Short-Sale Constraints and Pricing Discrepancies between Stocks and Bonds *

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February 1, 2024

Abstract

This paper examines the effect of short-sale constraints on pricing discrepancies between stocks and bonds issued by the same firms. Using data from 2006 to 2018, we find that both bond and stock short-sale constraints exert a positive impact on pricing discrepancies, which is robust to controlling for various measures of limit-to-arbitrage and firm/bond characteristics. Stock short-sale constraints have stronger effects on pricing discrepancies than bond short-sale constraints. Our findings provide compelling evidence that short-sale constraints can disrupt the equilibrium relationship between stocks and bonds, as implied by Merton (1974).

Keywords: Short-sale constraint, Pricing discrepancy, Market integration, Merton model

JEL Codes: G12, G14, G18

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1 Introduction

The structural model of Merton (1974) posits that changes in equity price and corresponding bond price must be precisely related to preventing arbitrage. In other words, any changes in equity returns should be mirrored in the corresponding bond returns. When this relationship is breached, the pricing discrepancy between equity and bond increases, and the market integration weakens. In such instances of violation, active arbitrageurs can quickly short securities with lower returns (high prices) and buy those with higher returns (lower prices) across different markets. These arbitrage activities lead to the convergence of the price of bonds and corresponding stocks, thereby reducing the pricing discrepancies (Xiong (2001); Kondor (2009)). Consequently, the market integration between the equity and bond markets becomes stronger. However, it is well-documented that financial markets frequently experience price violations (Kapadia and Pu (2012)). Moreover, the integration between equity and bond markets often appears weak (Collin-Dufresn et al. (2001), Blanco et al. (2005)). Therefore, it is crucial to understand what leads to the escalation of pricing discrepancy and the weakening of market integration implied by the Merton model.

Recent studies have suggested that limit-to-arbitrage plays a role in this process. Empirical investigations focusing on the equity and credit default swap (CDS) markets have demonstrated that the disintegration of equity and credit markets is related to impediments to arbitrage, with heightened limit-to-arbitrage conditions leading to more significant pricing discrepancies and lower market integration (Kapadia and Pu (2012); Bai and Collin-Dufresne (2018); Lin et al. (2020)). Given these findings, a question naturally arises: To what extent do limit-to-arbitrage factors, especially short-sale constraints, influence pricing discrepancies and the degree of integration between equity and bond markets? This study contributes to the existing literature by empirically examining how short-sale constraints impact pricing discrepancies between equities and bonds issued by the same firms.

We begin our analysis by estimating the pricing discrepancies between equities and bonds. Based on the Merton model, the returns of bonds and stocks issued by the same firms are linked by the debt-to-equity sensitivity (i.e., hedge ratio) (Strebulaev and Schaefer (2008); Choi (2013); Kuehn and Schmid (2014); Choi and Kim (2018)). Hence, bond returns can be estimated by multiplying the hedge ratio with the stock returns of the corresponding firm (Choi and Kim (2018)). Utilizing these estimated corporate bond returns, we can then compare them with the actual bond returns to gauge the pricing discrepancies that exist between corporate bonds and stocks issued by the same firm. Besides considering the returns of bond and stock for the same firm, we extend our analysis by using bond and stock return volatility to measure the volatility discrepancies. Merton's model posits that the hedge ratio also links the volatility of bond and stock returns (Friewald et al. (2014)). Therefore, we estimate bond return volatility by multiplying the hedge ratio and stock return volatility. Then, we calculate the differences between the actual and estimated bond return volatility, which measures the volatility discrepancies between stocks and bonds.

This paper provides several findings that expand the understanding of the impact of short-sale constraints on pricing discrepancies and the integration of equity and bond markets. First, our research reveals that both stock and bond short-sale constraints exert a positive influence on pricing discrepancies between stocks and bonds. This observed positive relation is not only economically significant but also robust to controlling for various firm/bond characteristics, hedge ratio estimations, and different measures of short-sale constraints. Therefore, heightened short-sale constraints amplify pricing discrepancies and weaken the integration of markets between stocks and bonds. Our results are consistent with previous findings regarding the effects of short-sale constraints on stock and bond pricing (Jones and Lamont (2002); Lamont and Thaler (2003); Nagel (2005); Gromb and Vayanos (2010); Hendershott et al. (2020); Beber et al. (2021)), and suggest that short-sale constraints can contribute to the mispricing of securities. Second, unlike most previous studies, we use stock and bond short-sale constraints simultaneously in our empirical analysis. Our findings bring to light that stock short-sale constraints exhibit a comparatively more potent influence than bond short-sale constraints. This result aligns with the earlier research by Hendershott et al. (2020), who show that bond short interest contains less private information than equity short interest. Finally, subperiod analysis reveals that the positive relation is more pronounced during periods characterized by high sentiment and volatility, low economic growth, and information quality.

Our paper contributes to the literature by providing empirical evidence on the impact of short-sale constraints on pricing discrepancies between stocks and bonds. The positive relation between short-sale constraints and pricing discrepancies is consistent with Choi and Kim (2018). Choi and Kim (2018) find that the divergence in cross-sectional bond-equity premia is more pronounced on the short side, suggesting the influence of short-sale constraints in driving this anomaly. However, it's worth noting that while their study explores return anomalies in asset pricing, our paper concentrates on understanding the role of short-sale constraints in the equilibrium relationship between stock and bond returns. Our research demonstrates that short-sale constraints exert independent effects over and beyond other potential economic explanations, such as firm sizes and various firm/bond characteristics, in accounting for this positive relationship. Our work also aligns with Kapadia and Pu (2012), which find that high limit-to-arbitrage conditions are related to high pricing discrepancies between equity and CDS markets. In our study, instead of examining equity and CDS, we explore the relationship between equity and bond markets and affirm a strong positive relationship between short-sale constraints and pricing discrepancies between stocks and bonds.

The remainder of the paper is organized as follows. Section 2 reviews the literature, and Section 3 describes the data and variables used in this paper. Section 4 presents the baseline results about the relationship between short-sale constraints and pricing discrepancies. Section 5 provides further robustness tests. Finally, Section 6 concludes the paper

2 Literature review

2.1 The effect of short-sale constraints on stocks and bonds

The effect of short-sale constraints has been widely explored in the literature. Miller (1977) is among the first to demonstrate that short-sale constraints could lead to overvaluations in financial markets. Jones and Lamont (2002) provide empirical evidence supporting the overvaluation hypothesis in the stock market. They find that stocks with higher borrowing costs tend to be overvalued and experience lower future returns. Subsequent studies have enriched the theoretical and empirical understanding of the overvaluation hypothesis and its implications for return predictions. Meanwhile, several studies have introduced new proxies for short-sale constraints. For example, Asquith et al. (2005) use institutional ownership as a proxy for loan supply. Boehme et al. (2006) consider rebate rates, and Beneish et al. (2015) use lending fees and utilization rates. Collectively, these studies establish a negative relationship between stock short-sale constraints and future abnormal returns. Furthermore, Chen et al. (2022) show that short-selling effects on stock returns are more pronounced during periods of economic recession, high volatility, and low public information quality.

Another strand of research focuses on price discovery and market efficiency. Lenkey (2021) construct a model with asymmetrically informed investors who are identical except for their information sets and find that economies with short-sale bans tend to exhibit lower levels of informational efficiency. Saffi and Sigurdsson (2011) use the data from 2005 to 2008 and show that stocks with higher short-sale constraints have lower price efficiency. Hasan et al. (2015) consider a more extended sample from 2002 to 2009 across 33 countries and find similar results.

The extant literature has predominantly concentrated on short-sale constraints in the stock market, with limited attention dedicated to the bond market. Asquith et al. (2013) is among the first to investigate the relation between short-sale constraints and bond pricing. Using the corporate bond data from 2004 to 2007, they find that short-sale constraints cannot predict future bond returns. However, subsequent studies have shown a different picture. Anderson et al. (2018) extend the analysis with a broader sample period spanning from 2006 to 2015 and report that short-sale constraints indeed predict negative bond returns. Hendershott et al. (2020) examine the data before and after the collapse of Lehman Brothers in 2008. They find that before the collapse of Lehman Brothers, the relationship between short-selling and bond returns was weak. However, after Lehman's collapse, bond short selling can predict returns in high-yield bonds.

2.2 The credit-equity market integration

Previous studies have explored the issue of market integration between bonds and stocks, providing valuable insights that motivate our study. Strebulaev and Schaefer (2008) show the accuracy of the Merton model in estimating the hedge ratios between stock and bond returns. Choi and Kim (2018) use similar hedge ratios and find that the realized bond returns are significantly different from the implied bond returns estimated from equity returns and hedge ratios. Following these studies, we construct our measure that captures the pricing discrepancies between bonds and stocks issued by the same firms. Baker and Wurgler (2012) find that government bonds co-move more strongly with "bond-like" stocks, typically associated with large, mature, low-volatility, profitable, and dividend-paying firms. Bao and Hou (2017) find that bonds due relatively late in their issuers' maturity structure have greater co-movement with equities. Chordia et al. (2017) provide evidence that the stock market leads the bond market, and specific firm characteristics can predict corporate bond returns. Lastly, Koijen et al. (2017) show that bond market factors are priced in the cross-section of stock returns. All these papers provide valuable insights for our study.

Meanwhile, several studies have also delved into the integration between CDS and equity markets. Kapadia and Pu (2012) find that discrepancies between CDS and equity prices are closely tied to impediments to arbitrage. Friewald et al. (2014) find that firms' stock returns increase with credit risk premia estimated from CDS spreads. This finding supports the Merton (1974) model, which states that risk premia on stocks and credit derivatives are related. Augustin et al. (2020) examine the dynamics between firms' CDS and stock returns. They show that the participation of firms in global markets contributes to an improvement in the integration between credit and equity markets.

3 Data and variable description

3.1 Pricing discrepancies between bonds and stocks

The structural model of Merton (1974) suggests that the sensitivity of debt to equity, commonly referred to as the hedge ratio, can be used to estimate expected bond returns from expected equity returns (Strebulaev and Schaefer (2008); Choi (2013); Kuehn and Schmid (2014); Choi and Kim (2018)). In other words, expected bond returns can be reasonably approximated by multiplying the hedge ratios by expected equity returns. Therefore, the hedge ratio is a pivotal variable in assessing the pricing discrepancies between bonds and stocks of the same companies.

Assuming equity (E) and bonds (B) are issued by the same firm. Then, we have the following expression.

$$E[R_{i,t}^B] \approx h_i \cdot E[R_{i,t}^E] \tag{1}$$

$R_{i,t}^B$ denotes the bond return and $R_{i,t}^E$ represents the equity return.[1] h_i is the hedge ratio for firm i at time t. To estimate firm-level hedge ratios, we adopt the method outlined by Choi and Kim (2018) and employ the following equation.

$$R_{i,t}^B = \alpha_i + h_i \cdot R_{i,t}^E + u_{i,t} \tag{2}$$

Since Equation (1) only holds when stocks and bonds are issued by the same firms, we use the firm-

[1] We use returns in excess of risk-free rates for both stocks and bonds.

level bond return in the regression model.[2] To estimate Equation (2), we choose the previous 36 months as the rolling window and require a minimum of 24 months with valid return observations. We also control for various factors, including the Fama-French three factors (RMRF, SMB, and HML), the momentum factor (MOM), and bond TERM and DEF factors. After obtaining the regression results, we assign the estimated hedge ratio (h_i) to every bond issued by the same firm.

In addition to the aforementioned method, Strebulaev and Schaefer (2008) suggest that the Merton model can be used to estimate the hedge ratio, which works quite well. [3]. Meanwhile, Choi and Kim (2018) introduce a portfolio approach to estimate the hedge ratio, which served as an alternative and to ensure the robustness of our findings. Specifically, we first regress past 36-month bond returns against corresponding stock returns and obtain the pre-ranking bond-level hedge ratio for each bond. Then, each month, we sort the bonds into quintiles based on the pre-ranking hedge ratio, which are further sorted into rating quintiles. This sorting results in a total of 25 different portfolios. Finally, the post-ranking hedge ratio is estimated by regressing portfolio-level bond returns against portfolio-level stock returns.[4]

Utilizing the estimated hedge ratio allows us to quantify pricing discrepancies between stocks and bonds effectively. We begin by examining the intercept term in Equation (2), as α_i captures bond return premia that cannot be accounted for by the hedge ratio. Therefore, the intercept term is a good proxy for measuring pricing discrepancies. Moreover, we consider the differences between actual bond returns $R^B_{i,t}$ and implied bond returns $h_{i,t} \cdot R^E_{i,t}$, which is an alternative pricing discrepancy measure. Given that both the bonds and stock originate from the same firm, these return differences, denoted as $Diff_{ret}$, measure the deviations in cross-market integration (Choi and Kim (2018)).

The structural credit risk models of Merton (1974) and Friewald et al. (2014) have shown that the return and return volatility are closely related. Given this insight, we use return volatility differences to proxy for return differences ($Diff_{ret}$). Specifically, let σ_E be stock return volatility

[2]The firm-level bond return by is the value-weighted average return for bonds in the same firm.

[3]Under the Merton model, the hedge ratio is given by $h = \frac{1}{N(d_1)}, where, d_1 = \frac{(A/F)+(r+\sigma^2/2)T}{\sigma+\sqrt{T}}$. In this equation, T is determined as the value-weighted time-to-maturity for bonds issued by the same firm. Furthermore, we use market leverage as a proxy for (A/F) in the model. Following Bharath and Shumway (2008), the face value of debt (F) is given by debt in current liabilities plus one-half of long-term debt (both items are from Compustat). We use the 1-Year Treasury Constant Maturity Rate as the risk-free rate.

[4]We use equal-weighted returns.

and σ_B be bond return volatility. We have the following relations.

$$\frac{\sigma_E}{\sigma} = \frac{V}{E} \cdot \frac{\partial E}{\partial V} \tag{3}$$

$$\frac{\sigma_B}{\sigma} = \frac{V}{B} \cdot \frac{\partial B}{\partial V} \tag{4}$$

Since bonds and stock are from the same firm, it follows that the firm's asset value (V) and return volatility (σ) should be identical in both equations. Therefore, combining Equations (3) and (4), we have the following expression, which reveals the relation between bond return volatility and stock return volatility.

$$\sigma_B = \frac{E}{B} \cdot \frac{\partial B}{\partial E} \cdot \sigma_E \tag{5}$$

The partial derivative $\frac{E}{B} \cdot \frac{\partial B}{\partial E}$ is the sensitivity of the bond to equity (hedge ratio).[5] Monthly equity and bond return volatility are estimated via a rolling window approach using data from the previous 12 months. Then, we calculate the implied bond return volatility using the hedge ratio. Finally, the difference in return volatility, denoted as $Diff_{vol}$, is the difference between the actual and implied bond return volatility.

Since our primary focus is on quantifying changes in the pricing discrepancies, we use the absolute values of all these metrics in our empirical analysis.

3.2 Short-sale constraint measures

Previous literature has proposed several proxies for short-sale constraints. Among these, the most commonly used measure is short interest ratio (SIR) (Figlewski (1981); Figlewski and Webb (1993); Dechow et al. (2001)). SIR is defined as the ratio of shares sold short to the total shares outstanding and is often considered as a proxy for short-sale demand (Figlewski (1981)). However, some scholars have raised concerns regarding the appropriateness of using SIR to measure short-sale constraints. Jones and Lamont (2002) argue that the quantity of short selling results from the interaction between demand and supply, making it necessary to reconsider short interest as a straightforward indicator of short selling demand. Subsequent studies, such as Asquith et al. (2005) and Ramachandran and Tayal (2021), support this notion and suggest that institutional ownership (IO) can serve as a proxy for supply in the lending market. Consequently, an adjusted short-sale constraint measure, defined as the ratio of short interest to institutional ownership ($SIRIO$), is

[5] In the context of returns, bond return is related to stock return through $R_B = \frac{E}{B} \cdot \frac{\partial B}{\partial E} \cdot R_E$. For details, see Merton (1974), Choi (2013), Kuehn and Schmid (2014), Friewald et al. (2014).

suggested as a more accurate estimate of short-sale constraints.[6]

We also use the utilization rate ($Utilization$), which is directly available from the Markit securities lending database, as an alternative proxy for short-sale constraints. The utilization rate represents the ratio between borrowing demand and lending supply.[7] Due to the similarities, $Utilization$ and $SIRIO$ are closely related (Ramachandran and Tayal (2021)). Beneish et al. (2015) find a positive relation between the utilization rate and borrowing costs and argue that the utilization rate serves as "a reasonable measure of borrowing cost." Higher values indicate tighter short-sale constraints for both $Utilization$ and $SIRIO$.

In addition, several papers consider using lending fees as a measure of short-sale constraints (Jones and Lamont (2002); Ramachandran and Tayal (2021)), given that stock lending fees reflect the actual expenses incurred by short-sellers. The Markit database provides daily cost of borrowing scores ($DCBS$) for both stocks and bonds. This relative measure of borrowing cost ranges from 1 (the lowest cost) to 10 (the highest cost). Our empirical work uses $DCBS_S$ to denote the borrowing scores for stocks and $DCBS_B$ to denote the borrowing scores for bonds.

3.3 Data sample construction

The primary data for corporate bonds are sourced from the enhanced Trade Reporting and Compliance Engine (enhanced TRACE) and the Mergent Fixed Income Securities Database (FISD). Enhanced TRACE provides transaction data for all publicly traded corporate bonds dating back to July 2002, while FISD contains issuance information for all fixed-income securities. We merge the bond trading data with bond characteristics from FISD and use the following equation to calculate the monthly corporate bond return.

$$R_t^B = \frac{P_t + AI_t + C_t}{P_{t-1} + AI_{t-1}} - 1 \tag{6}$$

where P_t is the corporate bond price at time t, AI_t is the accrued interest and C_t represents the coupon payment (if any) at time t.

We obtain the stock and bond lending and loan data from the Markit securities lending database. This database provides information on the total shares borrowed from lenders (demand) and lend-

[6] In the empirical work, we use $SIRIO_S$ to represent stock short interest adjusted by stock institutional holdings and $SIRIO_B$ to represent bond short interest adjusted by bond institutional holdings.

[7] Markit provides both stock and bond utilization rates, denoted as $Utilization_S$ and $Utilization_B$, respectively.

able shares (supply). In addition, Markit provides a variable labeled "utilization rate," which is shares on loan divided by lendable shares. The CUSIP number links the lending data to the TRACE data. Since the Markit (bond) database started in October 2006, data related to corporate bonds between July 2002 and September 2006 is excluded from our analysis, as well as those observations not present in both the Markit and the TRACE.

Finally, we augment our sample with the institutional ownership information for stocks and bonds. The stock ownership data comes from Thomson/Refinitiv Institutional Holdings (13F), while the bond ownership data is obtained from eMAXX Refinitiv. Additionally, we acquire stock data from CRSP and financial information from Compustat. The final sample ranges from October 2006 to December 2018 and comprises 201,105 bond-month observations.

3.4 Summary statistics

Panel A of Table 1 reports the summary statistics for hedge ratios and pricing discrepancy measures. We report key statistics such as means, medians, and 1st and 3rd quartiles. The hedge ratios closely align with those reported by Choi and Kim (2018). For example, the mean Merton hedge ratio stands at 0.013, ranging from 0.011 to 0.015 in Choi and Kim (2018). For hedge ratios estimated by the portfolio method, the mean value is 0.028, varying from 0.029 to 0.038 in Choi and Kim (2018). Therefore, our estimations are consistent with previous work. Furthermore, the absolute return differences ($|Diff_{ret}|$) are close among different estimation methods, implying that the choice of method in estimating pricing discrepancies does not significantly impact our results. A similar situation holds for absolute volatility differences ($|Diff_{vol}|$). Panel B shows summary statistics for different short-sale constraint variables. We consider both stock and bond short-sale constraints. In Panel C, we present summary statistics for control variables considered in the empirical work.[8]

[Insert Table 1 about here]

[8]Detailed variable definitions are provided in Appendix A.

4 Pricing discrepancy and short-sale constraint

4.1 Univariate Portfolio Analysis

We first examine the relation between pricing discrepancies and short-sale constraints via univariate sorting. Each month, we sort bonds into quintile portfolios by ranking their short-sale constraint variables. The portfolio Low includes bonds with the lowest short-sale constraints, and High consists of bonds with the highest short-sale constraints. For each portfolio, we calculate the average values of $|\alpha|$, $|Diff_{ret}|$, and $|Diff_{vol}|$ and report them in Table 2. Panel A presents the results based on stock short-sale constraint variables. The first row shows that as stock short-sale constraint (measured by $Utilization_S$) increases from Low to High, the average values of $|\alpha|$ rise from 0.175% to 0.922%, and the difference between High and Low (H-L) amounts to 0.747%, which is significant at the 1% level. The second row shows similar results when we use adjusted stock short interest ($SIRIO_S$) to measure short-sale constraints. These results indicate that tighter stock short-sale constraints are associated with larger pricing discrepancies, measured by $|\alpha|$. When considering $|Diff_{ret}|$ and $|Diff_{vol}|$, we continue to find a positive relation between stock short-sale constraints and pricing discrepancies. In summary, the univariate portfolio analysis shows that stock short-sale constraints positively affect the pricing discrepancies between stocks and bonds, which is robust to different stock short-sale constraints and pricing discrepancy measures.

Panel B of Table 2 reports the findings related to bond short-sale constraint variables. The results are similar to those observed for stock short-sale constraints. One noteworthy observation in Panel B is that the differences between High and Low tend to be smaller than those reported in Panel A. For example, when sorting by stock utilization rate, the difference in $|\alpha|$ between High and Low is 0.747%, whereas it is 0.656% when sorting by bond utilization rate. A similar pattern is observed when considering stock and bond-adjusted short interest. These findings suggest that stock short-sale constraints exert a more pronounced impact than bond short-sale constraints on pricing discrepancies.

Hendershott et al. (2020) find that bond ratings can affect the relation between bond short selling and bond returns. Expanding on this, we examine the impact of short-sale constraints on pricing discrepancies across various rating samples. We divide the bond sample into four rating categories: AAA/AA (including AAA, AA+, AA, AA-), A (including A+, A, A-), BBB (including BBB+,

BBB, BBB-), and non-investment grade (NIG) (including BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, and C), and report the differences in $|\alpha|$, $|Diff_{ret}|$, and $|Diff_{vol}|$ between High and Low portfolio in Panel C of Table 2. The differences are positive and significant in most cases, except for some cases in AAA-rated bonds when using $|Diff_{vol}|$ as the pricing discrepancy measure.

[Insert Table 2 about here]

4.2 Bivariate Portfolio Analysis

The preceding univariate portfolio analysis shows a positive relation between short-sale constraints and pricing discrepancies between stocks and bonds. However, certain bond characteristics can affect this positive relationship as previous research has suggested that risky bonds are more difficult to short (Nashikkar et al. (2011)). Therefore, in this subsection, we investigate whether the effect of short-sale constraints is more significant for illiquid bonds and bonds with higher volatility.[9]

We employ a double-sorting approach. Each month, we first sort bonds into quintiles by bond characteristics ($ILLIQ_B$ or $IVOL_B$). Then, we further sort bonds into quintiles within each quintile by ranking short-sale constraints. This sorting results in a total of 5 $\times$ 5 portfolios. We report the differences in $|Diff_{ret}|$ between High (highest short-sale constraints) and Low (lowest short-sale constraints) for each characteristic quintile, as well as the averaged differences across characteristic quintiles in Table 3.[10]

Panel A shows the results when controlling for bond illiquidity. Across illiquidity quintiles, all the differences between High and Low portfolios are positive and significant, suggesting that higher short-sale constraints are associated with more substantial pricing discrepancies for bonds with similar levels of illiquidity. This pattern remains consistent across various stock and bond short-sale constraint variables. Notably, When comparing results among different illiquidity quintiles, we notice that the positive relationship is more pronounced for illiquid bonds. Finally, when averaging across illiquidity quintiles, a significant spread in $|Diff_{ret}|$ persists.

In Panel B, we control for bond idiosyncratic volatility ($IVOL_B$). The differences in pricing

[9] We use the method of Amihud (2002) to estimate bond illiquidity. And we follow the method of Chung et al. (2019) to estimate bond idiosyncratic volatility. Specifically, we regress bond returns against the Fama-French five-factor and VIX based on a 6-month rolling window. The standard deviation of the return residuals is the bond's idiosyncratic volatility.

[10] We also consider the differences in $|\alpha|$ and $|Diff_{vol}|$. The results are similar to the $|Diff_{ret}|$. The details are reported in Table A1 and A2.

discrepancies between the High and Low portfolios are overall positive and significant across $IVOL_B$ quintiles. Again, this pattern holds across various bond and stock short-sale constraint variables, with the effect being more pronounced for bonds exhibiting higher levels of $IVOL_B$. Lastly, we compute the average differences across $IVOL_B$ quintiles. This procedure effectively controls for the effect of $IVOL_B$, and results show that the positive relation between short-sale constraints and pricing discrepancies is robust to controlling for bond idiosyncratic volatility.

We further explore the robustness of the impact of short-sale constraints on pricing discrepancies by considering additional bond and firm characteristics, including stock illiquidity ($ILLIQ_S$), stock idiosyncratic volatility ($IVOL_s$), firm total asset ($Size$), and number of analysts following ($Coverage$). The rest panels of Table 3 present the results. The differences in $|Diff_{ret}|$ between High (highest short-sale constraints) and Low (lowest short-sale constraints) portfolios are overwhelmingly positive and significant. Although the effect is stronger for bonds with higher $ILLIQ_S$ and $IVOL_S$, those issued by smaller firms, and firms followed by fewer analysts, the positive impact of short-sale constraints on pricing discrepancies persists.

[Insert Table 3 about here]

4.3 Regression analysis

In this subsection, we investigate the robustness of the impact of short-sale constraints using multivariate regression analysis. We have opted to use $|Diff_{ret}|$ as the dependent variable, although results are qualitatively similar for the other two measures. Following Choi and Kim (2018), we control for the Fama-French three factors, the Momentum factor, and bond TERM and DEF factors. Additionally, we incorporate various firm and bond characteristics, such as firm ROA (ROA), firm age (Age), bond issue size ($Size_B$), and time to maturity (TTM).

$$|Diff_{ret}|_{i,t} = \alpha_0 + \alpha_1 \cdot Short_{i,t} + \alpha_2 \cdot X_{i,t} + u_{it} \tag{7}$$

The dependent variable is the absolute values of the differences between actual and implied bond returns ($|Diff_{ret}|$), and the independent variable $Short_{i,t}$ represents different measures for short-sale constraints. $X_{i,t}$ is a vector of control variables. Table 4 reports the regression results.

In Panel A of Table 4, short-sale constraints are proxied by $Utilization_S$ and $Utilization_B$. As shown in columns (1) and (3), the coefficient estimates are positive and significant, suggesting bonds with higher utilization rates tend to have higher price discrepancies. A comparison between these two columns reveals that the coefficient on $Utilization_S$ (3.197%) is larger than that on $Utilization_B$ (2.388%), consistent with previous findings that stock short-sale constraints exert a more pronounced impact than bond short-sale constraints. Next, we introduce a NIG dummy variable, which takes the value of one for non-investment grade bonds, and incorporates the interaction between the utilization rate and NIG. Results in columns (2) and (4) suggest that the effect is stronger for low-grade bonds, aligning with our findings in Panel C of Table 2. In the last two columns, we conduct a horse-race between $Utilization_S$ and $Utilization_B$, and the coefficient on $Utilization_S$ is three times larger than that on $Utilization_B$. The results for $SIRIO_S$ and $SIRIO_B$ are reported in Panel B, and the regression results are similar to those observed in Panel A.

[Insert Table 4 about here]

5 Robustness

5.1 Alternative hedge ratio estimates

In this subsection, we extend our analysis to consider the robustness of our findings by estimating the hedge ratio through both the Merton model (Strebulaev and Schaefer (2008)) and the portfolio method introduced by Choi and Kim (2018). Given that both methods provide direct estimates of the hedge ratio, we are no longer able to obtain alpha values. Therefore, we focus solely on the absolute values of return and volatility differences ($|Diff_{ret}|$ and $|Diff_{vol}|$). The results are presented in Table 5.

Panel A of Table 5 shows the results when using the hedge ratio estimated from the Merton model. Across all stock and bond short-sale constraint variables, the means of the absolute values of $Diff_{ret}$ and $Diff_{vol}$ increase from Low to High, and the differences between the High and Low portfolios are consistently positive and significant. Therefore, our results are robust to the use of hedge ratio from the Merton model. In Panel B, we consider the hedge ratio estimated by the portfolio method of Choi and Kim (2018). The results mirror those in Panel A, reinforcing the robustness of our findings. Furthermore, in both panels, we continue to observe a more pronounced impact of stock short-sale constraints than bond short-sale constraints on pricing discrepancies.

In Panel C of Table 5, we present the regression results with the dependent variable being

$|Diff_{ret}|$. We calculate the implied return using both types of hedge ratios, leading to the estimation of $Diff_{ret}$. The coefficients are overwhelming positive and significant, indicating that both stock and bond short-sale constraints positively affect pricing discrepancies. Notably, the coefficient on stock short-sale constraints is larger in magnitude than that on bond short-sale constraints, further underscoring the more substantial influence of stock short-sale constraints on pricing discrepancies.

Therefore, the choice of using the hedge ratio estimated from the Merton model or the portfolio method of Choi and Kim (2018) does not alter our findings. The robustness across different model choices suggests that choices in the estimation method are not a potential factor influencing the impact of short-sale constraints on pricing discrepancies.

[Insert Table 5 about here]

5.2 Alternative short-sale constraint measures

The cost of borrowing is the most direct way to gauge the difficulties in short selling. The Markit database provides metrics labeled $DCBS$ (daily cost of borrowing scores) for both stocks and bonds. These scores serve as a relative measure of borrowing costs, ranging from 1 (indicating the lowest cost) to 10 (indicating the highest cost).[11]

We divide our sample into low-constraint ($DCBS = 1$) and high-constraint ($DCBS > 1$) groups. For each group, we calculate the average values of $|\alpha|$, $|Diff_{ret}|$, and $|Diff_{vol}|$ and report them in Table 6. We also report the differences between high-constraint and low-constraint groups. All the differences are positive and significant, indicating that the firms in the high-constraint group exhibit higher pricing discrepancies. Notably, the H-L spreads based on $DCBS_S$ are two to three times larger than those based on $DCBS_B$, confirming our previous finding that stock short-sale constraints exert a more pronounced impact on pricing discrepancies than bond short-sale constraints.

[Insert Table 6 about here]

[11]Beneish et al. (2015) show that low $DCBS$ values correspond to stocks that are easy to borrow and use a threshold of 2 to define the *Special* dummy. In our sample, $DCBS$ values are concentrated at 1, so we choose this as the threshold to ensure an effective sample division.

5.3 Investor sentiment effects

The literature has shown that investor sentiment has a market-wide component capable of affecting security prices.[12] Additionally, Stambaugh et al. (2012) find that sentiment-driven mispricing is closely related to short-sale constraints. Thus, in this subsection, we explore whether the positive relation between price discrepancies and short-sale constraints is contingent on investor sentiment. We measure investor sentiment using the sentiment index introduced by Baker and Wurgler (2006).[13]

Following Stambaugh et al. (2012), we use the median value of the sentiment index to distinguish between low and high sentiment periods. Then we calculate the differences in pricing discrepancies between the high and low constraint quintiles during these periods, respectively. The results are shown in the first part of Table 7. Our findings reveal that short-sale constraints positively impact pricing discrepancies, with this effect being more pronounced in high sentiment periods. Moreover, stock short-sale constraints play a more substantial role than bond short-sale constraints, consistent with our earlier results. Overall, our findings are in line with Stambaugh et al. (2012), who show mispricing is more likely to happen during high sentiment periods than low sentiment periods.

[Insert Table 7 about here]

5.4 Subperiod analysis

In this subsection, we investigate whether the effect of short-sale constraints on pricing discrepancies depends on market information environments. Following Chen et al. (2022), we consider three different information-related market conditions: recession, market volatility, and the volume of public information.[14] Specifically, we use the NBER recession indicators to divide our original sample period into recession and expansion periods. Regarding market volatility, we use the median value of the CBOE VIX index to segment the sample into high and low VIX subperiods, respectively. Finally, high information periods refer to the first two months of each calendar quarter since earnings announcements tend to occur in these months (Chen et al. (2022)). For brevity, we use the absolute

[12] For details, see Yu and Yuan (2011), Stambaugh et al. (2012), Huang et al. (2015), Gao et al. (2020).

[13] The sentiment index is obtained from Professor Jeffrey Wurgler's personal website. Please refer to https://pages.stern.nyu.edu/ jwurgler/ for further details.

[14] Chen et al. (2022) propose a short selling efficiency measure and show it significantly and negatively predicts stock market return, with the predictive power stronger during periods of recession, high volatility, and low public information.

value of return differences as the measure for price discrepancies and report the corresponding portfolio results in the remaining parts of Table 7.

The second part of Table 7 presents the results during the recession and expansion periods. When sorting by $Utilization_S$, the H-L spreads is 1.13% in expansion periods and 2.97% in recession periods. Therefore, the effect of short-sale constraints on pricing discrepancies is robust to macroeconomic environments, though the effect is stronger during recession periods, which is consistent with Chen et al. (2022). Moreover, the impact of stock short-sale constraints on pricing discrepancies continues to surpass bond short-sale constraints. The remaining parts show the results based on CBOE VIX and the market information environment, and the results show that the effect of short-sale constraints is more pronounced when the market is more volatile or surrounded by stale information.

6 Conclusion

This paper explores the effect of short-sale constraints on pricing discrepancies between stocks and bonds issued by the same firms. We find that both stock and bond short-sale constraints positively affect the pricing discrepancies. The positive relation permeates all rating categories but becomes weaker for high-grade stocks. Moreover, we show this positive relation is robust to different short-sale constraints, pricing discrepancy measures, and controlling for various stock/bond characteristics. Furthermore, our results show that stock short-sale constraints have more significant effects than bond short-sale constraints. Examining the positive relation for different subperiods, we show it is stronger when the market is characterized by high sentiment and volatility, low economic growth, and information quality.

Appendix: Variable definitions

Variable	Definition and source
$Utilization_S$	Stock utilization rate. It is a ratio to measure the constraint slack in the loan market based on Markit demand and supply data.
$Utilization_B$	Bond utilization rate. It is a ratio to measure the constraint slack in the loan market based on Markit demand and supply data.
$SIRIO_S$	Adjusted stock short interest ratio. The stock short interest ratio is divided by stock institutional ownership. Stock short interest is obtained from COMPUSTAT and stock institutional ownership is obtained from Thomson/Refinitiv Institutional Holdings (13F). This ratio measures the constraint slack based on other public data resources.
$SIRIO_B$	Adjusted bond short interest ratio. Bond short interest ratio divided by bond institutional ownership. Bond short interest is obtained from Markit and bond institutional ownership is obtained from eMAXX. This ratio measures the constraint slack based on other public data resources.
$DCBS$	Daily Cost of Borrow Score - a relative measure of borrowing cost, constructed by Markit. $DCBS$ is available for both stocks and bonds.
h(Firm)	The hedge ratio estimated based on the regression model (2).
h(Merton)	The hedge ratio estimated based on the Merton model.
h(Portfolio)	The hedge ratio estimated based on the portfolio approach of Choi and Kim (2018).
$\|\alpha\|$	The absolute value of the intercept in the regression model when estimating the firm-level hedge ratio.
$\|Diff_{ret}\|$	The absolute value of the return differences between actual and implied bond returns.
$\|Diff_{vol}\|$	The absolute value of the differences between actual and implied bond return volatility.
$IVOL_S$	Stock idiosyncratic volatility.
$ILLIQ_S$	Stock illiquidity following Amihud (2002)'s method.
$IVOL_B$	Bond idiosyncratic volatility.
$ILLIQ_B$	Bond illiquidity following Amihud (2002)'s method.
$Coverage$	Number of analysts following. It is a proxy of information uncertainty and obtained from I/B/E/S.
$Size$	Logarithm value of firm total asset.
Age	Logarithm value of firm age (in months).
TTM	Corporate bond time-to-maturity. It is obtained from Mergent FISD.

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Table 1: Descriptive statistics

This table reports summary statistics (mean, median, the 1st and 3rd quartiles) for the main variables used in the empirical work. Panel A shows the descriptive statistics for the hedge ratios and the pricing discrepancy measures. h(Firm) refers to the hedge ratio estimated based on the regression model $R^B_{i,t} = \alpha_i + h_i \cdot R^E_{i,t} + u_{i,t}$. $R^B_{i,t}$ represents bond returns and $R^E_{i,t}$ is the equity return of the same firm. h(Merton) represents the hedge ratio from the Merton model, and h(Portfolio) is the hedge ratio based on Choi and Kim ((2018))'s method. $|\alpha|$ is the absolute value of the intercept in the regression model when estimating the h(Firm). $|Diff_{ret}|$ represents the absolute value of the return differences between real and estimated bond returns. $|Diff_{vol}|$ is the absolute value of the differences between real and estimated bond return volatility. Panel B shows the descriptive statistics for short-sale constraint measures. $Utilization_S$ and $Utilization_B$ are stock and bond utilization rates, respectively. $SIRIO_S$ and $SIRIO_B$ are the adjusted stock and short interest ratios, respectively. Panel C presents the descriptive statistics for control variables, including stock and bond idiosyncratic volatility ($IVOL_S$ and $IVOL_B$), stock and bond illiquidity ($ILLIQ_S$ and $ILLIQ_B$), number of analysts following ($Coverage$), and firm total asset ($Size$). The sample period is from October 2006 to December 2018.

	Mean	P25	Median	P75
Panel A: Hedge ratio and discrepancy measures				
h(Firm)	0.042	-0.002	0.026	0.057
h(Merton)	0.013	0.002	0.008	0.019
h(Portfolio)	0.028	-0.035	0.015	0.059
$\lvert\alpha\rvert$	0.003	0.000	0.001	0.003
$\lvert Diff_{ret}\rvert$(Firm)	0.017	0.004	0.009	0.017
$\lvert Diff_{ret}\rvert$(Merton)	0.010	0.003	0.007	0.015
$\lvert Diff_{ret}\rvert$(Portfolio)	0.011	0.003	0.008	0.016
$\lvert Diff_{vol}\rvert$(Firm)	0.015	0.003	0.009	0.019
$\lvert Diff_{vol}\rvert$(Merton)	0.009	0.003	0.007	0.014
$\lvert Diff_{vol}\rvert$(Portfolio)	0.010	0.002	0.007	0.010
Panel B: Short-sale constraint measures				
$Utilization_S$	0.074	0.007	0.026	0.081
$SIRIO_S$	0.049	0.016	0.026	0.049
$Utilization_B$	0.058	0.003	0.017	0.061
$SIRIO_B$	0.067	0.003	0.015	0.061
Panel C: Control variables				
$IVOL_S$	0.080	0.057	0.071	0.090
$ILLIQ_S$	0.003	0.001	0.002	0.004
$IVOL_B$	0.021	0.008	0.015	0.021
$ILLIQ_B$	0.004	0.000	0.001	0.002
$Coverage$	15.860	10.000	16.000	21.000
$Size$	10.219	9.225	10.245	11.027

Table 2: Univariate portfolio analysis for short-sale constraints

This table presents the univariate portfolio analysis results. $Utilization_S$ and $Utilization_B$ are stock and bond utilization rates, respectively. $SIRIO_S$ and $SIRIO_B$ are the adjusted stock and short interest ratios, respectively. Panel A includes the results for stock short-sale constraints, and Panel B shows the results for bond short-sale constraints. We sort the bonds into quintile portfolios each month based on their short-sale constraint variables. Low includes the bonds with the lowest short-sale constraints, and High contains the bonds with the highest short-sale constraints. H-L indicates the mean differences between High and Low portfolios. Panel C reports the differences between High and Low portfolios in different bond rating samples. We divide the bond sample into four rating categories: AAA/AA (including AAA, AA+, AA, AA-), A (including A+, A, A-), BBB (including BBB+, BBB, BBB-), and non-investment grade (NIG) (including BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, and C). All the results are in percentage levels. The sample period is from October 2006 to December 2018. ***,**,* indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Considering stock short-sale constraints							
	Low	P2	P3	P4	High	H-L	t-value
$\lvert\alpha\rvert$							
$Utilization_S$	0.175	0.185	0.489	0.388	0.922	0.747***	2.755
$SIRIO_S$	0.159	0.183	0.219	0.480	0.951	0.792**	2.237
$\lvert Diff_{ret}\rvert$							
$Utilization_S$	1.650	1.750	1.990	2.090	3.010	1.353***	7.443
$SIRIO_S$	1.600	1.850	1.980	2.020	2.820	1.227***	7.442
$\lvert Diff_{vol}\rvert$							
$Utilization_S$	1.670	1.700	1.870	2.030	3.160	1.491***	4.793
$SIRIO_S$	1.570	1.700	2.110	2.040	2.840	1.278***	5.668
Panel B: Considering bond short-sale constraints							
$\lvert\alpha\rvert$							
$Utilization_B$	0.208	0.282	0.255	0.260	0.864	0.656**	2.402
$SIRIO_B$	0.194	0.331	0.232	0.284	0.525	0.331*	1.758
$\lvert Diff_{ret}\rvert$							
$Utilization_B$	1.710	1.680	1.850	2.000	2.730	1.022***	6.855
$SIRIO_B$	1.610	1.580	1.640	1.870	2.260	0.649***	5.948
$\lvert Diff_{vol}\rvert$							
$Utilization_B$	1.850	1.750	1.980	2.380	2.810	0.954***	4.535
$SIRIO_B$	1.770	1.660	1.770	2.070	2.490	0.722***	2.902

Panel C: H-L by rating									
	AAA/AA	A	BBB	NIG		AAA/AA	A	BBB	NIG
$\lvert\alpha\rvert$									
$Utilization_S$	0.078***	0.046***	0.042***	0.836***	$Utilization_B$	0.041***	0.024***	0.027***	0.612***
$SIRIO_S$	0.046***	0.029***	0.012***	0.666**	$SIRIO_B$	0.022***	0.023***	0.015***	0.604***
$\lvert Diff_{ret}\rvert$									
$Utilization_S$	0.445***	0.381***	0.297***	1.747***	$Utilization_B$	0.439***	0.276***	0.596***	1.643***
$SIRIO_S$	0.178***	0.314***	0.266***	1.026***	$SIRIO_B$	0.338***	0.368***	0.692***	0.650***
$\lvert Diff_{vol}\rvert$									
$Utilization_S$	0.011	0.086**	0.236***	0.656***	$Utilization_B$	0.027	0.379***	0.409***	0.750***
$SIRIO_S$	0.019	0.161**	0.214***	0.297*	$SIRIO_B$	0.026	0.401***	0.489***	1.170***

Table 3: Bivariate portfolio analysis

This table reports the H-L of $|Diff_{ret}|$ for portfolios sorted by bond/firm characteristics and short-sale constraints. We first sort bonds into quintiles by bond/firm characteristics each month. In each characteristic quintile, we further sort the bonds into quintiles based on short-sale constraints. We then calculate the $|Diff_{ret}|$ difference between the High constraint quintile and Low constraint quintile. The bond/firm characteristics considered are bond illiquidity ($ILLIQ_B$), bond idiosyncratic volatility ($IVOL_B$), stock illiquidity ($ILLIQ_S$), stock idiosyncratic volatility ($IVOL_S$), firm total asset ($Size$), and number of analysts following ($Coverage$). $Utilization_S$ and $Utilization_B$ are stock and bond utilization rates, respectively. $SIRIO_S$ and $SIRIO_B$ are the adjusted stock and short interest ratios, respectively. All the results are in percentage levels. The sample period is from October 2006 to December 2018. ***,**,* indicate statistical significance at 1%, 5% and 10%, respectively.

	Low $ILLIQ_B$	2	3	4	High $ILLIQ_B$	Average	t-value
$Utilization_S$	0.295	0.447	0.580	1.498	2.886	1.144***	7.558
$Utilization_B$	0.722	0.686	0.625	1.111	1.951	1.022***	5.628
$SIRIO_S$	0.433	0.558	0.635	1.403	1.836	0.976***	8.150
$SIRIO_B$	0.532	0.683	0.564	0.687	0.802	0.654***	4.921
	Low $IVOL_B$	2	3	4	High $IVOL_B$	Average	t-value
$Utilization_S$	0.353	0.370	0.517	0.424	2.459	0.833***	5.222
$Utilization_B$	0.371	0.361	0.208	0.654	2.500	0.819***	4.716
$SIRIO_S$	0.407	0.380	0.387	0.242	1.266	0.536***	4.799
$SIRIO_B$	0.326	0.294	0.209	0.564	1.168	0.512***	4.947
	Low $ILLIQ_S$	2	3	4	High $ILLIQ_S$	Average	t-value
$Utilization_S$	0.565	0.198	0.186	0.441	2.775	0.794***	5.669
$Utilization_B$	0.278	0.834	0.748	0.692	2.060	0.942***	7.247
$SIRIO_S$	0.445	0.633	0.321	0.637	1.919	0.791***	6.029
$SIRIO_B$	0.263	0.853	0.708	0.597	1.145	0.713***	9.501
	Low $IVOL_S$	2	3	4	High $IVOL_S$	Average	t-value
$Utilization_S$	0.260	0.804	0.807	0.547	2.598	0.940***	7.453
$Utilization_B$	0.438	0.574	0.832	0.477	1.847	0.856***	9.523
$SIRIO_S$	0.393	0.284	0.704	0.416	2.064	0.796***	7.850
$SIRIO_B$	0.306	0.285	0.782	0.592	0.866	0.561***	9.994
	Low $Size$	2	3	4	High $Size$	Average	t-value
$Utilization_S$	2.208	1.627	0.548	0.338	0.509	1.098***	8.391
$Utilization_B$	1.761	1.474	1.328	0.722	0.207	1.026***	8.898
$SIRIO_S$	1.785	1.363	1.534	0.389	0.379	1.090***	8.689
$SIRIO_B$	0.748	1.462	0.628	0.611	0.311	0.752***	8.395
	Low $Coverage$	2	3	4	High $Coverage$	Average	t-value
$Utilization_S$	2.061	1.345	1.266	0.942	0.845	1.292***	8.097
$Utilization_B$	1.778	1.086	1.678	0.727	0.481	1.151***	7.716
$SIRIO_S$	1.622	1.140	0.841	0.858	0.733	1.039***	10.450
$SIRIO_B$	0.677	0.794	1.266	0.622	0.368	0.745***	7.862

Table 4: Regression analysis

This table reports the regression analysis results. The regression model is $|Diff_{ret}|_{i,t} = \alpha_0+\alpha_1\cdot Short_{i,t}+\alpha_2\cdot X_{i,t}+u_{it}$. We control the Fama-French three factors, the Momentum factor, and bond TERM and DEF factors. We further control firm ROA, firm age, bond issue size, and bond time-to-maturity in the regression model. $Utilization_S$ and $Utilization_B$ are stock and bond utilization rates, respectively. $SIRIO_S$ and $SIRIO_B$ are the adjusted stock and short interest ratios, respectively. NIG is a dummy variable, which is equal to one if the bond rating belongs to BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, and C. All the estimations are in percentage level. The sample period is from October 2006 to December 2018. ***,**,* indicate statistical significance at 1%, 5% and 10%, respectively. The numbers in parentheses are t-statistics.

Panel A. Use *Utilization* as short-sale constraints						
	(1)	(2)	(3)	(4)	(5)	(6)
$Utilization_S$	3.197***	1.375***			2.814***	1.323***
	(49.81)	(13.58)			(42.60)	(13.00)
$Utilization_S \times NIG$		2.074***				1.705***
		(15.66)				(12.68)
$Utilization_B$			2.388***	0.587***	1.665***	0.454***
			(35.08)	(5.60)	(23.84)	(4.31)
$Utilization_B \times NIG$				2.059***		1.431***
				(14.66)		(10.05)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2 (%)	7.155	7.722	6.570	7.320	7.420	7.908
Panel B. Use *SIRIO* as short-sale constraints						
	(1)	(2)	(3)	(4)	(5)	(6)
$SIRIO_S$	3.115***	0.496***			2.786***	0.433***
	(30.74)	(3.82)			(24.23)	(3.04)
$SIRIO_S \times NIG$		4.822***				4.710***
		(22.67)				(19.04)
$SIRIO_B$			1.326***	0.345***	0.003***	0.003
			(21.91)	(3.95)	(3.00)	(1.11)
$SIRIO_B \times NIG$				0.818***		0.001
				(6.50)		(0.31)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2 (%)	6.307	7.251	5.984	6.486	5.939	6.786

Table 5: Analysis for alternative hedge ratio estimations

This table presents the results using the hedge ratio estimated from the Merton model or Choi and Kim ((2018))'s method. Panels A and B show the results of univariate portfolio analysis. Panel C reports the results of the regression analysis. We use $|Diff_{ret}|$ as the dependent variable and the regression model is $|Diff_{ret}|_{i,t} = \alpha_0 + \alpha_1 \cdot Short_{i,t} + \alpha_2 \cdot X_{i,t} + u_{it}$. The control variables include firm ROA, age, bond issue size, and time to maturity. $Utilization_S$ and $Utilization_B$ are stock and bond utilization rates, respectively. $SIRIO_S$ and $SIRIO_B$ are the adjusted stock and short interest ratios, respectively. All the results are in percentage levels. The sample period is from October 2006 to December 2018. ***,**,* indicate statistical significance at 1%, 5% and 10%, respectively. The numbers in parentheses are t-statistics.

Panel A: Considering Merton hedge ratio (h(Merton))							
	Low	P2	P3	P4	High	H-L	t-value
$\vert Diff_{ret}\vert$							
$Utilization_S$	1.650	1.790	1.950	2.240	2.540	0.892***	5.408
$Utilization_B$	1.800	1.830	1.950	2.160	2.310	0.507***	5.034
$SIRIO_S$	1.700	2.000	2.000	1.880	2.570	0.869***	5.565
$SIRIO_B$	1.740	1.820	1.840	2.100	2.440	0.695***	5.718
$\vert Diff_{vol}\vert$							
$Utilization_S$	2.310	2.490	2.910	3.280	3.820	1.502***	7.800
$Utilization_B$	2.250	2.410	2.660	2.940	3.220	0.975***	8.413
$SIRIO_S$	2.260	2.700	3.020	2.930	3.830	1.568***	7.714
$SIRIO_B$	2.150	2.360	2.350	2.760	3.410	1.254***	8.614
Panel B: Considering hedge ratio of Choi and Kim ((2018)) (h(Portfolio))							
$\vert Diff_{ret}\vert$							
$Utilization_S$	1.670	1.660	2.100	2.520	3.330	1.656***	7.110
$Utilization_B$	1.730	1.820	2.100	2.240	2.630	0.890***	4.016
$SIRIO_S$	2.240	1.760	2.310	2.020	3.320	1.075***	5.122
$SIRIO_B$	1.630	1.640	1.890	2.000	2.970	1.345***	5.598
$\vert Diff_{vol}\vert$							
$Utilization_S$	1.980	2.020	2.540	2.840	2.740	0.755***	5.992
$Utilization_B$	2.050	2.140	2.340	2.630	2.750	0.701***	4.981
$SIRIO_S$	2.030	2.280	2.610	2.640	2.630	0.603***	4.607
$SIRIO_B$	2.060	2.080	2.170	2.420	2.890	0.835***	5.171

Panel C: Regression analysis				
	Merton model		Choi and Kim ((2018))	
$Utilization_S$	2.383***		2.143***	
	(43.434)		(25.400)	
$Utilization_B$	0.630***		1.799***	
	(11.589)		(16.510)	
$SIRIO_S$		0.469***		2.614***
		(6.245)		(18.473)
$SIRIO_B$		0.002**		0.004***
		(1.992)		(9.745)
Controls	Yes	Yes	Yes	Yes
Adj. R^2 (%)	5.069	2.754	12.310	10.440

Table 6: Alternative short-sale constraint measures

This table reports the results when considering Daily Cost of Borrowing scores ($DCBS$) as alternative short-sale constraint measures. $DCBS$ is a relative measure of borrowing cost. This score ranges from 1 (the lowest cost) to 10 (the highest cost). The sample is divided into low-constraint ($DCBS = 1$) and high-constraint ($DCBS > 1$) groups. For each group, we calculate the average value of $|\alpha|$, $|Diff_{ret}|$, and $|Diff_{vol}|$. We also report the differences between high-constraint and low-constraint groups across different pricing discrepancy measures. The sample period is from October 2006 to December 2018. ***,**,* indicate statistical significance at 1%, 5% and 10%, respectively.

	Low ($DCBS = 1$)	High ($DCBS > 1$)	H-L	t-value
Panel A: Stock $DCBS$				
$\|\alpha\|$	0.356	4.569	4.213***	2.549
$\|Diff_{ret}\|$	1.991	6.807	4.817***	4.973
$\|Diff_{vol}\|$	2.172	5.597	3.424***	6.347
Panel B: Bond $DCBS$				
$\|\alpha\|$	0.351	1.867	1.515***	2.729
$\|Diff_{ret}\|$	1.994	4.980	2.986***	4.451
$\|Diff_{vol}\|$	2.190	4.092	1.895***	5.421

Table 7: Subperiod analysis

This table reports the effects of short-sale constraints on price discrepancies during different subperiods. Pricing discrepancy is measured by the absolute value of return differences, $|Diff_{ret}|$. We use the sentiment index of Baker and Wurgler ((2006)) and the CBOE VIX index to divide the sample period into low and high subperiods. The expansion and recession periods are based on the NBER recession indicators. The high information periods correspond to the first two months of each quarter, as earnings announcements tend to occur in these months (Chen et al. ((2022))). H-L is the difference in pricing discrepancies between high-constraint and low-constraint groups. All results are expressed in percentage levels. The sample period is from October 2006 to December 2018. ***,**,* indicate statistical significance at 1%, 5% and 10%, respectively.

	Sentiment		Macroeconomic Environment		VIX		Information Environment	
	H-L	t-Value	H-L	t-Value	H-L	t-Value	H-L	t-Value
	Low		Expansion		Low		Low	
$Utilization_S$	1.094***	7.295	1.132***	6.461	1.230***	4.867	1.354***	5.616
$Utilization_B$	0.686***	5.698	1.125***	7.451	0.887***	4.251	1.108***	5.273
$SIRIO_S$	1.056***	5.889	0.668***	4.601	0.839***	3.299	0.931***	4.467
$SIRIO_B$	0.634***	3.934	0.646***	7.029	0.544***	3.773	0.707***	6.028
	High		Recession		High		High	
$Utilization_S$	1.842***	4.753	2.968***	4.428	1.428***	5.568	1.323***	5.405
$Utilization_B$	1.788***	4.468	2.282***	4.233	1.187***	5.606	0.837***	6.636
$SIRIO_S$	1.294***	6.094	1.184***	5.558	0.959***	5.128	0.891***	4.355
$SIRIO_B$	0.747***	5.489	0.932***	5.681	0.718***	4.458	0.605***	4.017

Table A1: Bivariate portfolio analysis considering $|\alpha|$

This table reports the H-L of $|\alpha|$ for portfolios sorted by bond/firm characteristics and short-sale constraints. We first sort bonds into quintiles by bond/firm characteristics each month. In each characteristic quintile, we further sort the bonds into quintiles based on short-sale constraints. We then calculate the $|Diff_{ret}|$ difference between the High constraint quintile and Low constraint quintile. The bond/firm characteristics considered are bond illiquidity ($ILLIQ_B$), bond idiosyncratic volatility ($IVOL_B$), stock illiquidity ($ILLIQ_S$), stock idiosyncratic volatility ($IVOL_S$), firm total asset ($Size$), and number of analysts following ($Coverage$). $Utilization_S$ and $Utilization_B$ are stock and bond utilization rates, respectively. $SIRIO_S$ and $SIRIO_B$ are the adjusted stock and short interest ratios, respectively. All the results are in percentage levels. The sample period is from October 2006 to December 2018. ***,**,* indicate statistical significance at 1%, 5% and 10%, respectively.

	Low $ILLIQ_B$	2	3	4	High $ILLIQ_B$	Average	t-value
Utilization_S	0.143	0.115	0.187	1.162	1.778	0.677***	3.551
Utilization_B	0.043	0.053	0.043	1.408	1.307	0.571***	2.632
SIRIO_S	0.174	0.113	0.175	1.125	0.743	0.466***	3.534
SIRIO_B	0.021	0.088	0.049	0.732	0.616	0.302**	1.966
	Low IVOL_B	2	3	4	High IVOL_B	Average	t-value
Utilization_S	0.066	0.144	0.145	0.619	1.774	0.814***	3.301
Utilization_B	0.048	0.015	0.058	1.127	1.823	0.812***	2.723
SIRIO_S	0.116	0.158	0.117	0.689	1.766	0.779***	3.263
SIRIO_B	0.072	0.042	0.037	0.474	1.704	0.458*	1.786
	Low ILLIQ_S	2	3	4	High ILLIQ_S	Average	t-value
Utilization_S	0.681	0.223	0.429	0.413	1.174	0.584***	2.718
Utilization_B	0.392	0.033	0.090	0.521	1.195	0.544***	2.782
SIRIO_S	0.376	0.174	0.483	0.439	0.893	0.787**	2.078
SIRIO_B	0.213	0.625	0.040	0.126	0.376	0.276**	2.053
	Low IVOL_S	2	3	4	High IVOL_S	Average	t-value
Utilization_S	0.048	0.055	1.061	0.054	1.379	0.445***	4.189
Utilization_B	0.029	0.033	1.212	0.051	1.192	0.425***	4.459
SIRIO_S	0.037	0.068	1.954	0.041	1.176	0.401***	3.712
SIRIO_B	0.045	0.009	1.012	0.027	0.868	0.163**	2.003
	Low Size	2	3	4	High Size	Average	t-value
Utilization_S	1.235	0.485	0.266	0.055	0.068	0.554***	4.849
Utilization_B	1.010	0.838	0.163	0.067	0.036	0.438***	5.593
SIRIO_S	1.035	0.369	0.310	0.091	0.051	0.432***	4.694
SIRIO_B	0.806	0.151	0.301	0.061	0.052	0.177***	2.852
	Low Coverage	2	3	4	High Coverage	Average	t-value
Utilization_S	1.787	0.058	1.022	0.770	0.064	0.507***	3.608
Utilization_B	1.291	0.029	1.216	0.273	0.052	0.373***	3.861
SIRIO_S	1.251	0.175	0.131	0.585	0.079	0.356***	3.652
SIRIO_B	1.266	0.037	1.165	0.057	0.042	0.092***	6.191

Table A2: Bivariate portfolio analysis considering $|Diff_{vol}|$

This table reports the H-L of $|Diff_{vol}|$ for portfolios sorted by bond/firm characteristics and short-sale constraints. We first sort bonds into quintiles by bond/firm characteristics each month. In each characteristic quintile, we further sort the bonds into quintiles based on short-sale constraints. We then calculate the $|Diff_{ret}|$ difference between the High constraint quintile and Low constraint quintile. The bond/firm characteristics considered are bond illiquidity ($ILLIQ_B$), bond idiosyncratic volatility ($IVOL_B$), stock illiquidity ($ILLIQ_S$), stock idiosyncratic volatility ($IVOL_S$), firm total asset ($Size$), and number of analysts following ($Coverage$). $Utilization_S$ and $Utilization_B$ are stock and bond utilization rates, respectively. $SIRIO_S$ and $SIRIO_B$ are the adjusted stock and short interest ratios, respectively. All the results are in percentage levels. The sample period is from October 2006 to December 2018. ***,**,* indicate statistical significance at 1%, 5% and 10%, respectively.

Utilization_S	0.285	0.428	0.244	1.919	2.583	1.729***	12.620
Utilization_B	0.684	0.562	0.494	1.107	1.522	1.718***	11.862
SIRIO_S	0.172	0.439	0.528	1.473	2.174	1.570***	13.212
SIRIO_B	0.642	0.587	0.525	1.328	0.732	1.465***	9.921
	Low IVOL_B	2	3	4	High IVOL_B	Average	t-value
Utilization_S	0.185	0.065	0.067	0.360	1.329	3.358***	19.042
Utilization_B	0.266	0.360	0.095	0.323	0.905	3.348***	18.560
SIRIO_S	0.219	0.125	0.063	0.285	1.081	3.282***	17.993
SIRIO_B	0.154	0.291	0.159	0.205	0.411	3.104***	16.505
	Low ILLIQ_S	2	3	4	High ILLIQ_S	Average	t-value
Utilization_S	0.482	0.215	0.316	0.465	1.980	1.125***	8.161
Utilization_B	0.157	0.439	1.008	0.607	1.193	1.017***	6.164
SIRIO_S	0.508	0.071	0.416	0.557	1.596	0.938***	6.760
SIRIO_B	0.203	0.459	0.847	0.527	0.935	0.644***	4.580
	Low IVOL_S	2	3	4	High IVOL_S	Average	t-value
Utilization_S	0.096	0.070	0.672	0.797	2.662	1.246***	7.850
Utilization_B	0.536	0.106	0.335	1.203	1.088	1.232***	10.055
SIRIO_S	0.288	0.025	0.576	0.832	2.196	1.158***	7.164
SIRIO_B	0.139	0.206	0.561	1.008	0.824	1.033***	8.517
	Low Size	2	3	4	High Size	Average	t-value
Utilization_S	1.674	1.569	0.156	0.410	1.111	0.579***	4.472
Utilization_B	1.217	1.347	0.728	0.679	0.547	0.273**	2.246
SIRIO_S	1.476	1.209	0.403	0.185	1.055	0.482***	4.038
SIRIO_B	0.868	0.819	0.629	0.772	0.387	0.149*	1.924
	Low Coverage	2	3	4	High Coverage	Average	t-value
Utilization_S	0.432	1.515	1.346	0.991	1.382	0.371**	2.315
Utilization_B	0.704	0.989	1.233	1.013	0.794	0.315**	2.513
SIRIO_S	0.491	1.333	0.933	0.838	1.085	0.286**	2.122
SIRIO_B	0.405	0.721	0.919	0.931	0.807	0.261*	1.916