Implied Default Probability and Corporate Bond Returns

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Abstract

We study the asset pricing implications of option-implied default probability in the cross-section of corporate bond returns. We find that corporate bonds with low changes in probability to default (ΔOPD) outperform those with large increases by 43 basis points. Such outperformance can be attributed to the enhanced information content of ΔOPD compared to existing default risk proxies used in bond pricing, particularly in accurately capturing the probability of actual bankruptcy. We provide evidence suggesting that the explanatory power of ΔOPD originates from continuous updates on balance sheet information and investors' preferences reflected in the options market. Such effect is amplified in regimes of bearish sentiment and periods of heightened aggregate risk level. This further reinforces our hypothesis on the diffusion of information from options to bonds.

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1. Introduction

The most crucial risk bondholders face is when the issuing firm defaults, a situation where the issuer cannot meet its financial obligation to repay interest and the principle. As such, the probability of default plays a vital role in bond pricing (Elton, et al., 1995; Bai, et al., 2019; Chen, et al., 2022). In the default risk literature, efforts have so far been focused on quantifying default risk using backward-looking information such as financial accounting data (Altman, 1968; Ohlson, 1980), the Merton Model (Hillegeist, et al., 2004; Bharath and Shumway, 2008), downside risk (Bai, Bali and Wen, 2019), and volatility (Chung, et al., 2019; Bali, et al., 2021). The use of forward-looking measures of default risk is relatively scarce. One exception is Conrad et al. (2020), who formalized the approach of estimating option-implied default probabilities. In the bond pricing literature, Cao et al. (2023, MS) document the pricing implication of implied volatility changes in cross-sectional bond returns. They hypothesized that an increase in implied volatility (ΔIMPVOL) represents an unexpected increase in default risk that leads to lower bond return.

In this paper, we investigate the asset pricing implications of the changes in option-implied probability of default (ΔOPD) in the cross-section of corporate bond returns. More specifically, we follow the approach of Conrad, et al. (2020) and estimate ΔOPD for each firm at each period in the cross-section. We investigate two research questions in this study: 1) if forward-looking option-implied probability captures more information regarding actual default probability in the cross-section; 2) if ΔOPD is priced in the cross-section of corporate bond returns. Using forward-looking information in corporate bond pricing is especially important given that corporate bond default rates are positively skewed (Giesecke et al., 2011). Our study indicates that ΔOPD negatively explains the future returns of bonds in the cross-section. Bonds in the bottom quintile (low ΔOPD) outperform those in the top quintile (high ΔOPD) by 43 basis points (bps) per month (t-stat = −3.67). Using Fama and French (1993) regressions and double sorts, we further confirm that ΔOPD remains a robust predictor of cross-sectional bond returns after controlling for an established list of bond return predictors in the literature. More importantly, the predictive power of ΔOPD remains consistent when ΔIMPVOL is controlled for in both firm-level regression and double sorts. This suggests that ΔOPD contains unique and significant incremental default risk information in explaining cross-sectional bond returns in contrast to ΔIMPVOL proposed by Cao et al. (2023, MS).

Additionally, we examine the performance of this long-short trading strategy over time and find that its profitability is amplified in regimes of bearish sentiment and heightened aggregate risk level. We also investigate the information content of ΔOPD in predicting bankruptcy or failure events in the following months. We provide evidence supporting our hypothesis on the diffusion of information from options to bonds. First, we relate ΔOPD to contemporaneous changes in option volume. We show that informed investors aware of increasing ΔOPD prefer to trade put options, thus enhancing its predictability. Second, firms exhibiting stronger bearish sentiment in options trading information

manifest higher levels of predictable bond return attributable to ΔOPD. Third, we show that bonds experiencing the highest trading volumes in both markets exhibit the most pronounced predictability of ΔOPD, suggesting that the options market leads the price discovery process of the corporate bond market. In further robustness checks, we confirm that our main findings hold across bonds with varying credit qualities and maturities. Moreover, we note that the predictability of ΔOPD is about two to three times stronger on the month of rating announcement, especially for downgrade announcements. These results point to the superior explanatory power originating from ongoing updates about balance sheet information and investors' preferences from the option market (Vasquez and Xiao, 2023).

The main contribution of this paper is threefold. First, we add to the extensive literature on default risk measures. Earlier literature in this area primarily focused on estimating default probabilities using financial accounting data (Altman, 1968; Ohlson, 1980), and structural model (Hillegeist, et al., 2004; Bharath and Shumway, 2008), replying on backward-looking inputs. Our paper demonstrates the limited ability of these measures to forecast firm failures. It differs from these studies in that we use the forward-looking information content obtained from the option market. Drawing on the construction of ΔOPD from Conrad, Dittmar and Hameed (2020), we confirm its predictive power as an effective indicator of future default events. In addition, we contribute to the groundwork laid by Vasquez and Xiao (2023), who explored the impact of a similar default risk measure on expected option returns. We believe ours is the first study to show its predictability over a comprehensive sample of US corporate bonds. The findings presented in this paper carry implications for a wide range of studies examining default risk, credit ratings, and portfolio allocation decisions in the corporate bond market, the derivative for insuring against corporate failures.

Our second contribution lies in enriching the empirical asset-pricing literature with fresh insights into the cross-section of corporate bond returns. Prior research on the credit spread puzzle well documents that credit risk can explain the majority of contemporary bond yield spreads through the use of a structural model (Collin-Dufresn, et al., 2001; Longstaff, et al., 2005). Our paper differs from these studies by analyzing the cross-section of future corporate bond returns instead of yield spreads. In the work of Driessen (2005), he models a firm's default intensity as a function of latent common factors and a latent firm-specific factor and confirms its importance as a determinant of corporate bond returns. However, these papers' central theme, focus, and methodological approaches are very different from ours, as we do not use any structural model to back out our risk measures. ΔOPD provides a market-based nonparametric alternative to agency credit ratings and structural models of default. Previous research has shown that options contain useful information for predicting credit spreads (see, for example, jump risk: Cremers, et al. (2008); variance risk premium: Wang et al. (2013)). In contrast to these studies, our paper takes a novel step and explores the predictive power of the option-implied default risk in the cross-section of bond returns, which, to our knowledge, has been examined only in the context of credit spread by Amin, Coval, and Seyhun (2004).

In terms of bond returns pricing literature, prior studies have primarily focused on explaining corporate bond returns through bond-specific characteristics (Elton, Gruber and Blake, 1995; Bai, Bali and Wen, 2019) or exposure to systematic risk (Gebhardt, et al., 2005; Chung, Wang and Wu, 2019). Our findings are consistent with this strand of literature that the predictability of our measure originates from the trading behaviors of safety-first bond investors who seek to minimize the risk of adverse events. In contrast to this line of inquiry, we use forward-looking default estimates to predict changes in bond prices that outperforms existing default measures. Few papers study the link between option information and the prices of bonds issued by the same firm (see, for example, implied volatility by Cao, et al. (2023); downside variance premium by Huang, et al. (2023); aggregate jump and volatility risk by Chen, Wang and Wu (2022)). Our paper complements these recent studies by identifying ΔOPD as a new predictor for the cross-section of corporate bond returns. Unlike these studies, which focus on default-like information inferred from the option market, we study the probability of default that carries distinct default information content. In addition, we are the first to examine the direct impact of default probability on corporate bond returns, aligning closely with the primary concerns of the bondholders.

Third, our findings contribute to the strand of literature on information spillover. As developed by Chowdhry and Nanda (1991) and Easley, et al. (1998), informed traders choose to trade in the options market before other markets, ensuring its quick reactions to the news at daily or even higher frequencies (An, et al., 2014). This dynamic positions the options market to lead the stock market, with option prices containing crucial information about the future directions of stock price changes (Cao, et al., 2005; Cremers and Weinbaum, 2010). We extend this line of studies by examining the option-implied content within an alternative asset class and providing an information transmission channel to understand how such information shapes future bond returns. On the other hand, prior research has demonstrated the integration between debt and equity markets, especially in terms of systematic risk rather than idiosyncratic risks (Schaefer and Strebulaev, 2008; Choi and Kim, 2018). However, our study contributes new evidence of information spillover at the firm level, which outperforms the impact of systematic risk documented in the previous literature. Moreover, our findings suggest a promising agenda for future research to explain abnormal risk premia with cross-asset measures at the firm level.

The remainder of this paper is organized as follows. Section 2 describes our datasets and the construction of ΔOPD. Section 3 discusses the primary empirical evidence on corporate bond returns. Section 4 investigates the informational content of ΔOPD and its pricing mechanisms. Section 5 discusses a battery of robustness tests and Section 6 concludes.

2. Measuring Default Probabilities from Option Prices

This section describes the construction of our main variables, including the ΔOPD, which captures the changes in the option-implied default probability, firm-level corporate bond returns, and control variables.

2.1 Option data

For the sample period from January 1996 to December 2020, we collect daily best bid and ask quotes, trading volume, option interest, implied volatility, delta, and various greeks for U.S. call and put individual stock options from the OptionMetrics Ivy DB database. We follow Conrad, et al. (2013) in using the method of Bakshi, et al. (2003) (BKM hereafter) to compute risk-neutral variance, skewness, and kurtosis from the quotes of call and put options. We follow the data cleaning process of Bali, et al. (2019) and remove all entries for which the bid or offer price is missing, the bid is equal to zero, the offer is less than or equal to the bid, and duplicate entries. For each stock *i* at the end of each month *t*, we retain only calls (puts) with strikes that are greater (less) than or equal to the adjusted underlying price with at least two observations. Given the discrete strike prices we have in our data, we follow Dennis and Mayhew (2002), Conrad, Dittmar and Ghysels (2013) and Bali and Murray (2013) and use a trapezoidal method to estimate V, W, and X used in the BKM method to calculate the risk-neutral variance, skewness, and excess kurtosis. [1] We estimate the moments for all available maturities and interpolate to a 1-month time to maturity using a cubic spline adheres to Chang, et al. (2013). Together with the mean value determined by the risk-free rate, the first four moments serve as the inputs to the Normal Inverse Gaussian (NIG) distribution method developed by Eriksson, et al. (2009). This method is chosen given its advantages to alternative expansion approaches in estimating the levels of skewness and kurtosis from negative probabilities implied by option prices. The option-implied probability of default (OPD) for firm *i* at time *t* under the cumulative density of the NIG distribution at a default threshold α is:

$$OPD_{it}^{\square}(\tau) = \int_{-\infty}^{\alpha} f_{NIG}\left(x, E_{i,t}(\tau), V_{it}(\tau), S_{it}(\tau), K_{it}(\tau)\right) dx \qquad (1)$$

where f_{NIG} is the NIG density function evaluated at the log return of stock *x*, with its exact functional form provided in Appendix A2. Following Carr and Wu (2011) and Conrad, Dittmar and Hameed (2020), we set up a range of values for the default threshold α to vary across credit ratings. This is to avoid that the density at zero value of equity (i.e., $x = \ln(0)$) cannot be computed in the case of default. Specifically, we assign α = 0.05 to AAA-rated firms and α = 0.10 to AA-rated firms, respectively. We assign α = 0.15 to A-rated firms and increment α by 0.05 as we move to lower levels of credit ratings from BBB to B, which is consistent with the lower price declines associated with these firms. Finally, firms with ratings of CCC and below are assigned α = 0.35. These choices imply an average default threshold of α = 0.11 in our sample based on Standard and Poor's (S&P) long-term credit ratings obtained from Capital IQ. [2] Our final sample yields option-implied default probabilities (OPD) for

[1] Technical details of the BKM method are summarized in the Internet Appendix A1.

[2] We also compute results based on default probabilities calculated using bond rating information consolidated at the firm level from the Mergent FISD and all results still hold.

2,711 firms out of the 2,794 firms with available S&P rating and implied moments information from January 1996 to December 2023. We adopt the innovation in the implied default probability (ΔOPD), expressed in basis points (bps), to capture news arrivals in the option market.

To validate the information content of OPD in capturing default risk probability, we run a logistic regression for predicting future bankruptcy (failure) events over the next 12, 24, and 36 months. Our sample of bankrupt firms is those that filed for Chapter 7 or 11 between January 1996 and December 2020 from the UCLA-LoPucki Bankruptcy Research Database. We also include non-overlapping observations on firms with reported court case information on bankruptcy in the Federal Judicial Center's (FJC) database and those deleted from the COMPUSTAT database for the reason of bankruptcy to avoid survival bias. The failure firms are defined as those that filed for bankruptcy, were delisted for financial reasons within the CRSP database, or received a D rating from the S&P Credit Rating database (Campbell, et al., 2008). Our final dataset consists of 3,301 bankruptcy-filing firms and 7,805 firms that experienced failure events. Following the bankruptcy model of Campbell, Hilscher and Szilagyi (2008), we additionally control for seven market value-based accounting variables: net income over the market value of total assets (NIMTA), total liabilities over the market value of total assets (TLMTA), firm's market equity (RSIZE), cash and short-term investments over the market value of total assets (CASHMTA), market-to-book value of the firm (MB), equity returns (EXRET) and volatility of stock returns over the past three months (SIGMA). We report the results alongside with coefficient estimates of the Campbell, Hilscher and Szilagyi (2008) bankruptcy prediction model in Table 1.

[Table 1]

Contributing to the work of Conrad, Dittmar and Hameed (2020), results from Panel A confirm that OPD is a significant predictor of future bankruptcy events. While the coefficients and significance levels decline with increasing horizons as expected, the coefficient of OPD remains positive and statistically significant at the 1% level at all forecast horizons up to 36 months ex-post. Higher OPD associates with an increased likelihood of default in the next three years. Compared with control variables from the prediction model, only TLMTA, RSIZE, and CASHMTA remain statistically significant with expected signs. SIGMA and MB do not exhibit significant predictive power over short horizons when including OPD in the model, the forward-looking information content of which subsumes the short-term overvaluation of the firm's equity. This is consistent with the findings of Chacko, et al. (2004), those who suggest changes in the default probability are primarily driven by price movements related to fundamental news that are unlikely to offset back to mean value in the long term. As we broaden the definition of bankruptcy to failure in Panel B, the effect of OPD becomes more substantial and statistically more significant for all horizons. Compared to extant backward-looking default risk measures, our results further suggest that OPD captures incremental information about default risk and vital deterioration in firm value.

Following Shumway (2001), we perform an informal examination of realized bankruptcy cases during the next year across different categories of default risk measures, including OPD, bond rating,

default risk, distance to default, Altman (1968) Z score, and option-implied volatility. We report the results in Table A1 of the Internet Appendix. In line with the literature, we show that all the measures above can predict future bankruptcies. Most bankruptcies appear in the highest risk categories, whereas these cases are distributed across all IMPVOL-sorted categories. This suggests that IMPVOL captures short-term price movements that may not carry fundamental information about future bankruptcy. In addition, we also show that OPD and DD are the most successful in informing bankruptcy cases in their highest-risk category. We further validate their predictive performance by applying the Cox proportional hazard model over the same set of default risk measures, reported in Table A2. We show that all the default measures tested remain positive and statistically significant at the 1% level. In all specifications, Cox partial likelihood ratios are significantly different from zero. These results are consistent with our informal predictions and prior literature, confirming the ability of OPD to forecast bankruptcies compared to the existing measures. More importantly, we report the results of the Receiver or Relative Operating Characteristic (ROC) analysis, a method commonly used for comparing and selecting the optimal default risk measures in the last row (Vassalou and Xing, 2004; Agarwal and Taffler, 2008). One that has the highest ROC ratio is considered superior, as a ratio closer to 1 indicates a model with ‘‘perfect’’ predictive ability. Column (6) suggests that OPD contributes significantly to forecasting bankruptcies beyond DD and Z scores. This provides additional evidence supporting the findings of Bharath and Shumway (2008) and Campbell, Hilscher and Szilagyi (2008) on the enhanced forecasting ability of option-implied measures in predicting bankruptcy compared to accounting-based measures, and establishes OPD as a potential predictor of cross-sectional bond returns.

2.2 Corporate bond data and bond returns

We use intraday bond transaction data from the TRACE Enhanced dataset and obtain information on bond issues and issuer characteristics from the Mergent FISD. For data cleaning, we follow Dick-Nielsen (2009) and Dick-Nielsen (2014) to remove transaction records that are canceled and adjust records that are subsequently corrected or reversed, as well as duplicate transactions documented in Asquith, et al. (2013). We also adhere to the filters outlined in Dickerson, et al. (2023) to remove i) bonds that are not publicly traded in the U.S. market, including bonds issued through private placement, bonds issued under Rule 144A, bonds that are not traded in US dollars, and bonds from issuers not based in the United States; ii) bonds that are classified as structured notes, mortgage-backed, asset-backed, agency-backed, equity-linked or convertible; iii) bonds that have a floating coupon rate; iv) bonds that have less than one year until maturity; v) bond transactions that are labeled as when-issued, locked-in, or have special sales conditions, and that have more than a two-day settlement; and vi) intraday transaction records that have a trading volume less than $10,000. Following Bessembinder, et al. (2008), we compute monthly bond returns as:

$$R_{B_{i,j,t}} = \frac{B_{i,j,t} + AI_{i,j,t} + Coupon_{i,j,t}}{B_{i,j,t-1} + AI_{i,j,t-1}} - 1 \quad (2)$$

where $B_{i,j,t}$ is the price of bond j issued by firm i in month t, $AI_{i,j,t}$ is the accrued interest, and $Coupon_{i,j,t}$ is the coupon payment (if available). In addition, we follow their approach to aggregate firms' outstanding bond returns into a value-weighted return to avoid bias in empirical findings from treating individual-level bond returns as separate observations among firms with multiple bond issues. We then exclude firms operating in financial and insurance-related sectors, as they are subject to specific regulations that influence their leverage policies and, thus, their default risk.

[Table 2]

[Table 3]

After merging the corporate bond data from TRACE with the option data from Option-Metrics, we have 881,625 bond–month observations for 1,614 unique firms from September 2002 to December 2020. In Panel A of Table 2, we report the summary statistics of ΔOPD, bond returns, and control variables, with definitions and construction methods summarized in Table 3. The ΔOPD of our sampled firms is slightly negatively skewed, with an average value of 0.066 basis points. In addition, it exhibits significant cross-sectional variation with a standard deviation of 38.6%. Bonds included in our sample have an average return of 0.61, an average rating score of 10 (BBB), and an average time to maturity of 9 years. Among the entire sample of bonds, around 75% are investment grade, and the remaining 25% are high-yield bonds. This suggests our results are not biased towards non-investment grade bonds or those with longer maturity. The consistent predicting power of our measure across different ratings and lengths of maturity will be discussed further in the following sections.

In Panel B of Table 2, we report the time-series average of the cross-sectional correlations of the variables. We observe a negative correlation between ΔOPD and bond returns, preliminarily validating our hypothesis that bond returns tend to be lower when default probability increases. While correlated negatively with bond returns, the bond idiosyncratic volatility ($IVOL_B$) and changes in implied volatilities (ΔIMPVOL) are not correlated with ΔOPD with a correlation of 0.01 and 0.05, respectively. The positive relationship confirms information overlaps between volatility changes induced by default information, whereas it represents distinct information from the volatility characteristics of the underlying asset as discussed in the following sections.

3. ΔOPD and the cross-section of corporate bond returns

In this section, we study the pricing implications of ΔOPD to cross-sectional bond returns. Our main hypothesis is that ΔOPD, measured as changes in the probability of default implied from option price distribution, can explain subsequent corporate bond returns in the cross-section. Specifically, given the outstanding role of institutional investors in the corporate bond market, we argue that risk-averse bond investors overvalue informed information about the decreased default probability of the underlying

asset. Therefore, we expect that ex-post bond returns to be significantly higher for firms with low ΔOPD in the cross-sections of corporate bonds.

3.1 Univariate portfolio analysis

To study whether firm-specific ΔOPD is priced in the cross-section of bond returns, we form five quintile portfolios at each month's end by sorting bonds based on the firm-specific ΔOPD over the past month.[3] The results of this analysis are reported in Table 4. The average ΔOPD of each quintile portfolio is summarized in basis points in the second column, where the quintile 1 (5) portfolio contains bonds with the lowest (highest) ΔOPD. The remaining columns report average excess bond returns and risk-adjusted alphas (α^i) for both equal-weighted and value-weighted quintile portfolios based on the following regression:

$$R_{t+1}^i = \alpha^i + \sum_{k=1}^{K} \beta_{k,t}^i X_{k,t} + \varepsilon_t^i, \tag{3}$$

where R_{t+1}^i is the excess return of the quintile portfolio i sorted on ΔOPD. $X_{\mathrm{k},t}$ is a collection of risk factors observed at time t that has been documented to display significant explanatory power for the cross-section of corporate bond returns. Following Bali, et al. (2023), we control for different combinations of factors, including the excess equity market returns (MKT_E), size factor (SMB_E), book-to-market factor (HML_E), momentum factor (MOM_E), liquidity factor (LIQ_E) and excess bond market returns (MKT_B). Additionally, we also show the alpha (α^1) relative to MKT_B only given its outperformance among other return-based bond anomalies reported by Dickerson, Mueller and Robotti (2023). The last row reports the differences in average returns and alphas between the quintiles 1 and 5 portfolios in the unit of monthly percentages. In other words, they are the returns (alphas) on a "high-minus-low (HML)" zero investment portfolio that longs the bonds in the highest ΔOPD quintile and shorts those in the lowest ΔOPD quintile. Newey and West (1987) adjusted t-statistics are reported in parentheses.

[Table 4]

Results show that the explanatory power of ΔOPD holds for both equal- and value-weighted HML portfolios in the bond cross-section. For equal-weighted portfolios, the average excess return decreases from 0.7% to 0.41% with increasing ΔOPD, resulting in a significant HML return difference of −0.29% per month (t-stat = −2.65). Moreover, it remains a robust predictor that generates significant alphas under different bond factor models. In Column (2), bonds in the lowest ΔOPD quintile generate an average excess monthly return of 0.3% (t-stat = −3.64), higher than those in the highest quintile after adjusting for equity-related risk factors. Column (3) shows that ΔOPD continues to yield a significantly negative return for the HML portfolio at −0.38% per month (t-stat = −3.13) when the outstanding impact of MKT_B is accounted for. In line with the findings of Cao, et al. (2023) and Huang, Jiang and

[3] Our results are consistent when corporate bond returns are sorted into tercile portfolios. Results based on tercile portfolio sorting are reported in Table A3 of the Appendix.

Li (2023), the relative outperformance of option-implied measures further confirms that investors trading first in options markets have better information about firm-specific events. This information superiority contributes to the price discovery not only among equities as in An, et al. (2014), but also bonds issued by the same firm.

The negative association between ΔOPD and future bond returns becomes more pronounced for value-weighted portfolios, yielding a significant return difference between the highest and lowest quintile portfolios at 0.43% (t-stat = -2.74). Results in column (9) show that ΔOPD continues to offer incremental information beyond the common risk factors of both the equity and bond markets, resulting in a strengthened alpha difference of -0.43% with higher t-statistics at -3.67. This implies that the significant difference from the high-minus-low portfolio is not led by the small-cap bonds with a higher possibility of default. More importantly, the significant alpha difference between extreme quintiles can be attributed to the persistent outperformance of the low-ΔOPD bonds across all the controls, pointing to slow diffusion of information as a likely cause of predictability. This pattern contrasts the findings of Vasquez and Xiao (2023) regarding the impact of such information on equity returns, where predictability stems from both the outperformance and underperformance of the highest and lowest quintile portfolios. Nevertheless, our findings corroborate the hypothesis that bond investors who trade at a lower frequency tend to underreact to information concerning the downward direction of future price changes signaled by purchases from informed option investors. Their risk-averse nature drives them towards mitigating uncertainty inherent in a firm's prospects rather than pursuing higher yields, resulting in the sustained outperformance of the lowest quintile portfolio. In addition, this is likely because institutions are typical traders in the corporate bond market, as they're more resourceful in conducting research at the firm level and diversifying risk across different asset classes.

In addition to the strong evidence of profitable trading on ΔOPD, we examine the persistence of such predictive power in the following six months, with results reported in Table A4 of the Internet Appendix. While most robust for the next month's horizon, the predictability persists for at least three months after the portfolio formation at a similar magnitude. This trading strategy yields significant returns ranging from -0.43% to -0.41% per month, even after controlling for both stock and bond factors, suggesting that it is unlikely due to microstructure trading effects. Nonetheless, we still observe consistently significant outperformance from firms in quintile 1 (lowest ΔOPD) and underperformance from firms in quintile 5 (highest ΔOPD). These results collectively suggest that default risk information from the option market consistently offers additional information beyond the fundamental bond market factors.

In summary, we confirm the predictive power of ΔOPD in the cross-section of bond returns. Additionally, we highlight that beyond the significant price discovery seen in the equity market, further evidence indicates that the options market harbors relevant information for possibly all securities issued by the same firm. Consequently, our findings suggest a new angle of explaining variations in corporate bond prices from the firm-level perspective, grounded in the forward-looking default risk information

from the options market. We contribute to the emerging strand of literature on the predictive power of option-implied information to the cross-section of future bond returns (see, for example, Cao, et al., 2023; Huang, Jiang and Li, 2023). Unlike their proxies for future volatility and downside risk, we employ a direct measure of default probabilities implied from the option market and examine its pricing implications for cross-sectional bond returns. In addition, statistics in columns (11)-(15) of Table 4 show that firms with significant changes in implied default probability, regardless of the directions, exhibit distinct patterns with relatively lower average ratings, time to maturity, and firm size. This mitigates the concerns that specific bond characteristics influence our results.

3.2 Bivariate portfolio analysis

To study the predictive power of ΔOPD when established risk anomalies in the corporate bond market are controlled for, we perform a double-sort analysis following Ang et al. (2006). Specifically, for each month from September 2002 to December 2020, we form five quintile portfolios by sorting bonds based on the various characteristics described in Panel A of Table 3. We further sort bonds within each quintile into five sub-quintile portfolios based on ΔOPD. The five sub-quintile portfolios are then averaged across quintiles of the control variable. We report the risk-adjusted alphas of the five ΔOPD-quintile portfolios on a value-weighted basis, along with the alpha difference between high- and low-ΔOPD quintile portfolios reported in the last column. Table 5 presents bivariate sorting analysis results of bond quintile portfolios with six-factor bond alphas (α^6), controlling for MKT_E, SMB_E, HML_E, MOM_E, LIQ, and MKT_B, as proposed by Bali, Subrahmanyam and Wen (2023). We also consider the data construction issue documented in Dickerson et al. (2023) and repeat the analysis adjusted for the MKT_B only as a robustness check.

[Table 5]

Our findings confirm the predictive power of ΔOPD over future bond returns after controlling for traded and non-traded factors documented in the bond pricing literature. Controlling for all the characteristics examined in rows (1)–(5), we observe an enhanced predictive power of ΔOPD, thereby confirming our hypothesis regarding the additional information derived from the option market. Notably, our measure yields a strengthened predictive performance controlling for reported changes in bond ratings, with a significant alpha difference of -0.3% (t-stats=-4.78). This finding aligns with Charitou, et al. (2011) on the unrelatedness between ratings and default risk, highlighting its noisy information content assuming assets within a rating category share the same default risk without timely adjustments. The outperformance can be attributed to ΔOPD providing the timely assessment of a firm's credit quality from the option market, as documented in Vasquez and Xiao (2023). Similarly, ΔOPD remains significant and provides incremental information in explaining bond returns when the impact of MOM_B is controlled in row (6). This highlights jumps in future default probability that cannot be solely attributed to the trend of being past losers.

Interestingly, we note a distinct performance of the long-short strategy regarding the impact of various measures of systematic risk level in rows (8)-(10). While the predictive power of ΔOPD becomes weaker controlling for MKT_B, its impact is further strengthened when accounting for individual exposures toward market-level volatility and uncertainty. Combined with its significant information overlap with $IVOL_B$ reported in row (11), we uncover empirical evidence supporting that the changes in the idiosyncratic, not systematic, components of volatilities drive the predictability of ΔOPD. This finding again validates the poorly diversified feature of the corporate bond market, where institutional investors dominate most bond transactions and seek companies with less fragility towards fundamental shocks (Chung, Wang and Wu, 2019; Darmouni, et al., 2022). Given the superior information content, ΔOPD posits a significant and consistently substantial impact beyond idiosyncratic risk at the firm level. In addition, we note that the high-minus-low portfolio yields an economically and statistically significant alpha difference at -0.33% (t-stats=-3.08) despite the prominent influence of MKT_B in corporate bond pricing highlighted by Dickerson, Mueller and Robotti (2023). This further underscores our argument that relying solely on information from the corporate bond market fails to adequately address firm-specific asset risk, thereby enabling cross-asset investors to achieve significant profits.

The results in rows (12)–(15) show that none of the accounting-based variables that are shown to associate with future bankruptcy can explain the cross-sectional variation induced by ΔOPD. However, one exception arises when accounting for DD estimated from the Merton model, which leads to a significant decrease in the alpha difference to -0.22% despite remaining significant (t-stats=-3.49). These findings add to the growing empirical evidence of the superiority of information offered by model-estimated default variables compared to purely accounting-based measures of default probabilities (Bharath and Shumway, 2008). The consistent predictive power of ΔOPD supports the findings of Campbell, Hilscher and Szilagyi (2008) on the limited ability to estimate default probabilities using backward-looking information. Our findings also align with Hillegeist, et al. (2004) who suggest that the predictive ability of these accounting-based variables is constrained by the assumption made during the construction of financial statements that the firm will not go bankrupt, thereby overlooking important pricing information contained in ΔOPD.

We further investigate the impact of volatility-related measures implied from options market information in rows (16)-(19), where ΔOPD remains economically and statistically significant throughout with comparable magnitudes.[4] The consistent impact of option-implied variables among all the control variables again underscores the bond market's tendency to underreact to the nontrivial information transmission channel between option and bond markets. Additionally, the significant information overlaps provide empirical evidence supporting that the volatility of firm value is

[4] For additional robustness, we use idiosyncratic measures of *ΔOPD* based on residuals obtained from regressions on IMPVOL. Portfolio sorting results based on these idiosyncratic measures (i.e., "cleaned" from option-implied volatility information), confirm that the explanatory power of *ΔOPD* is not affected by information overlaps (see Appendix Table A5).

detrimental to bondholders as it increases the chance of default. Our study also echoes the findings of Vasquez and Xiao (2023) that volatility-related variables do not overshadow default risk in predicting bond returns, which is of utmost concern to debtholders. Alternatively, we also control for the impact of quoted spread on CDS contracts, the insurance against companies' potential downfall, in row (20). The relative outperformance of ΔOPD again confirms the validity of option-implied default probabilities as a market-driven alternative estimate of the firm's propensity of failure, especially given the permanent reduction in the size of the CDS market documented in Conrad, Dittmar and Hameed (2020).

Overall, we observe a monotonically decreasing pattern across different controls when moving from the lowest to the highest quintiles of ΔOPD, suggesting that changes in default risk probability as captured in forward-looking option information is a widespread effect priced in bond returns across various categories of characteristics. Moreover, ΔOPD serves as a market-based nonparametric alternative that consistently outperforms agency credit ratings, structural models of default, and other option-implied credit risk measures in predicting corporate bond returns. The above findings support our hypothesis that cross-asset investors benefit from the general underreaction of bonds toward additional insights obtained from the option market, which cannot be adequately captured by bond characteristics and their exposure to systematic risk.

3.3 Fama Macbeth Regression

The results from the previous subsections suggest a consistent and significant negative effect of ΔOPD on cross-sectional bond returns at the portfolio level. We further investigate if such a relationship holds at the firm level using the Fama and MacBeth (1973) methodology. Specifically, monthly cross-sectional regressions are run from September 2002 to December 2020 on bond returns for the following econometric specification:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \Delta OPD_{i,t} + \lambda_{2,t} \cdot X_{i,t} + \epsilon_{i,t+1}, \quad (4)$$

where $R_{i,t+1}$ is the excess bond return of firm i in month t+1, and $\Delta OPD_{i,t}$ is the change in the default probability of firm i implied from the distribution of option prices at month t as defined in Eq. (1). $X_{i,t}$ is the same collection of market-specific control variables adopted in Section 3.2, observed at time t for firm i.

[Table 6]

Table 6 reports the time-series average of the coefficients on the independent variables based on bond returns. Results further support our hypothesis on the negative relations between ΔOPD and future bond returns. The average slope coefficient on ΔOPD is economically and statistically significant at −0.02 (t-stat = −3.53) without controls. This implies that a value-weighted portfolio of selling high-ΔOPD bonds and buying low-ΔOPD bonds could generate a return of 8.6 basis points in the following month. The ΔOPD variable retains significant predictive power throughout all specifications, while the

impact of controls constructed using information from option and bond markets varies. However, most patterns align with what has been documented in previous studies. The coefficients on ΔIMPVOL are negative and statistically significant across all regressions as in Cao, et al. (2023). Together with results from Table 5, our findings suggest that the impact of ΔOPD is distinct from that of changes in implied volatilities. Moreover, our findings highlight the need to account for default and volatility risks in the corporate bond market, as suggested in the work of Vasquez and Xiao (2023). This consideration is crucial, given debtholders' concerns about the possibility of not getting fully paid back. We also observe that the weak impact of call-put volatility spread diminishes after accounting for bond risk characteristics. This aligns with a similar effect documented in Cao, et al. (2023), where the fundamental news information in ΔCVOL-ΔPVOL is masked by the increase in default risk information captured by a combination of ΔIMPVOL and ΔOPD.

Similarly, we document a positive and statistically significant influence of MKT_B across all regressions, echoing the findings of Dickerson, Mueller and Robotti (2023). However, none exhibits a stronger impact compared to option-implied measures, where the dominant pricing power of MKT_B even diminishes when controlling for IVOL and VIX_B. This contrasts with the findings of Collin-Dufresn, Goldstein and Martin (2001) and Schaefer and Strebulaev (2008), who highlight the role of non-credit components from market-wide factors compared to credit components predicted by structural models in explaining changes in credit spread or corporate bond prices. ΔOPD and measures implied from other asset classes serve as the market perception of the firm risk level that outperforms MKT_B in explaining fluctuations in corporate bond prices. This finding underscores the nature of the corporate bond market, characterized by institutional investors adopting long-term buy and hold strategy and thus poorly diversified (Darmouni, Siani and Xiao, 2022). It also highlights the need to study the outstanding information spillover at the firm level in the corporate bond pricing literature, as proposed by the recent work of Dick-Nielsen, et al. (2023). In addition, we control various bond characteristics in column (5) and find that none hold significant explanatory power for future bond returns in any specification we explore. This suggests that bond prices are primarily affected by firm-level exposure to changes in market conditions rather than their own pricing structure. Moreover, neither IVOL nor VIX_B relates to the profitability of our strategy when option-implied measures are controlled for in column (6), aligning with the patterns documented in Cao, et al. (2023). The dominant role of option-implied measures further underscores the superior informational content in the options market, which holds greater importance than bond market information in explaining bond return variations, thereby supporting our portfolio-level findings.

While the predictability of ΔOPD remains statistically and economically significant at -0.015 (t-stat=-2.88) accounting for default-related variables in column (7), the results confirm the relatively weaker performance of accounting-based variables shown in the previous subsection. Nevertheless, we find evidence for the significant impact of DD and CS in the cross-section of bond returns. The predictability stems from backwards-looking information, reinforcing our argument on the general

underreaction of the corporate bond market in terms of default-related information. The persistence of ΔOPD predictability is further validated to be driven by the forward-looking information.

Overall, we show robust evidence of ΔOPD commanding statistically significant risk premia over and beyond the effects of conventional or known bond risk factors. The default risk level captured by ΔOPD is distinct from volatile price fluctuations observed in both options and bond markets, as it directly measures the risk of not getting paid back to bondholders. Nevertheless, the above findings also raise the question of if and how ΔOPD improves the risk-return trade-off for corporate bonds through the channel of informed trading, which we will further discuss in the next section.

3.4 Subperiod analysis

Having discovered evidence that the magnitude of the ΔOPD effect varies across firms, we now examine whether the predictive power of ΔOPD varies with time. This analysis is motivated by prior studies linking the strength of cross-sectional return anomalies to investor sentiment in the equity market (Stambaugh, et al., 2012; Antoniou, et al., 2016). As highlighted by Chen, Wang and Wu (2022), periods of increasing aggregated risk levels may expose firms to significant losses due to jumps in the discount factor, potentially triggering defaults on their debt obligations and jeopardizing bondholders' wealth. Cross-asset investors who anticipate potential risks from firms with fragile capital structures in advance could mitigate the impact of inflated risk levels and generate consistent profits from the long-short trading strategy on ΔOPD. Therefore, we expect to observe a more substantial ΔOPD effect in subperiods of high systematic risk levels.

We test this hypothesis by repeating our univariate analysis over subperiod samples divided using proxies of aggregated risk levels from three different perspectives. Panel A examines the ΔOPD effect during periods of better (worse) market conditions, proxied by volatility indexes for equity (CBOE Volatility (VIX) index) and the bond market (Merrill Lynch Option Volatility Estimate (MOVE) index), along with Jurado, et al. (2015) Macro Uncertainty (UNC) index and Economic Policy Uncertainty (EPU) index. Panel B investigates the impact of general market sentiment proxied by economic activity measures including the Misery index, Chicago Fed National Activity Index (CFNAI), Total Borrowings of Depository Institutions from the Federal Reserve, and Commercial Real Estate (CRE) price index. Panel C explores the impact of investors' pessimistic sentiment indicated by the Investor Intelligence Sentiment index (Fisher and Statman, 2000), FOMC Sentiment index (Gardner, et al., 2022), market states defined by Eisdorfer and Misirli (2020) and business condition index (Aruoba, et al., 2009). We define high (low) risk months as those in which the targeted index in the previous month is above (below) the median value for the sample period. Bond returns and six-factor alphas on ΔOPD-sorted portfolios are reported separately for high- and low-risk periods in Table 7.

[Table 7]

In line with our expectation, Panel A shows that the long-short trading strategy yields roughly tripled alpha differences during periods of heightened volatility in both markets, as proxied by the VIX and

MOVE indexes. Given that both ΔOPD and volatility indexes rely on forward-looking inputs, our findings again highlight the poorly diversified nature of the corporate bond market, resulting in a more pronounced impact of ΔOPD at the firm level. Combined with a widening and significant difference between periods of high and low uncertainty related to macroeconomic conditions and economic policies, our results point to a strengthened ΔOPD predictability at worsening market conditions. Results in Panel B and C provide further evidence that return spreads increase with pessimistic sentiment at both market and individual levels. During periods of widening difference between BAA and AAA corporate bond yield (high CRE) and higher total borrowings, we show that the monthly return on the high-minus-low ΔOPD portfolio equals -0.61% and -0.6% respectively (t-stats of 3.02 and 3.13). This is in line with our hypothesis that jumps in the discount factor have a less significant impact on firms with resilient capital structure, proxied by lower ΔOPD, thereby generating higher profit during the period of market-level pessimistic sentiment. With proxies of economic contraction by CFNAI and Misery index, we show that the predictability of ΔOPD remains highly significant at the same magnitude, while that of the economic expansion period exhibits half of its predicting power. This is consistent with the theory documented by Bates (2008), suggesting that investors are averse to crashes and seek to insure themselves against events like economic contraction and periods of high unemployment. They are willing to pay higher prices for bonds with lower ΔOPD that are resilient to such events, resulting in the consistent outperformance of our trading strategy during periods of market-level pessimistic sentiment.

Additionally, heightened bearish sentiment among advisors, the key players of the corporate bond market, contributes to a higher return spread at -0.59% (t-stats=-2.61). This effect becomes stronger during pessimistic periods indicated by the Federal Open Market Committee (FOMC) statements (Gardner, Scotti and Vega, 2022), where ΔOPD yields a quadrupled return spread of 0.85% (t-stats=-2.73). Similar patterns prevail when considering the investment-based market sentiment level. We show that the ΔOPD strategy generates significant premiums of 0.44% and 0.77%, respectively, during periods of adverse market state and poor business climate. Taken together, we find that the profitability of the long-short strategy on ΔOPD does vary with the aggregated risk level and enhances significantly during periods of worsening market conditions, poor economic activity, and pessimistic sentiment. These results align with corporate bond investors' intention to avoid the impact of fundamental shocks as documented in Chen, Wang and Wu (2022) and Darmouni, Siani and Xiao (2022).

4. The information content of ΔOPD

4.1 Proxy for cash flow uncertainty

To better understand the negative relationship between the ΔOPD and future corporate bond returns, we further investigate its information content. We provide evidence that ΔOPD predicts deterioration in firm value, manifested through increased uncertainty in future cash flow (Chan and Chen, 1991).

Following Kothari, et al. (2002), we implement cross-sectional regressions of future cash flows and cash flow uncertainties on the ΔOPD and control variables, including capital expenditure (CAPEX), market value of firm size (LNME), leverage (LEV), and lagged ROA (LROA) and earnings (LEARN), with results reported in Table 8. We use return-on-assets (ROA) and earnings (EARN) to measure firm cash flows, respectively, as reported in Panels A and B. Correspondingly, cash flow uncertainty is calculated as the standard deviation of the subsequent 3- or 5-quarter cash flows (VROA3/VEARN3, VROA5/VEARN5).

[Table 8]

We find that the coefficient on ΔOPD is negative and statistically significant at -0.223 (t-stats=-4.56) and -0.002 (t-stats=-1.70) when controlling for EARN and ROA, respectively. This suggests that the higher probability of defaulting predicted by ΔOPD tends to accompany a decrease in subsequent cash flow. Results from the remaining columns confirm a significantly positive relationship between ΔOPD and cash flow uncertainty, at 0.317 (t-stats=5.16) in the VEARN3 regression and 0.008 (t-stats=4.14) in the VROA3 regression. This relationship remains significant when controlling for cash flow uncertainty measured over five quarters. These results collectively suggest that our measure proxies for deteriorated profitability and unsustainable asset growth that may lead to bankruptcy in the instant future, aligning with the findings of Chordia, et al. (2017) regarding the influence on the cross-section of credit spreads. Note that indirect predictors of default risk documented in bond pricing literature (see, for example, Chen, Wang and Wu, 2022; Cao, et al., 2023; Huang, Jiang and Li, 2023) may contain mixed information about future liquidity that collectively influences subsequent bond returns. Higher uncertainty in cash flows is directly linked to the increased possibility of not paying back the principals, which is of the greatest concern to debtholders. This ensures the consistent outperformance of ΔOPD against other credit risk measures, as shown in Section 3. Moreover, this informational content is evident among option prices, as informed traders tend to engage in the option market upon receiving such signals. This preference arises because the option market offers higher leverage and greater profit potential before traders enter the corporate bond market. We next explore how such information is transmitted across markets and incorporated into bond prices in the following subsections.

4.2 Informed trading

Previous findings suggest that the predictive power of ΔOPD likely originated from firm-level information spillover through the channel of informed trading. Informed traders, through the use of prediction models or privileged access to the information, may have foreknowledge of pending default events, resulting in an increased number of informed tradings and abnormally high volatility when the news becomes public (Grossman and Stiglitz, 1980). In this section, we further investigate predictions on whether trading volumes and volatilities in bond and option markets play a crucial role in explaining the predictability of ΔOPD on future bond returns.

4.2.1 Interaction with option volume

We first relate changes in ΔOPD to contemporaneous changes in options volume, a proxy for informed trading identified in the options market. Following the model adopted in An, et al. (2014), we run Fama and MacBeth (1973) cross-sectional regressions with the same set of cross-sectional control variables in equation (4), using the interaction of ΔOPD and three dummy variables defined as follows:

$$
\begin{aligned}
High_OptionVol &= \begin{cases} 1, & if\ \Delta Option\ Volume\ > Median \\ 0, & otherwise \end{cases} \\
High_PutOptionVol &= \begin{cases} 1, & if\ \Delta Put\ Option\ Volume\ > Median \\ 0, & otherwise \end{cases} \\
High\ P/C\ Volume &= \begin{cases} 1, & if\ Put/Call\ Volume\ > Median \\ 0, & otherwise \end{cases}
\end{aligned}
\tag{5}
$$

which partition ΔOPD into whether default probability occurs with a relatively high or low level of informed trading in the options market based on the median change in options trading volume (OptionVol), put option volume (PutOptionVol), and the ratio of put option volume relative to call option volume (P/C Volume). A regression with these interaction terms nest the standard regression (5), where the coefficient of ΔOPD does not vary with option trading volume. Table 9 reports the time-series average of the coefficients on the independent variables based on bond returns.

[Table 9]

Results in Table 9 reject the hypothesis of equal coefficients on different sets of ΔOPD with t-statistics of -2.88 in Table 6. When conditioning on the total option trading volume, column (1) shows that average slope coefficients on ΔOPD**High_OptionVol* and ΔOPD are economically and significantly different, with values of -0.016 and -0.013 (t-stats=-2.64 and -2.14), respectively. As expected, the predictability of implied default probability innovation becomes slightly stronger when accompanied by higher than usual options volume, which is consistent with our hypothesis on the advanced option purchase of informed investors. In line with the fact that informed investors who are pessimistic about the future riskiness of the firm are likely to trade in put options, we find a stronger predictability of ΔOPD**High_PutOptionVol* at -0.018 (t-stats=-2.91) in column (2). More importantly, we observe a doubling impact of ΔOPD**High_P/C Vol*ume at -0.025 (t-stats = -3.85) when the put option volume is relatively higher than the call option volume in average, while the coefficient on ΔOPD is insignificant. This outstanding price discovery occurring predominantly in put options indicates that informed investors who trade in both markets pay close attention to the high-quality, sizeable information the firms are trending down. Such behavior further contributes to the information transmission from the option market to the bond market, resulting in increased default probability and enhanced predictability of future bond appreciation.

4.2.2 Interaction with option-implied bearish sentiment

Another important takeaway from the above findings is the directional guidance that risk-averse bond investors heavily rely on. Apart from the findings of Cao, Chen, and Griffin (2005), who noted that merger information hits the call option market before the stock market, we posit that the predictability of ΔOPD is affected by firm-level bearish sentiment implied from option prices. With option buyers exhibiting a high degree of confidence that the firm is trending down, we expect to observe a further enhanced impact on the bond market. We repeat our univariate portfolio analysis on ΔOPD across above- (below-) median groups of six proxies of bearish sentiment implied from the options market: changes in implied volatility for the put option (ΔPVOL), changes in option implied volatility (ΔIMPVOL), call-put volatility spread (ΔCVOL-ΔPVOL), realized-implied volatility spread (RVOL-IVOL), risk-neutral skewness (QSKEW) and multimarket information asymmetry (MIA), with details of construction described in Panel A of Table 3. The results of this subgroup analysis are summarized in Table 10.

[Table 10]

The predictability of ΔOPD remains consistently significant across subgroups of bonds with higher (lower) than median level of bearish sentiment. Consistent with our findings from bivariate portfolio analysis, this indicates that ΔOPD provides distinct information related to default events that directly affect debtholders' benefit. It helps the predictability of ΔOPD stand out from various measures of bearish sentiment, especially in the cross-section of bond returns. In line with our expectation, we observe stronger predictability of ΔOPD when high bearish sentiment towards individual firms is observed from options trading. Specifically, the alpha spreads remain economically and significantly stronger for higher-than-median ΔPVOL and ΔIMPVOL groups at -0.41% and -0.48% (t-stats=-3.32 and -3.63), respectively. This suggests that the strengthened predictability of ΔOPD mainly comes from the outstanding price discovery occurring in put options, thereby confirming our hypothesis regarding the amplifying impact of bearish sentiment.

Similarly, the predictability of ΔOPD becomes stronger when put options are more expensive than call options (higher-than-median ΔCVOL-ΔPVOL), further supporting our argument. As an alternative proxy of volatility risk, we continue to observe a tripling impact of predictability from ΔOPD when conditioning on RVOL-IVOL, with a significant alpha spread at -0.44% (t-stats=-3.65). The strengthened predictability could be attributed to the excessively pessimistic reactions about the future riskiness of the firm, as in Goyal and Saretto (2009), the effect of which is more significant among risk-averse investors who trade in both option and bonds markets. We document a similar magnitude of ΔOPD effect for the high QSKEW group, where informed bearish investors with a high degree of confidence in future price appreciation buy puts and sell calls (Xing, et al., 2010). We also control for MIA, the fraction of volume originating from informed traders, as a proxy of additional volatility that is incremental to ΔIMPVOL (Johnson and So, 2018). We continue to observe a more substantial impact

of ΔOPD on firms with higher levels of MIA, suggesting that the significant price pressure stems from informed traders creating profitable trading opportunities. The above results further confirm the leading position of the options market in the volatility spillover effect for the corporate bond market, which is consistent with the findings of Bali and Hovakimian (2009). Despite the differences in the information contents of the above measures, we show that a stronger directional sentiment helps ΔOPD explain the future changes in the bond returns.

4.2.3 Joint option and bond volume

Another pattern we expect to see is a more substantial predictive power of ΔOPD for bond returns among the ones with unusually large trading volume in both option and bond markets. Cross-asset investors with informed information from the option market are expected to trade in the bond market to secure against increasing risk levels, resulting in predictable bond returns. We investigate this prediction by forming ΔOPD-sorted quintile portfolios of bond conditions on option and bond trading volume. For each month, we first divide bonds into two groups based on the median changes in total options trading volume (ΔOption Vol) or put option volume (ΔPut Option Vol). Sampled bonds are then independently separated into two groups based on the median changes in bond trading volume (ΔBond Vol). For each of these four groups, we sort the bonds by ΔOPD into quintile portfolios and report returns and alphas adjusted for the six-factor model following Bali, Subrahmanyam and Wen (2023) in Table 11.

[Table 11]

Subgroup analysis results based on shocks in options and bond trading volume are summarized in Panel A (B). Consistent with our expectation, the ΔOPD effect is the strongest among bonds with the highest trading volume in both options and bonds, suggesting that informed investors trade across different asset classes. The risk-adjusted alpha for the 5-1 portfolio is statistically and economically significant at -0.44% (t-stats=-3.35), while that one for the group of lowest trading volume in both markets is the least significant at -0.22% (t-stats=-2.41). In line with our previous findings, we observe a stronger predictive power of ΔOPD when excessively trading bonds in response to bearish information exhibited in the unusually high trading in put options. The return difference of the group with the highest volume changes in put options and bonds remains economically and statistically strongest at -0.46% (t-stats=-3.62). Nevertheless, we do not observe outperformance in the group with High ΔOption Vol and low ΔBond Vol as documented in Cao, et al. (2023) for ΔIMPVOL. Since it may not necessarily capture deteriorated firm fundamentals, bondholders would profit the most trading on the informed information in an environment with the least frequent adjustments. Nonetheless, investors obtain a significant alpha from actively trading on the information of impending default events in the following months (higher ΔOPD) in both markets, where shock to firm fundamentals creates large enough gaps for arbitragers. This again highlights the distinct information contained in ΔOPD and ΔIMPVOL. It is important to note

that, despite the variations among profits in different groups, all high-minus-low returns and alpha remain. This echoes previous findings on the superior predictive power of forward-looking information displayed in the option price distribution to future equity returns (Cherian and Jarrow, 1998; Vasquez and Xiao, 2023). We again validate that corporate bonds are generally slow in reconciling new information, possibly due to their predominant ownership by institutional investors who primarily employ long-term buy-and-hold strategies. Aligning with the notion from Darmouni, Siani and Xiao (2022), institutional investors who have the capability to research both markets, also exhibit a stronger motivation to avoid bonds that are more fragile towards fundamental shocks.

5. Robustness

We examine the robustness of our main findings on the negative relationship between ΔOPD and future bond returns. First, we examine if the ΔOPD effect holds in bonds with different credit quality and maturity. Bonds with higher ratings and shorter maturities are expected to be more volatile and riskier, which coincides with the characteristics of firms with high default probabilities (Huang, Jiang and Li, 2023). We, therefore, implement univariate portfolio analysis for corporate bonds with different levels of credit quality and maturity, with results adjusted for the Bali, Subrahmanyam and Wen (2023) six-factor model reported in Table 12. Specifically, Panel A presents results for investment grade (IG) and noninvestment grade (NIG) bonds, respectively, where bonds with BBB- or better (BB+ or worse) ratings are classified as IG (NIG). Panel B of Table 12 presents the regression results for short-maturity (SHORT) bonds and long-maturity (LONG) bonds, defined as bonds with less (greater) than eight years to maturity.

[Table 12]

Results in Panel A show that the ΔOPD effect holds in both IG and NIG groups, confirming its consistency across different levels of credit quality. The NIG group exhibits a significantly higher alpha spread at -0.38% (t-stats=-2.91), highlighting the outstanding profit trading on ΔOPD among riskier bonds. More importantly, we find that ΔOPD contributes to an alpha difference of -0.3% for the IG group, with a higher t-statistic of -4.52 after controlling for stock and bond risk factors. This supports our expectation that institutional investors, who dominate trading in the bond market, contribute to the consistency of ΔOPD's predictability. As primary buyers of IG bonds, they leverage valuable insights from the option market and further enhance their predictability among the IG group. Nonetheless, this observed pattern contrasts the findings from Driessen (2005) and Huang, Jiang and Li (2023), where the predictive power of their factors becomes weaker or diminishes among IG bonds. This is likely because IG bonds that are not directly affected by the fundamental shock are less subjected to portfolio weight adjustments from institutions (Darmouni, Siani and Xiao, 2022). ΔOPD, on the other hand, captures incremental default-related information beyond what is accounted for by their factor, thereby confirming the enhanced predictability within the IG bond category.

Similarly, results from Panel B also confirm that ΔOPD remains significantly priced across different maturity lengths. It is economically and significantly stronger among bonds with maturities greater than eight years, with an alpha difference of -0.47% (t-stats=-4.2). In line with observations in Panel A, these results reaffirm that the significant contribution of cross-asset investors, possibly the dominant investors in the corporate bond market, can partially explain the predictability of change in implied default probability. They value the default information implied across asset classes and adjust accordingly when employing long-term buy-and-hold strategies.

[Table 13]

Second, we investigate the impact of ΔOPD on future corporate bond returns during the months of bond rating announcements, which are the most default-related news in the corporate bond market. Engelberg et al. (2018) show that anomaly returns in the stock market are 50% higher on corporate news days. Following this insight, we expect that the investors' biased expectation would drive up the returns of long–short ΔOPD-sorted portfolio at the month of announcements. Specifically, we run a panel regression of monthly bond returns in quintiles 1 and 5 on the rating day dummy variable. For each month, we define a Net variable equal to −1 (1) if the bond belongs to quintile 1 (5). The rating day indicator (RDAY) equals one if the adjustment on the rating is announced in that month and equals zero for other months. We also include an interaction term, Net × RDAY, indicating the direction of the ΔOPD-induced impact on returns at the month of rating announcements. We report the panel regression results in Table 13. The coefficient on Net × RDAY is 0.326 (t-stats=−8.61), twice the magnitude compared to that of Net itself, confirming higher long–short return on the month of rating announcements. We further split the rating announcement dates into downgrade (DGDAY) and upgrade days (UGDAY) and investigate their separate impacts in columns (2) and (3). While the channel through UGDAY is insignificant, we find a more significant impact of ΔOPD on the long–short return of downgrade announcement months at 0.488 (t-stats=3.16). The results collectively suggest that investors are more sensitive toward signals of an increase in implied default risk around downgrade announcements.

6. Conclusion

In this paper, we investigate the pricing implications of changes in default probability (ΔOPD) elicited from the option-implied distributions from 2002 to 2020. Our findings reveal that ΔOPD negatively predicts the cross-section of future bond returns. Even after accounting for the established bond factors in the literature, the monthly average raw and risk-adjusted return differences between the extreme quintile portfolios of ΔOPD are greater than 0.3% and remain highly significant. This predictive power persists, controlling for the characteristics and risk factors drawn from both bond and option markets. And it becomes more pronounced during heightened bearish sentiment and aggregated

risk. To further support our hypothesis, we also confirm its capacity to forecast forthcoming bankruptcy or failure events and the slow diffusion of this default information from options to bonds.

Our paper validates ΔOPD as a market-based nonparametric alternative that contributes to the most given agency credit ratings and structural default models presented in the corporate bond market. Its consistent predictability arises from significant information spillovers at the firm level. Cross-asset investors, possibly the institutional investors who dominate the corporate bond market, exploit such information in the 'seeking for non-fragility' behavior documented in Darmouni, Siani and Xiao (2022). This leads to consistent performance of our trading strategy across rating categories and superior performance compared to other risk factors with default-like information. Given its robust pricing power, investors and fund managers can explore exploiting diversification benefits in a multi-asset investment setting. Furthermore, a promising avenue for future research is examining the pricing dynamics inherent in these interconnected relationships at the firm level, spanning different markets.

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Table 1: Predicting Bankruptcy and Failure Events with OPD

This table reports results from logit regressions of the bankruptcy and failure indicators on predictor variables for the following 12, 24 and 36 months following Campbell, Hilscher and Szilagyi (2008). The dependent variable is an indicator that equals one if the firm goes bankrupt or fails in the following 12, 24, or 36 months. The explanatory variables include option-implied default probability (OPD), profitability (NIMTA), leverage (TLMTA), firm size (RSIZE), liquidity (CASHMTA), market-to-book ratio (MB), excess equity return (EXRET) and volatility (SIGMA). The sample period covers September 2002–December 2020. Details on the construction of these variables are summarized in the Panel B of Table 3. The absolute value of z-statistics is reported in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Panel A: Bankruptcy						Panel B: Failures					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lead (Months	12	12	24	24	36	36	12	12	24	24	36	36
OPD		2.958***		0.991***		0.526**		3.181***		1.163***		0.989***
		(5.80)		(3.96)		(2.44)		(7.86)		(5.27)		(4.94)
NIMTA	-0.121***	-0.085	-0.127***	0.012	-0.157***	0.126***	-0.216***	-0.322***	-0.191***	0.012	-0.195***	0.125***
	(-5.88)	(-0.73)	(-8.85)	(0.22)	(-12.30)	(2.63)	(-26.75)	(-3.87)	(-29.20)	(0.23)	(-31.66)	(2.73)
TLMTA	3.522***	3.053***	2.571***	2.379***	2.370***	2.671***	1.495***	2.252***	1.353***	2.081***	1.299***	2.618***
	(45.38)	(8.30)	(60.05)	(13.50)	(72.9(	(19.93)	(65.35)	(7.53)	(77.57)	(14.81)	(92.56)	(21.06)
RSIZE	-2.530***	-4.793***	-1.215***	-2.927***	-0.536***	-2.255***	-4.275***	-3.325***	-2.822***	-2.595***	-1.947***	-2.221***
	(-40.43)	(-11.74)	(-29.15)	(-14.92)	(-15.72)	(-15.70)	(-120.02)	(-10.14)	(-113.46)	(-15.71)	(-108.59)	(-16.27)
CASHMTA	-1.073***	-1.994***	-0.672***	-1.370***	-0.449***	-0.956***	-0.476***	-1.089***	-0.339***	-1.153***	-0.200***	-0.824***
	(-18.61)	(-5.85)	(-19.54)	(-8.48)	(-16.27)	(-8.50)	(-25.14)	(-4.59)	(-23.26)	(-8.66)	(-16.14)	(-7.86)
MB	-0.513***	0.088	-0.121***	0.332*	-0.116***	0.621***	0.378***	0.447	0.188***	0.382***	0.150***	0.761***
	(-6.77)	(0.20)	(-2.98)	(1.89)	(-3.61)	(4.44)	(19.65)	(1.57)	(13.05)	(2.59)	(11.99)	(6.58)
EXRET	-0.161***	-0.112	-0.191***	-0.154***	-0.196***	-0.145***	0.031***	-0.136**	-0.009*	-0.181***	-0.029***	-0.148***
	(-12.51)	(-1.52)	(-19.53)	(-3.52)	(-21.44)	(-3.76)	(5.60)	(-2.26)	(-1.79)	(-4.55)	(-6.26)	(-4.14)
SIGMA	0.198***	-0.049	0.120***	-0.058	0.088***	-0.066	0.025***	0.043	0.003	0.020	-0.029***	-0.107
	(11.28)	(-0.39)	(8.14)	(-0.71)	(6.46)	(-0.91)	(3.77)	(0.43)	(0.44)	(0.28)	(-4.84)	(-1.55)
constant	-23.623***	-17.900***	-16.820***	-11.727***	-16.430***	-12.002***	-10.679***	-11.463***	-10.721***	-11.213***	-13.310***	-11.655***
	(-104.28)	(-21.10)	(-143.25)	(-30.93)	(-205.32)	(-46.49)	(-145.49)	(-17.36)	(-170.27)	(-43.16)	(-506.86)	(-44.90)
N	1186260	132593	1186260	132593	1186260	132593	1186260	132593	1186260	132593	1186260	132593
Pseudo-R^2	0.407	0.363	0.324	0.277	0.264	0.256	0.354	0.335	0.262	0.244	0.202	0.249

Table 2: Summary Statistics

This table reports the summary statistics for the variables used in our analysis in Panel A and the correlation matrix in Panel B. ΔOPD is the changes in the implied default probability reported in basis points, computed as in Conrad, Dittmar and Hameed (2020). R_B is the monthly bond returns reported as percentages. $SIZE_B$ is the dollar amount of outstanding bonds reported in billions. RATING is in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. MATURITY is the time-to-maturity of the bond in years. $ILLIQ_B$ is the Bao, et al. (2011) illiquidity measure computed as the autocovariance of the daily price changes within the previous month. REV_B is the bond return over the prior month. MKT_B is the bond market beta estimated using the past 60 months' observations. $IVOL_B$ is the bond idiosyncratic volatility estimated using the past six months of monthly data as in Chung, Wang and Wu (2019). VIX_B is the exposure of bonds to the S&P 500 option implied volatility index. Z_SCORE is the accounting-based Altman Z-Score calculated as in Altman (1968). ΔIMPVOL is the changes in the average of the call and put at-the-money implied volatility as in Cao, et al. (2023). ΔCVOL-ΔPVOL is the difference between changes of the implied volatility of at-the-money call and put option with 365 days of maturity as in An, et al. (2014). Default-related measures such as leverage (MLEV) , distance-to-default (DD) , and credit spread (CS) measures are included as in Dickerson, et al. (2022). This sample period covers September 2002–December 2020.

Panel A: Summary Statistics

	ΔOPD	R_B	$SIZE_B$	RATING	MATURITY	$ILLIQ_B$	REV_B	MKT_B	$IVOL_B$	VIX_B	Z_SCORE	ΔIMPVOL	ΔCVOL-ΔPVOL	MLEV	DD	CS
Obs.	61444	61444	61444	61280	61444	49793	60455	51282	58177	51404	53930	61444	61444	60862	56778	61254
Mean	0.066	0.61	0.54	10	9	0.004	0.61	0.86	0.09	-0.04	3.12	0.00	0.00	0.42	23.67	18.19
1%	-7.997	-6.79	0.01	4	2	-0.002	-6.81	0.06	0.00	-0.51	-0.07	-0.08	-0.07	0.07	2.80	0.36
5%	-0.234	-2.48	0.02	5	3	0.000	-2.49	0.27	0.00	-0.31	0.75	-0.05	-0.03	0.13	5.65	0.64
25%	0.000	-0.27	0.07	8	5	0.000	-0.28	0.55	0.01	-0.10	1.77	-0.01	-0.01	0.26	13.31	1.19
50%	0.000	0.54	0.18	9	7	0.001	0.54	0.78	0.02	-0.01	2.85	0.00	0.00	0.40	21.04	1.68
75%	0.000	1.48	0.51	12	11	0.002	1.48	1.05	0.04	0.04	4.05	0.01	0.01	0.56	31.13	2.38
95%	0.183	3.90	2.23	16	17	0.011	3.90	1.63	0.23	0.11	6.59	0.05	0.03	0.83	50.79	5.47
99%	7.147	8.22	6.60	17	23	0.039	8.20	2.92	1.37	0.19	9.77	0.12	0.07	0.93	67.32	9.15
Std.	0.386	2.71	1.11	3.24	4.59	0.056	2.72	0.61	0.59	0.14	2.08	0.04	0.03	0.21	14.21	3964.59

Panel B: Correlation Matrix

	ΔOPD	R_B	$SIZE_B$	RATING	MATURITY	$ILLIQ_B$	REV_B	MKT_B	$IVOL_B$	VIX_B	Z_SCORE	ΔIMPVOL	ΔCVOL-ΔPVOL	MLEV	DD	CS
ΔOPD	1															
R_B	-0.03	1														
$SIZE_B$	0.00	0.00	1													
RATING	0.00	0.04	-0.30	1												
MATURITY	0.00	0.01	0.25	-0.36	1											
$ILLIQ_B$	0.00	-0.02	-0.02	0.02	0.00	1										
REV_B	-0.01	0.02	0.00	0.03	0.02	0.06	1									
MKT_B	0.00	0.07	0.06	0.19	0.21	0.05	0.05	1								
$IVOL_B$	0.01	-0.20	-0.03	0.05	0.00	0.04	0.00	0.05	1							
VIX_B	0.00	-0.02	0.14	-0.60	0.25	-0.05	-0.02	-0.26	-0.08	1						
Z_SCORE	0.00	-0.02	-0.11	-0.43	0.04	-0.01	-0.03	-0.22	-0.02	0.29	1					
ΔIMPVOL	0.05	-0.41	0.00	-0.01	0.00	0.01	-0.07	-0.02	0.13	0.00	0.00	1				
ΔCVOL-ΔPVOL	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	-0.01	-0.01	0.00	0.04	1			
MLEV	0.00	0.02	0.13	0.35	-0.11	0.03	0.01	0.13	0.04	-0.25	-0.62	0.04	0.00	1		
DD	0.00	-0.07	0.07	-0.51	0.13	-0.06	-0.06	-0.21	-0.07	0.40	0.44	0.02	0.00	-0.60	1	
CS	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.15	0.00	-0.29	0.00	0.00	0.00	0.00	0.01	1

Table 3: Variable Definitions

This table contains the definitions and descriptions of the variables used in the paper.

Variable	Definition	Source
	Panel A: Control variables	
Altman's Z-score (Z_SCORE)	Computed as: Z = 1.2 × (Working Capital/Total Assets) + 1.4 × (Retained Earnings/Total Assets) + 3.3 × (EBIT/Total Assets) + 0.6 × (Market Value of Equity/Total Liabilities) + 0.999 × (Sales/Total Assets)	Altman (1968)
Bond Market Beta (MKT_B)	Time-series regressions of bond excess returns on the excess bond market return over the prior 60 months.	Dickerson, Mueller and Robotti (2023)
Call-put Volatility Spread (ΔCVOL-ΔPVOL)	The difference between changes in the call and put at-the-money implied volatility with 365 days of expiration.	An, et al. (2014)
Changes in implied volatility (IMPVOL)	Changes in the average of the call and put at-the-money implied volatility with 365 days of expiration.	Cao, et al. (2023)
Changes in implied volatility of call options (ΔCVOL)	Changes in the call at-the-money implied volatility with 365 days of expiration.	An, et al. (2014)
Changes in implied volatility of put options (ΔPVOL)	Changes in the put at-the-money implied volatility with 365 days of expiration.	An, et al. (2014)
Credit default swap spread (CDS)	Par spread of credit default swap with one year time to maturity.	Markit
Credit spread (CS)	Difference between the yield of a corporate bond and the associated yield of the Treasury curve at the same maturity.	Collin-Dufresn, Goldstein and Martin (2001)
Default risk (DEFAULT)	Average of market leverage, distance-to-default (sign-corrected), and credit spread	Dickerson, et al. (2022)
Distance-to-Default (DD)	Log of the distance between firm assets (item AT) and one-half of long-term debt value plus short-term debt divided by asset volatility (the rolling 12-month standard deviation of asset returns).	Campbell and Thompson (2008)
Duration (DURATION)	Corporate bond duration, expressed in years	TRACE
Idiosyncratic volatility ($IVOL_B$)	Standard deviation of residuals from the regression of excess monthly bond returns on Fama and French five factor model over the past six months.	Chung, Wang and Wu (2019)

Illiquidity ($ILLIQ_B$)	The autocovariance of the daily bond price changes within the previous month, multiplied by –1.	Bao, Pan and Wang (2011)
Market leverage (MLEV)	The ratio between total book debt (item LT) and the market value of equity plus total book debt.	Dickerson, et al. (2022)
Maturity (MATURITY)	Corporate bond time-to-maturity, expressed in years	TRACE
Multimarket information asymmetry (MIA)	https://www.travislakejohnson.com/data.html	Johnson and So (2018)
Rating (RATING)	Historical ratings provided by both Standard & Poor and Moody's rating agencies are assigned numbers, where 1 refers to a AAA rating, 2 refers to AA + , …, and 21 refers to CCC. The bond's final rating is determined as the average of ratings when both are available or as the rating provided by one of the two rating agencies when only one rating is available.	Bai, Bali and Wen (2019)
Realized-Implied Volatility Spread (RVOL-IVOL)	The difference between the monthly realized volatility and the average of the at-the- money call and put implied volatilities (using the volatility surface standardized options with a delta of 0.50 and maturity of 30 days).	Goyal and Saretto (2009)
Reversal (REV_B)	Bond returns of the prior month.	Bai, Bali and Wen (2019)
Risk-neutral skewness (QSKEW)	The difference between the out-of-the-money put implied volatility (with delta of 0.20) and the average of the at-the-money call and put implied volatilities (with deltas of 0.50), both using maturities of 30 days.	Xing, Zhang and Zhao (2010)
Size ($SIZE_B$)	The natural logarithm of the product of the bond price and the number of bond amount outstanding.	CRSP
Uncertainty beta (UNC_B)	Exposure of individual stocks to the economic uncertainty index proposed by Jurado, Ludvigson and Ng (2015).	Bali, Subrahmanyam and Wen (2023)
VIX Beta (VIX_B)	Time-series regressions on daily observations of excess bond returns on corresponding excess market portfolio returns and changes in the S&P 500 index option implied variance.	Chung, Wang and Wu (2019)
Panel B: Bankruptcy predicting variables		
Profitability (NIMTA)	The net income relative to the sum of book value of liabilities and market value of equities.	
Leverage (TLMTA)	The total liabilities divided by the sum of market equity and book liabilities.	
Liquidity (CASHMTA)	A company's cash and short-term assets to the sum of market equity and book liabilities.	
Market-to-book Ratio (MB)	Market value of equity to book value of equity.	
Firm Size (RSIZE)	The relative size of each firm measured as the log ratio of its market capitalization to that of the S&P 500 index.	
Excess Equity Return (EXRET)	Monthly log excess return on each firm's equity relative to the S&P 500 index	

Equity Return Volatility (SIGMA)	The standard deviation of each firm's daily equity returns over the past 3 months

Table 4: Bond Quintile Portfolios Sorted on ΔOPD

For each month, quintile portfolios are formed by sorting bonds based on the ΔOPD, where quintile 1(5) portfolio contains bonds with the lowest (highest) ΔOPD during the previous month. The ΔOPD is the innovation of option-implied firm default probability calculated following Conrad, Dittmar and Hameed (2020). The second column reports the average ΔOPD in basis points for each quintile, and the remaining columns present the average bond excess returns and alphas for the equal-weighted and value-weighted portfolios separately. Following Bali, Subrahmanyam and Wen (2021), α^5 is the alpha relative to five stock market factors including the excess stock market return (MKT_E), equity size (SMB_E), book-to-market (HML_E), equity momentum (MOM_E), and equity liquidity factors (LIQ). α^1 is the alpha relative to excess bond market return (MKT_B) only to avoid data handling issue documented in Dickerson, Mueller and Robotti (2023). We also report α^6 relative to a combination of five stock market factors and MKT_B following Bali, Subrahmanyam and Wen (2023). The last five columns report average bond characteristics for each quintile, including rating, maturity, size, duration, and illiquidity. The last row presents return and alpha differences between quintiles 1 and 5. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period covers September 2002–December 2020.

		Equal weighted				Value weighted				Average Portfolio characteristics				
		(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)	(11)	(12)	(13)	(14)	(15)
Quintile	ΔOPD	R_B-R_f	α^5	α^1	α^6	R_B-R_f	α^5	α^1	α^6	Rating	Maturity	Size	Duration	Illiquidiy
1 [Low]	-0.0427	0.70	0.57	0.34	0.38	0.76	0.60	0.33	0.35	11.94	7.53	18.49	5.20	0.005
		(4.92)	(4.72)	(4.26)	(3.74)	(4.85)	(4.58)	(3.56)	(3.43)					
2	-0.0002	0.54	0.46	0.18	0.21	0.51	0.41	0.11	0.13	8.83	9.21	19.10	6.11	0.004
		(4.72)	(4.35)	(3.01)	(3.04)	(4.44)	(3.80)	(1.89)	(1.92)					
3	0.0000	0.42	0.35	0.06	0.10	0.41	0.33	0.00	0.03	7.68	9.80	19.39	6.35	0.007
		(4.23)	(3.49)	(1.13)	(1.73)	(3.84)	(2.98)	(0.06)	(0.55)					
4	0.0003	0.34	0.22	-0.06	-0.04	0.31	0.18	-0.15	-0.14	8.49	9.38	19.16	6.16	0.004
		(3.22)	(2.11)	(-1.03)	(-0.75)	(2.77)	(1.54)	(-2.50)	(-2.15)					
5 [High]	0.0438	0.41	0.27	-0.04	0.06	0.33	0.20	-0.23	-0.08	11.87	7.53	18.48	5.20	0.010
		(2.37)	(2.40)	(-0.38)	(0.67)	(1.89)	(1.54)	(-1.74)	(-1.00)					
5-1		-0.29	-0.30	-0.38	-0.31	-0.43	-0.40	-0.56	-0.43					
[High-Low]		(-2.65)	(-3.64)	(-3.13)	(-4.06)	(-2.74)	(-3.16)	(-2.94)	(-3.67)					

Table 5: Six-factor Alphas of Bond Portfolios Sorted on ΔOPD

This table reports six-factor alphas (α^6) relative to the five stock market factors including the excess stock market return (MKT_E), equity size (SMB_E), book-to-market (HML_E), equity momentum (MOM_E), and equity liquidity factors (LIQ), together with excess bond market return (MKT_B) following Bali, Subrahmanyam and Wen (2023). Newey and West (1987) *t*-statistics are reported in parentheses. The column "5–1" refers to the difference in α^6 between quintiles 5 and 1. For each month, we perform double sorts to control for various characteristics, which include bond size ($SIZE_B$), credit rating (RATING), time-to-maturity (MATURITY), duration (DURATION), bond illiquidity ($ILLIQ_B$), bond momentum (MOM_B), bond short-term reversal (REV_B), bond market beta (MKT_B), bond uncertainty beta (UNC_B), bond VIX beta (VIX_B), bond idiosyncratic volatility ($IVOL_B$), Altman (1968) Z score (Z_SCORE), market leverage (MLEV), distance-to-default (DD), credit spread (CS), changes in option-implied volatility (ΔIMPVOL), changes in the implied volatility of call options (ΔCVOL), changes in the implied volatility of put options (ΔPVOL), ΔCVOL-ΔPVOL and credit default swap spread (CDS). We first sort bonds into five quintile portfolios based on one of the characteristics from the past month. Within each characteristic quintile, we further sort bonds into five quintiles based on ΔOPD. The five ΔOPD-sorted portfolios are then averaged over each of the five characteristic portfolios, thus representing ΔOPD-sorted quintile portfolios controlling for the characteristics. Details on the construction of these variables are summarized in Panel A of Table 3. The sample period covers September 2002–December 2020 for all controls. All portfolios are value weighted.

		Ranking on the ΔOPD					
		1 [Low]	2	3	4	5 [High]	5-1 [High-Low]
(1)	$SIZE_B$	0.30(3.48)	0.18(3.12)	0.14(2.56)	-0.01(-0.16)	0.02(0.26)	-0.27(-4.01)
(2)	RATING	0.26(3.52)	0.13(2.21)	0.05(0.99)	0.02(0.21)	-0.04(-0.56)	-0.30(-4.78)
(3)	MATURITY	0.30(3.39)	0.15(2.56)	0.05(0.83)	-0.05(-1.04)	-0.05(-0.64)	-0.35(-4.16)
(4)	DURATION	0.30(3.36)	0.14(2.28)	0.04(0.84)	-0.05(-0.84)	-0.03(-0.42)	-0.33(-4.10)
(5)	$ILLIQ_B$	0.32(3.70)	0.11(1.60)	0.05(0.64)	-0.05(-0.83)	-0.01(-0.22)	-0.34(-4.16)
(6)	MOM_B	0.28(3.44)	0.14(1.97)	0.08(1.12)	-0.04(-0.52)	-0.03(-0.40)	-0.31(-3.81)
(7)	REV_B	0.32(3.17)	0.14(1.90)	0.10(1.45)	-0.06(-0.85)	-0.07(-1.02)	-0.38(-3.78)
(8)	MKT_B	0.28(3.03)	0.16(2.52)	0.08(1.25)	-0.07(-1.00)	-0.05(-0.77)	-0.33(-3.08)
(9)	UNC_B	0.27(3.30)	0.20(2.20)	0.09(1.11)	-0.02(-0.25)	-0.04(-0.72)	-0.31(-4.26)
(10)	VIX_B	0.30(3.99)	0.12(1.45)	0.09(1.19)	-0.01(-0.22)	-0.05(-0.72)	-0.35(-5.43)
(11)	$IVOL_B$	0.24(2.89)	0.17(2.23)	0.04(0.61)	-0.02(-0.28)	-0.02(-0.37)	-0.27(-3.28)
(12)	Z_SCORE	0.31(3.40)	0.18(2.38)	0.06(0.80)	-0.06(-0.80)	-0.06(-0.75)	-0.37(-3.59)
(13)	MLEV	0.31(3.13)	0.15(2.24)	0.02(0.39)	-0.07(-1.09)	-0.04(-0.55)	-0.35(-3.89)
(14)	DD	0.24(3.43)	0.11(1.63)	0.05(0.66)	-0.02(-0.32)	0.02(0.32)	-0.22(-3.49)
(15)	CS	0.25(3.61)	0.12(1.88)	0.05(0.75)	0.08(1.24)	-0.01(-0.20)	-0.26(-4.83)
(16)	ΔIMPVOL	0.28(3.22)	0.15(2.13)	-0.02(-0.27)	-0.04(-0.77)	0.02(0.27)	-0.26(-3.35)
(17)	ΔCVOL	0.28(3.27)	0.14(1.96)	0.01(0.18)	-0.04(-0.59)	0.01(0.22)	-0.26(-3.63)
(18)	ΔPVOL	0.26(3.07)	0.16(2.45)	0.04(0.60)	-0.07(-1.22)	0.00(0.04)	-0.25(-3.18)
(19)	ΔCVOL-ΔPVOL	0.30(3.24)	0.17(2.36)	0.06(0.93)	-0.09(-1.39)	-0.04(-0.63)	-0.34(-3.71)
(20)	CDS	0.22(2.75)	0.09(1.54)	0.06(0.87)	0.01(0.15)	-0.04(-0.53)	-0.26(-4.37)

Table 6: Bond-level Fama–Macbeth Regressions

This table reports the time-series average of slope coefficients obtained from regressing monthly excess bond returns on ΔOPD while controlling for a set of lagged predictive variables using the Fama and MacBeth (1973) method. The control variables include changes in option-implied volatility (ΔIMPVOL), ΔCVOL-ΔPVOL, bond market beta (MKT_B), bond size ($SIZE_B$), credit rating (RATING), time-to-maturity (MATURITY), bond illiquidity ($ILLIQ_B$), bond short-term reversal (REV_B), bond idiosyncratic volatility ($IVOL_B$), bond VIX beta (VIX_B), market leverage (MLEV), distance-to-default (DD) and credit spread (CS). Details on the construction of these variables are summarized in the Panel A of Table 3. Newey and West (1987) adjusted *t*-statistics are reported in parentheses. The sample period covers September 2002–December 2020. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

	(1) R_B	(2) R_B	(3) R_B	(4) R_B	(5) R_B	(6) R_B	(7) R_B
Intercept	0.526***	0.496***	0.489***	0.506***	0.530***	0.533**	1.688**
	(4.92)	(5.07)	(4.91)	(4.39)	(4.02)	(2.07)	(2.41)
ΔOPD	-0.020***	-0.016***	-0.015***	-0.018***	-0.022***	-0.021***	-0.015***
	(-3.53)	(-2.84)	(-2.69)	(-2.80)	(-2.69)	(-2.89)	(-2.88)
ΔIMPVOL		-0.191***	-0.189***	-0.141***	-0.162***	-0.160***	-0.140***
		(-4.92)	(-4.91)	(-3.54)	(-4.21)	(-4.57)	(-3.61)
ΔCVOL-ΔPVOL			-0.064*	-0.039	-0.049	-0.042	-0.038
			(-1.69)	(-1.32)	(-1.59)	(-1.33)	(-1.27)
MKT_B				0.182***	0.110**	0.072*	0.091**
				(2.78)	(2.04)	(1.81)	(2.13)
$SIZE_B$					0.010	0.014	0.032
					(0.33)	(0.50)	(1.08)
RATING					0.060	0.063	0.036
					(1.14)	(1.41)	(0.90)
MATURITY					0.035	0.022	0.005
					(0.89)	(0.58)	(0.14)
$ILLIQ_B$					0.512	0.515	0.279
					(0.86)	(1.05)	(0.62)
REV_B					-0.076	-0.071	-0.071
					(-1.55)	(-1.49)	(-1.55)
$IVOL_B$						1.383	1.256
						(1.20)	(1.15)
VIX_B						0.056	0.048
						(1.05)	(0.97)
MLEV							-0.027
							(-1.46)
CS							303.219**
							(2.09)
DD							0.057**
							(2.15)
N	60327	60327	60327	50886	42887	42685	42519
adj. R-sq	0.027	0.041	0.051	0.103	0.314	0.355	0.389

Table 7: Returns on ΔOPD-sorted portfolios during periods of high and low aggregated risk level

This table reports excess returns and return differences for ΔOPD-sorted quintile portfolios following periods of high and low aggregated risk level, adjusting for MKT_E, SMB_E, HML_E, MOM_E, LIQ and MKT_B following Bali, Subrahmanyam and Wen (2023). High (low) risk months are defined as those in which the aggregated risk level in the previous month is above (below) the median value for the sample period. The aggregated risk level is proxied by market condition measures in Panel A including MOVE index, VIX index, uncertainty indexes from Jurado, Ludvigson and Ng (2015) and economic policy uncertainty index (EPU). Panel B examines economic activity measures including misery index, Chicago Fed National Activity index (CFNAI), Total Borrowings from the Federal Reserve and CRE price index. Panel C examines sentiment measures proxied by Investor Intelligence Sentiment index, FOMC Sentiment index, market states as in Eisdorfer and Misirli (2020) and Business condition index (Aruoba, Diebold and Scotti, 2009). Newey and West (1987) *t*-statistics are reported in parentheses.

Panel A: Market condition measures

	MOVE Index			VIX Index			Jurado UNC Index			EPU Index		
Quintile	High	Low	Diff	High	Low	Diff	High	Low	Diff	High	Low	Diff
1 [Low]	0.89	0.59	0.30	1.15	0.36	0.79	0.96	0.56	0.40	1.39	0.13	1.26
	(3.39)	(3.88)	(1.17)	(4.58)	(2.81)	(3.21)	(3.50)	(4.46)	(1.59)	(6.42)	(0.92)	(5.32)
2	0.52	0.49	0.03	0.76	0.25	0.51	0.57	0.45	0.12	0.93	0.09	0.84
	(2.76)	(3.45)	(0.14)	(4.41)	(2.10)	(2.37)	(2.96)	(3.76)	(0.56)	(6.54)	(0.69)	(4.02)
3	0.41	0.42	-0.01	0.55	0.27	0.28	0.41	0.41	0.00	0.71	0.12	0.59
	(2.37)	(3.10)	(-0.05)	(3.42)	(2.17)	(1.20)	(2.40)	(3.14)	(0.02)	(5.16)	(0.93)	(2.57)
4	0.26	0.38	-0.12	0.45	0.18	0.27	0.26	0.37	-0.11	0.62	0.01	0.61
	(1.37)	(2.88)	(-0.44)	(2.49)	(1.48)	(1.00)	(1.41)	(2.88)	(-0.39)	(4.13)	(0.09)	(2.35)
5 [High]	0.24	0.38	-0.14	0.48	0.18	0.30	0.18	0.48	-0.30	0.72	-0.06	0.78
	(0.76)	(2.85)	(-0.43)	(1.52)	(1.34)	(0.89)	(0.55)	(3.86)	(-0.89)	(2.74)	(-0.40)	(2.36)
H-L return	-0.65	-0.21	-0.44	-0.68	-0.18	-0.50	-0.78	-0.08	-0.70	-0.67	-0.19	-0.48
	(-2.33)	(-2.03)	(-1.74)	(-2.35)	(-2.24)	(-1.96)	(-2.75)	(-1.01)	(-2.79)	(-2.54)	(-1.92)	(-1.90)
H-L α^6	-0.61	-0.25		-0.64	-0.22		-0.70	-0.15		-0.73	-0.18	
	(-3.02)	(-2.36)		(-3.20)	(-2.88)		(-3.85)	(-1.42)		(-4.06)	(-1.76)	

Panel B: Economic activity measures

	Misery Index			CFNAI			Total Borrowings			CRE Index		
Quintile	High	Low	Diff	High	Low	Diff	High	Low	Diff	High	Low	Diff
1 [Low]	0.72	0.79	-0.07	0.47	1.04	-0.57	1.00	0.51	0.49	1.26	0.22	1.04
	(3.84)	(3.15)	(-0.29)	(3.93)	(3.67)	(-2.28)	(3.96)	(2.86)	(1.97)	(4.99)	(1.90)	(4.31)
2	0.50	0.52	-0.02	0.34	0.68	-0.34	0.67	0.35	0.32	0.86	0.13	0.73
	(3.15)	(2.96)	(-0.10)	(2.97)	(3.35)	(-1.57)	(3.66)	(2.29)	(1.45)	(4.63)	(1.08)	(3.41)
3	0.35	0.47	-0.12	0.29	0.53	-0.24	0.53	0.30	0.23	0.69	0.11	0.58
	(2.32)	(2.60)	(-0.53)	(2.53)	(2.73)	(-1.01)	(3.04)	(1.97)	(0.99)	(3.74)	(0.87)	(2.51)
4	0.24	0.40	-0.16	0.22	0.41	-0.19	0.42	0.21	0.21	0.61	0.00	0.61
	(1.31)	(2.14)	(-0.60)	(1.79)	(2.01)	(-0.75)	(2.29)	(1.27)	(0.77)	(3.11)	(-0.02)	(2.37)
5 [High]	0.28	0.38	-0.10	0.33	0.32	0.01	0.47	0.19	0.28	0.69	-0.06	0.75
	(1.11)	(1.80)	(-0.31)	(2.56)	(0.99)	(0.03)	(1.62)	(0.79)	(0.83)	(2.39)	(-0.30)	(2.29)
H-L return	-0.44	-0.41	-0.03	-0.14	-0.72	0.58	-0.54	-0.32	-0.22	-0.57	-0.28	-0.29
	(-2.53)	(-2.02)	(-0.12)	(-1.61)	(-2.52)	(2.30)	(-2.21)	(-1.82)	(-0.84)	(-2.34)	(-1.63)	(-1.12)
H-L α^6	-0.61	-0.36		-0.28	-0.61		-0.60	-0.33		-0.61	-0.25	
	(-3.37)	(-2.11)		(-2.37)	(-3.17)		(-3.13)	(-2.09)		(-3.02)	(-2.17)	

Panel C: Sentiment measures

	Investor Intelligence Sentiment			FOMC Sentiment			Market state			Business condition index		
Quintile	More Bearish	Less Bearish	Diff	Good	Bad	Diff	Bull	Bear	Diff	Good	Bad	Diff
1 [Low]	1.07	0.44	0.63	0.42	1.31	-0.89	0.44	2.31	-1.87	0.74	0.77	-0.03
	(3.88)	(3.86)	(2.51)	(2.52)	(4.29)	(-3.00)	(3.39)	(4.92)	(-6.05)	(5.32)	(3.33)	(-0.12)
2	0.65	0.36	0.29	0.25	0.85	-0.60	0.31	1.48	-1.17	0.51	0.50	0.01
	(3.38)	(3.38)	(1.32)	(1.67)	(3.98)	(-2.36)	(2.55)	(4.67)	(-4.19)	(3.51)	(3.11)	(0.05)
3	0.49	0.33	0.16	0.26	0.58	-0.32	0.28	1.02	-0.74	0.42	0.40	0.02
	(2.85)	(2.58)	(0.71)	(1.89)	(2.32)	(-1.18)	(2.27)	(3.01)	(-2.40)	(3.02)	(2.72)	(0.08)
4	0.43	0.20	0.23	0.18	0.47	-0.29	0.16	1.07	-0.91	0.35	0.29	0.06
	(2.25)	(1.51)	(0.87)	(1.22)	(1.68)	(-0.95)	(1.15)	(3.25)	(-2.65)	(2.67)	(1.78)	(0.21)
5 [High]	0.49	0.17	0.32	0.18	0.53	-0.35	0.13	1.30	-1.17	0.53	0.21	0.32
	(1.60)	(0.90)	(0.95)	(1.10)	(1.42)	(-0.92)	(0.73)	(3.78)	(-2.68)	(3.80)	(0.82)	(0.93)
H-L return	-0.58	-0.28	-0.30	-0.24	-0.78	0.54	-0.31	-1.01	0.70	-0.20	-0.56	0.36
	(-2.31)	(-1.69)	(-1.21)	(-2.10)	(-2.43)	(1.85)	(-2.34)	(-2.10)	(2.08)	(-1.72)	(-2.41)	(1.34)
H-L α^6	-0.59	-0.33		-0.26	-0.85		-0.38	-0.77		-0.35	-0.44	
	(-2.61)	(-1.99)		(-2.22)	(-2.73)		(-3.29)	(-1.85)		(-2.69)	(-2.83)	

Table 8: ΔOPD Predicts Future Cash Flow and Cash Flow Uncertainty

This table presents the Fama and MacBeth (1973) regressions of future cash flows and cash flow uncertainty on the ΔOPD and various control variables commonly used in the literature, including the log market value of equity (LNME), capital expenditures (CAPEX), leverage (LEV), and lagged cash flow (LEARN/LROA). We use return-on-assets (ROA) and earnings (EARN) to measure firm-level cash flows. The cash flow uncertainty is defined as the standard deviation of the next 3- or 5-quarter return-on-assets and earnings (VROA3/VEARN3 or VROA5/VEARN5). The Newey and West (1987) t-statistics are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively. The sample period is from September 2002 to December 2020.

	Panel A: Earnings			Panel B: Return on assets		
	EARN	VEARN3	VEARN5	ROA	VROA3	VROA5
Intercept	1.265***	2.668***	3.034***	0.004	0.041***	0.043***
	(5.85)	(10.02)	(9.61)	(0.78)	(5.42)	(6.42)
ΔOPD	-0.223***	0.317***	0.375***	-0.002*	0.008***	0.008***
	(-4.56)	(5.16)	(5.06)	(-1.70)	(4.14)	(4.76)
LNME	0.122***	-0.058***	-0.155***	0.003***	-0.002***	-0.002***
	(5.46)	(-2.76)	(-6.36)	(13.53)	(-6.38)	(-6.56)
CAPEX	0.095**	0.256***	0.291***	-0.003***	0.001	0.001
	(2.18)	(5.17)	(7.16)	(-7.16)	(1.50)	(1.23)
LEV	0.009	-0.033	-0.065***	0.000	-0.002***	-0.002***
	(0.35)	(-1.59)	(-2.81)	(1.33)	(-5.72)	(-7.43)
LEARN	3.601***	0.901***	1.025***			
	(20.00)	(9.68)	(11.20)			
LROA				0.011***	-0.000	-0.001**
				(21.05)	(-1.09)	(-2.58)
N	58606	57821	56996	58647	57860	57047
adj. R-sq	0.557	0.227	0.231	0.262	0.063	0.065

Table 9: Predicting Bond Returns by Asymmetric Impact of ΔOPD

This table reports the firm-level Fama and MacBeth (1973) cross-sectional regressions in equation (4), with additional interaction terms with three dummy variables defined in equation (5), including ΔOPD**High_OptionVol*, ΔOPD**High_PutOptionVol*, ΔOPD**High_P/C*Volume. Other control variables are the same as the ones applied in Table 6, with details of construction summarized in Panel A of Table 3. Newey and West (1987) adjusted *t*-statistics are reported in parentheses. The sample period covers September 2002–December 2020. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

	(1) R_B	(2) R_B	(3) R_B
Intercept	1.452*	1.421*	1.391*
	(1.89)	(1.89)	(1.81)
ΔOPD**High OptionVol*	-0.016***		
	(-2.64)		
ΔOPD**High_PutOptionVol*		-0.018***	
		(-2.91)	
ΔOPD**High P/C Volume*			-0.025***
			(-3.85)
ΔOPD	-0.013**	-0.014**	-0.009
	(-2.14)	(-2.45)	(-1.60)
ΔIMPVOL	-0.131***	-0.131***	-0.128***
	(-3.47)	(-3.49)	(-3.42)
ΔCVOL-ΔPVOL	-0.028	-0.027	-0.033
	(-1.08)	(-1.01)	(-1.22)
MKT_B	0.092*	0.095*	0.091*
	(1.91)	(1.97)	(1.88)
$SIZE_B$	0.051	0.051*	0.048
	(1.65)	(1.69)	(1.61)
RATING	0.038	0.039	0.033
	(0.88)	(0.93)	(0.79)
MATURITY	0.008	0.006	0.008
	(0.20)	(0.16)	(0.21)
$ILLIQ_B$	0.230	0.197	0.202
	(0.54)	(0.47)	(0.47)
REV_B	-0.057	-0.061	-0.063
	(-1.37)	(-1.50)	(-1.51)
$IVOL_B$	0.842	0.821	0.971
	(0.89)	(0.86)	(1.02)
VIX_B	0.047	0.048	0.040
	(1.00)	(1.05)	(0.87)
MLEV	-0.044**	-0.045**	-0.045**
	(-2.22)	(-2.20)	(-2.18)
CS	257.945	251.025	237.915
	(1.58)	(1.58)	(1.45)
DD	0.034	0.032	0.036
	(1.44)	(1.36)	(1.49)
N	42519	42519	42519
adj. R-sq	0.353	0.353	0.355

Table 10: Subsample Analysis Conditional on Option-implied Bearish Sentiment

This table reports excess bond returns and α^6 of ΔOPD-sorted quintile portfolios for high and low subgroups based on different measures of option-implied bearish sentiment, controlling for MKT_E, SMB_E, HML_E, MOM_E, LIQ, MKT_B following Bali, Subrahmanyam and Wen (2023). Firms with high (low) bearish sentiment implied from option market are divided using the median value of changes in implied put option volatility (ΔPVOL), changes in implied volatility (ΔIMPVOL), call-put volatility spread (ΔCVOL-ΔPVOL), realized-implied volatility spread (RVOL-IVOL), risk-neutral skewness (QSKEW) and multimarket asymmetry (MIA), with construction details reported in the Panel A of Table 3. For each of the quintile portfolios, we report the value-weighted average monthly excess equity returns. Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors. The sample period covers September 2002 – December 2020.

	ΔPVOL		ΔIMPVOL		ΔCVOL–ΔPVOL		RVOL-IVOL		QSKEW		MIA	
Quintile	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
1 [Low]	0.65	0.81	0.66	0.81	0.68	0.77	0.76	0.54	0.82	0.59	0.66	0.61
	(4.44)	(4.79)	(4.57)	(4.76)	(4.77)	(4.94)	(4.37)	(4.74)	(4.77)	(4.89)	(4.88)	(3.80)
2	0.43	0.60	0.40	0.59	0.60	0.49	0.55	0.44	0.57	0.50	0.48	0.43
	(3.65)	(5.07)	(3.41)	(5.08)	(4.74)	(4.15)	(3.73)	(4.17)	(4.05)	(4.46)	(3.78)	(3.71)
3	0.29	0.48	0.30	0.50	0.41	0.38	0.40	0.40	0.35	0.42	0.36	0.33
	(2.53)	(4.43)	(2.70)	(4.52)	(3.87)	(3.30)	(2.80)	(3.96)	(2.72)	(4.15)	(2.83)	(3.24)
4	0.16	0.48	0.16	0.45	0.35	0.32	0.32	0.40	0.30	0.37	0.27	0.26
	(1.28)	(4.20)	(1.20)	(4.10)	(2.96)	(2.68)	(1.97)	(3.61)	(2.03)	(3.49)	(2.12)	(2.30)
5 [High]	0.21	0.56	0.16	0.57	0.35	0.39	0.38	0.40	0.35	0.39	0.35	0.38
	(1.06)	(3.64)	(0.80)	(3.63)	(2.17)	(2.14)	(1.73)	(3.72)	(1.70)	(3.41)	(2.04)	(2.67)
H-L return	-0.44	-0.25	-0.51	-0.25	-0.33	-0.38	-0.38	-0.14	-0.47	-0.21	-0.31	-0.24
	(-2.33)	(-2.35)	(-2.67)	(-2.07)	(-2.61)	(-2.41)	(-2.81)	(-2.36)	(-2.88)	(-2.37)	(-2.25)	(-1.89)
H-L α^6	-0.41	-0.34	-0.48	-0.30	-0.35	-0.40	-0.44	-0.13	-0.49	-0.22	-0.39	-0.20
	(-3.32)	(-2.99)	(-3.63)	(-2.63)	(-2.92)	(-3.41)	(-3.65)	(-3.21)	(-4.04)	(-2.51)	(-2.97)	(-1.95)

Table 11: Six-factor Alphas of ΔOPD-sorted Bond Portfolio Conditional on Changes in Option and Bond Trading Volume

This table reports returns and α^6 of ΔOPD-sorted portfolios conditional on changes in (put) option and bond trading volume, controlling for MKT_E, SMB_E, HML_E, MOM_E, LIQ, MKT_B following Bali, Subrahmanyam and Wen (2023). For each month, we separate the bonds into two groups based on the median change in (put) option trading volume (Δ(Put) Option Vol) or median change in bond trading volume (ΔBond Vol). For bonds in the intersection of each of these four groups, we further sort by ΔOPD. For each of the quintile portfolios, we report the value-weighted average monthly excess bond returns. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period is from September 2002 to December 2020.

	Panel A: Total Option Volume					Panel B: Put Option Volume				
	ΔOption Vol	High	High	Low	Low	ΔPut Option `	High	High	Low	Low
	ΔBond Vol	High	Low	High	Low	ΔBond Vol	High	Low	High	Low
1 [Low]		0.74	0.65	0.71	0.55		0.76	0.60	0.74	0.56
		(4.98)	(4.83)	(4.69)	(3.57)		(5.06)	(4.21)	(4.74)	(3.79)
2		0.46	0.52	0.55	0.57		0.48	0.58	0.52	0.56
		(4.08)	(4.65)	(4.59)	(4.95)		(4.43)	(4.79)	(4.71)	(4.57)
3		0.43	0.43	0.42	0.38		0.45	0.38	0.40	0.42
		(4.03)	(4.01)	(3.94)	(3.49)		(3.95)	(3.50)	(3.85)	(3.89)
4		0.30	0.32	0.38	0.32		0.31	0.39	0.33	0.30
		(2.79)	(2.80)	(2.81)	(2.62)		(2.89)	(3.15)	(2.65)	(2.71)
5 [High]		0.31	0.45	0.37	0.32		0.29	0.41	0.40	0.33
		(1.91)	(2.35)	(1.98)	(1.74)		(1.79)	(2.34)	(2.25)	(1.79)
H-L return		-0.43	-0.21	-0.34	-0.23		-0.47	-0.19	-0.33	-0.23
		(-2.93)	(-1.75)	(-2.07)	(-2.09)		(-3.08)	(-1.63)	(-2.20)	(-2.24)
H - L α^6		-0.44	-0.31	-0.40	-0.22		-0.46	-0.21	-0.35	-0.26
		(-3.35)	(-3.20)	(-2.77)	(-2.41)		(-3.62)	(-2.27)	(-2.59)	(-2.86)

Table 12: Bond Return Predictability across Credit Quality and Maturity

This table presents ΔOPD-sorted portfolio returns with different levels of credit quality and maturity. Panel A is for investment-grade corporate bonds (IG) and noninvestment-grade corporate bonds (NIG). Bonds with ratings of 1–10 (larger than 10) are regarded as IG (NIG). Panel B is for short-maturity corporate bonds (SHORT) and long-maturity corporate bonds (LONG). Bonds with maturities less (greater) than 8 years are regarded as SHORT (LONG). For each month, we separate the bonds into two groups based on their rating or time to maturity. We then sorted the grouped bonds into quintile portfolios based on ΔOPD, where quintile 1(5) portfolio contains bonds with the lowest (highest) ΔOPD within the characteristic group. ΔOPD is the innovation of option-implied default probability of the firm calculated following Conrad, Dittmar and Hameed (2020). We report the average ΔOPD in basis points, mean returns of the 5 portfolios and the H-L portfolio returns, and α^6 controlling for MKT_E, SMB_E, HML_E, MOM_E, LIQ, MKT_B following Bali, Subrahmanyam and Wen (2023). Newey and West (1987) *t*-statistics are reported in parentheses. The sample period is from September 2002 to December 2020.

	Panel A: Credit Quality				Panel B: Maturity			
	IG		NIG		SHORT		LONG	
Portfolio	ΔOPD	α^6	ΔOPD	α^6	ΔOPD	α^6	ΔOPD	α^6
1 [Low]	-0.0065	0.61	-0.1041	0.80	-0.0614	0.68	-0.0185	0.75
		(4.83)		(4.19)		(4.60)		(5.04)
2	0.0000	0.45	-0.0038	0.62	-0.0008	0.45	0.0000	0.50
		(4.07)		(4.20)		(4.29)		(4.20)
3	0.0000	0.40	0.0004	0.55	0.0000	0.35	0.0000	0.43
		(3.79)		(3.95)		(4.00)		(3.74)
4	0.0000	0.38	0.0044	0.49	0.0008	0.33	0.0001	0.33
		(3.51)		(2.96)		(3.10)		(2.74)
5 [High]	0.0081	0.28	0.1060	0.57	0.0594	0.46	0.0243	0.24
		(2.19)		(2.51)		(2.77)		(1.34)
H-L return		-0.33		-0.23		-0.22		-0.51
		(-3.92)		(-1.78)		(-2.09)		(-3.22)
H - L α^6		-0.30		-0.38		-0.33		-0.47
		(-4.52)		(-2.91)		(-3.39)		(-4.20)

Table 13: Bond Return Predictability Around Rating Announcement Month

This table reports bond returns around rating announcement days from a panel regression of monthly bond returns on time fixed effects, the Net anomaly variable, rating announcement dummy variable RDAY, and interaction between Net and RDAY. For each month, we define the Net variable to be equal to −1 (1) if the bond belongs to quintile 1 (5). RDAY is a dummy variable that equals one if the rating announcement day is included in the reported months and zero otherwise. We further split the rating announcement months into downgrades (DGDAY) and upgrade (UGDAY) months and repeat the same analysis. T-statistics are reported in parenthesis using standard errors clustered on time. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively. The sample period is from September 2002 to December 2020.

	(1)	(2)	(3)
	R_B	R_B	R_B
Interept	0.848***	0.861***	0.842***
	(5.81)	(5.91)	(5.78)
Net	-0.154***	-0.145***	-0.153***
	(-8.61)	(-8.21)	(-8.64)
Net*RDAY	0.326***		
	(2.90)		
RDAY	0.375***		
	(4.44)		
Net*UGDAY		0.040	
		(0.24)	
UGDAY		0.000	
		(0.00)	
Net*DGDAY			0.488***
			(3.16)
DGDAY			0.711***
			(5.95)
N	60327	60327	60327
R-sq	0.037	0.037	0.037

Appendix A

A.1 BKM method

We calculate risk-neutral volatility, skewness, and kurtosis using the methodology of Bakshi, Kapadia and Madan (2003) (BKM hereafter). BKM demonstrate that the annualized variance (Var^{BKM}), skewness ($Skew^{BKM}$), and excess kurtosis ($Kurt^{BKM}$) of the risk-neutral distribution of a stock's log return from present (t) until a τ years in the future are given by:

$$Var^{BKM} = \frac{e^{r\tau}V_{i,t} - \mu^2}{\tau} \tag{1}$$

$$Skew^{BKM} = \frac{e^{r\tau}W - 3\mu e^{r\tau}V + 2\mu^3}{[e^{r\tau}V - \mu^2]^{\frac{3}{2}}} \tag{2}$$

$$Kurt^{BKM} = \frac{e^{r\tau}X - 4\mu e^{r\tau}W + 6e^{r\tau}\mu^2 V - 3\mu^4}{[e^{r\tau}V - \mu^2]^2} - 3 \tag{3}$$

Where

$$\mu = e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V - \frac{e^{r\tau}}{6}W - \frac{e^{r\tau}}{24}X \tag{4}$$

r is the continuously compounded risk-free rate for the period from time t to time t + τ, and V, W, and X are the risk-neutral expectation of the squared, cubed, and fourth power, respectively, of the log of the stock return during the same period. Following Dennis and Mayhew (2002), Conrad, Dittmar and Ghysels (2013), and Bali and Murray (2013), we then use a trapezoidal method to calculate V, W, and X from observed option prices with discrete strikes. The data required for performing the calculations are the price of stock i on date t, the date t prices of options on stock i with expiration date t + τ, and the continuously compounded rate of return on a risk-free investment purchased on date t to be withdrawn on date t + τ. We denote the stock price as S, the risk-free rate as r, and the time until option expiration as τ. We take the price of all options to be the average of the bid price and the offer price. For the calculation of the risk-free rate, we follow the BKM estimation using the continuously compounded risk-free rates for each trading day provided by Option Metrics. Specifically, for each date t, we apply a cubic spline on the risk-free rate data with various time to maturity to estimate the risk-free rate for the periods from t to t+τ. On days when the U.S. equity and option markets are open but banks are closed, Option Metrics does not provide risk-free rate data. For these days, we use the risk-free rate data in Option Metrics from the previous trading day.

We then sort the calls (puts) in ascending (descending) order by strike prices. Letting n_C (n_P) denote the number of call (put) options that pass the data screens, we denote the prices of the call (put) options as C_i (P_i) and the strike prices of the call (put) options as K_i^C, $i \in \{1, \dots, n_C\}$ (K_i^P, $i \in \{1, \dots, n_P\}$), where $K_{i+1}^C > K_i^C$ for $i \in \{1, \dots, n_{C-1}\}$ ($K_{i+1}^P < K_i^P$ for $i \in \{1, \dots, n_{P-1}\}$). No-arbitrage conditions require that option prices strictly decrease as the option strike goes further out-of-the-money. Thus, if

$C_i \le C_{i+1}$ for any $i \in \{1, \dots, n_{C-1}\}$ or $P_i \le P_{i+1}$ for any $i \in \{1, \dots, n_{P-1}\}$), we deem the values of the risk-neutral moments for the given date/stock/expiration combination to be incalculable.

The values V, W, and X used in the BKM estimation to calculate the risk-neutral variance, skewness, and excess kurtosis, given by equations (1), (2), (3) respectively, are given by:

$$V = \int_{K=S}^{\infty} \frac{2\left(1 - \ln\left[\frac{K}{S}\right]\right)}{K^2} C(K)dK + \int_{K=0}^{S} \frac{2\left(1 + \ln\left[\frac{S}{K}\right]\right)}{K^2} P(K)dK \tag{5}$$

$$W = \int_{K=S}^{\infty} \frac{6\ln\left[\frac{K}{S}\right] - 3\left(\ln\left[\frac{K}{S}\right]\right)^2}{K^2} C(K)dK - \int_{K=0}^{S} \frac{6\ln\left[\frac{S}{K}\right] + 3\left(\ln\left[\frac{S}{K}\right]\right)^2}{K^2} P(K)dK \tag{6}$$

$$X = \int_{K=S}^{\infty} \frac{12\left(\ln\left[\frac{K}{S}\right]\right)^2 + 4\left(\ln\left[\frac{K}{S}\right]\right)^3}{K^2} C(K)dK + \int_{K=0}^{S} \frac{12\left(\ln\left[\frac{S}{K}\right]\right)^2 + 4\left(\ln\left[\frac{S}{K}\right]\right)^3}{K^2} P(K)dK \tag{7}$$

where $C(K)$ $(P(K))$ is the price of a call (put) option with strike K.

To estimate the integrals in equations (5), (6), and (7) from prices of options with discrete strikes, we define the strike differences for calls (puts) as $\Delta K_i^C = K_i^C - K_{i-1}^C$ for $i \in \{2, \dots, n_C\}$ and $\Delta K_1^C = K_1^C - S^*$ ($\Delta K_i^P = K_{i-1}^P - K_i^P$ for $i \in \{2, \dots, n_P\}$and $\Delta K_1^P = S^* - K_1^P$). We then approximate the BKM intergals for V, X, and W as:

$$V = v_C(K_1^C)C_1\Delta K_1^C + \sum_{i=2}^{n_C} \frac{1}{2}\left[v_C(K_i^C)C_i + v_C(K_{i-1}^C)C_{i-1}\right]\Delta K_i^C + v_P(K_1^P)P_1\Delta K_1^P + \sum_{i=2}^{n_P} \frac{1}{2}\left[v_P(K_i^P)P_i + v_P(K_{i-1}^P)P_{i-1}\right]\Delta K_i^P \tag{8}$$

$$W = w_C(K_1^C)C_1\Delta K_1^C + \sum_{i=2}^{n_C} \frac{1}{2}\left[w_C(K_i^C)C_i + w_C(K_{i-1}^C)C_{i-1}\right]\Delta K_i^C - w_P(K_1^P)P_1\Delta K_1^P + \sum_{i=2}^{n_P} \frac{1}{2}\left[w_P(K_i^P)P_i + w_P(K_{i-1}^P)P_{i-1}\right]\Delta K_i^P \tag{9}$$

$$X = x_C(K_1^C)C_1\Delta K_1^C + \sum_{i=2}^{n_C} \frac{1}{2}\left[x_C(K_i^C)C_i + x_C(K_{i-1}^C)C_{i-1}\right]\Delta K_i^C + x_P(K_1^P)P_1\Delta K_1^P + \sum_{i=2}^{n_P} \frac{1}{2}\left[x_P(K_i^P)P_i + x_P(K_{i-1}^P)P_{i-1}\right]\Delta K_i^P \tag{10}$$

Where:

$$v_C(K) = \frac{2\left(1 - \ln\left[\frac{K}{S^*}\right]\right)}{K^2} \tag{11}$$

$$v_P(K) = \frac{2\left(1 + \ln\left[\frac{S^*}{K}\right]\right)}{K^2} \tag{12}$$

$$w_C(K) = \frac{6\ln\left[\frac{K}{S^*}\right] - 3\left(\ln\left[\frac{K}{S^*}\right]\right)^2}{K^2} \tag{13}$$

$$w_P(K) = \frac{6\ln\left[\frac{S^*}{K}\right] + 3\left(\ln\left[\frac{S^*}{K}\right]\right)^2}{K^2} \tag{14}$$

$$x_C(K) = \frac{12\left(\ln\left[\frac{K}{S^*}\right]\right)^2 + 4\left(\ln\left[\frac{K}{S^*}\right]\right)^3}{K^2} \tag{15}$$

$$x_P(K) = \frac{12\left(\ln\left[\frac{S^*}{K}\right]\right)^2 + 4\left(\ln\left[\frac{S^*}{K}\right]\right)^3}{K^2} \tag{16}$$

Plugging the values from equations (8), (9), and (10) into equations (1), (2), and (3) yields discrete strike price-based estimates of the variance, skewness, and kurtosis of the risk-neutral distribution of the stock's return for the period from t to t + τ.

A.2 NIG distribution

The Normal Inverse Gaussian (NIG) distribution developed by Eriksson, Ghysels and Wang (2009) is characterized by the density function

$$f(x;\alpha,\beta,\mu,\delta) = \frac{\alpha}{\pi\delta}\exp\left(\sqrt{\alpha^2-\beta^2} - \frac{\beta\mu}{\delta}\right)\frac{K_1\left(\alpha\sqrt{1+(\frac{x-\mu}{\delta})^2}\right)}{\sqrt{1+(\frac{x-\mu}{\delta})^2}}\exp\left(\frac{\beta}{\delta}x\right) \tag{37}$$

In this expression, $x \in \Re$, $\alpha > 0$, $\delta > 0$, $\mu \in \Re$, $0 < |\beta| < \alpha$, and $K_1(\cdot)$ is the modified Bessel function of the third kind with index 1. The density is completely characterized by its first four moments. More specifically, let the mean, variance, skewness and excess kurtosis be denoted as $\mathcal{M}, \mathcal{V}, \mathcal{S}, \mathcal{K}$. The parameters are non-linearly related to the moments by

$$\alpha = \frac{3(4\rho^{-1}+1)}{\mathcal{K}\sqrt{1-\rho^{-1}}} \tag{48}$$

$$\beta = sign(\mathcal{S})\frac{3(4\rho^{-1}+1)}{\mathcal{K}^{-1}\sqrt{\rho-1}} \tag{59}$$

$$\mu = \mathcal{M} - sign(\mathcal{S})\sqrt{\frac{3(4\rho^{-1}+1)\mathcal{V}}{\mathcal{K}\rho}} \tag{20}$$

$$\delta = \sqrt{\frac{3(4\rho^{-1}+1)(1-\rho^{-1})\mathcal{V}}{\mathcal{K}}} \tag{21}$$

where $\rho = 3\mathcal{K}\mathcal{S}^{-2} - 4 > 1$ and $sign(\cdot)$ is the sign function. Thus, given risk neutral moments, one can compute the risk neutral density.

Table A1: Comparison of the default risk measures in predicting bankrupt events

All the sample firm-months are equally sorted into five categories according to their default risk measures, including ΔOPD reported in basis points, bond rating (RATING), default risk (DEFAULT), distance-to-default (DD), Altman (1968) Z score (Z_SCORE) and option-implied volatility (IMPVOL). Panel A reports the estimated average risk level for each category. Panel B reports the number of actual bankruptcy cases in each default-risk-sorted category.

	OPD	RATING	DEFAULT	DD	Z_SCORE	IMPVOL
A. Average bankruptcy scores						
1 [Low]	0.000000	5.79	-1.52	4.56	0.79	-0.045
2	0.000000	8.38	-0.67	9.76	1.78	-0.012
3	0.000000	9.81	-0.12	14.09	2.61	-0.002
4	0.000004	12.31	0.42	19.03	3.52	0.009
5 [High]	1.991473	15.28	1.22	28.11	5.69	0.050
B. In-sample prediction test						
1 [Low]	0	0	0	25	16	21
2	0	0	0	0	2	8
3	1	0	0	0	2	8
4	3	4	1	0	1	10
5 [High]	24	23	11	0	2	23

Table A2: Cox proportional hazard models of default risk measures

This table provides Cox proportional hazard ratios across the default risk measures, including ΔOPD, default risk (DEFAULT), distance-to-default (DD), Altman (1968) Z score (Z_SCORE) and option-implied volatility (IMPVOL). The ROC curve ratio indicates the area covered by the model's average function divided by that of a perfect model. A higher ROC ratio indicates a model with better predictive ability. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
OPD	1.044***					1.016***
	(0.0000)					(0.0071)
DEFAULT		4.630***				1.110
		(0.0000)				(0.4760)
Z_SCORE			0.418***			0.512***
			(0.0000)			(0.0000)
DD				0.051***		0.046***
				(0.0000)		(0.0000)
IMPVOL					1.123***	1.052
					(0.0000)	(0.1580)
Obs.	70915	54688	86051	93527	96967	38670
# of Bankrupt	709	351	845	940	990	253
Cox partial -2LL	-7425.670	-3065.038	-8609.581	-8673.927	-10602.067	-2005.558
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ROC curve ratio	0.890	0.900	0.742	0.896	0.518	0.936

Table A3: Bond Tercile Portfolios Sorted on ΔOPD

For each month, tercile portfolios are formed by sorting bonds based on the ΔOPD, where quintile 1(3) portfolio contains bonds with the lowest (highest) ΔOPD during the previous month. The ΔOPD is the innovation of option-implied default probability of the firm calculated following Conrad, Dittmar and Hameed (2020). The second column reports the average ΔOPD in basis points for each tercile, and the remaining columns present the average bond excess returns and alphas for the equal-weighted and value-weighted portfolios separately. Following Bali, Subrahmanyam and Wen (2021), α^5 is the alpha relative to five stock market factors including the excess stock market return (MKT_E), equity size (SMB_E), book-to-market (HML_E), equity momentum (MOM_E), and equity liquidity factors (LIQ). α^1 is the alpha relative to excess bond market return (MKT_B) only to avoid data handling issue documented in Dickerson, Mueller and Robotti (2023). We also report α^6 relative to a combination of five stock market factors and MKT_B following Bali, Subrahmanyam and Wen (2023). The last five columns report average bond characteristics for each tercile, including rating, maturity, size, duration, and illiquidity. The last row presents return and alpha differences between quintiles 1 and 5. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period covers September 2002–December 2020.

		Equal weighted				Value weighted				Average Portfolio characteristics				
		(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)	(11)	(12)	(13)	(14)	(15)
Quintile	ΔOPD	R_B-R_f	α^5	α^1	α^6	R_B-R_f	α^5	α^1	α^6	Rating	Maturity	Size	Duration	Illiquidiy
1 [Low]	-0.03	0.64	0.53	0.28	0.32	0.65	0.52	0.25	0.26	10.82	8.14	18.71	5.53	0.005
		(4.95)	(4.73)	(4.36)	(3.74)	(4.87)	(4.39)	(3.37)	(3.11)					
2	0.00	0.43	0.36	0.07	0.1	0.41	0.32	-0.01	0.02	7.82	9.71	19.34	6.32	0.006
		(4.29)	(3.58)	(1.25)	(1.79)	(3.78)	(2.84)	(-0.15)	(0.25)					
3 [High]	0.03	0.37	0.24	-0.06	0.01	0.3	0.19	-0.2	-0.1	10.65	8.21	18.72	5.56	0.008
		(2.59)	(2.30)	(-0.69)	(0.15)	(2.21)	(1.59)	(-2.28)	(-1.48)					
High-Low		-0.27	-0.29	-0.35	-0.3	-0.35	-0.34	-0.44	-0.36					
		(-2.97)	(-3.93)	(-3.29)	(-4.46)	(-3.19)	(-3.55)	(-3.35)	(-4.09)					

Table A4: Persistence of the Predictability of ΔOPD

This table reports average bond excess returns, return difference and six-factor alphas (α^6) for the ΔOPD-sorted portfolio for up to six months after the portfolio formation. For each month, quintile portfolios are formed by sorting bonds based on the ΔOPD, where quintile 1(5) portfolio contains bonds with the lowest (highest) ΔOPD during the previous month. ΔOPD is defined as the innovation of option-implied default probability of the firm calculated following Conrad, Dittmar and Hameed (2020). The alphas are adjusted using 6-factor model that combines 5 stock market factors (MKT_E, SMB_E, HML_E, MOM_E, LIQ_E) and bond market beta (MKT_B) following Bali, Subrahmanyam and Wen (2023). Portfolios are value-weighted using the portfolio formation month's equity market capitalization as weights. Newey–West adjusted t-statistics are given in parentheses. ∗, ∗∗, and ∗∗∗ indicate the significance at the 10%, 5%, and 1% levels, respectively.

Portfolio	t + 1	t + 2	t + 3	t + 4	t + 5	t + 6
1 [Low]	0.76	1.47	2.11	2.72	3.39	4.21
	(4.85)	(5.04)	(5.00)	(5.07)	(5.28)	(5.74)
2	0.51	1.12	1.66	2.14	2.77	3.36
	(4.44)	(5.22)	(5.46)	(5.50)	(5.98)	(6.33)
3	0.41	0.95	1.47	2.00	2.53	3.10
	(3.84)	(4.95)	(5.45)	(5.72)	(6.05)	(6.38)
4	0.31	0.82	1.33	1.90	2.47	3.03
	(2.77)	(4.08)	(4.67)	(5.16)	(5.55)	(5.85)
5 [High]	0.33	1.05	1.65	2.35	3.07	3.78
	(1.89)	(3.63)	(4.18)	(4.68)	(5.08)	(5.40)
H-L return	-0.43	-0.43	-0.45	-0.38	-0.32	-0.42
	(-2.74)	(-2.25)	(-2.60)	(-2.03)	(-1.53)	(-2.01)
H - L α^6	-0.43	-0.50	-0.41	-0.29	-0.28	-0.40
	(-3.67)	(-2.89)	(-2.34)	(-1.48)	(-1.32)	(-1.89)

Table A5: Bond Quintile Portfolios Sorted on ΔOPD_{res}

This table reports average excess returns and alphas based on the idiosyncratic component of ΔOPD. In particular, we run the following regressions using a 36-month rolling window with minimum 24 observations: $\Delta OPD_t = \alpha_t + \beta_t IMPVOL_t + \varepsilon_t$. The ΔOPD is the innovation of option-implied default probability of the firm calculated following Conrad, Dittmar and Hameed (2020). IMPVOL is the option-implied volatility measure as in Cao and Han (2013). For each month, quintile portfolios are formed by sorting bonds based on the ε_t as ΔOPD_{res}, where quintile 1(5) portfolio contains bonds with the lowest (highest) ΔOPD_{res} during the previous month. The second column reports the average ΔOPD_{res} in basis points for each quintile, and the remaining columns present the average bond excess returns and alphas for the equal-weighted and value-weighted portfolios separately. Following Bali, Subrahmanyam and Wen (2021), α^5 is the alpha relative to five stock market factors including the excess stock market return (MKT_E), equity size (SMB_E), book-to-market (HML_E), equity momentum (MOM_E), and equity liquidity factors (LIQ). α^1 is the alpha relative to excess bond market return (MKT_B) only to avoid data handling issue documented in Dickerson, Mueller and Robotti (2023). We also report α^6 relative to a combination of five stock market factors and MKT_B following Bali, Subrahmanyam and Wen (2023). The last five columns report average bond characteristics for each quintile, including rating, maturity, size, duration, and illiquidity. The last row presents return and alpha differences between quintiles 1 and 5. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period covers September 2002–December 2020.

		Equal weighted				Value weighted				Average Portfolio characteristics				
		(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)	(11)	(12)	(13)	(14)	(15)
Quintile	ΔOPD_{res}	R_B-R_f	α^5	α^1	α^6	R_B-R_f	α^5	α^1	α^6	Rating	Maturity	Size	Duration	Illiquidiy
1 [Low]	-0.0536	0.63	0.47	0.29	0.30	0.69	0.51	0.30	0.30	11.00	7.78	18.80	5.35	0.004
		(3.99)	(4.02)	(3.60)	(3.27)	(3.97)	(3.96)	(3.14)	(3.13)					
2	-0.0003	0.46	0.38	0.15	0.17	0.44	0.34	0.09	0.10	7.85	10.02	19.46	6.45	0.003
		(3.70)	(3.60)	(2.19)	(2.11)	(3.32)	(2.95)	(1.29)	(1.27)					
3	0.0000	0.38	0.29	0.06	0.07	0.41	0.30	0.06	0.05	7.03	10.34	19.62	6.64	0.003
		(3.54)	(2.88)	(1.03)	(1.01)	(3.56)	(2.64)	(0.90)	(0.71)					
4	0.0002	0.41	0.31	0.07	0.09	0.35	0.23	-0.02	0.00	8.99	9.45	19.16	6.21	0.004
		(3.42)	(2.87)	(1.04)	(1.45)	(2.96)	(2.11)	(-0.25)	(-0.07)					
5 [High]	0.0457	0.35	0.24	-0.07	0.04	0.36	0.20	-0.15	-0.09	11.64	7.73	18.74	5.26	0.005
		(2.00)	(2.25)	(-0.64)	(0.48)	(2.13)	(1.75)	(-1.16)	(-1.02)					
5-1		-0.28	-0.23	-0.37	-0.26	-0.33	-0.31	-0.45	-0.39					
[High-Low]		(-2.50)	(-2.94)	(-2.72)	(-3.31)	(-2.40)	(-2.86)	(-2.39)	(-3.29)					

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