	-0.06 (-0.54)	-0.05 (-0.45)	-0.10 (-0.94)
Exclude $R_tR_{t-1} < -0.04$	369130	99.740	0.50	4.09	100	24	0.01 (0.06)	-0.05 (-0.46)	-0.04 (-0.44)	-0.09 (-0.86)
Exclude $R_tR_{t-1} < -0.02$	368275	99.509	0.50	3.95	100	25	0.00 (0.06)	-0.05 (-0.47)	-0.04 (-0.40)	-0.09 (-0.95)
$P < 1,000$	370093	100.000	0.52	4.71	100	21	-0.02 (-0.21)	-0.08 (-0.72)	-0.07 (-0.65)	-0.12 (-1.09)
$P < 200$	370065	99.992	0.52	4.70	100	21	-0.02 (-0.22)	-0.08 (-0.73)	-0.07 (-0.65)	-0.12 (-1.10)
$P > 1$	370032	99.983	0.51	4.62	100	22	-0.02 (-0.22)	-0.08 (-0.73)	-0.07 (-0.66)	-0.12 (-1.10)
$P > 5$	369971	99.967	0.51	4.59	100	22	-0.02 (-0.22)	-0.08 (-0.73)	-0.07 (-0.66)	-0.12 (-1.09)
Maturity > 1 year	360984	97.538	0.53	4.74	100	21	-0.04 (-0.41)	-0.09 (-0.88)	-0.06 (-0.60)	-0.13 (-1.13)
Rated by any agency	370094	100.000	0.52	4.71	100	21	-0.01 (-0.06)	-0.08 (-0.75)	-0.04 (-0.35)	-0.11 (-1.00)
Exclude Face=$10	369917	99.952	0.52	4.71	100	21	-0.01 (-0.09)	-0.09 (-0.80)	-0.04 (-0.41)	-0.11 (-1.01)
Corp. Debentures only	357900	96.705	0.52	4.75	100	21	-0.02 (-0.17)	-0.09 (-0.85)	-0.07 (-0.60)	-0.11 (-0.90)
$\|R\| < 100\%$	370016	99.979	0.49	4.45	97	22	-0.01 (-0.09)	-0.07 (-0.64)	-0.07 (-0.62)	-0.12 (-1.06)
$\|R\| < 90\%$	370003	99.975	0.49	4.41	90	20	-0.01 (-0.09)	-0.07 (-0.63)	-0.07 (-0.62)	-0.12 (-1.06)
$R < 90\%$	370008	99.977	0.49	4.42	90	20	-0.01 (-0.09)	-0.07 (-0.62)	-0.07 (-0.63)	-0.12 (-1.05)
$\|R\| < 60\%$	369856	99.936	0.48	4.10	60	14	-0.01 (-0.14)	-0.07 (-0.65)	-0.07 (-0.63)	-0.12 (-1.05)
$R < 60\%$	369919	99.953	0.47	4.24	60	14	-0.00 (-0.04)	-0.06 (-0.56)	-0.06 (-0.60)	-0.11 (-1.03)
$\|R\| < 30\%$	368898	99.677	0.48	3.40	30	9	0.01 (0.15)	-0.03 (-0.35)	-0.03 (-0.33)	-0.08 (-0.81)
$R < 30\%$	369434	99.822	0.40	3.91	30	8	0.03 (0.35)	-0.01 (-0.09)	-0.03 (-0.29)	-0.06 (-0.56)

Table B.8 (continued)

Panel B: Raw WRDS sample as starting sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	IG momentum profits (%): Equally weighted $\pi_{3,3}$	Equally weighted $\pi_{6,6}$	Value-weighted $\pi_{3,3}$	Value-weighted $\pi_{6,6}$
Starting sample	370063	100.000	0.53	5.04	295	58	-0.02 (-0.18)	-0.09 (-0.82)	-0.07 (-0.70)	-0.13 (-1.13)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	369929	99.964	0.54	5.12	295	57	-0.01 (-0.15)	-0.09 (-0.83)	-0.04 (-0.31)	-0.12 (-1.04)
$R(def) = ave(R(def))$	370063	100.000	0.53	5.01	295	59	-0.02 (-0.19)	-0.09 (-0.83)	-0.08 (-0.73)	-0.13 (-1.15)
$missR(def) = ave(R(def))$	370063	100.000	0.53	5.12	295	58	-0.01 (-0.15)	-0.09 (-0.82)	-0.04 (-0.34)	-0.12 (-1.05)
Exclude $+95\%/-45\%$	370038	99.993	0.52	4.89	295	60	-0.02 (-0.19)	-0.07 (-0.70)	-0.07 (-0.64)	-0.12 (-1.08)
$Exclude + 60\%/-60\%$	370042	99.994	0.52	4.92	295	60	-0.02 (-0.18)	-0.07 (-0.69)	-0.07 (-0.63)	-0.12 (-1.08)
$Exclude + 30\%/-30\%$	369868	99.947	0.52	4.72	295	62	-0.01 (-0.08)	-0.07 (-0.62)	-0.06 (-0.53)	-0.11 (-1.05)
Exclude $+20\%/-20\%$	369493	99.846	0.51	4.57	295	64	-0.00 (-0.03)	-0.06 (-0.55)	-0.05 (-0.45)	-0.10 (-0.94)
Exclude $R_tR_{t-1} < -0.04$	369124	99.746	0.51	4.36	294	67	0.01 (0.06)	-0.05 (-0.46)	-0.04 (-0.45)	-0.09 (-0.86)
Exclude $R_tR_{t-1} < -0.02$	368273	99.516	0.50	4.23	294	69	0.01 (0.06)	-0.05 (-0.48)	-0.04 (-0.40)	-0.09 (-0.95)
$P < 1,000$	370063	100.000	0.53	5.04	295	58	-0.02 (-0.18)	-0.09 (-0.82)	-0.07 (-0.69)	-0.12 (-1.13)
$P < 200$	370039	99.994	0.53	5.03	295	58	-0.02 (-0.19)	-0.09 (-0.84)	-0.07 (-0.70)	-0.13 (-1.15)
$P > 1$	370013	99.986	0.51	4.78	295	62	-0.02 (-0.18)	-0.09 (-0.82)	-0.07 (-0.70)	-0.13 (-1.13)
$P > 5$	369952	99.970	0.51	4.74	295	62	-0.02 (-0.18)	-0.09 (-0.82)	-0.07 (-0.69)	-0.12 (-1.11)
Maturity > 1 year	360956	97.539	0.54	5.05	295	58	-0.04 (-0.36)	-0.11 (-0.98)	-0.06 (-0.60)	-0.14 (-1.18)
Rated by any agency	370063	100.000	0.53	5.04	295	58	-0.00 (-0.02)	-0.09 (-0.84)	-0.04 (-0.40)	-0.11 (-1.03)
Exclude Face=\$10	369886	99.952	0.53	5.04	295	58	-0.01 (-0.06)	-0.10 (-0.89)	-0.05 (-0.46)	-0.12 (-1.04)
Corp. Debentures only	357868	96.705	0.53	5.07	295	58	-0.01 (-0.12)	-0.10 (-0.94)	-0.06 (-0.56)	-0.11 (-0.93)
$\|R\| < 100\%$	370003	99.984	0.49	4.42	97	22	-0.01 (-0.11)	-0.07 (-0.66)	-0.07 (-0.63)	-0.12 (-1.07)
$\|R\| < 90\%$	369993	99.981	0.49	4.39	90	20	-0.01 (-0.11)	-0.07 (-0.64)	-0.07 (-0.63)	-0.12 (-1.05)
$R < 90\%$	369995	99.982	0.49	4.39	90	20	-0.01 (-0.11)	-0.07 (-0.64)	-0.07 (-0.64)	-0.12 (-1.05)
$\|R\| < 60\%$	369855	99.944	0.48	4.10	60	14	-0.01 (-0.14)	-0.07 (-0.65)	-0.07 (-0.63)	-0.12 (-1.05)
$R < 60\%$	369907	99.958	0.47	4.21	60	14	-0.01 (-0.07)	-0.06 (-0.58)	-0.06 (-0.61)	-0.11 (-1.04)
$\|R\| < 30\%$	368897	99.685	0.48	3.40	30	9	0.01 (0.15)	-0.03 (-0.35)	-0.03 (-0.33)	-0.08 (-0.81)
$R < 30\%$	369422	99.827	0.40	3.88	30	8	0.03 (0.33)	-0.01 (-0.12)	-0.03 (-0.29)	-0.06 (-0.59)

Table B.8 (continued)

Panel C: DS Confirmed sample as starting sample

Sample	Total obs	% of total obs	Bond return statistics: Mean (%)	SD (%)	Max (%)	n-sigma of Max	IG momentum profits (%): Equally weighted $\pi_{3,3}$	$\pi_{6,6}$	Value-weighted $\pi_{3,3}$	$\pi_{6,6}$
Starting sample	369497	100.000	0.48	4.06	265	65	-0.01	-0.06	-0.05	-0.11
							(-0.09)	(-0.61)	(-0.52)	(-1.00)
$R(def) = \frac{P_t}{P_{t-1}+AI_{t-1}}$	369306	99.948	0.50	4.07	265	65	-0.00	-0.06	-0.02	-0.10
							(-0.05)	(-0.62)	(-0.14)	(-0.91)
$R(def) = ave(R(def))$	369497	100.000	0.49	4.03	265	66	-0.01	-0.06	-0.06	-0.11
							(-0.09)	(-0.62)	(-0.55)	(-1.02)
$missR(def) = ave(R(def))$	369497	100.000	0.49	4.07	265	65	-0.01	-0.06	-0.04	-0.10
							(-0.07)	(-0.62)	(-0.32)	(-0.98)
Exclude $+95\%/-45\%$	369497	100.000	0.48	4.05	265	65	-0.01	-0.06	-0.05	-0.11
							(-0.09)	(-0.61)	(-0.52)	(-1.00)
$Exclude + 60\%/-60\%$	369495	99.999	0.48	4.05	265	65	-0.01	-0.06	-0.05	-0.11
							(-0.09)	(-0.61)	(-0.52)	(-1.00)
$Exclude + 30\%/-30\%$	369449	99.987	0.48	4.00	265	66	0.00	-0.04	-0.04	-0.09
							(0.00)	(-0.44)	(-0.43)	(-0.89)
Exclude $+20\%/-20\%$	369210	99.922	0.48	3.89	265	68	0.01	-0.04	-0.04	-0.08
							(0.06)	(-0.37)	(-0.39)	(-0.81)
Exclude $R_tR_{t-1} < -0.04$	369000	99.865	0.47	3.78	206	54	0.02	-0.03	-0.03	-0.07
							(0.17)	(-0.32)	(-0.30)	(-0.75)
Exclude $R_tR_{t-1} < -0.02$	368221	99.655	0.47	3.66	206	56	0.01	-0.03	-0.03	-0.07
							(0.15)	(-0.29)	(-0.34)	(-0.75)
$P < 1,000$	369497	100.000	0.48	4.06	265	65	-0.01	-0.06	-0.05	-0.11
							(-0.09)	(-0.61)	(-0.52)	(-1.00)
$P < 200$	369474	99.994	0.48	4.05	265	65	-0.01	-0.06	-0.05	-0.11
							(-0.10)	(-0.63)	(-0.52)	(-1.01)
$P > 1$	369474	99.994	0.48	4.05	265	65	-0.01	-0.06	-0.05	-0.11
							(-0.09)	(-0.61)	(-0.52)	(-1.00)
$P > 5$	369428	99.981	0.48	4.04	265	65	-0.01	-0.06	-0.05	-0.10
							(-0.08)	(-0.61)	(-0.51)	(-0.99)
Maturity $>$ 1 year	360414	97.542	0.49	4.12	265	64	-0.03	-0.08	-0.05	-0.11
							(-0.30)	(-0.76)	(-0.50)	(-1.04)
Rated by any agency	369497	100.000	0.48	4.06	265	65	0.01	-0.07	-0.02	-0.10
							(0.10)	(-0.64)	(-0.23)	(-0.92)
Exclude Face=$10	369320	99.952	0.48	4.05	265	65	0.01	-0.07	-0.03	-0.10
							(0.08)	(-0.67)	(-0.28)	(-0.93)
Corp. Debentures only	357316	96.703	0.48	4.10	265	65	0.00	-0.07	-0.05	-0.09
							(0.02)	(-0.67)	(-0.49)	(-0.83)
$\lvert R\rvert < 100\%$	369486	99.997	0.48	3.96	100	25	-0.01	-0.06	-0.05	-0.11
							(-0.09)	(-0.61)	(-0.52)	(-1.00)
$\lvert R\rvert < 90\%$	369482	99.996	0.48	3.94	87	22	-0.01	-0.06	-0.05	-0.10
							(-0.07)	(-0.58)	(-0.52)	(-0.99)
$R < 90\%$	369483	99.996	0.48	3.95	87	22	-0.01	-0.06	-0.05	-0.10
							(-0.07)	(-0.58)	(-0.52)	(-0.99)
$\lvert R\rvert < 60\%$	369412	99.977	0.47	3.80	60	16	-0.00	-0.06	-0.05	-0.10
							(-0.05)	(-0.56)	(-0.51)	(-0.97)
$R < 60\%$	369447	99.986	0.47	3.87	60	15	-0.01	-0.06	-0.05	-0.10
							(-0.06)	(-0.56)	(-0.51)	(-0.97)
$\lvert R\rvert < 30\%$	368897	99.838	0.48	3.40	30	9	0.01	-0.03	-0.03	-0.08
							(0.15)	(-0.35)	(-0.33)	(-0.81)
$R < 30\%$	369210	99.922	0.44	3.70	30	8	0.02	-0.03	-0.03	-0.06
							(0.19)	(-0.26)	(-0.28)	(-0.62)

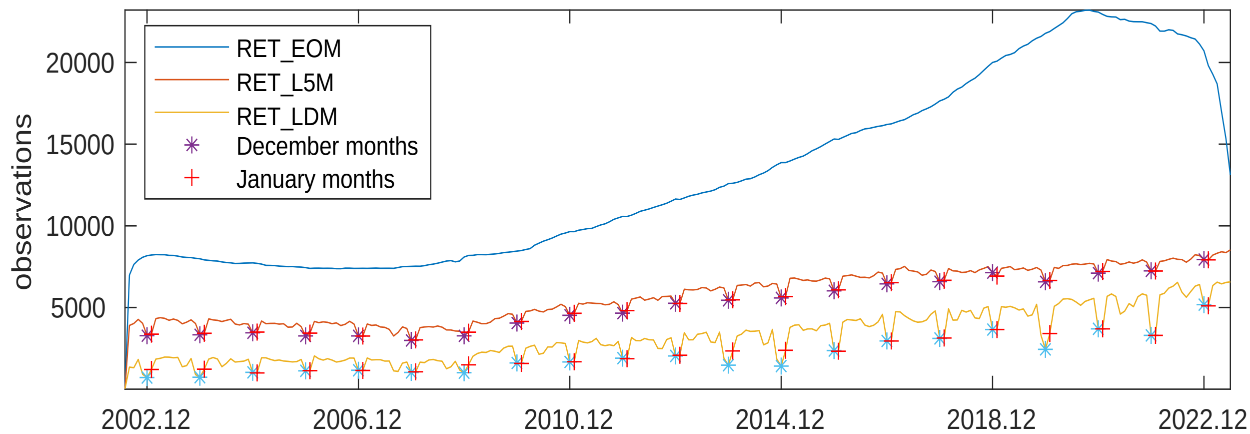
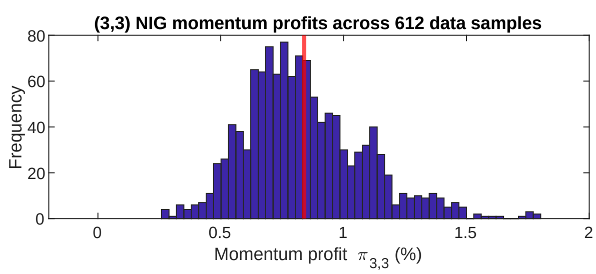


Figure B.I. Time series of monthly return observations. The figure presents the time series of the number of monthly return observations in the WRDS sample under three alternative data choices. The monthly return is based on (1) the last trade of the month (RET_EOM), (2) last trade within the last 5 trading days of the month (RET_L5M), or (3) last trading day of the month (RET_LDM).

Plot A



Plot B

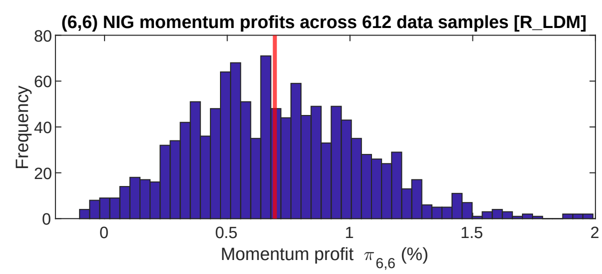
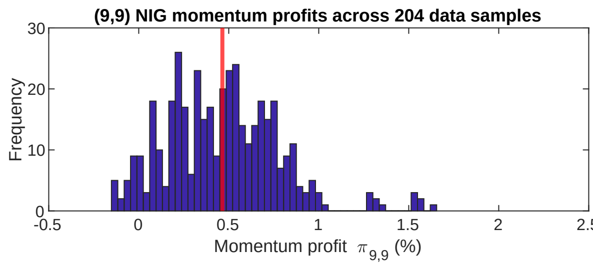
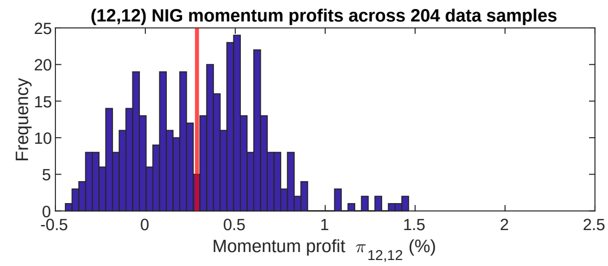


Figure B.II. Frequency distribution of NIG momentum profit estimates across 612 samples of R_L5M, R_LDM, and R_EOM returns. The figure repeats the analysis in Figure V using last-five-trading-days (R_L5M), last-day-of-month (R_LDM), and end-of-month (R_EOM) returns, instead of the paper's baseline case of only R_L5M. Plots A and B present the frequency distribution of (3,3) and (6,6) monthly NIG momentum strategy profits across the resultant 612 samples. Both equally and value-weighted profits are included for a total of 1,224 $\pi_{3,3}$ and 408 $\pi_{6,6}$. The red line represents the average of the 1,224 sample momentum profit estimates in each plot.

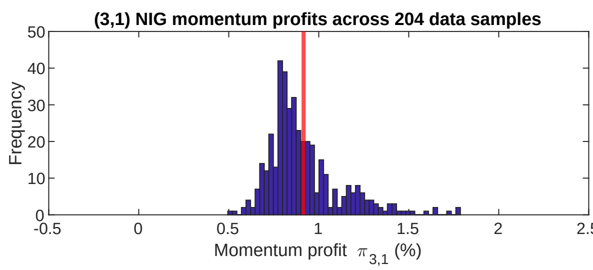
Plot A



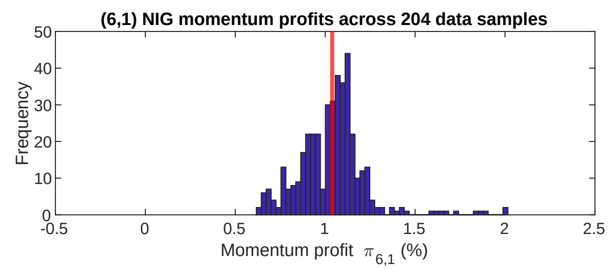
Plot B



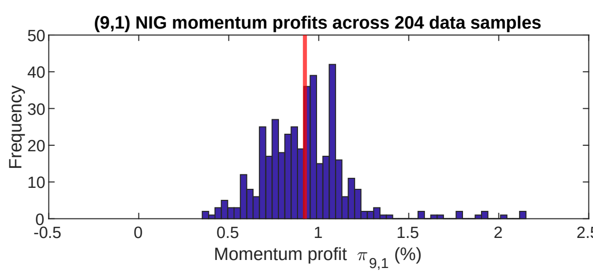
Plot C



Plot D



Plot E



Plot F

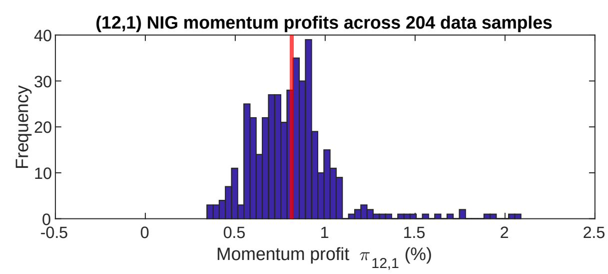
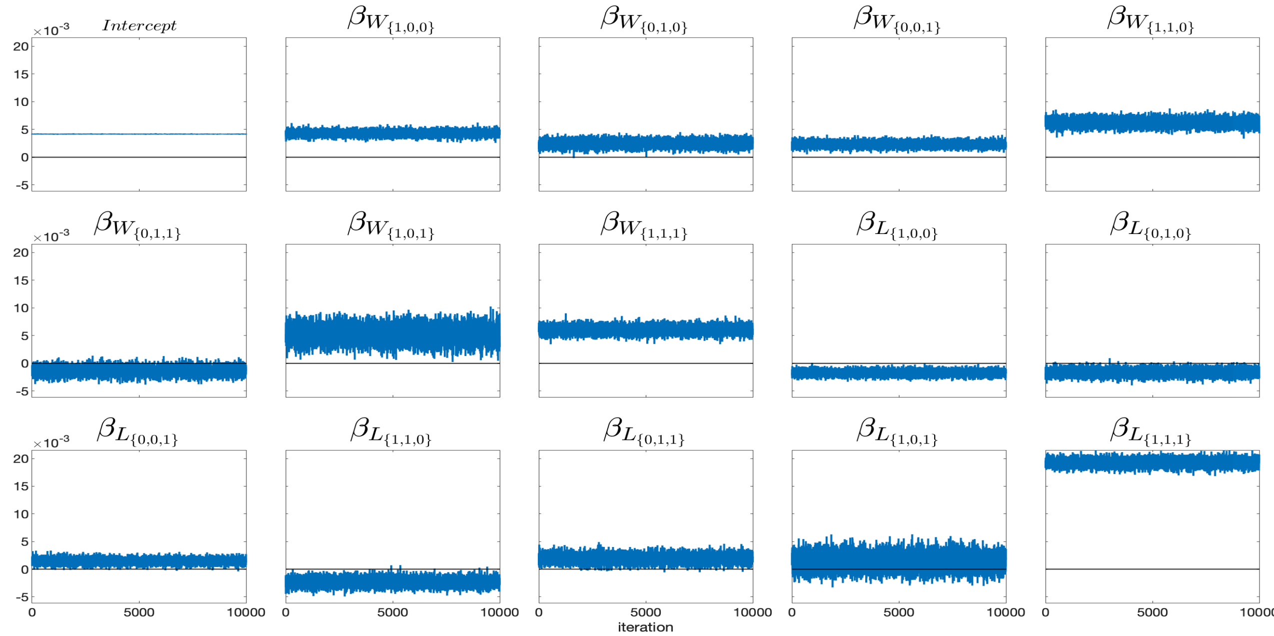


Figure B.III. Frequency distribution of NIG momentum profit estimates across 204 samples for other formation and holding periods. The figure repeats the analysis in Figure V but for other formation and holding periods, noted in the heading of each figure. For each strategy, we skip a month between the formation and holding period. The figure includes the EW and VW momentum estimates from the same 204 data samples. The red line represents the average of the 408 sample momentum profit estimates in each plot.

Plot A: WRDS sample



Plot B: Raw WRDS sample

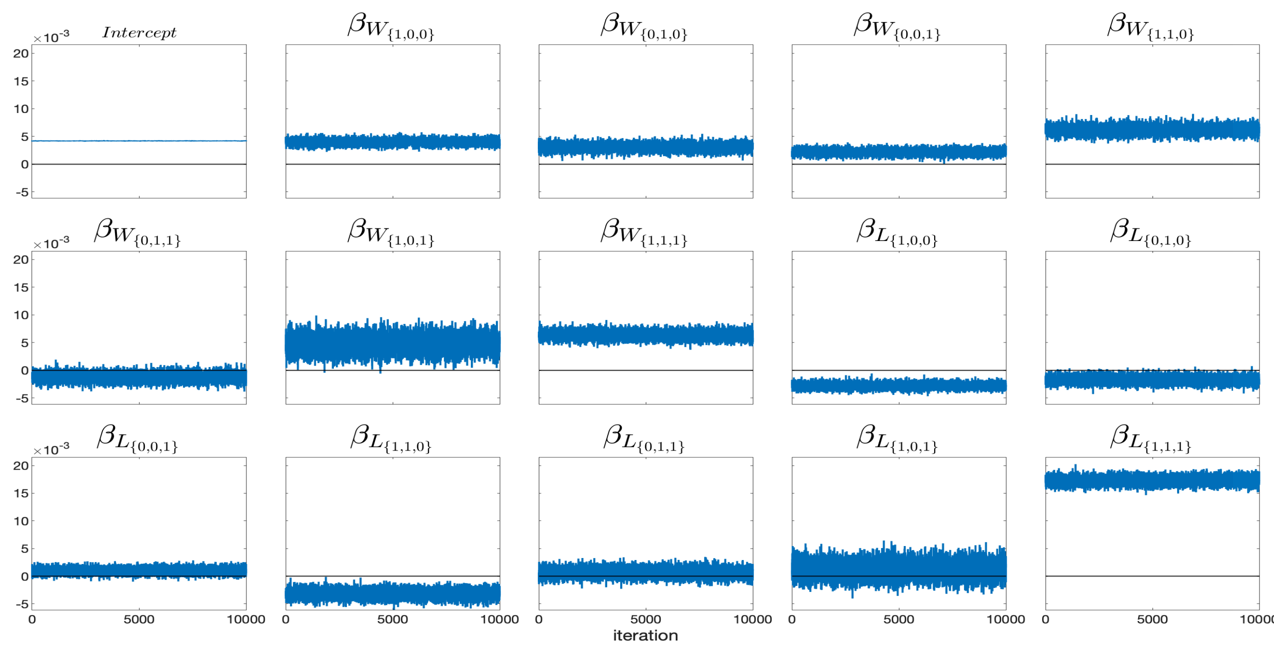


Figure B.IV. Gibbs sampler posterior estimates of NIG momentum profits. The figure presents estimation results for the regression model, Equation 3:

$$r^s_{i,t+1} = \alpha^s + \boldsymbol{W}^s_{i,t}\boldsymbol{\beta}^s_W + \boldsymbol{L}^s_{i,t}\boldsymbol{\beta}^s_L + \sigma^s \varepsilon_{i,t+1} \qquad \varepsilon_{i,t+1} \sim N(0,1)$$

for $K = 3$, using 10,000 draws of the Gibbs sampler (1000 burn-in iterations). Plot A (B) uses returns in the WRDS (Raw WRDS) sample for r^s_{it+1}. Results for the DS Confirmed sample are in Figure VII. Each plot presents the marginal posterior draws for each parameter of the model: the intercept (α^s), the winners' contributions ($\boldsymbol{\beta}^s_W$), and the losers' contributions ($\boldsymbol{\beta}^s_L$) to momentum profits.

Appendix C

Summary of filters used in WRDS corporate bond cleaning program

This appendix briefly summarizes the filters used in the official WRDS program for computing monthly returns. This summary is based on the April 2022 version of the program (v9). We highlight some incomplete or inconsistent filtering, e.g., instances where a similarly intentioned filter implemented through a different variable may produce a different sample. Note that there are no bond-level filters in the official WRDS programs for cleaning TRACE Standard and TRACE Enhanced, hence all bond-level filters come from the program that computes monthly returns.

Let F1 is the file with code cleaning trace standard: https://wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/wrds-bond-return/cleaning-trace-data/wrds-clean-standard-trace-file/ Let F2 is the file with code cleaning trace enhanced: https://wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/wrds-bond-return/cleaning-trace-data/wrds-clean-trace-enhanced-file/ Let F3 is the file with code computing trace monthly returns: https://wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/wrds-bond-return/sas-code-behind-the-scene/sas-code-behind-the-scene/

We identify the operation in the above programs as L<line number>F<file number>

- exclude commission trades and zero prices –L54F3, L60F3
- delete negative prices –L90F3
- compute large price reversals (as a dollar price change if change is more than 20%), but not used as filter – L93F3
- remove cancellations –L100F1, L95F2
- remove corrections – L122F1, L214F2

- remove reversals – L255F1, L314F2
- remove agency transactions – L340F1, L485F2
- Limit sample to corporate securities
  - Filter is implemented by limiting the sample to bonds where bond_type is CDEB,CCOV, CMTN, CMTZ, or CP – L291F3. CCOV convertible bond type is kept at first but deleted later in the code – L336F3
    * Filter effectively excludes the following non-corporate security types and corporate securities for which return calculation may be complex:
      · Asset-, LOC-, mortgage-, and insurance-backed securities (ABS, CLOC, MBS, and UCID)
      · Agency securities (ADEB, ADNT, AMTN, ARNT, and ASPZ)
      · Government securities (BBON, C10Y, C1Y, C2Y, C30Y, C3M, C5Y, C6M, CTBD, CTBL, FGOV, FGS, MUNI, O10Y, O13W, O26W, O2Y, O30Y, O3Y, O4W, O52W, O5Y, O7Y, TXMU, USBD, USBL, USNT, USSI, USSP, USTC,
      · Inflation-indexed securities (CCPI and IIDX)
      · Preferred securities (PS and PSTK)
      · Euro bonds and notes (EBON and EMTN)
      · Trust securities (CPAS, TPCS, and CUIT)
      · Foreign-currency bonds (CCUR)
      · Convertible bonds (CCOV). Note that there is also a convertible flag in FISD that does not always agree with the bond_type;
      · Other complex bond types: corporate pay-in-kind bonds (CPIK), corporate strips (CS), and retail notes (RNT)
    * Filter also excludes the following corporate security types that could feasibly be included:

- · US corporate zeros (CZ)
- · US corporate bank notes (USBN). Note that Bessembinder et al. (2018, JF) includes this in the set of corporates

- Exclude securities issued under Rule 144A – L291F3
- Exclude securities with a variable coupon – L291F3
  - This leaves in the sample fixed-coupon and zero-coupon bonds. However, some but not all zero-coupon bonds are excluded above through the bond_type CZ
- Include only bonds with principal amount of $10 or $1000 – L633F3
- if it is the first observation for every issue ID, the three ratings (Moody's, S&P, and Fitch) are set to empty values – L447F3
- Returns and yields are winsorized between -1 and 1 (-100% and $+100\%$) Duration between 0 and 30 – L663F3
- delisting returns are computed for all companies with a default date, over 1, 2 and three months around the default month, and averaged separately across investment and non-investment grade – L705F3
- the 3-month delisting return averages are assigned as (the same) default month return across all bonds in the defaulted IG and NIG groups –L731F3
- remove all observations that are after the default date–L744F3