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Asymmetric Information, Predictability and Momentum in the Corporate Bond Market

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Abstract

We show that firm-level cross-asset predictability for bonds with a high incidence of informed trading is mostly driven by information diffusion. In contrast, the activities of uninformed investors dominate in originating predictability for the remaining bonds in the firm-level cross-section. Capitalizing on these results, we explore the role of informed and uninformed trading in determining the momentum effect. We find that gradual information diffusion is the main driver of short-term momentum. However, the effect of uninformed trading may outweigh that of information in generating large momentum returns, as it is the case for private-issuer bonds.

Keywords: asymmetric information; informed trading; uninformed trading; predictability; momentum; corporate bonds.

JEL: G10, G14

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Introduction

Asymmetric information influences security prices because of the interaction of informed and uninformed traders. Microstructure considerations (e.g., Glosten and Milgrom (1985) and Easley and O'hara (2004)) predict that uninformed investors trade less intensively assets with higher concentration of informed trading, due to risks associated with informational disadvantage. In the corporate bond market, informed trading can be positively linked to trade size (Han and Zhou (2013), Wei (2018)), as, in contrast with the common practice in the equity market, bond traders do not break orders to minimize price impact, because of the higher transaction costs associated with smaller bond trades.[1] This characteristic of the bond market suggests that, among the bonds issued by a given firm, those attracting high degrees of large trades should be traded less intensively by uninformed investors than the remaining bonds in the firm-level cross-section. Put differently, asymmetric information causes uninformed and informed investors to focus their trading activities on different bonds of the same firm.

In this study, we explore this clientele effect and its implications for asset predictability. We consider both serial cross-asset return predictability, and return continuation, as measured by the profitability of the momentum strategy. Hence, our analysis sheds some light on bond market informational efficiency, which is measured along two key dimensions: the speed of information diffusion and the incidence of uninformed trading.

Following Ronen and Zhou (2013), we propose that, among all the bonds issued by a given firm, those attracting the highest levels of aggregate monthly volume of institutional-sized trades are the bonds associated with high levels of informed trading (henceforth, top bonds).[2] The remaining bonds issued by the same firm are henceforth called non-top bonds. Using transaction-level data from the TRACE for the 2002-2017 time period, we find that the ratio of retail to institutional-sized trades, both in terms of the number of trades and of total trading monthly volume, is higher for non-top than top bonds. Hence, the analysis of the concentration of retail and institutional-sized trades suggests the possibility that top and non-

[1] In particular, strategic use of trade size on behalf of informed investors, as described in the stealth trading literature (e.g., Kyle (1985) and Barclay and Warner (1993)), are less of a concern for corporate bonds than equities.

[2] The term top bond is from Ronen and Zhou (2013), who, however, focus on the one bond attracting the highest volume of institutional-sized trades, around earnings announcements.

top bonds are characterized by a different incidence of informed and uninformed trading. In other words, the stylized evidence suggests that top bonds are more informationally efficient than non-top bonds.

Informational inefficiency causes return predictability. For instance, in the literature, cross-asset lead-lag relationships can be explained by different degrees of informed trading for different assets, or asset classes (e.g., Kwan (1996), Ronen and Zhou (2013)). Further, previous contributions have shown that the activities of uninformed traders contribute to explain same-asset return predictability, as argued by Barber et al. (2008) for equities and by Wei (2018) in the corporate bond market. Building on the insights of this literature, in this study we evaluate the relative informational efficiency of top and non-top bonds by examining both cross and same-asset return predictability.

Using an issuer-level vector autoregression (VAR) analysis, we provide direct evidence that information diffuses faster for top than non-top bonds, which is consistent with informed trading being more prevalent in top bonds. Further, we show that uninformed trading has a more prominent role in determining the predictive power of the lagged returns on non-top bonds for the current returns on top and non-top bonds. Notably, these findings are robust to the inclusion of several market-wide risk factors, including a liquidity risk factor, in the evaluation of the VAR systems. Hence, the examination of predictability for top and non-top bonds yields results that are consistent with top bonds being characterized by high (low) incidence of informed (uninformed) trading, with the reverse characterization applying to non-top bonds.

To capitalize on the heterogeneity in informational efficiency within the firm-level bond cross-section, from an investment perspective, we evaluate the profitability of the momentum strategy in top and non-top bonds. In the theoretical framework of Hong and Stein (1999) (henceforth, HS), fast information diffusion (i.e., high concentration of informed trading) yields strong but short-lived price trends, which in turn generate short-lived momentum gains. Lower speed, instead, makes for weaker but more persistent price trends, which originate momentum gains that are weaker in the short-run but stronger afterward. In view of the insights of the HS model, and of the results of the VAR analysis, we expect the momentum effect in top bonds to be more short-lived than that in non-top bonds.

Empirically, top bond momentum strategies yield momentum gains that are significant, or even just weakly significant (i.e., at the 10% level), only when the combined duration of the formation and holding periods is at most five months. In contrast, momentum portfolios in non-top bonds with significant, or weakly significant, gains are characterized by combined durations ranging from 4 to more than 14 months. Further, non-top bond momentum gains are, over time, weaker and then stronger than those yielded by top bonds, with the non-top bond peak momentum profitability being 33% higher than the peak profitability of top bonds. In a separate analysis, we further confirm the role of information diffusion speed in explaining the differences in the momentum effect between top and non-top bonds using a simple calibration exercise. Notably, we find that the differences between top and non-top bond momentum returns are even more marked when we restrict the analysis to private issuers.

A comparison of non-top bond momentum in the private and all-issuer samples provides further insights on the causes of the momentum effect in the corporate bond market. We find that virtually all non-top bond momentum returns in the private-issuer sample more than double those obtained, for the same strategies, in the whole-firm sample. For example, in the all-issuer sample, non-top bond momentum peak profitability is 40 bps per month, whereas for the same strategy in private-firm non-top bonds the momentum return is 88 bps per month. This improvement in momentum profitability cannot be explained by a slower information diffusion speed, as the stronger non-top bond momentum returns are not associated with longer investment horizons in the private-issuer subsample.

According to the HS model, higher aggregated uninformed trading strengthens the momentum profits that are generated by gradual information diffusion. From this perspective, stronger non-top momentum returns in the private-firm sample than in the all-issuer sample are consistent with a higher concentration of uninformed trading for private firms than in the whole-firm sample, for non-top bonds. A calibration exercise confirms this conclusion. Hence, the subsample analysis highlights that uninformed trading is an important driver of the momentum effect.

To ensure that the differences between top and non-top momentum returns are not driven by systematic risk, we risk-adjust returns using a rich set of factors, which includes a bond-market liquidity innovation factor (e.g., Lin et al. (2011)). Controlling for liquidity risk is particularly relevant in the context of this study, as the average trading volume supporting the prices of top bonds is, by construction, significantly larger than that supporting the prices of non-top bonds. We find that risk-adjustment leaves the momentum return patterns essentially unaltered, for both top and non-top bonds.

Overall, we conclude that the analysis of the profitability of the momentum strategy in top and non-top bonds yields results that are consistent with top bonds attracting more (less) informed (uninformed) trading, as already established by the results of the VAR analysis. Further, by exploiting heterogeneity in informational efficiency between top and non-top bonds, our study provides strong support for the ability of the HS model to explain the momentum effect in the corporate bond market.

This study contributes to several streams of the literature. Han and Zhou (2013) specialize to the corporate bond market two microstructure measures of asymmetric information that have been previously used for equities (e.g., Glosten and Milgrom (1985) and Madhavan et al. (1997)). These measures decompose the bid-ask spread into asymmetric information and liquidity components. Their results show that the asymmetric information component is strongly linked to trade size, so that, in the end, these microstructure measures gauge, indirectly, the activities of institutional investors. Building on their findings, this study's analysis relies directly on the activities of institutional investors to identify same-class and same-issuer securities with high and low levels of informed trading. By taking full advantage of the richness of the firm-level bond cross-section, our approach dispenses with the need of estimating the bid-ask spread asymmetric information component. From this perspective, our work contributes to the literature on asymmetric information by proposing a direct and security-based methodology to investigate the effect of informed and uninformed trading, in the corporate bond market.

Ronen and Zhou (2013) and Wei and Zhou (2016) have documented variations across bonds in their predictive ability for the same-issuer stock, around earnings announcements. Our study complements their analysis by examining the cross-asset predictability among the bonds issued by the same firm. We find levels of predictability that are substantial, for monthly returns. In particular, our evidence is strongly consistent with information spreading at different rates for top and non-top bonds. To the authors' knowledge, no previous study has provided direct evidence of predictability within the firm-level bond cross-section.

There is a vast literature exploring the lead-lag relationship between the returns of same-issuer stocks and bonds (e.g., Kwan (1996), Bittlingmayer and Moser (2014), Tsai (2014)), but almost no contribution evaluates predictability across same-issuer bonds. In this study, we argue that the firm-level bond cross-section constitutes a particularly suitable environment to examine the implications of informational efficiency for cross-asset predictability. Indeed, a methodological contribution of this study resides in the interpretation of the sign of the lead-lag return correlation between top and non-top bonds. We propose that a positive sign of the serial cross-asset correlation is evidence of different information diffusion rates, whereas a negative sign is caused by the activities of uninformed traders. This identification strategy is not applicable when comparing equities and bonds, given the fundamentally different nature of equity and debt (e.g., Merton (1974), Garlappi et al. (2008), Avramov et al. (2017)).

To our knowledge, this study is the first to exploit informational efficiency heterogeneity within the firm-level bond cross-section to discuss the causes of the momentum effect in the bond market. For instance, Avramov et al. (2017) study a selection of asset pricing anomalies, including momentum, and aggregate bond returns at the issuer level, for publicly owned firms, by considering the return on the equally weighted portfolio of all the bonds issued by a firm.[3] Our results show that discriminating top and non-top bonds yields drastically different results for the profitability of the momentum strategy.

Beside the HS model, other contributions have provided explanations for the profitability of the momentum strategy (e.g., Barberis et al. (1998) and Daniel et al. (1998)). The characterizing feature of the HS framework is its emphasis on gradual information diffusion, caused by informed trading. This focus on information explains why the literature linking the profitability of the momentum strategy to information shocks refer to HS to interpret their results (e.g., Hong et al. (2000)), especially to explain the momentum effect over short time horizons (e.g., Savor (2012), Da et al. (2013), Jiang and Zhu (2017)). These empirical studies, however, do not contrast the role of uninformed and uninformed trading in causing return continuation. In the HS framework, in the absence of uninformed traders, the momentum effect would be limited to the underreaction phase. Our results show that uninformed trading plays a crucial role in determining momentum gains beyond the very short term, especially for firms for which information is hard to get, like private firms. Hence, our study indicates that examinations of long-run momentum should take into consideration the role of uninformed

[3] Chordia et al. (2017) partially recognize the impact of heterogeneity in the firm level cross-section, as they extract from the issuer cross-section one randomly chosen bond, the bond with the shortest maturity, and the most recently issued bond.

trading to at least the same extent with which information diffusion is discussed in explaining short-term momentum.

This study's results are consistent with substantial heterogeneity in the degree of informational efficiency in the firm-level bond cross-section, for private issuers. As we link variations of informational efficiency with informed trading, our results contribute to the literature on the effect of asymmetric information on the cost of debt for private firms (Fenn (2000), Santos (2006), Wittenberg-Moerman (2008)). Including private issuers to the examination of information efficiency has become particularly relevant over the recent years, as the number of firms eschewing the US public market to raise capital has been steadily increasing over time (e.g., Gao et al. (2013), Doidge et al. (2017)). For instance, more than half of the issuers in our sample have been private firms throughout the almost 14 years examined in this study.

1 Top and Non-top Bonds

In the corporate bond market, informed investors have incentives to inject their information by large trades, because of transaction cost advantages.[4] A series of recent studies have shown that the large trades characterizing the trading activities of institutional investors can be used to identify securities with high degree of informational efficiency, within the firm-level bond cross-section (Ronen and Zhou (2013), and Wei and Zhou (2016)), around information intensive firm level events like earnings announcements. Moreover, Wei (2018) finds that small-sized trades are more likely to be of uninformed investors. Consistently with these series of results, Han and Zhou (2013) documents a positive relationship between measures of asymmetric information based on bid and ask spread decomposition and trade size, in the corporate bond market. Taking stock on the results of this stream of literature, we hypothesize that among the bonds issued by a given firm, those attracting the high volume of institutional investor-sized trades are characterized by a higher degree of informed trading than the remaining bonds in the firm-level cross-section.

The market microstructure literature (e.g. Kyle (1985), Glosten and Milgrom (1985)) argues that informed traders can impose adverse selection risk on market makers, who in

[4] The literature in corporate bonds documents a negative relationship between transaction costs and trade size (e.g., Edwards et al. (2007) and Feldhütter (2011)).

turn recoup their losses from uninformed traders. From this perspective, uninformed traders have the incentive to avoid trading bonds that attract excessive informed traders. Further, as a result of information risk, the trading activities of informed and uninformed investors should be concentrated on different assets (e.g., Easley and O'hara (2004)). Consistently with these microstructure considerations, we further conjecture that among the bonds issued by a given firm, the bonds attracting the high volume of institutional investor-sized trades are characterized by a lower degree of uninformed trading than the remaining bonds in the firm-level cross-section.

Our empirical analysis relies on transaction-level data from TRACE. Following the literature (Ronen and Zhou (2013) and Wei and Zhou (2016)), trades with par value greater than \$500,000 are classified as institutional trades. In month t, and for each issuer i, the three bonds with the highest total dollar volume of institutional trades (if any) are identified as firm i's top-three bonds in month t. Henceforth, top-three bonds are called, for brevity, the top bonds. All the remaining bonds issued by firm i in month t are the non-top bonds of firm i, in the same month. In our sample, on average (over issuers), the number of bond per month per firm is 2.47, while the analogous figure for top bonds is 1.63. Hence, on average, there is at least one top bond and one non-top bond per firm per month. Notably, from month to month, the set of top and non-top bonds, for a given firm, may comprise different bonds. Adopting this taxonomy, in this study, we argue that top bonds are characterized by high (low) incidence of informed (uninformed) trading and that the reverse characterization applies to non-top bonds.

Focusing on corporate bonds issued by private firms reduces the chance of information spillover across different asset markets (e.g., between equities and corporate bonds), and thus reduces noise in the evaluation of information diffusion. From this perspective, the analysis of the private-firms subsample allows a more precise evaluation of the effect of informed trading in determining market efficiency, and it, therefore, constitutes an important part of this study.

1.1 Data

Our empirical analysis relies on data from TRACE Enhanced, matched with Mergent FISD, for the period spanning from July 2002 to June 2017. We include in our sample only publicly traded bonds.[5] Following the cleaning procedure in Dick-Nielsen (2014), we minimize data reporting errors by removing all transactions that are marked as cancellation, correction, and reversals, as well as their matched original trades. Agency transactions that may raise concerns of double-counting are also deleted.

We select bonds that are US-dollar denominated and pay a fixed-coupon (or zero-coupon). Further, we include in the sample only bonds issued by corporations, and that are not part of unit deals. We exclude bonds with warrants and special contingencies (i.e., preferred shares, puttable, convertible, exchangeable, asset-backed, etc.). The final sample contains 961,833 monthly transaction-based price observations for 17,936 bonds issued by 2,578 firms. We use the TRACE Masterfile to classify bonds into the speculative and investment grade categories. Information on credit grade is available for about 72% of the bond-month observations in the final sample.

To identify firms that are publicly listed, we match firms in our TRACE sample with data from CRSP using company symbol (i.e., ticker). Among the 2,578 firms in our sample, 1,195 cannot be matched to CRSP, in any month, which indicates that those firms, while being incorporated in the US, were not listed on the NYSE, Amex, or NASDAQ over the period covered by our analysis. The bonds issued by these firms constitute the private-issuer bond subsample. We restrict our private-issuer sample to firms that were not listed throughout the period covered by our sample, to focus on private firms for which the firm-level information dissemination mechanisms are consistent over time.

We obtain the month-end prices for each bond in the sample by extracting the last available trade-size weighted daily price in each month, where the weights for the calculation of daily prices are backed by intra-day transactions. The monthly return $r_{i,t+1}$ of bond i over the holding period from month t to $t+1$ is defined as follows:

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

where, $P_{i,t+1}$ is the price of bond i in month $t+1$, $C_{i,t+1}$ is the amount of coupon payment yielded by the bond between time t and $t+1$ (if any), which is calculated as the ratio of

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

the annual coupon rate of bond i to its coupon frequency.[6] The accrued interest $AI_{i,t+1}$ is defined as follows:

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

where d_{t+1} is the number of days between time $t+1$ and the last coupon payment date, and D_{t+1} is the number of days between the two consecutive coupon payment dates leading to, and following, the price $P_{i,t+1}$.[7] To ensure our results are not driven by outliers, we winsorize returns at the 1% level (i.e., 0.5% for each tail of the return distribution).

1.2 Sample Description

Table 1 reports basic summary statistics for the returns of top and non-top bonds, for the whole sample of issuers and, separately, for bonds of private and non-private firms.[8] Average maturities appear to be quite similar, between top and non-top bonds, across all categories. However, average trading volume for non-top bonds is less than half of that for top-bonds, which is consistent with top bond attracting larger volumes of institutional investor-sized trades. The average (over months) share of investment and non-investment grade bonds is comparable, across top and non-top bonds. However, speculative bonds appear to be more often classified as top than non-top bonds. The reverse applies to the share of investment grade bonds. Han and Zhou (2013) have shown that asymmetric information is higher for high-yield bonds than for investment grade bonds. Consistently with the existence of a positive information risk premium (e.g., Easley and O'hara (2004)), average returns for top bonds are higher, by about a fifth, than those of non-top bonds, despite very similar standard deviations of returns.

Microstructure theories suggest that uninformed investors concentrate their activities on bonds that are less likely to attract informed trading. A crude gauge of the activities of

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

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

[8] The focus on non-private firms, rather than public firms, allows the examination of a larger sample and biases our results toward finding homogeneity in the informational efficiency of private and non-private top and non-top bonds.

uninformed investors is yielded by retail-sized trades. We, therefore, calculate, for both top and non-top bond portfolios, the average percentages of retail trades in terms of monthly trade number, trade size, and total trade volume.[9] As tabulated in Table 2, the non-top bond portfolio, on average, has more retail trades than its top-bond counterpart.

2 VAR Analysis

Information diffusing at different speed is invoked to explain lead-lag relationship across markets (e.g., Kwan (1996), Ronen and Zhou (2013)). We build on this literature to characterize the difference between top and non-top bonds in terms of the effect of information by focusing on top and non-top bond return predictability, at the issuer level. Presently, for each firm we consider the following VAR system:

$$\begin{cases} r_t^N = \alpha_0^N + \sum_{k=1}^{l} \beta_k^N r_{t-k}^N + \sum_{k=1}^{l} \gamma_k^N r_{t-k}^T + \varepsilon_t^N \\ r_t^T = \alpha_0^T + \sum_{k=1}^{l} \gamma_k^T r_{t-k}^N + \sum_{k=1}^{l} \beta_k^T r_{t-k}^T + \varepsilon_t^T \end{cases} \tag{2}$$

where r_t^N and r_t^T are the monthly returns on the firm-level equally-weighted (EW) portfolios of non-top and top respectively, and ε_t^N and ε_t^T are mean-zero error terms.[10] Broadly speaking, the firm-level top and non-top EW indexes gauge the evaluations of the firm's prospects, from the perspective of informed and uninformed investors.

The predictability of lagged for current top bond returns, and of lagged for current non-top bond returns, is called same-asset predictability. Same-asset predictability is evaluated by the β coefficients in equations (2). In contrast, the predictability of top (non-top) bonds lagged returns for current non-top (top) bond returns is called cross-asset predictability. Cross-asset predictability is gauged by the γ coefficients in equations (2). The coefficient γ_k^N pertains to the predictive power of non-top bonds lagged returns in explaining top bond current returns. Henceforth, this cross-asset predictability is denoted by predictability NT-T. The analogous coefficient, namely γ_k^T, gauges the predictive power of top bonds lagged returns in explaining non-top bond current returns. This predictability is shorthanded by predictability T-NT.

[9] In this study, trades with par value lower than \$250,000 are classified as retail-sized.

[10] We filter out issuers for which there are less than 24 contemporaneous returns for the top and non-top EW indexes. Relying on higher (48) or lower (12) thresholds yields similar results.

The results of the issuer-level VAR analysis are summarized in Table 3 and Table 4 for same-asset and cross-asset predictability, respectively. The results are reported for the whole sample of issuers and, separately, for private and non-private firms.

As shown in the first two columns of results in Table 3, same-asset predictability at lag 1 is significant for more than 20% of the 771 issuers, in the whole-firm sample, which is evidence of sizeable levels of autocorrelation in the average returns of top and non-top bonds. Similar levels of autocorrelation in average returns are found in the private and non-private subsamples. As tabulated in the first column of Table 4, focusing on one-month lags, the percentage of issuers for which top lead non-top bonds is higher than the percentage of firms for which non-top lead top bonds. This result holds in the whole sample as well as for private and non-private firms. For instance, in the whole-firm sample, the one-month lagged returns of top bonds have predictive power for the non-top bond returns in 38% more of the instances in which the reverse lead relationship holds.[11]

The degree of cross-asset predictability, in itself, is remarkable, with the lag-1 top bond returns being significant in predicting current non-top bonds for 35% of the issuers, at the 10% significance level. For private and non-private firms the analogous figures are 33% and 36%. To provide some context to these percentages, using 5-minute equity and bond returns, Tsai (2014) shows that the equity return is significant in predicting the return on the same-issuer bond that attracts the highest number of institutional trades for about 31% of the firms, at the 10% significance level.

Since predictability may also be driven by autocorrelation of systematic risk factors on which top and non-top bonds have significant loading, we have also considered VAR systems that include the lagged values of a selection of risk factors. The selection of the factors considered for this robustness check is discussed in Section 3.2.1. None of the conclusions of this study changes when relying on the results of the augmented VAR systems.

2.1 Informed and Uninformed-Driven Predictability

The significance of the coefficients of the cross-asset returns in the VAR system (i.e., coefficients γ_k^N and γ_k^T, in the equations displayed in (2) provides evidence on cross-asset

[11]The frequencies with which top lead non-top bonds and non-top lead top bonds are 35.1 and 23.9 respectively, as reported in Table 4. These figures correspond to a 38% improvement. For private firms, the corresponding percentage is 23, while for non-private issuers is 47.

predictability. However, we argue that these coefficients yield insights beyond the existence of predictability. Specifically, if information diffusion lays at the root of predictability T-NT and NT-T, then these coefficients should also be positive, as gradual information diffusion causes a trend in the fundamental valuation of the firm. In particular, if news spread faster for top than non-top bonds, then the sheer incidences in which predictability is associated to information diffusion should be larger for top bonds predicting non-top bonds, than for the reverse evaluation. Hence, we should expect that the coefficient γ_k^T is significant and positive in more instances than those in which γ_k^N satisfies the same conditions. Put differently, we should expect that predictability T-NT is more often driven by information than predictability NT-T. The results reported in the four and fifth columns of Table 4 confirm this prediction. We find that the predictive power of top for non-top bonds is driven by information diffusion in virtually all the instances in which there is evidence of predictability.[12] Specifically, information drives predictability in 72% more instances for top leading non-top bonds than for non-top leading top bonds.[13] The inclusion of a second lag in the issuer-level VAR systems yields consistent conclusions. The incidence of information-driven predictability is lower, for both top and non-top bonds across the subsamples, for lag two than for lag one returns, which is consistent with information diffusing gradually over time.

While the results of cross-asset predictability support the view that informed traders inject information using top bonds rather than non-top bonds, in 41.3% of the instances in which there is predictability NT-T this does not appear to be linked to information diffusion. As information is imbued in prices through the activities of informed investors, the predictability that is not driven by information should be associated with uninformed trading. From this perspective, predictability NT-T appears to be associated both to the activities of informed and uninformed investors, whereas predictability T-NT is mostly driven by those of informed investors. A stronger role of uninformed trading in non-top bonds is consistent with the insights yielded by the analysis of retail-sized trades (i.e., see Table 2).

Previous contributions have shown that the activities of uninformed traders contribute to explain same-asset return predictability, as argued by Barber et al. (2008) for equities

[12] We find evidence of some two-way lead-lag relationship, which, however, is driven by information only in very few instances, i.e., for about 1% of all the issuers, in all subsamples.

[13] The frequencies of information-driven cross-asset predictability for top and non-top bonds are 29.8 and 14 respectively, as reported in Table 4. These figures correspond to a 72% improvement. For private and non-private issuers the corresponding percentages are 64.6 and 75.6.

and by Wei (2018) in the corporate bond market. These authors find that concentration of retail trading activities has predictive ability for future asset returns.[14] They explain this conclusion by arguing that retail investors are uninformed and prone to overreacting behavior. Building on these insights, we next examine the effect of uninformed trading in originating same-asset predictability. We thus examine the sign of the estimates of the same-asset coefficients yielded by the VAR system (i.e., coefficients β_k^N and β_k^T, in the equations displayed in (2).

Columns 3 and 4 of Table 3 report the percentage of instances in which same-asset predictability is associated with a negative coefficient on the lagged return. Focusing on the coefficients of one-month lagged returns, we find that the results are consistent with predictability being driven by uninformed trading for 8% and 22.7% of the issuers for top and non-top bonds, respectively. A comparison with the percentages reported in Columns 1 and 2 of the same table shows that for top bonds same-asset predictability is driven by uninformed trading in 37.6% of the instances in which there is evidence of predictability. The corresponding percentage for non-top bonds is much higher, at 77.1%. Analogous patterns are found for private and non-private issuers.[15] These results are consistent with uninformed trading playing a stronger role in price formation for non-top than for top bonds. Consequently, these findings lend support to our interpretation of the negative sign of the cross-sectional serial correlation as the effect of uninformed trading.

The analysis of the sign of the coefficients obtained from the estimation of the issuer-level VAR systems, both for same and cross-asset predictability, yield conclusions that are consistent with top bonds attracting more informed trading than non-top bonds, and with the activities of uninformed investors playing a stronger role in determining asset serial correlation for non-top than top bonds. In particular, the results are consistent with news spreading faster for top than non-top bonds, and with non-top bonds being more likely than top bonds to attract uninformed investors who are prone to overreaction.

[14] For the corporate bond market, Wei (2018) focuses on monthly retail investors trades and finds that a portfolio that is long in heavily bought bonds and short in heavily sold bonds yields negative average returns over the next month. As in this study we rely on monthly bond returns, his conclusions are pertinent to our discussion.

[15] For private issuers, the results are consistent with unformed trading same-asset predictability in 39.1% and 76.7% of the instances for which there is evidence of predictability, for top and non-top bonds, respectively. For non-private issuers, the corresponding percentages are 39.8 and 78.6, for top and non-top bonds, respectively.

Our interpretation of the sign of the serial cross-asset correlation in terms of the effects of informed and uninformed trading is novel to the literature on predictability. In particular, we argue that our approach to evaluating the causes of predictability across bonds is precluded to studies aiming to explain the lead-lag relationship between stocks and bonds. For instance, a negative serial correlation between same-issuer equity and bonds may be due to news affecting the firm-asset volatility, but also to mispricing of opposite nature.[16] Focusing on the lead-lag relationship within the firm-level bond cross-section, hence comparing the returns of similar financial contracts issued by the same entity, allows eschewing these complications in interpreting the sign of the serial cross-asset correlations yielded by the VAR analysis.

2.1.1 Private and Non-Private Issuers

The results reported in the first column of Table 5 quantify the difference in the degree of information-driven predictability between top and non-top bonds. Specifically, we report the percentage difference in the incidence of information-driven predictability between top and non-top bonds, for the whole-firm sample, and for bonds issued by private and non-private firms. To illustrate, for the whole sample of firms, predictability is driven by information diffusion in 72.2% more instances for top than non-top bonds. According to this measure of the incidence of information-driven predictability, information spreads faster for top and non-top bonds, in all samples. However, the rates at which news spread for top and non-top bonds are more similar for bonds issued by private firms than in the whole-firm sample and for non-private firms. Put differently, the difference in the degree with which informed trading causes cross-asset predictability for top and non-top bonds is at its lowest for bonds issued by private firms.

The last two columns of Table 5 report the loss of cross-asset predictive power for top

[16]Structural models (e.g., Merton (1974)) propose that the sign of the correlation between the value of equity and debt, at the firm level, depends on the nature of the information shock causing price changes, namely on whether the shock is affecting firm-level volatility or mean asset value. Hence, elaborating on the conclusion of the structural models, positive (negative) serial correlation between bond and equity returns may be due to firm-level shocks to asset means (volatility), if information diffuses gradually. From another perspective, the sign of the relationship between same-issuer equity and bond values may also stem from non-information driven mispricing. Garlappi et al. (2008) argue that shareholders may use strategic default to extract value from the bondholders, thus yielding overpricing for equity and underpricing for bonds, at the issuer level. As bonds are less liquid assets than equities, the mispricing for equity and bonds may be corrected over different time horizons, thus causing a negative cross-asset serial correlation.

and non-top bonds when instances of information-driven predictability are dropped. These percentages measure the incidence of predictability driven by the effects of uninformed trading. For instance, in the whole sample of firms, predictability caused by uninformed trading represents 15.1% of the instances in which top lead non-top bonds. The results clearly show that uninformed trading causes cross-asset predictability at a much lower extent for top than for non-top bonds.

Comparing across subsamples, the results indicate that, with respect to the sample of all the issuers and of non-private firms, private-firm non-top bonds have the highest incidence of sentiment-based predictability, at about 43%. In contrast, top bonds of private firms display the lowest incidence of uninformed trading predictability across subsamples: only in 11.3% of the instances in which top lead non-top private-firm bonds the predictability is caused by uninformed trading. Hence, the difference in the degree with which uninformed trading causes cross-asset predictability for top and non-top bonds is at its highest for bonds issued by private firms.

Combining all the results of Table 5 yields the insight that uninformed trading has a more prominent role than informed trading in differentiating top and non-top bonds, for bonds issued by private firms relative to bonds issued by non-private firms. This conclusion is consistent with the theoretical implications of informed trading outlined in the microstructure literature (e.g., Glosten and Harris (1988)), given the empirical evidence that trades in private-firm bonds have higher levels of asymmetric information than trades in bonds issued by public firms (Han and Zhou (2013)). For top (non-top) bonds, the incidence of uninformed trading is smaller (larger) for private than for non-private issuers, due to higher levels of asymmetric information in top bonds for private firms.

3 Momentum and Information

This section aims to explore the role of informed and uninformed trading in determining the momentum effect by exploiting the differences between top and non-top bonds highlighted by the VAR analysis. The core of the profitability of the momentum strategy lies in asset return continuation, where past performance predicts future returns. In the framework proposed by HS, asset-level predictability is due to underreaction caused by gradual information diffusion or by overreaction due to uninformed trading. The results of the VAR analysis indicate that top bond prices imbue information at a faster rate than non-top bonds. Further, non-top bonds returns appear to be driven by uninformed trading to a higher degree than top bonds. This characterization of top and non-top bonds yield precise predictions on the profitability of the momentum strategy in each category.

3.1 Momentum Strategies in Top and Non-top bonds

The momentum strategy in top and non-top bonds is characterized by a formation and a holding period, which are separated by a formation month, to avoid the bid-ask bounce. In each formation month t, for a formation period of j months, we identify bonds that have been continuously top or non-top bonds over the months spanning from $t-j-1$ to $t-1$. We sort the top bonds into deciles, on the basis of their historical cumulative returns over the formation period. An equally weighted portfolio of the top bonds in the highest (lowest) decile identifies the long (short) leg of the momentum portfolio in top bonds. The bonds falling into the winner minus loser portfolio of top bonds are held for the entire duration of the holding period. The momentum portfolio for non-top bonds is defined analogously. Crucially, the top and non-top bonds included in the buy-and-hold momentum portfolios are identified in the formation month, on the basis of past institutional-sized trades. Thus, the top and non-top bond momentum strategies are implementable by real-time investors.

For both the top and non-top momentum portfolios, the holding period monthly return is defined, following Jegadeesh and Titman (1993), as the cross-sectional average of the monthly returns of the overlapping winner-minus-loser portfolios. The number of overlapping portfolios depends on the length of the holding period. We consider momentum strategies with formation and holding periods of different length, ranging from one month up to one year.[17] We construct top and non-top momentum strategies in the whole-firm sample and for bonds issued by private and non-private firms.

Since top and non-top bonds are identified at the issuer level, an alternative approach is to define momentum portfolios of EW indexes of top and non-top bonds, at the firm level, rather than relying on individual bonds. Appendix A discusses this possibility and shows that the conclusions of this study are confirmed by the firm-level approach. The firm-level analysis

[17] Bonds for which one or more monthly returns are unavailable during the period spanned by the start of the formation period and the end of the holding period are not considered for the formation of the momentum deciles, both for the top and non-top momentum strategy.

also allows us to experiment with an alternative definition of top bonds. Ronen and Zhou (2013) examine the predictive power of the one bond (i.e., the top-one bond) that attracts the highest volume of institutional investor-sized trades, around earnings announcements. Following their approach to examining the momentum effect in top-one bonds is problematic, especially for the implementation of momentum strategies with formation period longer than few months. The reason is that, in most instances, a bond remains the top-one bond of a firm for only few periods. Hence the bond-level top-one momentum portfolios would include only bonds that are continuously top-one bonds over the entire formation period, which would considerably reduce the top-bond cross-section. We have explored the use of top-one bonds for firm-level momentum strategies in Appendix A and found results that are consistent with those obtained relying on the top bond definition employed in this study (i.e., the top-three bonds).

3.2 Momentum Effect in Top and Non-top Bonds

Panel A in Table 6 reports the average monthly returns for the momentum portfolios for top bonds. The results indicate that momentum strategies in top bonds yield significant profits only for very short time-horizons. There are significant momentum gains in top bonds for strategies for which the combined duration of the formation and holding periods is less than four months. Allowing for weak (i.e., at 10%) statistical significance, fails to stretch the horizon over which the momentum strategy is profitable beyond the two-month formation and three-month holding period strategy. Further, top bond momentum gains appear to peak over the very short-term. The highest average return, at 28.7 bps, is observed for the two-month formation and one-month holding period strategy.

The returns for momentum portfolios of non-top bonds are reported in Panel A of Table 7. The average monthly returns are statistically significant for strategies with formation periods as short as two months and holding periods as long as ten months. The maximum combined duration of the formation and holding periods for which momentum returns are significant is of 14 months. Peak profitability of non-top bond momentum, at 40 bps, is yielded by the strategy with formation and holding periods of six and two months, respectively.

To provide some terms of comparison, we find that the momentum strategy in the whole-bond sample (i.e., not partitioned into top and non-top bonds), yields insignificant returns for the vast majority of the considered 144 momentum strategies. The few instances in which the momentum profitability is significant, it yields average returns of about 26 bps (untabulated result).[18]

3.2.1 Risk-Adjusted Returns

A potential explanation of the difference in the profitability of top and non-top bond momentum portfolios is that these subsamples are fundamentally different in terms of exposure to systematic risk. For instance, as shown in Table 1, the average trading volume is much smaller for non-top than top bonds. The implication is that differences between top and non-top momentum return patterns may be linked to different levels of exposure to liquidity risk.

In order to explore the possibility that the differences between top and non-top bond momentum returns may be driven by systematic risk, we evaluate risk-adjusted momentum returns. In order to do so, we rely on the same collection of eight risk factors employed to perform the augmented VAR analysis. To provide more details, we consider the five systematic risk factors for equity and bonds proposed in Fama and French (1993).[19] We further include the equity momentum factor (Carhart (1997)), and the liquidity innovation factor for the bond market proposed in Lin et al. (2011).[20] We also include the changes in

[18]In their transaction-based bond sample covering the period 1994-2011, Jostova et al. (2013) find average momentum returns that are higher than the ones we have calculated, using TRACE data for the 2002-2017 period. This discrepancy is confirmed by the results of our calculations for the 2002-2011 sample. We attribute this difference to the fact that Jostova et al. drop from the bond return distribution the top 0.5% of returns. This filtering erases outliers for the winner side of the momentum strategy, but not for the short leg of the momentum portfolio. An unreported analysis shows that much of 2002-2011 large momentum returns documented in Jostova et al. stems from the months from September to November, 2008. We suspect that the larger momentum returns documented in Jostova et al. are associated with great losses for the bonds falling in the bottom momentum decile. In this study, we winsorize returns at the 0.5th percentile on both sides of the return distribution. Further discussion on the treatment of outliers when evaluating the momentum strategy is forthcoming from the authors.

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

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

the implied volatility index, as Chung et al. (2018) have shown that this factor is priced in the corporate bond market.

The risk-adjusted returns are reported in Panel B of Tables 6 and 7, for top and non-top bond, respectively. A comparison of the raw and risk-adjusted returns reveals that accounting for risk fails to explain the dissimilarities between the momentum effect in top and non-top bonds. In particular, risk-adjusted momentum returns display the same patterns as those found in raw returns, for top and non-top bonds, respectively. If anything, the risk adjustment has a limited effect of slightly increasing peak momentum profitability for both top and non-top bonds. However, peaks in raw and risk-adjusted momentum returns are obtained for very similar strategies, both for top and non-top bonds.[21]

Untabulated results show that both top and non-top momentum strategies load positively on the equity momentum factor, which suggests a certain degree of consistency in investors' behavior, across markets. The value-minus-growth factor is also significant, again with positive loadings, for a large share of the momentum strategies considered, for both top and non-top bonds. The liquidity innovation factor is significant only for non-top bonds, and only for strategies for which the combined duration of the formation and holding periods is longer than six months. Even when the factor is significant, controlling for liquidity risk has a minimal impact on the risk-adjusted returns of the momentum strategy in non-top bonds. For the remaining five factors, loadings are insignificant for all the momentum strategies.

Given that in this study we explain the differences between top and non-top momentum return patterns by referring to the incidence of informed and uninformed trading, it is possible that a private-information factor for the bond market would be relevant to our analysis. A series of contributions building around a private information measure proposed by Easley et al. (1997) argue that private information is a priced factor in the equity market. For the bond market, however, no contribution has explored this line of research, to the writers' knowledge.

[21] Peak profitability in risk-adjusted terms for top bond momentum portfolios, at 29.1 bps, is obtained for the two-month formation one-month holding period strategy. The highest non-top bond momentum return, at 47.1 bps, is obtained for the seven-month formation two-month holding period portfolio.

3.3 Information Diffusion Speed

The VAR analysis yields evidence that is consistent with information transmission speed being faster for top than non-top bonds. This finding offers a line of explanation for the differences in the respective momentum gains, which is best illustrated making reference to the theoretical model by HS.[22] The model stipulates that information diffuses gradually as prices adjust over time to news, thus causing information-driven mispricing due to price underreaction. The price trends caused by the spreading of news are exploited and reinforced by trend chasers (i.e., the momentum traders), who are uninformed investors. The activities of momentum traders cause prices to deviate from the information-supported trend and eventually lead to price overreaction. Over time, the overreaction dissipates, in the absence of news supporting the price trend, and prices gravitate to the level implied by the information shock.

Fast information diffusion causes short-lived price trends, thus short underreaction/overreaction (U/O) momentum cycles. Momentum strategies are characterized by a formation period, over which price trends are revealed, and a holding period. Hence, when news spread quickly, the momentum effect should generate gains only for strategies with short formation and holding periods. While the momentum effect peters out quickly when information diffuses at a fast pace, as the U/O cycle is short, slow information diffusion yields protracted price trends. These persistent trends, in turn, trigger a build-up of trend-chasing activities, causing valuations to diverge from fundamentals for quite some time. Hence, in the framework of the HS model, that information diffuses faster for top than non-top bonds suggests that momentum strategies in top bonds should yield profitable opportunities only in the short-run, whereas non-top bond momentum profits should be more spread out in time, and become stronger beyond short horizons. The momentum gains reported up to this point (i.e., in Tables 6 and 7) confirm these predictions.

Analyzing the returns of momentum strategies with the same holding period, but different formation periods, provide a series of snapshots of the mispricing over the life of the U/O cycle. In particular, for a given holding period, the duration of the formation period for which

[22] To the writers' knowledge, in the literature, there is no available measure of firm-level information diffusion speed, for corporate bonds. In the stock market Hong et al. (2000) use analyst coverage and size to control for information diffusion rate, under the assumption that high coverage and large size are positively associated with information diffusion speed.

momentum profitability peaks provides insights on the speed of information diffusion, with an early (late) peak indicating fast (slow) information diffusion. We note that comparing momentum strategies with the same holding period allows to abstract from the effect of momentum traders' investment horizons, as modeled in HS.[23]

According to the U/O cycle explanation of momentum, peak profitability corresponds to the overreaction phase. Consistently with the cycle being more short-lived when information diffuses quickly, the peak of the profitability of the momentum strategy should occur earlier for top rather than non-top bonds. This prediction is a direct consequence of Proposition 1 in Hong and Stein (1999) where the authors show that the cumulative price-impulse-response function peaks earlier when news spread at a faster rate (see also their figure two in the same study).

Focusing on momentum strategies with one-month holding period, we find that peak momentum profitability is spaced three months apart for top and non-top bonds, being obtained for formation periods of two and five months, respectively.[24] The peaks for the two-month holding period strategies are spaced four months apart, being obtained for the two and six-month formation periods for top and non-top bonds, respectively.[25] Hence, the predictions of the HS model for differences in information diffusion speed are supported by the analysis of the one and two-month holding periods for top and non-top bonds. Beyond the two-month holding periods, top bonds yield no momentum returns, so a comparison between peaks is unfeasible.

Figure 1 plots the one and two-month holding period average raw returns and risk-adjusted returns, for top and non-top bonds. At a glance, the figure reveals that for short-term formation periods, top bond momentum strategies yield larger returns than those offered by the analogous strategies in non-top bonds, with the relationship reversing thereafter.

[23] Parameter j in the HS model.

[24] For both top and non-top bonds, the peak for the one-month holding period (i.e., $j = 1$) portfolios occurs for formation periods longer than one month. According to Point iii) in Proposition 1 in HS, this scenario is consistent with information being diffused completely after one month (as the peak is timed no earlier than j), and that speed, rather than the investment horizon of the momentum traders, determines the timing of the peak.

[25] The peak for the two-month holding period (i.e., $j = 2$) top bond momentum portfolios occurs for the formation period of two months. According to Point ii) in Proposition 1 in HS, this scenario is consistent with information being diffused completely within two months. For non-top bonds, according to Point iii) of the same proposition, the information diffuses completely in more than two months.

For both the momentum portfolios in top and non-top bonds the returns are increasing until they reach their respective peaks. For both series, a decline follows the peak, with the descent being more precipitous for top bonds. This inverted U-shaped trajectory, which is consistent with the momentum effect being originated by a cycle of U/O, shall be exploited later on in this article to propose a simple calibration exercise.

3.4 The Role of Uninformed Trading

Up to this point, we have interpreted the differences in momentum returns for top and non-top bonds along the dimension of information diffusion speed. However, speed is not the only channel through which the HS model originates different momentum return dynamics, as also the relative proportion of uninformed to informed traders causes different underreaction-overreaction cycles.[26] Their prediction is for higher aggregate levels of uninformed trading yielding higher momentum returns. More precisely, higher degrees of uninformed trading yield higher momentum profits over a time horizon that is determined by the speed of information diffusion.

As discussed in Section 2.1.1, uninformed trading has a more prominent role than informed trading in differentiating top and non-top bonds for private issuers relative to the whole-firm sample. In particular, private-firm non-top bonds have the highest incidence of predictability driven by uninformed trading with respect to top and non-top bonds in the all-issuer sample and the non-private firm subsample. In this section, we bring to the data the theoretical predictions of the HS model for the role of uninformed trading in determining the momentum effect, by analyzing the momentum effect in top and non-top bonds for private issuers.

Table 8 reports the average monthly raw and risk-adjusted returns for the momentum portfolios for top bonds issued by private firms. Once more, the results indicate that momentum strategies in top bonds yield significant profits only over short horizons. However, significant momentum gains for private-firm top bonds are spread over longer horizons than those observed in the whole-firm sample, for top bonds. This result suggests that for private firms information may spread at a slightly slower pace than for other issuers. Private-firm top bond momentum gains appear to peak, at 36.8 bps, for the strategy with two-month forma-

[26] Parameter γ in HS. The parameter γ can be equivalently interpreted as the risk tolerance of momentum trades, see their discussion on page 2157.

tion and one-month holding periods. The same strategy also yields the highest risk-adjusted momentum returns, at 35.9 bps, referring to the 5% significance level.

Table 9 displays the average returns for momentum portfolio of non-top bonds. The average monthly raw and risk-adjusted returns are statistically significant for strategies with formation and holding periods as short as two months and as long as five (formation) and ten (holding) months, respectively. The maximum combined duration of the formation and holding periods for which momentum returns are significant is of 16 months. The momentum effect in non-top bonds appears to be more spread out for private-firm bonds than in the whole-firm sample, which, as it was the case for top bonds, suggests that information may spread at a slightly slower rate for private firms than in the whole-firm sample. Peak profitability of non-top bond momentum, at 93.8 bps and 111 bps in raw and risk-adjusted terms, respectively, is yielded by the strategy with seven month formation period and one month holding period. In terms of information diffusion speed, the results reported in Tables 8 and 9 are consistent with news spreading faster for top than non-top bonds, for private-issuer bonds.

According to the HS model, different timing of peak momentum gains, for a given holding period, are associated with different information diffusion rates. Crucially, the relative proportion of momentum traders does not affect the timing of the peak, but it affects its magnitude. Non-top momentum for private issuers yields peak returns that are much stronger than those found for the whole-firm sample, for any given holding period. These peaks are, however, obtained for strategies that are similar in terms of the length of the formation and holding periods. This similarity makes unlikely that it is the difference in speed for non-top bonds, between the private and all-firm samples, that explains the substantially higher peaks of momentum returns observed for private issuers. In contrast, a higher incidence of uninformed trading for non-top bonds in the private-firm sample than in the whole-firm sample is consistent with very different levels of peak momentum profitability being yielded by strategies with similar formation and holding periods.

In terms of information diffusion speed, the results reported in Tables 8 and 9 are consistent with news spreading faster for top than non-top bonds, for private-issuer bonds, as already found in the whole-firm sample. As information diffusion for private-firm top bonds is faster than for private-firm non-top bonds, we should expect that top bond momentum returns are higher than those yielded by non-top bonds over the very short run. The opposite relationship should hold thereafter. Figure 1 illustrates this point in the whole-firm sample, by showing a crossing of the average momentum returns in top and non-top bonds for the strategies with one and two months holding periods, for formation periods ranging from 1 to 12 months.

Figure 2 plots the analogous average momentum returns for private-firms top and non-top bonds. The comparison of Figures 1 and 2 reveals that for private firms momentum in non-top bonds is higher than in top bonds, for all formation periods, i.e. the plots of the momentum returns in Figure 2 do not show a crossing. The absence of the crossing is mainly due to higher momentum returns in non-top bonds in the private firm subsample than in the all-issuer sample, as top bond momentum returns are rather similar in the two samples. This result is consistent with high levels of uninformed trading boosting the momentum returns in private-firm non-top bonds.

3.5 A Simple Calibration Exercise

In order to illustrate the interaction of speed and uninformed trading in determining the momentum effect, we experiment with a simple calibration exercise of the momentum returns in the whole sample and for private-firms, for top and non-top bonds. Consistently with the momentum effect being originated by an underreaction and overreaction cycle, we fit with a second-degree polynomial the momentum returns of strategies with a fixed holding period and varying formation period. The equation describing the fitted momentum return r_t^m for a given holding period is:

$$r_t^m = at^2 + bt, \tag{3}$$

where t is the length of the formation period. Combining the insights offered by the simulations in HS, we interpret the coefficients in the equation 3 in terms of information diffusion speed and of the relative proportion of uninformed traders. Following the notation of HS, information diffusion speed is $1/z$, and the relative proportion of uninformed trading is γ. We impose $z = -b/2a$ and $r^{\max} = \gamma z$, where $r^{\max}$ is the peak of the fitted momentum return. As a result, and consistently with the HS framework, a higher γ increases momentum profitability but does not affect the timing of peak profitability. Higher information diffusion speed, that is, lower value of z, entails later and higher momentum peak returns.

Table 10 reports the fitted coefficients for $1/z$ and γ for strategies that yield significant risk-adjusted momentum gains, in top and non-top bonds, in the whole-firm sample and for private-issuer bonds. In the table, we report the coefficients for top bonds only for the holding periods for which top bonds yield significant momentum returns (i.e., holding periods of one and two months). Figure 3 and Figure 4 show the plots of the fitted equation, together with the risk-adjusted returns, for the two-month holding period momentum strategies in top and non-top bonds, for the whole sample and private-firm subsample, respectively.

In the whole sample, the estimated coefficients for the top and non-top series are consistent with information diffusion speed in non-top bonds being slower than that in top bonds, which confirms the conclusions drawn from the VAR analysis. In particular, the fitted values of the speed parameter for top bonds more than double those yielded by the non-top strategies with the same holding period. For the same holding periods, however, the uninformed trading parameter is lower for non-top than for top bonds. In the HS framework, lower incidence of uninformed trading in non-top bonds entails a lower momentum effect, which is not what the empirical evidence shows for top and non-top bonds. Hence, the calibration results are consistent with speed being the dominant driver of the difference in the profitability of the momentum strategy in top and non-top bonds, in the whole-issuer sample.

For the corresponding holding periods of strategies in bonds issued by private firms, the speed (uninformed trading) fitted coefficient for non-top bonds is smaller (larger) than that obtained for the top bond strategies. Faster information diffusion should entail stronger but shorter price trends, which should be revealed by higher momentum returns for top than non-top bonds, over short-term horizons, and higher momentum for non-top than top bonds beyond the short-run. However, as shown in Figure 2, non-top private-firm bond momentum returns are stronger than those found for top private-firm bonds, across the considered horizons. Higher momentum gains across all horizons are consistent with the effect of large levels of uninformed trading, which boost momentum profitability in both the underreaction and overreaction phase.

Comparing the fitted parameters for strategies in the private-issuer subsample and the all-issuer sample, we find that estimated speed (uninformed trading) is higher (lower) in the all-firm sample than for private firms, which is consistent with the results of the VAR analysis. However, the most salient difference between the whole-firm and private-issuer samples is the very large value of the estimated uninformed trading coefficient for momentum strategies for non-top bonds of private firms, which is about twice as large as the corresponding value for non-top bonds, in the whole sample, for all the holding periods considered (i.e., from 1 to 12 months). This calibration result confirms the view that the strongest profitability of the momentum strategy, with risk-adjusted monthly returns as high as 1.1%, is to be ascribed to both low information diffusion speed and high levels of uninformed trading in private-issuer non-top bonds.

4 Conclusions

This study finds that informed trading originates heterogeneity in informational efficiency within the firm-level bond cross-section. Informational efficiency is measured along two dimensions: the speed of information diffusion and the incidence of uninformed trading. The empirical evidence indicates that news spread faster, and uninformed trading is less relevant, for bonds attracting the highest levels of trading volume of institutional investors (i.e., for top bonds) than for the remaining bonds issued by the same firm. These features result in significant and information-driven cross-asset predictive power of top bonds, and in top bond momentum returns that are concentrated over very limited time horizons. A short-lived momentum effect for bonds with high information diffusion speed and low levels of uninformed trading is consistent with the prediction of the HS model of gradual information diffusion. For non-top bonds, the predictability analysis and the returns on the momentum strategy are consistent with these securities being less informationally efficient than top bonds.

The literature has found that momentum returns in the corporate bond markets are weak and short-lived. Different studies view the weakness of the momentum effect in the corporate bond market as the result of aggregating momentum returns over credit rating categories and ownership status (e.g., Jostova et al. (2013)), or market states and sentiment (Li and Galvani (2018)). Our evidence indicates that informational efficiency is the dimensions along which bond aggregation yields weak momentum returns.

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Table 1: Descriptive Statistics for Top and Non-top Bonds in TRACE

The table reports basic statistics for top and non-top bonds, in the whole-firm sample, and for private and non-private issuers. The first column of results lists the total number of monthly observations. Column 2 displays the average number of top and non-top bonds, per issuer per month. The following four columns list the average (in percentage terms) and the standard deviation of bond returns, average time-to-maturity (in months), average monthly trading volume (in million dollars). The last two columns report the percentage of investment-grade and non-investment grade bonds in each category. The time period covered is from August 2002 to June 2017.

	N	per firm-month	R(mean %)	R(std)	Maturity(months)	Volume(millions)	IG share(%)	NIG share(%)
Top bonds								
Whole	366316	1.63	0.684	0.03	108	65.017	54.826	16.543
Private	156274	1.533	0.742	0.032	106	53.399	51.848	19.149
Non-private	210042	1.699	0.64	0.028	110	73.661	57.042	14.604
Non-top bonds								
Whole	595517	2.65	0.554	0.03	112	17.78	60.561	12.272
Private	195770	1.92	0.6	0.033	115	12.515	56.182	16.565
Non-private	399747	3.234	0.532	0.028	111	20.358	62.705	10.17

Table 2: Share of Retail Trades in Top and Non-top Bonds

The table reports the mean and median of the share of retail trades over those of institutional and retail investors combined, in terms of monthly trade number, total trade volume, and trade size, for top and non-top bonds. The last row displays the difference of the mean retail share between top and non-top bonds. Significance level at 5% is marked by **. The time period covered is from August 2002 to June 2017.

retail/(inst+retail)	n. trades (%)	total vol.(%)	trade size (%)
Top bonds			
mean	64.15	4.94	1.86
median	68.93	3.17	1.52
Non-top bonds			
mean	88.58	46.97	40.17
median	94.44	22.66	6.5
mean(nontop-top)	24.43**	42.03**	38.31**

Table 3: **Firm-level Same-asset Predictability for Top and Non-top Bonds**

The table summarizes the results of the issuer-level VAR models, for lag 1 and lag 2, evaluated for EW portfolios of top and non-top bonds. The whole sample results are in Panel A, while Panel B and C pertain to private and non-private firms, respectively. The first column of results reports the percentage of issuers for which lagged top bond returns predict current top bond returns, followed, in Column 2, by the percentage of issuers for which the same-asset predictability stems from non-top bonds. Column 3 and 4 report the analogous percentages for top and non-top bonds with the predictability being associated with a negative sign. Column 5 and 6 display the analogous percentages for top and non-top bonds with the predictability being associated with a positive sign. The last column is the number of issuer-level VAR system evaluated. The time period covered is from August 2002 to June 2017.

	(%)Top bond	(%)Non-top bond	(%)Top (-)	(%)Non-top (-)	(%)Top (+)	(%)Non-top (+)	N
Panel A: Whole Sample							
lag1(l=1)	21.4	29.4	8	22.7	13.4	6.7	771
lag2(l=2)							
k=1	22.9	30.5	9.1	22.3	13.8	8.2	717
k=2	24.4	27.9	18.5	20.9	5.9	7	
Panel B: Private Firm Subsample							
lag1(l=1)	23.2	30.2	9.1	23.2	14.1	7	298
lag2(l=2)							
k=1	23.7	31.7	10.1	23.4	13.7	8.3	278
k=2	26.3	29.9	20.1	22.3	6.1	7.6	
Panel C: Non-private Firm Subsample							
lag1(l=1)	20	28.6	8	22.4	12	6.2	490
lag2(l=2)							
k=1	21.7	29.2	8.9	21.2	12.7	8	448
k=2	23.7	27.9	17.6	21	6	6.9	

Table 4: **Firm-level Cross-asset Lead-lag Relationship for Top and Non-top Bonds**

The table summarizes the results of the issuer-level VAR models, for lag 1 and lag 2, evaluated for EW portfolios of top and non-top bonds. The whole sample results are in Panel A, while Panel B and C pertain to private and non-private firms, respectively. The first column of results reports the percentage of issuers for which top bonds lead non-top bonds, followed, in Column 2, by the percentage of issuers for which non-top lead top bonds. Column 3 displays the analogous percentages for the two-way lead-lag relationship. Columns 4 and 5 report the percentages of issuers for which the cross-asset leading relationship is associated with positive coefficients on the lagged returns of top and non-top bond index, respectively. Column 6 reports the percentages of the two-way positive relationship. The last column is the number of issuer-level VAR system evaluated. The time period covered is from August 2002 to June 2017.

	(%)Top lead	(%)Non-top lead	(%)Two-way	(%)Top lead+	(%)Non-top lead+	(%)Two-way+	N
Panel A: Whole Sample							
lag1(l=1)							
	35.1	23.9	8.2	29.8	14	1.4	771
lag2(l=2)							
k=1							
	35.6	24.5	8.5	30.7	15.5	2.5	717
k=2							
	23.3	22.7	7.4	11.6	9.2	0.6	
Panel B: Private Firm Subsample							
lag1(l=1)							
	32.6	25.8	7	28.9	14.8	1.3	298
lag2(l=2)							
k=1							
	31.7	28.4	9	29.5	16.9	2.9	278
k=2							
	21.9	23.7	5	9.7	11.2	0.7	
Panel C: Non-private Firm Subsample							
lag1(l=1)							
	35.7	22	8.4	29.4	13.3	1.2	490
lag2(l=2)							
k=1							
	36.2	21.4	8.3	30.1	14.3	2.2	448
k=2							
	23.7	21.2	8.9	12.9	7.8	0.4	

Table 5: Cross-asset Predictability Analysis

The first column of results reports the percentage change in the incidence of information-driven cross-asset predictability (i.e., the positive serial cross-asset correlation for lag 1 in the VAR system) comparing top to non-top bonds. The following two columns report the percentage of instances in which predictability is driven by uninformed trading (i.e., the negative serial cross-asset correlation for lag 1 in the VAR system), for top and on-top bonds, respectively.

	info	uninfo-top	uninfo-nontop
Whole	72.2	15.1	41.3
Private	64.6	11.3	42.9
Non-private	75.6	17.7	39.8

Table 6: **Top Bond Raw and Risk-adjusted Momentum Returns**

For each t, for a formation period of j months, we identify bonds that have been continuously top bonds over the months spanning from $t-j-1$ to $t-1$. In month t, we sort the top bonds into deciles, on the basis of their historical cumulative returns over the formation period. An equally weighted portfolio of the top bonds in the highest (lowest) decile identifies the long (short) side of the momentum portfolio. The bonds falling into the winner minus loser portfolio of top bonds are held for the entire duration of the holding period. The holding period monthly return is the average of the cross-section monthly returns of the overlapping winner-minus-loser portfolios. We consider momentum strategies with formation (F) and holding (H) periods ranging between 1 to 12 months. Panel A displays the average monthly holding periods raw returns of the resulting 144 momentum strategies. Panel B reports the corresponding risk-adjusted returns. Significance level at 1%, 5%, and 10% are indicated by ***, **, and *, respectively. Peak momentum raw and risk-adjusted returns are framed.

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
Panel A: Top bond momentum raw returns												
F1	0.2*	0.192**	0.143*	0.111	0.103	0.044	0.027	0.035	0.025	0.026	0.024	0.014
F2	$\boxed{0.287^{**}}$	0.261**	0.189*	0.15	0.075	0.03	0.028	0.038	0.032	0.035	0.033	0.009
F3	0.276*	0.198	0.146	0.088	0.038	0.021	0.023	0.036	0.039	0.043	0.03	0.002
F4	0.246	0.179	0.106	0.051	0.034	0.018	0.025	0.049	0.052	0.045	0.028	0.005
F5	0.168	0.099	0.03	0.02	0.004	−0.011	0.015	0.025	0.014	0.008	−0.005	−0.017
F6	0.044	0.012	0.015	0.003	−0.011	−0.003	0.013	0.011	−0.001	−0.009	−0.025	−0.026
F7	0.036	0.042	0.03	0.008	0.007	0.001	0	−0.006	−0.018	−0.024	−0.03	−0.048
F8	0.071	0.035	0.024	0.022	0.017	−0.002	−0.007	−0.019	−0.033	−0.035	−0.045	−0.06
F9	0.064	0.026	0.015	0.014	−0.005	−0.019	−0.023	−0.023	−0.034	−0.041	−0.063	−0.074
F10	0.043	0.016	0.004	−0.014	−0.037	−0.043	−0.042	−0.05	−0.062	−0.074	−0.094	−0.111
F11	0.061	0.03	−0.003	−0.024	−0.041	−0.037	−0.033	−0.046	−0.057	−0.061	−0.08	−0.091
F12	0.033	−0.039	−0.071	−0.069	−0.076	−0.069	−0.074	−0.072	−0.088	−0.096	−0.11	−0.121

Panel B: Top bond momentum risk-adjusted returns

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
F1	0.187	0.197**	0.145*	0.135*	0.129*	0.072	0.054	0.05	0.032	0.017	0.021	0.015
F2	$\boxed{0.291^{**}}$	0.261**	0.202*	0.179*	0.104	0.058	0.049	0.042	0.019	0.017	0.024	0.016
F3	0.257	0.195	0.155	0.102	0.048	0.026	0.02	0.012	0.007	0.012	0.019	0.001
F4	0.262	0.203	0.142	0.09	0.068	0.044	0.035	0.036	0.039	0.043	0.037	0.014
F5	0.193	0.125	0.072	0.068	0.047	0.018	0.021	0.024	0.023	0.017	0.005	−0.003
F6	0.078	0.048	0.058	0.054	0.026	0.014	0.017	0.016	0.008	0	−0.014	−0.02
F7	0.087	0.085	0.081	0.058	0.043	0.027	0.019	0.009	−0.002	−0.009	−0.017	−0.034
F8	0.116	0.072	0.064	0.06	0.05	0.019	0.002	−0.015	−0.025	−0.029	−0.034	−0.039
F9	0.112	0.059	0.034	0.037	0.011	−0.017	−0.03	−0.028	−0.039	−0.05	−0.052	−0.072
F10	0.07	0.023	0.02	0.005	−0.032	−0.05	−0.049	−0.057	−0.062	−0.065	−0.085	−0.11
F11	0.051	0.019	−0.012	−0.03	−0.054	−0.052	−0.051	−0.062	−0.063	−0.078	−0.093	−0.105
F12	0.033	−0.051	−0.088	−0.083	−0.084	−0.081	−0.092	−0.084	−0.102	−0.121	−0.126	−0.134

Table 7: **Non-top Bond Raw and Risk-adjusted Momentum Returns**

For each t, for a formation period of j months, we identify bonds that have been continuously non-top bonds over the months spanning from $t-j-1$ to $t-1$. In month t, we sort the non-top bonds into deciles, on the basis of their historical cumulative returns over the formation period. An equally weighted portfolio of the non-top bonds in the highest (lowest) decile identifies the long (short) side of the non-top momentum portfolio. The bonds falling into the winner minus loser portfolio of non-top bonds are held for the entire duration of the holding period. The holding period monthly return is the average of the cross-section monthly returns of the overlapping winner-minus-loser portfolios. We consider momentum strategies with formation (F) and holding (H) periods ranging between 1 to 12 months. Panel A displays the average monthly holding periods raw returns of the resulting 144 momentum strategies. Panel B reports the corresponding risk-adjusted returns. Significance level at 1%, 5%, and 10% are indicated by ***, **, and *, respectively. Peak momentum raw and risk-adjusted returns are framed.

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
Panel A: Non-top momentum returns												
F1	0.086	0.149	0.093	0.107	0.123*	0.088	0.088	0.073	0.063	0.067	0.065	0.05
F2	0.214	0.228*	0.211*	0.226**	0.191**	0.164*	0.153*	0.146*	0.141	0.142	0.128	0.091
F3	0.201	0.265*	0.257*	0.25 * *	0.234**	0.205*	0.201*	0.204*	0.196*	0.196*	0.166	0.131
F4	0.288	0.355**	0.308**	0.312**	0.29 * *	0.25*	0.26*	0.26*	0.242*	0.227*	0.199	0.159
F5	0.368**	0.382**	0.334**	0.318**	0.285*	0.274*	0.284*	0.268*	0.234	0.21	0.179	0.132
F6	0.349*	$\boxed{0.4^{**}}$	0.346*	0.322*	0.296	0.281	0.278	0.243	0.208	0.178	0.14	0.098
F7	0.334*	0.381*	0.332*	0.318	0.296	0.27	0.251	0.212	0.172	0.132	0.095	0.045
F8	0.332	0.34	0.319	0.305	0.282	0.244	0.217	0.169	0.128	0.09	0.048	0.004
F9	0.295	0.35	0.324	0.306	0.268	0.221	0.188	0.135	0.096	0.059	0.012	−0.032
F10	0.272	0.323	0.296	0.266	0.217	0.18	0.14	0.093	0.046	0.008	−0.042	−0.093
F11	0.282	0.32	0.28	0.238	0.203	0.152	0.114	0.068	0.021	−0.019	−0.074	−0.12
F12	0.276	0.264	0.222	0.201	0.158	0.117	0.079	0.03	−0.011	−0.052	−0.099	−0.144

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
Panel B: Non-top momentum risk-adjusted returns												
F1	0.116	0.169*	0.127	0.145*	0.155**	0.126**	0.124**	0.106*	0.079	0.074	0.074	0.066
F2	0.225	0.247*	0.243**	0.262**	0.23 **	0.201**	0.183**	0.163*	0.139	0.135	0.129	0.094
F3	0.256	0.319*	0.312**	0.303**	0.281**	0.25 **	0.233**	0.212*	0.193*	0.193*	0.168	0.136
F4	0.361*	0.418**	0.38 **	0.382**	0.359**	0.313**	0.308**	0.287**	0.262*	0.248*	0.223*	0.187
F5	0.423**	0.438**	0.398**	0.389**	0.35 **	0.329**	0.32 **	0.294*	0.257*	0.236	0.206	0.163
F6	0.43 **	0.47 **	0.43 **	0.403**	0.366**	0.34*	0.321*	0.28	0.241	0.213	0.176	0.134
F7	0.436**	$\boxed{0.471^{**}}$	0.419**	0.396**	0.364*	0.332*	0.299	0.259	0.219	0.179	0.141	0.089
F8	0.416*	0.41*	0.394*	0.37*	0.343	0.297	0.26	0.211	0.168	0.128	0.084	0.044
F9	0.37	0.419*	0.389*	0.37*	0.324	0.27	0.23	0.175	0.135	0.094	0.049	0.005
F10	0.348	0.383	0.356	0.327	0.271	0.229	0.183	0.137	0.086	0.049	−0.003	−0.054
F11	0.338	0.365	0.335	0.293	0.247	0.193	0.149	0.101	0.056	0.014	−0.04	−0.088
F12	0.307	0.298	0.27	0.247	0.199	0.154	0.106	0.058	0.016	−0.026	−0.077	−0.119

Table 8: **Private-firm Top Bond Raw and Risk-adjusted Momentum Returns**

For each t, for a formation period of j months, we identify private-firm bonds that have been continuously top bonds over the months spanning from $t-j-1$ to $t-1$. In month t, we sort the top bonds into deciles, on the basis of their historical cumulative returns over the formation period. An equally weighted portfolio of the top bonds in the highest (lowest) decile identifies the long (short) side of the momentum portfolio. The bonds falling into the winner minus loser portfolio of top bonds are held for the entire duration of the holding period. The holding period monthly return is the average of the cross-section monthly returns of the overlapping winner-minus-loser portfolios. We consider momentum strategies with formation (F) and holding (H) periods ranging between 1 to 12 months. Panel A displays the average monthly holding periods raw returns of the resulting 144 momentum strategies. Panel B reports the corresponding risk-adjusted returns. Significance level at 1%, 5%, and 10% are indicated by ***, **, and *, respectively. Peak momentum raw and risk-adjusted returns are framed.

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
Panel A: Private-firm top momentum raw returns												
F1	0.197	0.238**	0.175*	0.141	0.136*	0.067	0.049	0.053	0.041	0.046	0.048	0.031
F2	$\boxed{0.368^{**}}$	0.35 * *	0.289**	0.234*	0.14	0.072	0.075	0.08	0.075	0.077	0.073	0.042
F3	0.324*	0.297*	0.231	0.165	0.092	0.055	0.056	0.068	0.08	0.076	0.06	0.02
F4	0.359*	0.302	0.208	0.147	0.105	0.066	0.081	0.1	0.099	0.082	0.047	0.029
F5	0.275	0.19	0.106	0.089	0.067	0.05	0.079	0.082	0.061	0.043	0.024	0.006
F6	0.115	0.074	0.075	0.053	0.033	0.036	0.068	0.047	0.022	0.021	0.001	−0.007
F7	0.062	0.109	0.101	0.084	0.081	0.071	0.063	0.059	0.033	0.018	0.013	−0.021
F8	0.099	0.087	0.062	0.045	0.04	0.026	0.018	0.003	−0.031	−0.021	−0.038	−0.059
F9	0.094	0.104	0.074	0.087	0.069	0.05	0.04	0.023	0.001	−0.008	−0.028	−0.041
F10	0.067	0.097	0.089	0.061	0.034	0.013	0.017	−0.005	−0.027	−0.038	−0.059	−0.076
F11	0.153	0.138	0.097	0.073	0.043	0.022	0.031	0.007	−0.005	−0.006	−0.029	−0.027
F12	0.158	0.114	0.062	0.04	0.009	0.003	0.021	−0.005	−0.012	−0.03	−0.046	−0.056

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
Panel B: Private-firm top momentum risk-adjusted returns												
F1	0.134	0.237**	0.175*	0.17*	0.168**	0.1	0.08	0.069	0.047	0.036	0.044	0.036
F2	0.359**	0.341**	0.303**	0.269**	0.175	0.104	0.104	0.093	0.071	0.065	0.075	0.062
F3	0.292	0.291	0.242	0.191	0.113	0.074	0.069	0.054	0.055	0.06	0.067	0.034
F4	$\boxed{0.38^*}$	0.331*	0.259	0.204	0.155	0.11	0.108	0.099	0.102	0.104	0.08	0.059
F5	0.315	0.231	0.161	0.153	0.129	0.098	0.098	0.098	0.092	0.073	0.051	0.038
F6	0.159	0.114	0.125	0.115	0.082	0.067	0.082	0.069	0.053	0.054	0.037	0.014
F7	0.112	0.161	0.16	0.143	0.122	0.108	0.092	0.088	0.054	0.047	0.039	0.01
F8	0.154	0.127	0.103	0.087	0.079	0.057	0.034	0.009	−0.017	−0.012	−0.023	−0.032
F9	0.126	0.127	0.095	0.111	0.097	0.065	0.042	0.033	0.006	−0.003	0	−0.025
F10	0.097	0.092	0.108	0.09	0.057	0.026	0.023	−0.002	−0.016	−0.022	−0.039	−0.074
F11	0.155	0.128	0.107	0.085	0.059	0.039	0.037	0.015	0.006	−0.016	−0.035	−0.039
F12	0.15	0.103	0.065	0.045	0.027	0.006	0.017	−0.001	−0.016	−0.043	−0.051	−0.056

Table 9: **Private-firm Non-top Bond Raw and Risk-adjusted Momentum Returns**

For each t, for a formation period of j months, we identify private-firm bonds that have been continuously non-top bonds over the months spanning from $t - j - 1$ to $t - 1$. In month t, we sort the non-top bonds into deciles, on the basis of their historical cumulative returns over the formation period. An equally weighted portfolio of the non-top bonds in the highest (lowest) decile identifies the long (short) side of the non-top momentum portfolio. The bonds falling into the winner minus loser portfolio of non-top bonds are held for the entire duration of the holding period. The holding period monthly return is the average of the cross-section monthly returns of the overlapping winner-minus-loser portfolios. We consider momentum strategies with formation (F) and holding (H) periods ranging between 1 to 12 months. Panel A displays the average monthly holding periods raw returns of the resulting 144 momentum strategies. Panel B reports the corresponding risk-adjusted returns. Significance level at 1%, 5%, and 10% are indicated by ***, **, and *, respectively. Peak momentum raw and risk-adjusted returns are framed.

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
Panel A: Private-firm non-top momentum raw returns												
F1	0.171	0.325**	0.212*	0.258**	0.264***	0.203**	0.2 * *	0.168*	0.178*	0.176*	0.14	0.107
F2	0.4 * *	0.469***	0.444***	0.478***	0.414***	0.376***	0.356***	0.333***	0.305**	0.286**	0.261**	0.211*
F3	0.522**	0.579***	0.573***	0.559***	0.515***	0.472***	0.448***	0.424***	0.403***	0.385**	0.34 * *	0.287**
F4	0.601**	0.773***	0.644***	0.657***	0.633***	0.571***	0.564***	0.537***	0.493***	0.466***	0.417**	0.365**
F5	0.898***	0.873***	0.761***	0.739***	0.678***	0.626***	0.61***	0.561***	0.506**	0.457**	0.41 * *	0.342*
F6	0.872***	0.883***	0.78***	0.74***	0.674***	0.628***	0.604***	0.551**	0.487**	0.433**	0.372*	0.315
F7	$\boxed{0.938^{***}}$	0.904***	0.801***	0.751***	0.685***	0.632**	0.589**	0.519**	0.45*	0.392*	0.326	0.265
F8	0.882***	0.833***	0.76***	0.713***	0.651**	0.593**	0.528**	0.455*	0.389	0.334	0.265	0.206
F9	0.822***	0.834***	0.784***	0.72***	0.65 * *	0.574**	0.507*	0.419	0.362	0.296	0.241	0.168
F10	0.793***	0.791***	0.757***	0.672**	0.587**	0.517*	0.437	0.364	0.282	0.227	0.157	0.093
F11	0.8 * **	0.805***	0.732**	0.652**	0.575**	0.482*	0.409	0.334	0.278	0.213	0.14	0.078

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
F12	0.763**	0.713**	0.656**	0.567*	0.482*	0.41	0.348	0.27	0.199	0.147	0.096	0.048

Panel B: Private-firm non-top momentum risk-adjusted returns

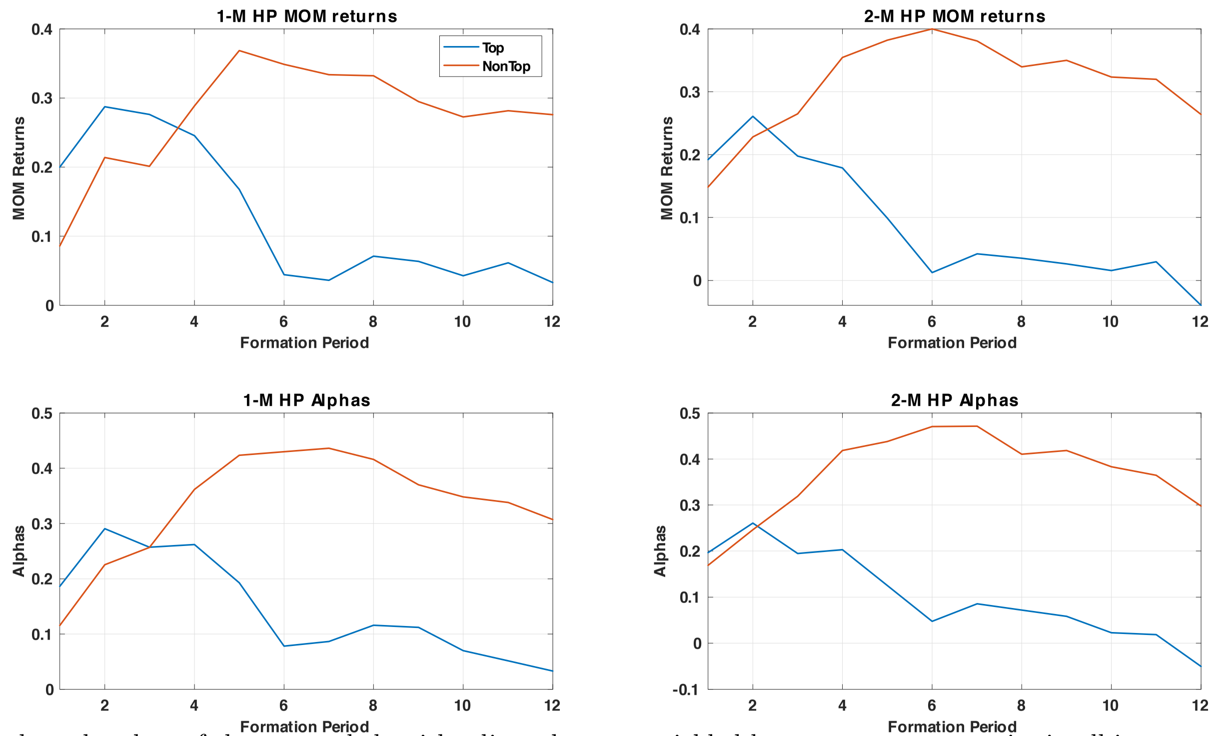
F1	0.157	0.371***	0.282**	0.334***	0.332***	0.278***	0.266***	0.23 * *	0.225**	0.211**	0.179**	0.15*
F2	0.438**	0.539***	0.533***	0.56***	0.494***	0.451***	0.423***	0.377***	0.329***	0.307**	0.284**	0.236**
F3	0.679***	0.709***	0.692***	0.664***	0.607***	0.556***	0.512***	0.461***	0.427***	0.403***	0.367**	0.313**
F4	0.761***	0.908***	0.769***	0.773***	0.74***	0.667***	0.647***	0.595***	0.545***	0.52***	0.476***	0.428**
F5	1.042***	1.002***	0.883***	0.862***	0.787***	0.731***	0.688***	0.624***	0.563***	0.518**	0.471**	0.406**
F6	1.031***	0.994***	0.891***	0.85***	0.78***	0.731***	0.684***	0.619***	0.553**	0.497**	0.442**	0.379*
F7	$\boxed{1.11^{***}}$	1.049***	0.925***	0.866***	0.793***	0.733***	0.678***	0.604**	0.529**	0.471**	0.404*	0.335
F8	1.036***	0.963***	0.879***	0.826***	0.757***	0.689***	0.611**	0.536**	0.463*	0.401	0.333	0.27
F9	0.952***	0.963***	0.903***	0.83***	0.747***	0.664**	0.586**	0.496*	0.434*	0.364	0.307	0.232
F10	0.917***	0.896***	0.857***	0.771***	0.677**	0.6 * *	0.51*	0.444	0.353	0.298	0.222	0.154
F11	0.915***	0.914***	0.835***	0.751**	0.667**	0.566**	0.484*	0.405	0.348	0.276	0.201	0.136
F12	0.869***	0.82***	0.764**	0.657**	0.568*	0.481*	0.41	0.331	0.254	0.201	0.147	0.098

Table 10: **Calibration of Momentum Risk-Adjusted Returns**

The table reports the results of the calibration of a second-degree polynomial $r_t^m = at^2 + bt$, where t is the formation periods, to the risk-adjusted momentum returns for top and non-top bond momentum strategies, in the whole sample, and for private issuer bonds. The polynomial coefficients are interpreted by imposing $z = -b/2a$ and $r^{max} = \gamma z$ where r^{max} is the peak of the fitted momentum return for a given holding period. The parameters $1/z$ and γ are interpreted as the speed of information diffusion and the relative proportion of uninformed traders, as in the framework of the model proposed by Hong and Stein (1999). The goodness of the fit (GoF) is measured by the R-squared adjusted for the degrees of freedom (df).

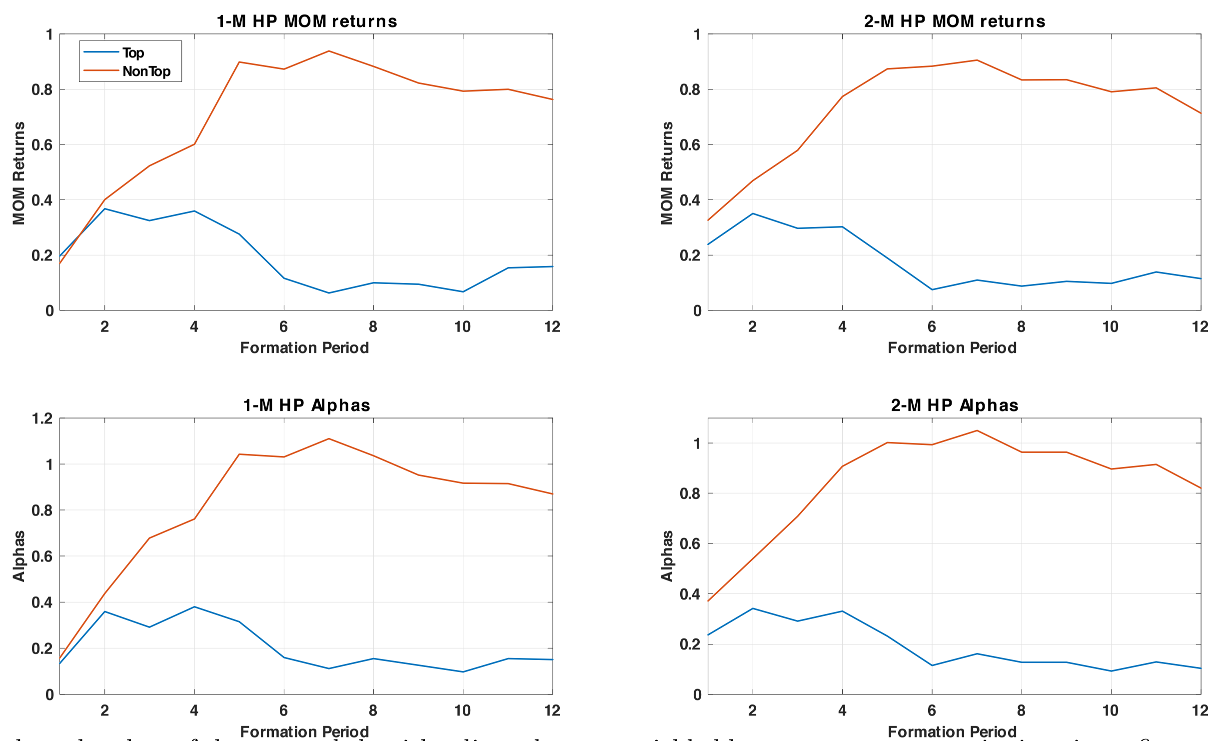
	Whole Sample			Private Firms			
Holding period	Speed	Gamma	GoF	Speed	Gamma	GoF	df
			Top bond momentum alpha				
1	0.318	0.093	0.923	0.286	0.104	0.86	4
2	0.338	0.081	0.766	0.314	0.109	0.882	4
			Non-top bond momentum alpha				
1	0.135	0.058	0.957	0.126	0.135	0.958	10
2	0.139	0.065	0.958	0.13	0.137	0.953	10
3	0.139	0.06	0.97	0.128	0.122	0.962	10
4	0.144	0.059	0.947	0.135	0.122	0.94	10
5	0.149	0.056	0.943	0.138	0.114	0.937	10
6	0.153	0.051	0.956	0.141	0.106	0.951	10
7	0.16	0.05	0.935	0.146	0.101	0.929	10
8	0.168	0.046	0.915	0.15	0.093	0.924	10
9	0.174	0.041	0.904	0.154	0.085	0.909	10
10	0.185	0.039	0.887	0.159	0.079	0.881	10
11	0.201	0.036	0.896	0.165	0.072	0.858	10
12	0.218	0.03	0.906	0.17	0.063	0.831	10

Figure 1: **Top and Non-top Bond Momentum (Whole-issuer Sample)**



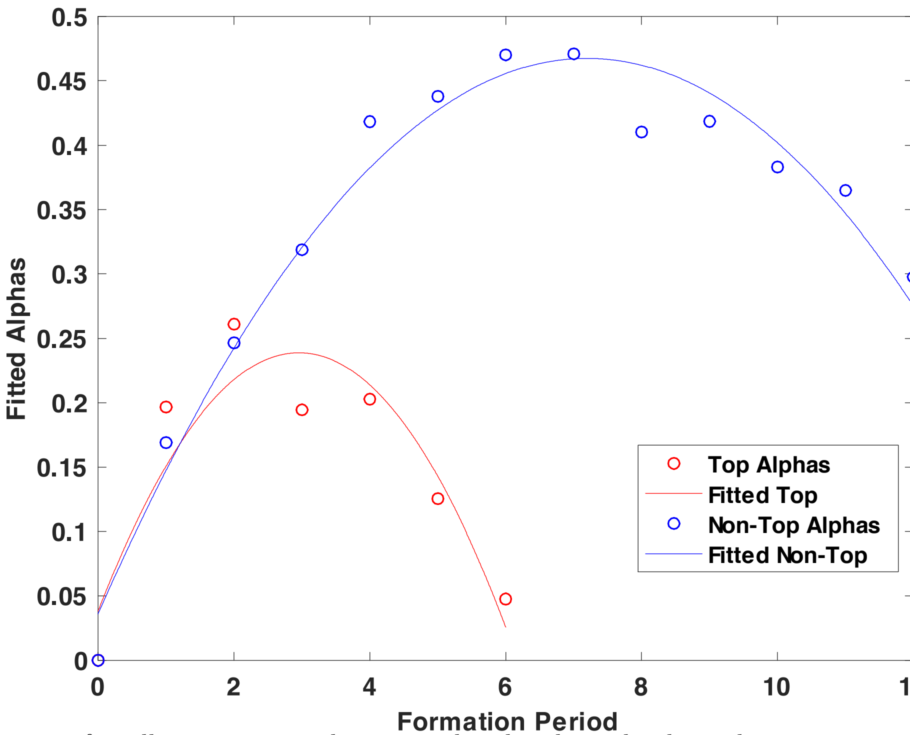
The figure displays the plots of the raw and the risk-adjusted returns yielded by momentum strategies in all-issuer top and non-top bonds with holding period (HP) of one or two months. Formation periods range from one to 12 months.

Figure 2: **Private-issuer Top and Non-top Bond Momentum**



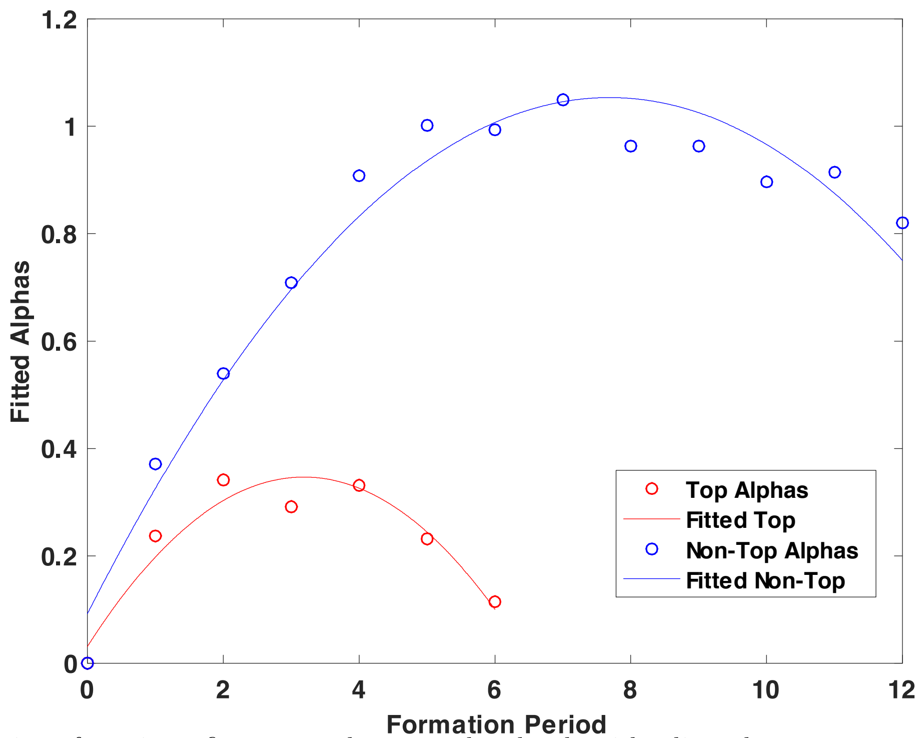
The figure displays the plots of the raw and the risk-adjusted returns yielded by momentum strategies in private-firm top and non-top bonds with holding period (HP) of one or two months. Formation periods range from one to 12 months.

Figure 3: **Calibration of the Top and Non-top Risk-adjusted Momentum Returns (Whole Sample)**



The figure depicts, for all-issuer top and non-top bonds, the risk-adjusted momentum returns and the fitted second-degree polynomials. The top bond risk-adjusted returns are for the two-month holding period momentum portfolio, for formation periods ranging from 1 to 6 months. The non-top bond risk-adjusted returns stem from the two-month holding momentum portfolio with formation period horizons ranging from 1 to 12 months.

Figure 4: **Calibration of the Top and Non-top Risk-adjusted Momentum Returns (Private Firms)**



The figure depicts, for private-firm top and non-top bonds, the risk-adjusted momentum returns and the corresponding fitted second-degree polynomials. The top bond risk-adjusted returns are for the two-month holding period momentum portfolio, for formation periods ranging from 1 to 6 months. The non-top bond risk-adjusted returns stem from the two-month holding momentum portfolio with formation period horizons ranging from 1 to 12 months.

A Appendix: Firm-level Momentum Strategies

As the identification of top and non-top bonds is at the issuer level, an alternative approach is to define firm-level top and non-top bond momentum strategies. To form the firm-level top-bond (non-top-bond) momentum strategy, past winners and losers are identified by ranking firms into deciles, on the basis of the cumulative returns of an EW portfolio of their top bonds (non-top bonds), over the formation period. The long and short legs of the top and non-top momentum strategy, along with the holding period returns are then defined analogously to the bond-level strategy, but for the use of firm-level EW portfolios of top and non-top bonds, instead of individual bonds. Again, we consider the top and non-top firm-level momentum strategies with formation and holding periods ranging from one month up to two years.

We note that each the top and non-top firm-level strategy identifies a set of firms, rather than a set of bonds, as winners and losers. In this sense, the firm-level momentum strategies are comparable to momentum strategies in equities. However, the focus on top and non-top bonds issued by the same firm allows to take into account the effect of information heterogeneity in the firm-level bond cross-section.

The firm-level approach yields conclusions that are consistent with those presented for the bond-level analysis, as shown in Table 11, for the whole-firm sample and in Table 12 for private issuers. The disadvantage of the firm-level approach is that it does not yield fully real-time momentum portfolios, as, in the formation month, investors do not know which bonds will be top and non-top during the holding period.

In Ronen and Zhou (2013), there is one top bond per issuer, which is identified, among the bonds populating the firm-level bond cross-section, as the bond attracting the highest institutional trade volume in the hours following earnings announcements, but preceding the NYSE market open. Wei and Zhou (2016) identify one firm-level top bond as the bond attracting the highest institutional trade volume in the hours preceding earnings announcements.[27] Notably, in this study, we discuss information diffusion without taking an event-based approach, an endeavor requiring a definition of top bonds that is not event-specific. Hence, we identify the top-one bond for each firm in each month, on the basis of the highest volume of institutional trades.

[27] Tsai (2014) relies on an alternative identification strategy of high-information bonds, which we use as a robustness check of our results. In untabulated results, we confirm that this study's conclusions remain unchanged using the approach proposed by Tsai.

While Ronen and Zhou (2013) and Wei and Zhou (2016) focus on one top-bond per issuer, in this study we allow three top bonds per firm. This approach increases the number of top bonds used to form the bond-level momentum deciles, thus yielding bond-level momentum strategies with returns that are less driven by outliers.[28] However, as a robustness check, we experiment with top-one firm-level momentum portfolios, in which firms, rather than bonds, are ranked by the cumulative return of their top-one bonds, over the formation period.[29] The firm-level top-one bond momentum strategy average returns are displayed in Table 13, and are similar to those observed in Panels A and B of Tables 11 and 12 for the firm-level analysis, using top-three bonds.

[28] At the firm level, bonds retain the status of top-one bonds only for few months, which would make the implementation of bond-level momentum strategies for top-bonds problematic, especially for formation periods longer than few periods.

[29] In month t, and for each issuer i, the bond with the highest total dollar volume of institutional trades (if any) is identified as firm i's top-one bond, in month t.

Table 11: **Firm-level Top and Non-top Bond Raw and Risk-adjusted Momentum Returns**

For each month, we identify bonds that are top and non-top bonds for each firm and form firm-level EW portfolios of top and non-top bonds. We sort issuers into deciles, on the basis of the historical cumulative returns of the top-bond EW firm-level portfolio, over the formation period. An equally weighted portfolio of the EW top bond indexes falling into the highest (lowest) decile identifies the long (short) side of the firm-level momentum portfolio. The (monthly recalibrated) EW firm-level top bond indexes falling into the winner minus loser portfolio are held for the entire duration of the holding period. The holding period monthly return is the average of the cross-section monthly returns of the overlapping winner-minus-loser portfolios. We consider momentum strategies with formation (F) and holding (H) periods ranging between 1 to 12 months. Panel A displays the average monthly holding periods raw returns for the top bond firm-level momentum strategies. Panel B reports the corresponding risk-adjusted returns. The non-top firm-level momentum strategies are designed analogously. Panel C displays the average monthly holding periods raw returns for the non-top bond firm-level momentum strategies. Panel D reports the corresponding risk-adjusted returns. Significance level at 1%, 5%, and 10% are indicated by ***, **, and *, respectively. Peak momentum raw and risk-adjusted returns are framed.

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
Panel A: Top Firm-level Momentum Raw Returns												
F1	0.259**	0.279***	0.21**	0.174**	0.156**	0.1	0.086	0.082	0.068	0.068	0.069	0.049
F2	$\boxed{0.367^{***}}$	0.317***	0.227**	0.192*	0.125	0.09	0.087	0.084	0.076	0.086	0.084	0.064
F3	0.328**	0.258*	0.212*	0.141	0.105	0.089	0.085	0.092	0.098	0.104	0.093	0.073
F4	0.314**	0.266*	0.183	0.14	0.12	0.097	0.102	0.122	0.125	0.121	0.107	0.093
F5	0.287*	0.208	0.142	0.124	0.1	0.089	0.101	0.118	0.12	0.107	0.1	0.088
F6	0.158	0.15	0.124	0.091	0.078	0.079	0.093	0.109	0.099	0.092	0.084	0.076
F7	0.137	0.142	0.101	0.082	0.084	0.081	0.088	0.092	0.085	0.083	0.071	0.05
F8	0.186	0.144	0.109	0.103	0.093	0.087	0.093	0.095	0.086	0.083	0.066	0.042
F9	0.115	0.124	0.121	0.108	0.098	0.099	0.103	0.112	0.108	0.097	0.071	0.046
F10	0.13	0.14	0.119	0.095	0.078	0.073	0.082	0.084	0.061	0.043	0.023	0.003
F11	0.176	0.168	0.13	0.099	0.088	0.09	0.1	0.092	0.07	0.048	0.023	0.003
F12	0.16	0.13	0.095	0.081	0.084	0.084	0.082	0.065	0.04	0.027	0.008	−0.011
Panel B: Top Firm-level Momentum Risk-adjusted Returns												

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
F1	0.26**	0.275***	0.208**	0.189**	0.171**	0.115*	0.098	0.086	0.065	0.053	0.062	0.047
F2	$\boxed{0.362^{***}}$	0.308**	0.229**	0.203**	0.135	0.095	0.092	0.079	0.06	0.064	0.068	0.057
F3	0.299**	0.243*	0.2	0.135	0.099	0.083	0.076	0.072	0.073	0.079	0.079	0.061
F4	0.31**	0.275*	0.194	0.156	0.137	0.108	0.102	0.109	0.11	0.108	0.098	0.085
F5	0.296*	0.219	0.159	0.148	0.117	0.096	0.098	0.106	0.111	0.096	0.087	0.076
F6	0.167	0.162	0.142	0.11	0.088	0.078	0.087	0.1	0.09	0.078	0.07	0.06
F7	0.153	0.157	0.119	0.098	0.09	0.082	0.084	0.085	0.072	0.069	0.058	0.041
F8	0.202	0.153	0.115	0.104	0.09	0.079	0.078	0.078	0.068	0.063	0.047	0.024
F9	0.105	0.109	0.103	0.092	0.077	0.072	0.073	0.084	0.076	0.066	0.043	0.017
F10	0.129	0.119	0.101	0.079	0.055	0.042	0.05	0.052	0.03	0.011	−0.009	−0.03
F11	0.146	0.143	0.106	0.071	0.058	0.058	0.066	0.057	0.033	0.009	−0.015	−0.035
F12	0.137	0.103	0.064	0.051	0.053	0.049	0.044	0.027	−0.001	−0.018	−0.034	−0.053
Panel C: Non-top Firm-level Momentum Raw Returns												
F1	0.129	0.15**	0.147**	0.127**	0.136***	0.094*	0.078	0.074	0.063	0.064	0.052	0.047
F2	0.198**	0.245***	0.24***	0.198***	0.165**	0.137**	0.119*	0.114*	0.1*	0.094*	0.08	0.062
F3	0.272***	0.255***	0.261***	0.223***	0.18**	0.15**	0.139*	0.139**	0.134**	0.129**	0.107*	0.091
F4	$\boxed{0.284^{**}}$	0.284***	0.253***	0.225**	0.202**	0.179**	0.162**	0.167**	0.159**	0.143**	0.125*	0.107
F5	0.275**	0.247**	0.211**	0.192**	0.161*	0.138	0.135	0.142*	0.133*	0.116	0.102	0.095
F6	0.218*	0.189*	0.178*	0.163	0.151	0.133	0.129	0.129	0.118	0.105	0.089	0.075
F7	0.187	0.196*	0.177*	0.163	0.145	0.126	0.123	0.122	0.104	0.092	0.074	0.05
F8	0.21*	0.18	0.16	0.156	0.135	0.109	0.103	0.097	0.083	0.071	0.051	0.032
F9	0.186	0.194*	0.176	0.16	0.134	0.121	0.112	0.098	0.083	0.063	0.04	0.018
F10	0.13	0.143	0.12	0.116	0.101	0.082	0.073	0.064	0.043	0.019	0.004	−0.013
F11	0.17	0.167	0.159	0.153	0.12	0.1	0.085	0.076	0.049	0.022	−0.001	−0.019
F12	0.135	0.136	0.134	0.113	0.089	0.079	0.069	0.051	0.026	0.006	−0.014	−0.032
Panel D: Non-top Firm-level Momentum Risk-adjusted Returns												
F1	0.152*	0.148**	0.165***	0.135**	0.149***	0.101**	0.095**	0.094**	0.077*	0.07*	0.066*	0.051
F2	0.179*	0.232**	0.236***	0.198***	0.164**	0.137**	0.124**	0.118**	0.097*	0.092*	0.075	0.059
F3	0.266**	0.248**	0.263***	0.219**	0.177**	0.149**	0.14*	0.134*	0.125*	0.12*	0.104*	0.09
F4	0.277**	0.281***	0.26***	0.226**	0.217**	0.194**	0.176**	0.17**	0.155**	0.143**	0.128*	0.108
F5	$\boxed{0.283^{**}}$	0.243**	0.215**	0.203**	0.172*	0.149*	0.143	0.142*	0.134*	0.12	0.106	0.092

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
F6	0.213*	0.179	0.183*	0.168*	0.159*	0.141	0.129	0.127	0.116	0.105	0.088	0.068
F7	0.187	0.204*	0.192*	0.176*	0.16*	0.137	0.13	0.126	0.105	0.09	0.071	0.047
F8	0.217*	0.185*	0.171*	0.163*	0.143	0.112	0.101	0.096	0.079	0.062	0.043	0.023
F9	0.191*	0.198*	0.185*	0.163	0.134	0.119	0.106	0.089	0.07	0.05	0.029	0.005
F10	0.125	0.132	0.108	0.104	0.092	0.074	0.064	0.053	0.028	0.007	−0.009	−0.031
F11	0.162	0.157	0.149	0.141	0.111	0.091	0.072	0.061	0.033	0.002	−0.02	−0.038
F12	0.116	0.126	0.125	0.102	0.078	0.067	0.052	0.035	0.008	−0.015	−0.034	−0.052

Table 12: **Private-issuer Firm-level Top and Non-top Bond Raw and Risk-adjusted Momentum Returns**

For each month, we identify bonds that are top and non-top bonds for each private issuer and form firm-level EW portfolios of top and non-top bonds. We sort issuers into deciles, on the basis of the historical cumulative returns of the top-bond EW firm-level portfolio, over the formation period. An equally weighted portfolio of the EW top bond indexes falling into the highest (lowest) decile identifies the long (short) side of the firm-level top bond momentum strategy. The (monthly recalibrated) EW firm-level top bond indexes falling into the winner minus loser portfolio are held for the entire duration of the holding period. The holding period monthly return is the average of the cross-section monthly returns of the overlapping winner-minus-loser portfolios. We consider momentum strategies with formation (F) and holding (H) periods ranging between 1 to 12 months. Panel A displays the average monthly holding periods raw returns for the top bond firm-level momentum strategies. Panel B reports the corresponding risk-adjusted returns. The non-top firm-level momentum strategies for private-bonds are designed analogously. Panel C displays the average monthly holding periods raw returns for the non-top bond firm-level momentum strategies. Panel D reports the corresponding risk-adjusted returns. Significance level at 1%, 5%, and 10% are indicated by ***, **, and *, respectively. Peak momentum raw and risk-adjusted returns are framed.

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
Panel A: Firm-level Private-issuer Top Bond Momentum Raw Returns												
F1	0.316**	0.356***	0.283***	0.239***	0.221***	0.161**	0.133*	0.133*	0.119*	0.122**	0.12 **	0.091*
F2	0.44***	0.426***	0.323***	0.276**	0.2*	0.165*	0.166*	0.163*	0.16 **	0.156**	0.148**	0.12*
F3	0.399**	0.364**	0.319**	0.249*	0.186	0.172	0.163	0.182*	0.18*	0.182**	0.158*	0.129
F4	$\boxed{0.442^{**}}$	0.394**	0.313**	0.237	0.206	0.168	0.183	0.2*	0.188*	0.172	0.148	0.12
F5	0.41 **	0.324**	0.24	0.205	0.181	0.154	0.18	0.195	0.185	0.177	0.153	0.126
F6	0.274	0.233	0.208	0.174	0.158	0.151	0.175	0.18	0.159	0.149	0.136	0.117
F7	0.217	0.237	0.194	0.159	0.158	0.165	0.164	0.175	0.155	0.139	0.12	0.097
F8	0.279	0.228	0.18	0.165	0.175	0.174	0.182	0.179	0.159	0.154	0.117	0.086
F9	0.233	0.223	0.203	0.179	0.161	0.158	0.171	0.171	0.158	0.147	0.113	0.075
F10	0.178	0.199	0.2	0.155	0.146	0.129	0.138	0.14	0.116	0.101	0.055	0.029
F11	0.244	0.253	0.209	0.163	0.144	0.138	0.156	0.144	0.118	0.086	0.057	0.032

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
F12	0.237	0.209	0.16	0.11	0.121	0.133	0.123	0.11	0.078	0.066	0.036	0.022
Panel B: Firm-level Private-issuer Top Bond Momentum Risk-adjusted Returns												
F1	0.29 ∗ ∗	0.347∗∗∗	0.284∗∗∗	0.259∗∗∗	0.234∗∗∗	0.176∗∗	0.146∗∗	0.135∗	0.111∗	0.106∗	0.113∗	0.088
F2	0.416∗∗∗	0.411∗∗∗	0.321∗∗∗	0.284∗∗	0.204∗	0.172∗	0.172∗	0.159∗	0.145∗	0.136∗	0.138∗∗	0.12∗
F3	0.373∗∗	0.358∗∗	0.313∗∗	0.25∗	0.185	0.174	0.162	0.17∗	0.161∗	0.168∗	0.154∗	0.128
F4	$\boxed{0.455^{**}}$	0.413∗∗	0.342∗∗	0.27∗	0.238∗	0.193	0.2	0.2∗	0.188∗	0.177	0.155	0.128
F5	0.423∗∗	0.344∗∗	0.262∗	0.239	0.205	0.174	0.183	0.192	0.188	0.179	0.152	0.125
F6	0.297∗	0.257	0.24	0.203	0.18	0.164	0.183	0.181	0.158	0.142	0.132	0.104
F7	0.239	0.261	0.218	0.177	0.168	0.175	0.169	0.175	0.15	0.137	0.11	0.09
F8	0.306∗	0.259	0.199	0.176	0.185	0.179	0.175	0.167	0.15	0.144	0.107	0.076
F9	0.251	0.224	0.197	0.178	0.152	0.147	0.154	0.157	0.138	0.129	0.097	0.057
F10	0.185	0.191	0.19	0.146	0.132	0.111	0.117	0.115	0.093	0.081	0.035	−0.002
F11	0.243	0.243	0.202	0.15	0.128	0.121	0.132	0.123	0.092	0.061	0.034	0.001
F12	0.219	0.193	0.136	0.089	0.099	0.106	0.092	0.079	0.043	0.03	0.001	−0.015
Panel C: Firm-level Private-issuer Non-top Bond Momentum Raw Returns												
F1	0.266∗∗	0.246∗∗∗	0.208∗∗∗	0.209∗∗∗	0.202∗∗∗	0.169∗∗	0.148∗∗	0.12∗	0.113∗	0.114∗∗	0.089	0.081
F2	0.275∗∗	0.318∗∗∗	0.296∗∗∗	0.276∗∗∗	0.251∗∗∗	0.217∗∗∗	0.188∗∗	0.169∗∗	0.153∗∗	0.151∗∗	0.13 ∗ ∗	0.107∗
F3	0.316∗∗	0.31 ∗ ∗	0.321∗∗∗	0.307∗∗∗	0.256∗∗	0.237∗∗	0.226∗∗	0.209∗∗	0.222∗∗	0.217∗∗	0.184∗∗	0.151∗∗
F4	0.346∗∗	0.333∗∗	0.313∗∗	0.324∗∗∗	0.301∗∗∗	0.281∗∗	0.274∗∗	0.288∗∗∗	0.281∗∗∗	0.264∗∗∗	0.231∗∗	0.195∗∗
F5	$\boxed{0.398^{**}}$	0.379∗∗∗	0.357∗∗∗	0.333∗∗∗	0.303∗∗	0.286∗∗	0.28 ∗ ∗	0.285∗∗	0.266∗∗	0.233∗∗	0.216∗∗	0.205∗∗
F6	0.382∗∗	0.348∗∗	0.352∗∗	0.325∗∗	0.308∗∗	0.292∗∗	0.294∗∗	0.281∗∗	0.268∗∗	0.246∗∗	0.203∗	0.181∗
F7	0.356∗∗	0.324∗∗	0.302∗∗	0.295∗∗	0.277∗∗	0.276∗∗	0.271∗∗	0.247∗∗	0.229∗∗	0.199∗	0.176	0.137
F8	0.374∗∗	0.325∗∗	0.289∗∗	0.289∗∗	0.278∗∗	0.265∗∗	0.24∗	0.226∗	0.187	0.155	0.118	0.097
F9	0.331∗∗	0.289∗	0.274∗	0.272∗	0.257∗	0.235∗	0.213∗	0.181	0.158	0.121	0.088	0.049
F10	0.286∗	0.274∗	0.276∗	0.286∗∗	0.262∗∗	0.231∗	0.213	0.184	0.156	0.124	0.091	0.06
F11	0.327∗∗	0.299∗∗	0.295∗∗	0.273∗∗	0.253∗	0.236∗	0.203	0.17	0.141	0.097	0.063	0.036
F12	0.311∗∗	0.296∗∗	0.287∗∗	0.249∗	0.226	0.193	0.178	0.145	0.107	0.081	0.046	0.013
Panel D: Firm-level Private-issuer Non-top Bond Momentum Risk-adjusted Returns												
F1	0.304∗∗	0.263∗∗∗	0.25∗∗∗	0.241∗∗∗	0.231∗∗∗	0.192∗∗∗	0.178∗∗∗	0.16∗∗∗	0.131∗∗	0.123∗∗	0.113∗∗	0.093∗
F2	0.28 ∗ ∗	0.339∗∗∗	0.321∗∗∗	0.286∗∗∗	0.258∗∗∗	0.225∗∗∗	0.202∗∗	0.179∗∗	0.15 ∗ ∗	0.147∗∗	0.128∗	0.112∗
F3	0.368∗∗∗	0.348∗∗∗	0.356∗∗∗	0.326∗∗∗	0.269∗∗	0.253∗∗	0.233∗∗	0.211∗∗	0.218∗∗	0.216∗∗	0.198∗∗	0.16 ∗ ∗

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
F4	0.38 * *	0.371***	0.34***	0.341***	0.326***	0.307***	0.302***	0.308***	0.292***	0.281***	0.259***	0.221**
F5	$\boxed{0.485^{***}}$	0.42***	0.387***	0.364***	0.324***	0.309**	0.303**	0.305***	0.289***	0.266**	0.249**	0.234**
F6	0.419***	0.37 * *	0.374***	0.342**	0.328**	0.319**	0.313**	0.305**	0.293**	0.273**	0.236**	0.204*
F7	0.389**	0.371**	0.334**	0.33 * *	0.314**	0.31 * *	0.306**	0.281**	0.254**	0.229*	0.21*	0.17
F8	0.419***	0.362**	0.313**	0.319**	0.314**	0.302**	0.273**	0.256**	0.215*	0.176	0.144	0.118
F9	0.378**	0.321**	0.301**	0.294**	0.286**	0.261**	0.232*	0.2	0.17	0.134	0.108	0.067
F10	0.307**	0.3 * *	0.293**	0.309**	0.29 * *	0.255*	0.229*	0.199	0.169	0.136	0.107	0.073
F11	0.367**	0.328**	0.318**	0.291**	0.271**	0.254*	0.213	0.18	0.147	0.104	0.068	0.042
F12	0.338**	0.337**	0.321**	0.275**	0.251*	0.212	0.192	0.159	0.117	0.088	0.059	0.025

Table 13: **Firm-level Top1 Bond Raw and Risk-adjusted Momentum Returns**

For each t, for a formation period of j months, we identify the top-one bond. We sort issuers into deciles, on the basis of the historical cumulative returns of their respective top-one bond, over the formation period. An equally weighted portfolio of the top-one bonds of the issuers falling into the highest (lowest) firm decile identifies the long (short) side of the firm-level top-one bond momentum portfolio. For each month of the holding period, the portfolio is updated to include the top-one bond issued by the firms falling into the winner minus loser portfolio. The holding period monthly return is the average of the cross-section monthly returns of the overlapping winner-minus-loser portfolios. We consider momentum strategies with formation (F) and holding (H) periods ranging between 1 to 12 months. Panel A displays the average monthly holding periods raw returns for the top-one bond firm-level momentum strategies. Panel B reports the corresponding risk-adjusted returns. Panel C and D report the analogous raw and risk-adjusted returns for private issuers. Significance level at 1%, 5%, and 10% are indicated by ***, **, and *, respectively. Peak momentum raw and risk-adjusted returns are framed.

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
Panel A: Firm-level Top1 Momentum Raw Returns (Whole Sample)												
F1	0.206*	0.193**	0.153*	0.115	0.106	0.061	0.055	0.057	0.046	0.039	0.047	0.034
F2	$\boxed{0.32^{**}}$	0.275**	0.198**	0.154*	0.102	0.073	0.066	0.062	0.049	0.051	0.041	0.023
F3	0.282**	0.221*	0.184	0.142	0.101	0.096	0.095	0.092	0.091	0.083	0.074	0.057
F4	0.261*	0.24*	0.185	0.133	0.126	0.11	0.108	0.115	0.107	0.098	0.083	0.073
F5	0.265*	0.203	0.143	0.118	0.105	0.091	0.106	0.116	0.109	0.095	0.082	0.071
F6	0.163	0.13	0.113	0.092	0.078	0.086	0.093	0.099	0.085	0.074	0.059	0.056
F7	0.15	0.149	0.112	0.084	0.077	0.077	0.077	0.081	0.069	0.06	0.05	0.031
F8	0.159	0.134	0.108	0.088	0.084	0.078	0.076	0.078	0.067	0.06	0.05	0.031
F9	0.135	0.112	0.112	0.091	0.072	0.069	0.07	0.078	0.07	0.056	0.042	0.024
F10	0.14	0.129	0.108	0.079	0.06	0.053	0.061	0.058	0.048	0.029	0.01	−0.009
F11	0.156	0.139	0.104	0.071	0.063	0.064	0.072	0.065	0.044	0.029	0.011	0
F12	0.112	0.084	0.072	0.057	0.052	0.049	0.046	0.037	0.015	0	−0.014	−0.028
Panel B: Firm-level Top1 Risk-adjusted Momentum Returns (Whole Sample)												
F1	0.196*	0.182*	0.15*	0.126*	0.114*	0.067	0.067	0.062	0.052	0.03	0.041	0.033
F2	$\boxed{0.317^{**}}$	0.271**	0.208**	0.164*	0.105	0.078	0.072	0.064	0.04	0.031	0.026	0.02

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
F3	0.264*	0.208*	0.174	0.129	0.088	0.087	0.088	0.074	0.07	0.061	0.061	0.048
F4	0.26*	0.247*	0.189	0.14	0.132	0.12	0.111	0.105	0.096	0.088	0.078	0.068
F5	0.257*	0.195	0.147	0.127	0.112	0.094	0.102	0.105	0.1	0.085	0.069	0.06
F6	0.152	0.122	0.12	0.102	0.081	0.083	0.086	0.087	0.074	0.06	0.046	0.038
F7	0.156	0.151	0.123	0.093	0.078	0.074	0.072	0.072	0.056	0.045	0.034	0.014
F8	0.168	0.134	0.112	0.085	0.077	0.068	0.063	0.062	0.05	0.041	0.03	0.01
F9	0.13	0.1	0.098	0.078	0.056	0.049	0.044	0.055	0.044	0.03	0.014	−0.006
F10	0.121	0.11	0.089	0.061	0.034	0.027	0.035	0.029	0.019	−0.002	−0.024	−0.042
F11	0.132	0.123	0.087	0.05	0.041	0.039	0.041	0.031	0.009	−0.008	−0.025	−0.04
F12	0.097	0.073	0.051	0.035	0.031	0.02	0.014	0.006	−0.02	−0.036	−0.051	−0.066
Panel C: Firm-level Top1 Momentum Returns (Private Issuers)												
F1	0.263**	0.249**	0.211**	0.166*	0.157**	0.098	0.084	0.098	0.074	0.077	0.071	0.039
F2	0.395***	$\boxed{0.4^{***}}$	0.318***	0.246**	0.197**	0.161*	0.157*	0.149*	0.127*	0.125*	0.113*	0.07
F3	0.355**	0.344**	0.289**	0.234*	0.179	0.182	0.179*	0.183*	0.172*	0.17 * *	0.14*	0.117
F4	0.352**	0.33 * *	0.275*	0.205	0.178	0.155	0.168	0.18	0.183*	0.167*	0.137	0.113
F5	0.33 * *	0.273*	0.19	0.151	0.121	0.107	0.128	0.15	0.137	0.113	0.092	0.069
F6	0.175	0.195	0.186	0.148	0.133	0.146	0.148	0.153	0.12	0.103	0.089	0.075
F7	0.232	0.258	0.213	0.172	0.142	0.145	0.149	0.147	0.118	0.11	0.091	0.06
F8	0.195	0.181	0.149	0.123	0.12	0.114	0.11	0.111	0.091	0.08	0.061	0.025
F9	0.182	0.153	0.148	0.133	0.123	0.108	0.104	0.103	0.084	0.07	0.051	0.015
F10	0.192	0.189	0.185	0.132	0.122	0.092	0.095	0.089	0.064	0.043	0.012	−0.02
F11	0.235	0.23	0.176	0.132	0.101	0.092	0.089	0.073	0.059	0.037	0.009	−0.011
F12	0.239	0.182	0.128	0.079	0.057	0.059	0.055	0.044	0.019	−0.001	−0.02	−0.055
Panel D: Firm-level Top1 Risk-adjusted Momemtum Returns (Private issuers)												
F1	0.234*	0.233**	0.22 * *	0.19 * *	0.175**	0.114	0.107	0.107	0.076	0.07	0.065	0.044
F2	0.37 * *	$\boxed{0.386^{***}}$	0.324***	0.255**	0.199**	0.172*	0.172**	0.151*	0.116	0.105	0.1	0.076
F3	0.329**	0.34 * *	0.29 * *	0.236*	0.177	0.187*	0.178*	0.171*	0.151*	0.155*	0.136*	0.12
F4	0.359**	0.346**	0.294**	0.233*	0.2	0.175	0.177	0.175*	0.178*	0.167*	0.142	0.119
F5	0.329**	0.289*	0.212	0.18	0.14	0.122	0.126	0.146	0.141	0.115	0.089	0.067
F6	0.174	0.201	0.197	0.163	0.135	0.144	0.144	0.147	0.114	0.096	0.084	0.063
F7	0.237	0.267*	0.229	0.189	0.147	0.147	0.151	0.143	0.113	0.108	0.084	0.052

	$H1$	$H2$	$H3$	$H4$	$H5$	$H6$	$H7$	$H8$	$H9$	$H10$	$H11$	$H12$
F8	0.19	0.172	0.142	0.116	0.106	0.103	0.09	0.09	0.072	0.059	0.04	0.003
F9	0.181	0.138	0.125	0.116	0.103	0.086	0.08	0.079	0.058	0.048	0.028	−0.016
F10	0.171	0.161	0.161	0.111	0.084	0.057	0.067	0.058	0.037	0.017	−0.016	−0.053
F11	0.209	0.211	0.158	0.1	0.064	0.055	0.05	0.037	0.023	−0.003	−0.029	−0.055
F12	0.242	0.182	0.105	0.051	0.022	0.019	0.014	0.004	−0.026	−0.048	−0.068	−0.102

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