Contents lists available at ScienceDirect



journal homepage: www.elsevier.com/locate/jempfin

Prospect theory and corporate bond returns: An empirical study

Xiaoling Zhong^a, Junbo Wang^{b,*}

^a International Institute of Finance, School of Management, University of Science and Technology of China, China
 ^b Department of Economics and Finance, City University of Hong Kong, Hong Kong

ARTICLE INFO

JEL classification: D03 G12

Keywords: Prospect theory Bond return Loss aversion Probability weighting

ABSTRACT

Since the 1980s, prospect theory has been considered as the most successful descriptive theory for decision making. In this paper, we examine the predictive power of prospect theory in the U.S. corporate bond market. The empirical evidence shows that prospect theory has significant predictive power for corporate bond returns, especially for junk bond returns. Unlike the findings for the stock market, the loss aversion component plays the most important role in predicting corporate bond returns. The probability weighting component also plays a predictive role for junk bonds, but not for investment-grade bonds.

© 2018 Elsevier B.V. All rights reserved.

1. Introduction

Kahneman and Tversky (1979) propose prospect theory and Tversky and Kahneman (1992) modify it into the known cumulative prospect theory. Since then, prospect theory has been widely considered to be the most successful descriptive theory for decision making. A number of studies have reported that prospect theory can explain some financial phenomena, such as the long-run underperformance of initial public offerings (IPOs) (Ma and Shen, 2003), skewness of stock returns (Barberis and Huang, 2008), inflation perceptions (Brachinger, 2008), stock option pricing (Gurevich et al., 2009), stock momentum (Menkhoff and Schmeling, 2006), and etc.

Benartzi and Thaler (1995) propose that investors evaluate the stock/bond market by calculating the prospect theory value of its historical return distributions. Barberis et al. (2016) propose a stock-level analog of Benartzi and Thaler's (1995) market-level model. Their empirical evidence shows that prospect theory based on a stock's historical return distributions has significant predictive power for subsequent stock returns.

Although it has been shown that prospect theory has predictive power for stock returns, there is a paucity of studies implementing prospect theory in the corporate bond market. This raises a natural question: Does prospect theory have predictive power in the corporate bond market? Furthermore, unlike the stock market, institutional investors hold most of the investment-grade corporate bonds, while individual investors play an important role in junk bonds.¹ The different investors' structure between the investment-grade and junk bonds provides an ideal setting to test whether institutional investors make decisions differently from individual

* Corresponding author.

https://doi.org/10.1016/j.jempfin.2018.02.005

Received 21 October 2016; Received in revised form 29 October 2017; Accepted 25 February 2018 Available online 5 March 2018

0927-5398/ \odot 2018 Elsevier B.V. All rights reserved.







E-mail addresses: sherry.zxling@gmail.com (X. Zhong), jwang2@cityu.edu.hk (J. Wang).

¹ The Securities Industry and Financial Markets Association 2015 report shows that the total outstanding of U.S. corporate bond volume is about \$8 trillion, among which \$6.2 trillion is in investment-grade bonds and \$1.8 trillion is in junk bonds (Acciavatti et al., 2015). Becker and Ivashina (2015) report that insurance companies hold around 70% of the newly-issued investment-grade bonds and less than 40% of junk bonds. Also, dealers may redistribute bonds to individual investors after their issuance (e.g., Goldstein and Hotchkiss, 2007), there are still a significant proportion of the corporate bonds that are held by individual investors. Based on the 2014 Federal Reserve Board report, individual investors owned around 20% of the total outstanding corporate bonds. Since institution investors have stricter capital requirements for bonds with lower ratings, we can infer that individual investors should hold much more than 20% of the junk bonds.

investors. In this paper, we develop our hypotheses around these questions and test them by using both investment-grade and junk bonds.

The essential concept of prospect theory is called "mental accounting" (Kahneman and Tversky, 1984; Thaler, 1985). It involves the mental process of an investor in both coding and evaluating financial assets. For the process of coding a financial asset, the historical return distribution is the most convenient, easily accessible, and intuitive information that investors can get when they make investment decisions. As proposed by Benartzi and Thaler (1995), investors evaluate a corporate bond's historical returns through a mental mechanism that is captured by prospect theory.

To explain the rationality of this, we start by introducing two closely related concepts in cognitive psychology: System 1 and System 2 thinking processes. In these two concepts of cognitive psychology, people follow a two-step mental procedure when making decisions (Kahneman and Frederick, 2002). Stanovich and West (2000) named them as System 1 and System 2 thinking processes, respectively. System 1 thinking is quick with little consciousness, and is basically pretty primitive. In contrast, System 2 thinking is slower, more reflective, and acquire proficiency and skills. In the first step, people use System 1 thinking to make a quick, intuitive judgment to a problem. There is little effort exerted in this step and it does not require the use of learned rules and skills. In the second step, people use System 2 thinking to evaluate the judgment made in the first step and accept, revise, or override it.

Frederick (2005) uses an example of when people solve the cognitive reflection test problem: If it takes 5 machines 5 min to make 5 widgets, how long would it take 100 machines to make 100 widgets? An intuitive answer to this problem would be 100 min. The thinking process that leads to this intuitive answer is System 1 thinking. A reevaluation of the answer will then recognize that the original 5 machines are enough to make 100 widgets in 100 min. A more careful and elaborative calculation will then lead to the correct answer of 5 min. The thinking process that reevaluates System 1 thinking and may override the incorrect answer from System 1 thinking with the correct answer is System 2 thinking.

System 1 thinking is mainly intuitive, while System 2 thinking is more sophisticated and requires related proficiency and skills. Thus, some individual investors are likely to make decisions based on System 1 thinking, while the decisions of institutional investors are more determined through System 2 thinking. Since prospect theory is a way of quantitatively measuring System 1 thinking, individual investors who rely more on System 1 thinking are more likely to evaluate a bond according to prospect theory. This does not mean that institutional investors' evaluation procedure does not involve System 1 thinking. In fact, System 1 thinking often involves the entire thinking process even if System 2 thinking also involves (e.g., Frederick, 2005). Therefore, we expect the prospect theory value to have some predictive power for future bond returns, and the predictive power should be stronger for bonds in which individual investors play a more active role, such as junk bonds.

The above discussion leads to the prediction that investors evaluate a bond by its historical return distributions through a mental mechanism that is captured by prospect theory. If the prospect theory value of this bond is higher (lower), then this bond is attractive (unattractive) to investors. Investors tend to tilt toward (away) this bond in their portfolios, causing the bond to be overvalued (undervalued) and to earn lower (higher) future returns. In short, bonds with higher (lower) prospect theory value are attractive (unattractive) to investors, which may cause them to be overvalued (undervalued) and hence earn lower (higher) future returns.

The prospect theory value we employ in this paper, which is constructed to quantitatively measure System 1 thinking, is a transformation of a bond's historical return distribution. It is constructed in a unique way to capture information in the full bond return distribution, as opposed to other transformations like volatility, skewness, and etc. We show the specificity in the transformations of the prospect theory value by controlling these variables. In addition, we consider the possibility that investors evaluate a bond according to expected utility, instead of prospect theory. We find that the expected utility shows little predictive power for future returns. Although this finding does not provide evidence against the expected utility function, it suggests that the prospect theory value transfers the historical returns in a uniquely informative way that can capture investors' evaluation process.

Investment-grade bonds and junk bonds are held by different investors, and the market behavior for them is totally different (Avramov et al., 2007; Bao et al., 2011; Lin et al., 2013; Liu et al., 2009; Longstaff et al., 2005). The psychological biases in investment behaviors typically affect individual investors more severely than institutional investors due to their lack of professionalism. Therefore, we expect that the predictability of prospect theory should hold more strongly for bonds held by more individual investors, for example, junk bonds.

In summary, our main empirical prediction is that a bond's prospect theory value based on its historical return distributions has predictive power for its future returns with a negative sign. This predictive power should be stronger for junk bonds in which individual investors play a more important role.

We test our prediction using corporate bond data from January 1973 to December 2013. Both portfolio and regression analyses show that bonds with higher (lower) prospect theory value will earn lower (higher) future returns. In other words, prospect theory values can predict future returns. Our findings are robust to various specifications of prospect theory value and model specifications. We also find that the predictive power is much stronger for junk bonds, where individual investors typically play a more important role. This finding further supports our prediction that investors evaluate a bond according to its prospect theory value.

We also try to identify which aspect of prospect theory explains why some bonds are appealing to investors. We explore this problem by looking at three embedded components of prospect theory: loss aversion, probability weighting, and concave/convex. We find that unlike the findings for the stock market, the loss aversion component accounts for most of prospect theory's predictive power in the bond market, while the probability weighting component contributes to the predictability of prospect theory only for junk bonds.

The corporate bond market is largely dominated by institutional investors. Barberis et al. (2001), Haigh and List (2005), and Connell and Teo (2009) show that due to fear of being less respected by their peers, institutional investors are generally more loss-averse than individual investors. The loss aversion of institutional investors explains why the loss aversion accounts for most predictive power of prospect theory in bond market.

The probability weighting component captures two types of investors' demand: the lottery type and the insurance type. Gompers and Metrick (2001), Frieder and Subrahmanyam (2005), and Kumar (2009) find that individual investors have a strong preference for the lottery-type demand, while institutional investors lean toward insurance-type demand. On one hand, since individual investors account for a much larger proportion of junk bonds holdings, it is natural to expect that the lottery-type demand is stronger for junk bonds. On the other hand, the "floor" nature of bonds leads to little downside risk for investment-grade bonds. Since the downside risk protection is the main resource where the insurance-type demand comes from Ilmanen (2012), this demand should be much greater among junk bonds investors due to the default risks. Simultaneously considering these two types of demands, it is not surprising that the probability weighting component contributes to the predictability of prospect theory for junk bonds only.

Our research is related to recent work by Bai et al. (2016), who examine the predictability of distributional characteristics, such like volatility, skewness, kurtosis, and etc. for future bond returns. Their results suggest a significantly positive (negative) link between volatility (skewness) and expected returns, and the findings are robust after controlling for transaction costs, liquidity, and bond characteristics. In this paper, we examine the predictability of prospect theory for future bond returns after controlling bond characteristics and return distribution characteristics, such as volatility, skewness, and etc. We also examine the robustness of our results by accounting for transaction costs and at firm level, our findings remain unchanged.

The remainder of the paper is organized as follows. Section 2 presents the model and develops testable hypotheses. We describe the data in Section 3. In Section 4, we examine the predictive power of prospect theory, as well as which aspect of prospect theory accounts for the predictive power. Some robustness tests are discussed in Section 5, and Section 6 concludes.

2. Prospect theory value and hypothesis development

In the following Section 2.1, we describe the prospect theory value that is constructed based on a bond's historical returns. In Section 2.2, we develop four hypotheses on the predictive power of prospect theory.

2.1. Prospect theory value based on a bond's historical return

We employ Barberis et al.'s (2016) model to construct a bond's prospect theory value based on its past 60-month return.² These returns³ are sorted in an increasing order, which leads to a series of r_i . We assume n of these returns are negative, and the remaining m = 60 - n are positive. Applying Tversky and Kahneman's (1992) value function, the prospect theory value based on a bond's historical returns can be calculated as:

$$PTV = \sum_{i=-n}^{m} E(r_i) \cdot \pi_i,$$
(1)

where:

$$E\left(r_{i}\right) = \begin{cases} r_{i}^{c} & r_{i} \ge 0\\ -\lambda\left(-r_{i}\right)^{c} & r_{i} < 0 \end{cases}$$

$$\tag{2}$$

is the value function for each return, and:

$$\pi_{i} = \begin{cases} f\left(\frac{m-i+1}{60}\right) - f\left(\frac{m-i}{60}\right) & r_{i} \ge 0\\ f\left(\frac{i+n+1}{60}\right) - f\left(\frac{i+n}{60}\right) & r_{i} < 0 \end{cases}$$
(3)

with:

$$f(p) = \frac{p^{\delta}}{[p^{\delta} + (1-p)^{\delta}]^{1/\delta}}$$
(4)

is known as the probability weighting function.

In the definition of the prospect theory value in Eqs. (1)–(4), there are three parameters, λ , δ , and c, corresponding to the three components of prospect theory: loss aversion, probability weighting, and concave/convex. The loss aversion component is accounted for by the coefficient of λ in Eq. (2). Specifically, a λ larger than 1 implies that the investor is more sensitive to losses than to gains of the same magnitude, while a higher value of λ implies a greater sensitivity to losses. When $\lambda = 1$, the investor has no loss aversion, that is, the investor is indifferent between the sensitivity of the same magnitude of losses and gains.

The second component, probability weighting, is reflected in Eqs. (3) and (4). Probability weighting captures the behavior of investors who need to make a decision between an extremely large gain (loss) with small probability and a certain small gain (loss). Investors tend to choose the former when facing potential gains, but to choose the latter when facing potential losses. For example, investors tend to choose a gain of \$1000 with a probability of 0.001 over a certain gain of \$1, which is a lottery-type demand. However, investors tend to choose a certain loss of \$1 over a loss of \$1000 with a probability of 0.001, which is an insurance-type demand. A logit function like in Eq. (4) will overweight the extreme outcomes with small probability, which simultaneously reflects the investors' demand of extreme gains and avoidance of extreme losses. The parameter $\delta \in (0, 1)$ is used to control the magnitude of

² Robustness checks show that the results do not change materially for other time windows.

³ We calculate *PTV* only when there is more than 10 months' return within the past five years. When there is less than 60 months' return, the *PTV* is calculated based on available monthly returns.

overweighting. The smaller δ is, the more overweighting of extreme outcomes. Setting $\delta = 1$ leads to f(p) = p, which means that the extreme outcomes will not be overweighted.

The third component is the concave/convex element, which is reflected in the value function of returns in Eq. (2). Note that the value function in Eq. (2) is concave over gains and convex over losses. By varying the value of parameter c, we can control the concavity/convexity of the value function. The smaller c is, the larger concavity/convexity the value function has. Like the other two parameters, setting c = 1 leads to a linear value function, which means that the function has no concavity or convexity.

All three parameters need to be estimated before calculating the prospective theory value in Eq. (1). Researchers have estimated these parameters through experiments. For the loss aversion parameter λ , Tversky and Kahneman (1992) estimate it to be 2.25 for their median subject. Gonzalez and Wu (1999) and Abdellaoui (2000) use nonparametric methods and obtain similar estimates. This means that investors have twice as much sensitivity to losses as to gains. The concave/convexity parameter *c* estimated by Tversky and Kahneman (1992) is around 0.88.

The probability weighting parameter δ in Eq. (4) has also been estimated. Due to loss aversion, investors tend to weight losses relatively more than gains. According to this, δ should be larger for $r_i < 0$ than it is for $r_i > 0$. This is consistent with the findings in Tversky and Kahneman (1992), Gonzalez and Wu (1999), and Abdellaoui (2000). In particular, Tversky and Kahneman (1992) estimate δ to be 0.61 for gains and 0.69 for losses. Other studies have similar estimates (Abdellaoui, 2000; Gonzalez and Wu, 1999).

There are two reasons we use the parameter estimates from the experiments to calculate our prospect theory value for the bonds. Firstly, we use experiments that do not have pre-assumptions on the type of financial markets to estimate the parameters. Secondly, although many mechanisms for the cumulative prospect theory have been developed (e.g., Abdellaoui et al., 2007; Bleichrodt and Pinto, 2000), the prospect theory parameters elicited via standardized computer tools are generally not suitable for investment counseling (Erner et al., 2008). Therefore, we use the parameters obtained by Tversky and Kahneman (1992) as our start points.

2.2. Hypotheses development

In this section, we develop four testable hypotheses. We employ our first hypothesis to examine whether a bond's prospect theory value has predictive power for its future returns. Using both cross-sectional and time series analyses, researchers have found that prospect theory value has predictive power for future stock returns (e.g., Barberis et al., 2016; Zhang and Semmler, 2009). Although the correlation between stock and bond returns is time-varying and highly unstable (Campbell and Ammer, 1993; Gulko, 2002; Lan, 2008), stock and bond investors generally use the same mental process to evaluate financial assets. It is intuitive that bond investors also evaluate bonds by their prospective theory values. If this is the case, investors tend to buy (sell) bonds with high (low) prospect theory values, causing these bonds to become overvalued (undervalued) and earn low (high) future returns. In addition, Tversky and Kahneman (1992) imply that bond investors evaluate a bond by its prospective utility. Based on these factors, we propose our first hypothesis:

H1. Bonds with higher (lower) prospect theory values will earn lower (higher) future returns.

When investors face a problem, they first use intuitive thinking, or System 1 thinking. They next use System 2 thinking to rethink/reevaluate the problem and their decision in a more complex way. System 1 thinking often involves the entire thinking process (e.g., Frederick, 2005), while System 2 does not. Even if System 2 thinking is involved in the thinking process, it tends to accept the conclusion from the System 1 thinking process, or to only slightly revise it. This implies that, although institutional investors may be more likely to engage in System 2 thinking, System 1 thinking may still be involved when they evaluate a bond.

Many institutional investors are only allowed to invest in investment-grade bonds. Becker and Ivashina (2015) document that the investment-grade bonds market is dominated by institutional investors. We thus propose our second hypothesis as:

H2. Prospect theory values can be predictive of both investment-grade and junk bonds' subsequent returns, and the predictive power is stronger for junk bonds.

We propose our third hypothesis to examine which components of prospect theory account for its predictive power. Barberis et al. (2016) show that in the stock market the probability weighting component accounts for the predictive power of prospect theory, while the loss aversion and concave/convex components do not contribute much. The investor composition of the corporate bond market is significantly different from the stock market, and the three components may play different roles in it (Connell and Teo, 2009; Han and Zhou, 2013; Shapira and Venezia, 2001).

Institutional investors are generally more loss-averse than individual investors. Connell and Teo (2009) argue that the loss aversion of institutional investors is mainly due to their self-esteem. Compared to individual investors, institutional investors care more about whether they are viewed as "second rate" investors. This may cause them to be less respected by their peers and be a major reason as to why they may be loss-averse (Barberis et al., 2001). This argument is supported by experimental studies, such as Haigh and List (2005). According to above discussion, we propose our third hypothesis as:

H3. Among the three components of prospect theory, unlike the stock market, the predictive power of prospect theory mainly comes from its loss aversion component.

Our fourth hypothesis is to compare the behavior of the probability weighting component between investment-grade and junk bonds. The probability weighting component captures two types of investors' demand: the lottery type and the insurance type. Investors generally favor small opportunities for large gains, even though there is a general tendency for risk aversion. Investors also have a tendency to try to avoid large losses. Gompers and Metrick (2001), Frieder and Subrahmanyam (2005), and Kumar (2009) find that individual investors have a strong preference for the lottery-type demand, while institutional investors lean toward insurance-type demand. Since individual investors hold more of the junk bonds, it is natural to expect that the lottery-type demand is stronger for junk bonds.

Ilmanen (2012) argues that the insurance-type demand mainly comes from downside risk protection. Obviously, downside risk is much larger for junk bonds due to the default risks. The "floor" nature of bonds makes the downside risk of investment-grade bonds so small that it can almost be ignored.

Simultaneously considering insurance-type and lottery-type demands for investment-grade and junk bonds leads to our final hypothesis:

H4. The probability weighting component contributes significantly to the predictive power of prospect theory for junk bonds, but it does not contribute for investment-grade bonds.

3. Data

Our U.S. corporate bond data are constructed from several sources: The Lehman Brothers Fixed Income (LBFI) database, the Merrill Lynch database, National Association of Insurance Commissioners' (NAIC) transaction data, the Trading Reporting and Compliance Engine (TRACE), and Mergent's Fixed Investment Securities Database (FISD). The sample covers from January 1973 to December 2013.

The Lehman database consists of monthly information on corporate and government debt issues in the U.S. from 1973 to March 1998. We include all U.S. corporate fixed-coupon bonds that are not backed by mortgages or other assets, and collect data on month-end price, accrued interest, rating, amount outstanding, issue date, maturity date, provisions, and other characteristics for these bonds. While most prices in the Lehman database reflect dealer quotes, some are "matrix" prices, which are derived from the price quotes of bonds with similar characteristics. We only keep bonds with dealer quotes, as Sarig and Warga (1989) show that matrix prices are less reliable than dealer quotes.

The Merrill Lynch database is retrieved from Datastream International. The bond price is an average price across all market makers for the bond. We construct monthly bond returns from the month-end bond prices. We exclude non-U.S. dollar-denominated bonds, as well as bonds with unusual coupons and backed by mortgages or other assets.

The TRACE database was established in July 2002 and covers the transactions of most publicly traded bonds since October 1, 2004. The current TRACE database contains the vast majority of corporate bond trades in the U.S. fixed-income market (Lin et al., 2013). It includes the transaction data of publicly traded corporate bonds from July 2002 to December 2013. We use the CUSIP Master File, which contains bond characteristics, to identify and eliminate non-U.S. dollar-denominated bonds and bonds backed by mortgages or other assets. We follow the data cleaning procedure in Bessembinder et al. (2009) to eliminate canceled, corrected, and commission trades.

We obtain all transaction data of publicly traded corporate bonds from January 1994 from the NAIC database, by life and property and casualty insurance companies and health maintenance organizations (HMOs).

The FISD database includes issuance information for all fixed-income securities that have a CUSIP number and those likely to receive one soon. It contains issue- and issuer-specific information such as coupon rate, issue date, maturity date, issue amount, rating, and other bond characteristics for bonds maturing in 1990 or later. We exclude non-U.S. dollar-denominated bonds, as well as bonds backed by mortgages or other assets.

The Lehman database contains monthly bond prices and returns. Datastream provides monthly gross bond price, which can be used to calculate the monthly bond return. TRACE and NAIC are trade-based databases. For most bonds, the NAIC provides both the clean and gross trading prices, whereas TRACE only provides the clean trading price.

To obtain monthly bond returns using the TRACE/NAIC data, we first compute daily bond prices as the trade size-weighted average of intraday prices. Monthly holding period returns are then calculated using month-end prices as:

$$r_t = \frac{(P_t + AI_t) + C_t - (P_{t-1} + AI_{t-1})}{P_{t-1} + AI_{t-1}},$$

where P_t is the price, AI_t is accrued interest, and C_t is the coupon payment, if any, in month *t*. We use the last day's price of each month to calculate the bond's monthly return.⁴ If the price record does not fall on the last trading day of the month, we use the last available price to calculate the return and rescale it to monthly return.

$$r'_t = r_t \cdot \frac{\# of \ days \ for \ that \ month}{\# of \ days \ between \ last \ aviable \ prices \ of \ two \ sequential \ months}$$

We merge the Lehman, Datastream, TRACE, and NAIC data to form a long-span comprehensive return series from January 1973 to December 2013. There are times when information on the same bond is covered in more than one source. To avoid double counting, when returns for the same bond-month are available from more than one source, we only keep one return record for a bond for this month using the following sequence: TRACE, NAIC, Lehman, and Datastream.⁵

To prevent the confounding effects of embedded options, we only keep straight bonds in our sample, and exclude bonds with any provisions, such as callable, puttable, convertible, exchangeable, refundable, sinkable, and etc. If a firm defaults, only its monthly

⁴ In a robustness check, we calculate the return by interpolating the last price of the month and the first price of the following month, which is a commonly used strategy to calculate returns (e.g., Lin et al., 2011). The results based on interpolating prices are similar. The results are omitted for brevity and available upon request.

⁵ Datastream data are generally perceived as not as high quality as other sources.

Variable	Definition
PTV	Prospect theory value based on a bond's historical return distribution.
Coupon	Coupon rate.
Size	Bond issue size.
Rating	The bond credit rating. It is coded in the following way: AAA-rated bonds are coded as 0, AA-rated bonds are coded as 1-3, A-rated bonds are
	coded as 4-6, BAA-rated bonds are coded as 7-9, BA-rated bonds are coded as 10-12, B-rated bonds are coded as 13-15, CAA-rated bonds are
	coded as 16–18, CA-rated bonds are coded as 19–20, and C-rated bonds and below are coded as 21.
TM	Time to maturity of a bond.
REV	Short-term reversal, the lagged monthly return
LTREV	Long-term reversal, the cumulative return from month <i>t</i> -60 to <i>t</i> -13.
MOM	Momentum, calculated as the cumulative return (in percent) from month t-12 to t-2.
VOL	Volatility, calculated as the sample variance over the past five years' monthly bond returns.
SK	Skewness, calculated as the sample skewness over the past five years' monthly bond returns.
IndSK	Following Zhang (2006), cross-sectional skewness of bonds within an industry. All firms in the industry will be assigned the same industry
	skewness. The 48 industries are defined following Fama and French (1993).
MKT	Fama and French (1993) factor.
SMB	Fama and French (1993) factor.
HML	Fama and French (1993) factor.
DEF	Following Amihud (2002), the DEF factor is calculated as the difference between yield to maturity on long-term BAA-rated and AAA-rated
	bonds. The yield information is obtained from the Federal Reserve Board.
TERM	Following Amihud (2002), the TERM factor is calculated as the difference between the yields on long-term Treasury bonds and three-month
	Treasury bills. The yield information is obtained from the Federal Reserve Board.
LIQ	Amihud's (2002) liquidity risk measure.
MV	Firm size, the market value of a firm's equity.
PROFIT	Following Fama and French (2008), profitability is calculated as the ratio of equity income to book equity.
STKMOM	Stock's momentum, calculated as the cumulative stock return from month $t-12$ to $t-2$.
STKREV	Stock's short-term reversal, the lagged monthly stock return (in percent).
STKIVOL	Stock's idiosyncratic volatility, calculated as the volatility of the stock's daily idiosyncratic returns over month t-1 as in Ang et al. (2006).

returns before it defaults are kept in the sample. Since extreme bond prices may indicate recording errors, we winsorize prices and returns using the 1st and 99th percentiles of the distribution each month. The final sample contains 1,393,225 bond-month observations. Before January 1994, the number of bonds in each month is between 392 and 2946, while after January 1994, the number of bonds in each month increases to between 974 and 9279.⁶

It is well known that bond characteristics such as coupon, rating,⁷ maturity, and issue size can be used to explain bond returns (e.g., Green and Odegaard, 1997; Lin et al., 2013), so we include these bond characteristics as control variables in the analysis.

Traditional analysis of asset pricing based on expected utility suggests that a security whose future returns are expected to be positively skewed will be "overpriced" and will earn a lower future return (Bali et al., 2011; Boyer et al., 2010; Chiang, 2016; Conrad et al., 2013; Kumar, 2009). Further, skewness is a result of the probability weighting component. In fact, the correlation between *PTV* and skewness is high in our sample. To avoid confounding effects, we include bond returns' skewness and industry skewness as control variables. Following Zhang (2006), we calculate each industry's skewness⁸ and assign it to all firms in that industry.

Short-term reversal, long-term reversal, and momentum are known predictor for bond returns. Therefore, we also include these as control variables. The short-term reversal is the lagged monthly return; the long-term reversal is calculated as the cumulative return during month *t*-60 to *t*-13; and the momentum is the cumulative return during month *t*-12 to *t*-2.

Stocks and bonds are based on the same underlying firm assets, thus the factors that are important for stock returns are expected to also help explain bond returns. Elton et al. (2001) show that the three Fama and French (1993) factors are important for corporate bond pricing. Thus, we include the three Fama–French factors, *MKT*, *SMB*, and *HML*, in our analysis. In addition, the default and term factors for bond return, *DEF* and *TERM*, are also included.⁹ Since liquidity risk is priced in the bond market (Lin et al., 2011), we also include Amihud's liquidity risk measure, *LIQ*, as a control variable in both our portfolio and regression analysis. Bai et al. (2016) document the significant predictive power of volatility and skewness for corporate bond returns, so we include total volatility and skewness-related variables as control variables. The detailed definitions of the variables are in Table 1.

Table 2 presents the summary statistics. Panel A reports the means and standard deviations of the variables for all samples, investment-grade bonds, and junk bonds. The average size of the investment-grade bonds, \$218.75 million, is significantly larger than that of the junk bonds, which is \$160.82 million. The average rating for the investment-grade (junk) bonds is about 4.27

⁶ Before January 1994, the average number of stale quotes for a given five-year window varies from 0.03% to 1.24%, with a mean of 0.4%. After January 1994, the average number drops to 0% to 0.05%, with a mean of 0.03%.

⁷ In our analysis, the bond rating is coded in the following way: AAA-rated bonds are coded as 0, AA-rated bonds are coded as 1–3, A-rated bonds are coded as 4–6, BAA-rated bonds are coded as 7–9, BA-rated bonds are coded as 10–12, B-rated bonds are coded as 13–15, CAA-rated bonds are coded as 16–18, CA-rated bonds are coded as 19–20, and C-rated bonds and below are coded as 21.

⁸ The 48 industries are defined following Fama and French (1993).

⁹ Following Amihud (2002), the *DEF* factor is calculated as the difference between yield to maturity on long-term BAA-rated and AAA-rated bonds, and the *TERM* factor is calculated as the difference between the yields on long-term Treasury bonds and yields on three-month Treasury bills. The yield information for calculating *DEF* and *TERM* is obtained from the Federal Reserve Board.

Table 2

Data summary. This table presents the summary statistics. The sample period is from January 1978 to December 2013. Panel A reports time series means and standard deviations. Panel B reports correlations among the variables over the sample period. *PTV* is the prospect theory value of a bond's historical return distributions. *Size, Coupon, Rating,* and *TM* are four characteristic variables, which are the market value (in millions), coupon rate, credit rating, and time to maturity of the bond, respectively. *REV* is the short-term reversal, which is measured by the lagged monthly return (in percent). *LTREV* is the long-term reversal, which is calculated as the cumulative return (in percent) from month *t*-60 to *t*-13. *MOM* is the momentum which is the cumulative return (in percent) from *t*-12 to *t*-2. *SK* is the skewness of bonds within an industry. All firms in the same industry are assigned the same industry skewness. The 48 industries are defined following Fama and French (1993). *VOL* is the return volatility, which is calculated as the sample variance of the past five years' monthly bond returns.

Panel A: Sur	anel A: Summary statistics												
			PTV	Coupon	Size	Rating	TM	REV	LTREV	МОМ	SK	IndSK	VOL
A11.comm1co		Mean	-0.73	7.56	220.92	4.97	6.80	0.12	5.63	1.12	0.14	0.29	3.32
All samples		Std. Dev.	0.33	1.22	80.75	2.14	2.02	1.58	10.20	5.60	0.20	0.89	3.28
Increase	ana da han da	Mean	-0.74	7.40	218.75	4.27	6.86	0.11	6.06	1.14	0.15	0.30	2.87
investment-	grade bolids	Std. Dev.	0.35	1.29	82.48	1.73	2.37	1.58	10.35	5.60	0.20	0.90	2.91
Turnly hondo		Mean	-0.66	8.29	160.82	13.78	6.42	0.14	3.20	0.98	0.15	0.29	3.26
JUNK DONDS		Std. Dev.	0.31	1.18	92.08	2.37	2.62	1.56	11.64	5.85	0.34	0.83	3.24
Panel B: Cor	rrelation matrix	c .											
	PTV	Coupon	Size		Rating	TM	REV		LTREV	MOM	S	K	IndSK
Coupon	0.10												
Size	-0.06	0.12											
Rating	0.08	0.16	-0.2	21									
TM	-0.21	0.13	-0.0)6	0.05								
REV	0.08	-0.09	-0.0)2	0.03	0.04							
LTREV	0.13	-0.45	-0.1	12	0.01	0.01	0.0	6					
MOM	0.17	-0.24	-0.0)7	0.04	0.04	0.0	0	0.11				
SK	0.49	-0.08	-0.0)7	0.05	-0.03	0.0	3	0.12	0.08			
IndSK	0.00	-0.02	-0.0)2	-0.01	-0.01	-0.0	5	0.02	0.01	C	0.01	
VOL	-0.36	0.07	0.0	00	0.15	0.52	0.0	5	0.02	0.08	C	0.08	-0.01

(13.78), which corresponds to rating between A + and A (B + and B). Panel B presents the correlations among the variables over the sample period.¹⁰

The prospect theory value should be generally increasing with bond past returns and skewness due to the probability weighting function,¹¹ and generally decreasing with bond past volatility. The pairwise correlations in the column of *PTV* in Panel B are consistent with these properties. Specifically, *PTV* is positively correlated with measures of past returns (*REV, LTREV, MOM*) and past skewness (*SK*), and is negatively correlated with the measure of past return volatility (*VOL*). The correlations among other variables are mild.

4. Empirical results

In this section, we test our hypotheses using both portfolio and regression analysis. In Section 4.1, we perform univariate portfolio analysis based on *PTV*. In Section 4.2, we perform multivariate portfolio analysis based on *PTV* and other predictors of bond returns. Section 4.3 reports results of regression analysis. Section 4.4 investigates which aspects of prospect theory account for its predictive power on future returns. In Section 4.5, we examine the predictive power of prospect theory for different maturity bonds.

4.1. Univariate portfolio analysis

At the start of each month, we sort all bonds into deciles based on their prospect theory values. The average value-weighted¹² return of each decile portfolio over the subsequent month is then calculated. The excess return is the return in excess of the market return.¹³ The three-factor alpha is the return adjusted by the three Fama–French factors. The five-factor alpha is the return adjusted by three Fama–French factors and the *TERM* and *DEF* factors. The six-factor alpha is the return adjusted by the previous five factors and *LIQ*. The characteristics-adjusted return is the return adjusted by the bond characteristic variables, which are size, rating, coupon, and time to maturity.

The portfolio excess returns for investment-grade and junk bonds are plotted in Fig. 1, which clearly shows consistent declining patterns. That is, the returns of the ten *PTV* portfolios decrease as we move from the lowest to the highest *PTV* portfolio.

Table 3 reports the results of the 10 *PTV* portfolios. Panels A–C present the results for the whole sample, investment-grade bonds, and junk bonds, respectively. The right-most column in Panel A reports the average return of a portfolio that longs the bonds in the lowest *PTV* decile and shorts the bonds in the highest *PTV* decile. All the differences between the lowest and highest *PTV* portfolios are positive and significant at the 1% level. The results strongly support hypothesis H1, prospect theory has predictive power for future bond returns.

¹⁰ We calculate the pairwise correlations of the variables for each month. Panel B of Table 2 reports the averaged correlations over time.

¹¹ Probability weighting raises the prospect theory value of a positively skewed gamble (Barberis et al., 2016).

¹² Using equal-weighted average returns generates similar results, which are available upon request.

¹³ The market return is calculated as the overall equal-weighted return of the corporate bond market portfolio.



Portfolio Returns of Investment-Grade vs. Junk Bonds

Fig. 1. PTV decile portfolio performance. This figure shows the average excess returns of 10 PTV decile portfolios for investment-grade and junk bonds. The sample period is from January 1978 to December 2013.

As reported in Panels B and C of Table 3, most of the differences between the lowest *PTV* and highest *PTV* portfolios are significantly larger for junk bonds than those for investment-grade bonds. This pattern can also be seen in Fig. 1, where the line of the junk bonds is much steeper than that of the investment-grade bonds.

The results reported in Panels B and C of Table 3 and the pattern shown in Fig. 1 provide evidence that supports hypothesis H2. The individual investors who contribute more in trading junk bonds rely more on System 1 thinking when evaluating a bond's performance.

Table 4 reports the summary statistics of the bond characteristics of each *PTV* portfolio. To calculate the summary statistics, we first calculate the mean value of bond characteristic for each *PTV* portfolio for each month. Then the time series average of these mean bond characteristics are computed, covering our full sample period from January 1978 to December 2013.

The results in Table 4 are generally consistent with the pairwise correlation reported in Table 2. The measures of historical returns (*REV*, *MOM*) and historical skewness (*SK*) increase monotonically from the lowest to the highest *PTV* decile.

4.2. Multivariate portfolio analysis

PTV is correlated with some variables that are known predictors of bond returns, which causes a difficulty in disentangling the effects of *PTV* and other predictors on bond returns. To see whether prospect theory has additional predictive power beyond that provided by these predictors, in this subsection, we perform a series of double- and triple-sort tests. In Section 4.2.1, we test predictive power of prospect theory based on portfolios that are sorted by *PTV* and another known predictor of bond returns. In Section 4.2.2, we perform our tests based on portfolios that are sorted by *PTV*, volatility and skewness.

4.2.1. Double sorts

To control the effects of a correlated variable of *PTV*, for example, bond credit ratings, we first sort bonds into quintiles based on their credit rating. Within each rating quintile, we again sort bonds into quintiles based on *PTV*.¹⁴ We denote r_{ij} as the portfolio return of the *i* th quintile of credit rating and *j*th quintile of *PTV*. For each *PTV* quintile, we compute the average return across the five rating quintiles as:

$$\bar{r}_j = \frac{1}{5} \sum_{i=1}^5 r_{ij}.$$

The average returns for each *PTV* quintile, \dot{r}_j , j = 1, ..., 5, are reported in Table 5 for both equal-weighted (EW) and value-weighted (VW) returns. The Low–High rows of the table report the differences in returns between the lowest and the highest *PTV* quintiles (i.e., $\dot{r}_1 - \dot{r}_5$). All the differences are positive and significant at the 5% level. These double-sort analysis results provide further assurance for the predictive power of *PTV* on future bond returns, which we posit in hypothesis H1.

¹⁴ We also did independent sorting. The results are pretty similar. The results are available upon request.

Table 3

Portfolio analysis. This table presents decile portfolio returns and alphas, sorted by *PTV*. *PTV* is the prospect theory value of a bond's historical return distributions. For each month, all the bonds are sorted into deciles based on *PTV*. We report the excess return, three-factor alpha, five-factor alpha, six-factor alpha, and characteristic-adjusted returns calculated following Daniel et al. (1997). The three-factor alpha is the return adjusted by the three Fama–French factors. The five-factor alpha is the return adjusted by the three Fama–French factors and the *TERM* and *DEF* factors. The six-factor alpha is the return adjusted by the three Fama–French factors and the *TERM* and *DEF* factors. The six-factor alpha is the return adjusted by the three Fama–French factors and the *TERM* and *DEF* factors. The six-factor alpha is the return adjusted by the three Fama–French factors and the *TERM*, *DEF*, and *LIQ* factors. The characteristic-adjusted return is the return adjusted by the bond characteristic variables, size, coupon, rating, and maturity. The rightmost column lists the average returns. Panels A, B, and C report the results for all samples, investment-grade bonds, and junk bonds, respectively. The sample period is from January 1978 to December *T*-statistics are reported in the parentheses. ^{*}, ^{**}, and ^{***} indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Low	PTV2	PTV3	PTV4	PTV5	PTV6	PTV7	PTV8	PTV9	High	L-H
Panel A: All samples											
Excess return	0.155 ^{***}	0.110 ^{***}	0.059 ^{**}	0.037	0.011	0.001	-0.025	-0.049**	-0.020	-0.027	0.182 ^{***}
	(3.98)	(3.67)	(2.29)	(1.57)	(0.52)	(0.04)	(-1.08)	(-2.14)	(-0.77)	(-1.05)	(3.91)
Three-factor alpha	0.151 ^{***}	0.094 [*]	0.072	0.057	0.039	0.064 ^{**}	0.053 ^{**}	0.032	-0.001	-0.071**	0.222 ^{***}
	(2.44)	(1.91)	(1.49)	(1.42)	(1.23)	(2.13)	(2.09)	(1.12)	(-0.03)	(-2.31)	(3.09)
Five-factor alpha	0.088 [*]	0.026	-0.001	-0.013	-0.009	0.022	0.027	0.024	-0.005	-0.092***	0.180 ^{***}
	(1.66)	(0.65)	(-0.01)	(-0.43)	(-0.33)	(0.85)	(1.13)	(0.83)	(-0.14)	(-3.03)	(2.62)
Six-factor alpha	0.100 [*]	0.036	0.007	-0.011	-0.011	0.020	0.022	0.016	-0.012	-0.097***	0.197 ^{***}
	(1.87)	(0.91)	(0.18)	(-0.36)	(-0.43)	(0.77)	(0.90)	(0.57)	(-0.35)	(-3.22)	(2.89)
Characteristic-adjusted return	0.118***	0.091***	0.049***	0.044***	-0.023	-0.033**	-0.029*	-0.057***	-0.050***	-0.062***	0.180***
	(4.35)	(4.75)	(2.83)	(2.86)	(-1.53)	(-2.02)	(-1.73)	(-3.74)	(-2.85)	(-3.83)	(3.79)
Panel B: Investment-grade bonds											
Excess return	0.201 ^{***}	0.101 ^{**}	0.018	-0.034	-0.061 ^{***}	-0.096 ^{***}	-0.086 ^{***}	-0.123***	-0.100 ^{***}	-0.052	0.253 ^{***}
	(3.31)	(2.15)	(0.52)	(-1.19)	(-2.55)	(-4.16)	(-3.41)	(-4.08)	(-3.33)	(-1.58)	(3.51)
Three-factor alpha	0.176	0.178	0.050	-0.054	-0.052	-0.010	0.068	-0.055	-0.010	-0.058	0.234 ^{***}
	(0.11)	(0.13)	(0.07)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.04)	(0.08)	(2.42)
Five-factor alpha	0.087	0.167	-0.021	-0.155	-0.108	-0.088	0.218	-0.184	0.011	-0.170	0.256 ^{**}
	(0.37)	(0.23)	(0.17)	(0.08)	(0.09)	(0.12)	(0.10)	(0.19)	(0.06)	(0.17)	(2.22)
Six-factor alpha	0.154	0.245	-0.012	-0.153	-0.104	-0.120	0.208	-0.236	-0.019	-0.140	0.293 ^{**}
	(0.37)	(0.23)	(0.17)	(0.08)	(0.09)	(0.12)	(0.11)	(0.18)	(0.06)	(0.17)	(1.98)
Characteristic-adjusted return	0.208 ^{***}	0.112 ^{***}	0.038 ^{**}	-0.007	-0.023	-0.066 ^{***}	-0.055 ^{***}	-0.087 ^{***}	-0.067 ^{***}	-0.053 [*]	0.261 ^{***}
	(5.14)	(3.68)	(1.96)	(-0.38)	(-1.40)	(-3.53)	(-2.49)	(-3.34)	(-2.62)	(-1.91)	(6.85)
Panel C: Junk bonds											
Excess return	0.282	-0.007	-0.060	-0.145 ^{**}	-0.158 ^{***}	-0.225***	-0.284 ^{***}	-0.356 ^{***}	-0.394 ^{***}	-0.143	0.425 [*]
	(1.59)	(-0.08)	(-0.32)	(-2.20)	(-2.58)	(-3.38)	(-3.59)	(-3.60)	(-4.56)	(-1.07)	(1.93)
Three-factor alpha	0.131	0.245	0.012	-0.069	-0.010	-0.030	0.001	-0.024	-0.004	-0.089	0.220 ^{***}
	(0.11)	(0.12)	(0.08)	(0.06)	(0.07)	(0.05)	(0.06)	(0.07)	(0.05)	(0.08)	(2.40)
Five-factor alpha	0.470	0.162	0.030	-0.279	-0.023	-0.101	0.113	-0.047	0.035	-0.171	0.641**
	(0.28)	(0.19)	(0.17)	(0.09)	(0.13)	(0.10)	(0.10)	(0.19)	(0.07)	(0.14)	(1.96)
Six-factor alpha	0.477	0.193	0.023	-0.288	-0.040	-0.096	0.094	-0.096	0.015	-0.184	0.661 ^{**}
	(0.28)	(0.20)	(0.17)	(0.09)	(0.12)	(0.10)	(0.11)	(0.18)	(0.07)	(0.14)	(2.07)
Characteristic-adjusted return	0.405 ^{***}	-0.029	0.121	0.057	-0.021	-0.069	0.017	-0.156 [*]	-0.262***	-0.079	0.485 ^{***}
	(3.89)	(-0.39)	(0.71)	(0.73)	(-0.29)	(-1.01)	(0.24)	(-1.90)	(-2.82)	(-0.79)	(3.21)

Table 4

Characteristics of PTV portfolios. This table presents the characteristics of decile portfolios based on *PTV*. For each month, bonds are sorted into deciles based on *PTV*. *PTV* is the prospect theory value of a bond's historical return distributions. *Size, Coupon, Rating,* and *TM* are four characteristic variables, which are the market value, coupon rate, credit rating, and time to maturity of the bond, respectively. *REV* is the short-term reversal, which is measured by the lagged monthly return (in percent). *LTREV* is the long-term reversal, which is calculated as the cumulative return (in percent). All other variables are defined as in Table 1.

	Low	PTV2	PTV3	PTV4	PTV5	PTV6	PTV7	PTV8	PTV9	High
PTV	-1.570	-1.146	-0.957	-0.832	-0.729	-0.641	-0.556	-0.458	-0.328	-0.038
Coupon	7.276	7.318	7.316	7.335	7.355	7.454	7.550	7.695	7.825	8.157
Size	235.273	226.459	226.370	222.783	216.620	216.427	212.023	209.843	212.256	203.421
Rating	5.085	4.798	4.661	4.664	4.700	4.825	4.922	5.149	5.409	6.212
TM	9.821	8.686	7.534	6.901	6.514	6.153	5.728	5.633	5.760	6.383
REV	-0.157	0.002	0.049	0.100	0.128	0.148	0.154	0.204	0.299	0.432
LTREV	3.314	4.351	5.714	6.552	6.680	6.592	6.119	6.504	6.198	6.713
MOM	-0.176	0.492	0.799	0.885	1.077	1.250	1.400	1.803	2.148	2.550
SK	-0.547	-0.286	-0.160	-0.042	0.082	0.198	0.318	0.435	0.624	1.155
IndSK	0.282	0.287	0.297	0.297	0.305	0.302	0.302	0.296	0.291	0.275
VOL	3.837	3.430	3.080	2.831	2.683	2.627	2.626	2.683	2.833	3.091

Table 5

Double sorting. This table presents the results of double sorting analysis. For each month, the bonds are first sorted into quintiles based on one of the control variables (*Coupon, Rating, Size, TM, SK, IndSK, REV, LTREV, MOM, MV, VOL*). Then within each quintile, bonds are sorted into quintiles based on *PTV*. The five *PTV* portfolios are averaged across different control variable quintiles. We report the excess return of the five *PTV* portfolios, either equal-weighted (EW) or value-weighted (VW). The Low–High rows report the difference in returns between the lowest and the highest *PTV* quintiles. *Size, Coupon, Rating*, and *TM* are four characteristic variables, which are the market value, coupon rate, credit rating, and time to maturity of the bond, respectively. *REV* is the short-term reversal which is measured by the lagged monthly return (in percent). *LTREV* is the long-term reversal, which is calculated as the cumulative return (in percent) from month *t*-12 to *t*-2. *SK* is the skewness of past five years' monthly bond returns. *IndSK* is the cross-sectional skewness of bonds within an industry. All firms in the same industry are assigned the same industry skewness. The 48 industries are defined following Fama and French (1993). *MV* is the market value of equity in month *t*-1. *VOL* is the return volatility, which is calculated as the sample variance over the past five years' monthly bond returns. The sample period covers from January 1978 to December 2013. ^{*, **,} and ^{***} indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

PTV	Coupon				Rating				<i>TM</i>			
	EW	T-Stat.	VW	T-Stat.	EW	T-Stat.	VW	T-Stat.	EW	T-Stat.	VW	T-Stat.
Low	0.115	3.33	0.142	2.79	0.084	2.41	0.124	2.40	0.106	2.93	0.128	2.57
PTV2	-0.012	-0.49	-0.022	-0.68	0.006	0.26	-0.045	-1.40	-0.026	-1.09	-0.048	-1.60
PTV3	-0.066	-3.31	-0.102	-3.86	-0.058	-3.06	-0.098	-3.68	-0.063	-3.18	-0.095	-3.73
PTV4	-0.091	-4.81	-0.132	-4.92	-0.081	-4.29	-0.122	-4.57	-0.085	-4.23	-0.122	-4.55
High	-0.059	-3.04	-0.107	-3.74	-0.063	-3.12	-0.111	-3.79	-0.044	-2.02	-0.090	-3.13
Low–High	0.175***	3.80	0.249***	4.09	0.147***	3.14	0.236***	3.79	0.149***	3.10	0.218***	3.61
	Size				SK				IndSK			
Low	0.108	3.08	0.145	2.80	0.078	2.31	0.094	1.93	0.078	2.24	0.134	2.55
PTV2	-0.018	-0.80	-0.038	-1.22	-0.020	-0.86	-0.041	-1.38	0.009	0.38	-0.040	-1.23
PTV3	-0.059	-3.17	-0.111	-3.81	-0.046	-2.43	-0.090	-3.74	-0.067	-3.43	-0.096	-3.50
PTV4	-0.083	-4.62	-0.147	-5.41	-0.075	-4.15	-0.112	-4.20	-0.088	-4.59	-0.137	-5.01
High	-0.061	-2.98	-0.106	-3.59	-0.049	-2.34	-0.118	-4.19	-0.046	-2.19	-0.087	-3.04
Low–High	0.169***	3.67	0.252***	4.02	0.128***	2.78	0.212***	3.70	0.124***	2.60	0.221***	3.53
	REV				LTREV				МОМ			
Low	0.042	1.38	0.073	1.56	0.072	2.11	0.142	2.81	0.043	1.65	0.092	2.04
PTV2	-0.010	-0.47	-0.036	-1.19	0.015	0.61	-0.039	-1.15	-0.002	-0.10	-0.039	-1.38
PTV3	-0.043	-2.33	-0.066	-2.41	-0.064	-3.45	-0.089	-3.39	-0.044	-2.52	-0.088	-3.57
PTV4	-0.061	-3.36	-0.111	-4.31	-0.084	-4.42	-0.135	-5.03	-0.060	-3.47	-0.124	-4.92
High	-0.040	-2.17	-0.085	-3.26	-0.050	-2.47	-0.098	-3.50	-0.049	-2.63	-0.093	-3.54
Low–High	0.082**	2.11	0.158***	3.01	0.122^{***}	2.65	0.240***	4.00	0.093***	2.80	0.185***	3.85
	MV				VOL							
Low	0.081	2.22	0.144	2.73	0.022	0.93	0.053	1.56				
PTV2	0.011	0.44	-0.042	-1.31	0.004	0.17	-0.040	-1.53				
PTV3	-0.067	-3.51	-0.099	-4.03	-0.038	-1.90	-0.074	-2.63				
PTV4	-0.088	-4.36	-0.127	-4.63	-0.051	-2.64	-0.098	-3.62				
High	-0.050	-2.29	-0.098	-3.35	-0.049	-2.49	-0.102	-3.78				
Low-High	0.131***	2.64	0.242***	3.84	0.072**	2.04	0.155***	3.81				

4.2.2. Triple sorts

Since prospect theory is a way of characterizing a bond's historical return distribution, *PTV* may correlate with other moments like volatility and skewness. In order to examine whether *PTV* captures the explanatory power of volatility and skewness, or it has additional predictive power beyond that provided by volatility and skewness, we conduct a series of triple-sort tests. We first independently sort bonds into quintiles based on volatility and skewness.¹⁵ Within each volatility × skewness portfolio, we again sort bonds into quintiles based on *PTV*. We denote r_{ikj} as the portfolio return of the *i*th quintile of volatility, *k*th quintile of skewness, and *j*th quintile of *PTV*. For each *PTV* quintile, we compute the average return across the 25 volatility × skewness portfolios as:

$$\bar{r}_j = \frac{1}{25} \sum_{i,k} r_{ikj}.$$

The average returns for each *PTV* quintile, \dot{r}_j , j = 1, ..., 5, are then reported in Table 6. As in Table 3, we report the excess return, three- and five-factor alphas, and characteristic-adjusted return for both the equal-weighted (EW) and value-weighted (VW) returns. The Low–High rows of the table that report $\dot{r}_1 - \dot{r}_5$ show that all the differences between the lowest and the highest *PTV* quintiles are positive and significant at the 5% level. This indicates that *PTV* has additional explanatory power for future returns beyond volatility and skewness.

¹⁵ We also sort the bonds into higher half and lower half groups, or three groups based on the breakpoints for the bottom 30%, middle 40%, and top 30% of volatility and skewness. The results do not change materially. The results are available upon request.

Triple sorting. This table presents results of triple sorting analysis. For each month, the bonds are first independently sorted into quintiles based on volatility and skewness. Within each volatility \times skewness portfolio, bonds are again sorted into quintiles based on *PTV*. We report the excess return, three- and five-factor alphas, and characteristic-adjusted returns for both equal-weighted (EW) and value-weighted (VW) returns. The three-factor alpha is the return adjusted by the three Fama-French factors. The five-factor alpha is the return adjusted by the three Fama-French factors and the *TERM*, and *DEF* factors. The six-factor alpha is the return adjusted by the three Fama-French factors. Size, coupon, rating, and maturity. The Low-High rows report the difference in returns 1978 to December 2013. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

PTV	Excess return			
	EW	T-Stat.	VW	T-Stat.
Low	0.024	1.06	0.036	1.03
PTV2	-0.020	-1.09	-0.042	-1.48
PTV3	-0.031	-1.71	-0.060	-2.43
PTV4	-0.047	-2.74	-0.097	-3.84
High	-0.037	-1.84	-0.104	-3.71
Low–High	0.061**	1.97	0.140***	3.47
	3-factor alpha			
Low	0.122	1.71	0.074	1.29
PTV2	0.043	0.65	0.003	0.05
PTV3	-0.032	-0.51	0.008	0.14
PTV4	-0.069	-1.15	-0.100	-1.71
High	-0.122	-1.95	-0.145	-2.39
Low–High	0.243***	5.33	0.219***	5.44
	5-factor alpha			
Low	0.082	1.13	0.088	1.52
PTV2	-0.017	-0.26	-0.019	-0.32
PTV3	-0.088	-1.40	-0.027	-0.47
PTV4	-0.120	-1.97	-0.136	-2.29
High	-0.157	-2.49	-0.170	-2.76
Low–High	0.239***	5.15	0.258***	6.33
	Characteristic	-adjusted return	1	
Low	0.085	6.13	0.090	4.80
PTV2	0.018	2.59	0.010	0.91
PTV3	-0.015	-2.72	-0.014	-1.34
PTV4	-0.039	-5.28	-0.053	-3.81
High	-0.049	-4.06	-0.083	-4.61
Low-High	0.134***	5.55	0.173^{***}	5.32

4.3. Regression analysis

In this subsection, we employ the Fama–MacBeth regression methodology to test our hypotheses. The results are reported in Table 7. Each column corresponds to a different model specification, which includes different control variables. Panel A reports the results for the whole sample, while Panels B and C present the results for investment-grade bonds and junk bonds.

The results in Panel A of Table 7 show that *PTV* retains significant predictive power even after we control variables the known predictors of bond returns.¹⁶ These results further support hypothesis H1 that prospect theory has predictive power.

The results in Panels B and C of Table 7 lead to similar conclusions. The coefficients for *PTV* are negative and significant for both investment-grade and junk bonds, even after controlling bond characteristic, skewness, and other predictors of bond returns. In addition, the coefficients of *PTV* for junk bonds are much larger than the coefficients for investment-grade bonds. In other words, *PTV* has more explanatory power for junk bonds. This result provides strong support for hypothesis H2.

Overall, the evidence strongly supports our hypothesis H1 and H2 that bonds with higher prospect theory values will on average earn lower future returns. The predictive power is much stronger for junk bonds than that for investment-grade bonds.

¹⁶ We perform the robustness test of replacing credit rating by the Merton "distance to default" variable, and the results do not change materially. Since the distance to default variable can only be estimated for publicly listed firms, the sample size is much smaller.

(2.78)

0.529

(1.32)

Coupon

(1.91)

0.367

(0.95)

Table 7

Fama–MacBeth regression analysis. This table represents results of Fama–MacBeth regressions. *PTV* is the prospect theory value of a bond's historical return distributions. Each column corresponds to a different regression model, which includes different control variables. *Size, Coupon, Rating*, and *TM* are four characteristic variables, which are the market value, coupon rate, credit rating, and time to maturity of the bond, respectively. *REV* is the short-term reversal, which is measured as the lagged monthly return (in percent). *LTREV* is the long-term reversal, which is calculated as the cumulative return (in percent) from month *t*-60 to *t*-13. *MOM* is the momentum, which is the cumulative return (in percent) from month *t*-12 to *t*-2. *VOL* is the return volatility, which is calculated as the sample variance of the past five years' monthly bond returns. *SK* is the skewness of past five years' monthly bond returns. *IndSK* is the cross-sectional skewness of bonds within an industry. All firms in the same industry are assigned the same industry skewness. The 48 industries are defined following Fama and French (1993). Panels A, B, and C report the results for all samples, investment-grade bonds, and junk bonds, respectively. The sample period covers from January 1978 to December 2013. All the *t*-statistics in parentheses are Newey– West adjusted with 12 lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Panel A. All s	amples						
	-0.149***	-0.117***	-0.163***	-0.126***	-0.107***	-0.198***	-0.208***
PTV	(-4.91)	(-4.39)	(-5.24)	(-4.71)	(-4.21)	(-3.68)	(-3.85)
	0.138***	0.143***	0.130***	0.127***	0.133***	0.113***	0.108***
Rating	(4.03)	(4.19)	(3.85)	(3.88)	(4.13)	(3.63)	(3.46)
_	0.224***	0.196***	0.256***	0.210***	0.216***	0.175***	0.171***
Coupon	(4.30)	(3.82)	(4.83)	(3.83)	(4.09)	(3.51)	(3.45)
-	0.538	0.388	0.472	0.205	0.076	0.032	0.060
TM	(1.16)	(0.92)	(1.05)	(0.53)	(0.22)	(0.10)	(0.19)
0	-0.019^{*}	-0.005	-0.019^{*}	-0.009	0.000	0.002	0.003
Size	(-1.85)	(-0.48)	(-1.93)	(-1.00)	(0.00)	(0.18)	(0.37)
DEV		-0.050***			-0.059***	-0.074***	-0.074***
REV		(-2.99)			(-4.03)	(-5.99)	(-6.12)
ITDEV			-0.031***		-0.016^{*}	-0.016**	-0.015^{*}
LIKEV			(-2.98)		(-1.88)	(-1.98)	(-1.85)
MOM				-0.608	-0.753	-0.988**	-1.036**
MOM				(-1.51)	(-1.54)	(-2.16)	(-2.30)
VOI						0.268***	0.311^{***}
VOL						(2.47)	(2.70)
SK							-0.032
bit							(-0.47)
IndSK							-0.019
							(-1.08)
R^2	0.18	0.25	0.19	0.22	0.28	0.31	0.32
Panel B. Inve	stment-grade bonds						
DTU	-0.166***	-0.140***	-0.178^{***}	-0.150***	-0.133***	-0.111**	-0.124**
PIV	(-5.70)	(-5.27)	(-6.00)	(-5.66)	(-5.18)	(-2.04)	(-2.29)
Ratina	0.180***	0.180***	0.170^{***}	0.157***	0.156***	0.138***	0.124^{***}
Ruing	(4.71)	(4.69)	(4.49)	(4.31)	(4.31)	(3.79)	(3.33)
Coupon	0.241***	0.206***	0.258***	0.231***	0.229***	0.190***	0.189***
Coupon	(4.23)	(3.73)	(4.68)	(3.76)	(4.03)	(3.47)	(3.49)
TM	0.348	0.242	0.281	0.045	-0.028	-0.257	-0.192
	(0.74)	(0.56)	(0.62)	(0.11)	(-0.08)	(-0.78)	(-0.59)
Size	-0.011	0.001	-0.011	-0.002	0.006	0.007	0.009
	(-1.28)	(0.09)	(-1.37)	(-0.20)	(0.83)	(0.94)	(1.08)
REV		-0.054			-0.065	-0.092	-0.093
		(-3.11)	0.001***		(-4.30)	(-8.16)	(-8.32)
LTREV			-0.031		-0.014	-0.009	-0.009
			(-2.92)	0.610	(-1.60)	(-1.10)	(-1.08)
MOM				-0.018	-1.020	-1.234	-1.280
				(-1.40)	(-1.80)	(-2.35)	(-2.49)
VOL						0.015	0.047
						(0.15)	0.053
SK							(0.76)
IndSK							-0.034*
mabit							(-1.81)
R ²	0.19	0.26	0.20	0.24	0.30	0.32	0.33
Panel C: Junk	c bonds						
	-0.211***	-0.175****	-0.235****	-0.186***	-0.183***	-0.098***	-0.142***
PTV	(-3.17)	(-2.54)	(-3.31)	(-3.10)	(-2.79)	(-2.44)	(-2.51)
	0.297***	0.223*	0.245**	0.411***	0.382***	0.160	0.119
Rating	(0.50)	(1.01)	(0.00)	(0.50)	(0.5.4)	(1 50)	(0.0.1)

(continued on next page)

(0.94)

-0.176

(-0.78)

(1.58)

-0.130

(-0.70)

(3.58)

0.577

(1.39)

(2.74)

0.409

(1.02)

(2.23)

0.440

(1.08)

Table 7 (continued)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
TM	2.230***	3.267***	2.123***	1.936***	3.259**	0.510	0.486
1101	(3.20)	(2.54)	(3.03)	(2.49)	(2.07)	(0.47)	(0.41)
Sigo	0.375	0.322	0.387	0.869*	0.873	0.508	0.601
5120	(0.62)	(0.46)	(0.60)	(1.92)	(1.45)	(0.93)	(0.93)
DEV		-0.131***			-0.125^{***}	-0.068***	-0.069***
KE V		(-4.15)			(-3.36)	(-2.74)	(-2.63)
ITDEV			-0.098**		-0.023	-0.063	-0.024
LIKEV			(-2.01)		(-0.63)	(-0.83)	(-0.28)
MOM				-2.857***	-2.869***	-1.584***	-1.302^{**}
WOW				(-3.61)	(-2.64)	(-2.46)	(-2.18)
VOI						0.391*	0.371^{*}
VOL						(1.79)	(1.78)
SV							0.452
5K							(1.38)
IndSK							-0.017
							(-0.36)
<i>R</i> ²	0.21	0.27	0.23	0.25	0.32	0.38	0.40

4.4. Components of prospect theory

To further investigate which aspects of prospect theory make a bond appealing or unappealing, we do analysis for each of the three *PTV* components. We first examine which of the three components contributes the most to *PTV*'s predictive power: loss aversion (*LA*), probability weighting (*PW*), or concave/convex (*CC*). Table 8 reports the Fama–MacBeth regression results of the *LA*, *PW*, and *CC* components, along with their combinations (*LACC*, *LAPW*, and *CCPW*) for all samples, investment-grade bonds, and junk bonds, respectively.

The *LA* corresponds to the prospect theory variable where only the loss aversion component is featured. This is equivalent to setting c and δ to 1.0 while keeping $\lambda = 2.25$ in Eqs. (2) and (4). Similarly, *PW* or *CC* corresponds to the prospect theory variables where the corresponding parameter is kept as it is in the baseline model while setting the other parameters to 1.0. *LAPW* corresponds to the prospect theory variable that features both the loss aversion and probability weighting components. This prospect theory variable is obtained by setting c = 1 while keeping δ and λ as they are in the baseline model. Similarly, *LACC* and *PWCC* are obtained by setting δ or λ to 1 while keeping other parameters as they are in the baseline model.

The results in Panel A of Table 8 show that the negative value of the *PTV* mainly comes from the loss aversion component (*LA*). The combinations related to loss aversion (*LACC* and *LAPW*) are also negative.

Panels B1–B3 of Table 8 report the Fama–MacBeth regressions results for the whole sample, investment-grade bonds, and junk bonds, respectively. To be concise, we only report the regression results of the comprehensive model specification, which includes all control variables. Each column corresponds to a prospect theory variable that consists of a component or a combination of two components. The column of *PTV* corresponds to the results reported in the Model 7 of Table 7, and serves as the baseline model. In the other six columns, one or two components are featured, while the other component(s) are "turned off".

The results in the first row of Panel B1 of Table 8 show that the loss aversion component contributes the most to the predictive power of prospect theory. The four significant coefficients in the first row all correspond to prospect theory variables that involve loss aversion (*LA*, *LACC*, *LAPW*, and *PTV*). The other three coefficients corresponding to prospect theory variables that loss aversion has been turned off (*PW*, *CC*, and *CCPW*) are all insignificant. One standard deviation increase in *LA* is associated with about a 2.6% return decrease, while one standard deviation increase in *LAPW* and *LACC* is associated with about a 3.2% and 1.9% return decrease, respectively.¹⁷ If we turn off the *LA* component, prospect theory loses its predictive power. This evidence supports hypothesis H3 that loss aversion accounts for most of the predictive power of *PTV* in the bond market.

Panels B2 and B3 of Table 8 reports the results for investment-grade and junk bonds. The results provide evidence that supports hypothesis H4. Specifically, the *PW* component behaves differently for investment-grade bonds and junk bonds. The *PW* component has significant predictive power for junk bond returns, but has little predictive power for investment-grade bond returns. As discussed above, junk bonds have more individual investors and higher default risk than investment-grade bond, which induces stronger lottery-type and insurance-type demands. This helps explain why the *PW* component has significant predictive power for junk bond returns.

In summary, in contrast to the previous findings for the stock market, the *LA* component of prospect theory plays the most important role in predicting future bond returns. Moreover, the *PW* component also plays an important role in predicting junk bonds' future returns.

4.5. Predictive power for different maturity bonds

In this section, we perform both portfolio and Fama–MacBeth regression analysis for short-, medium-, and long-maturity bonds. Bonds that have less than five years' time to maturity are classified into the short-maturity buckets, bonds that have more than ten years' time to maturity are classified into the long-maturity buckets, and those with five to ten years' time to maturity are classified into the medium-maturity buckets.

¹⁷ Standardized regression results are omitted for brevity and are available upon request.

Table 8

Fama–MacBeth regressions for different PTV components. This table reports the Fama–MacBeth regression results of different components of the prospect theory value. LA is the loss aversion component. PW is the probability weighting component. CC is the convexity/concave component. Panel A reports the mean and standard deviation of each component for all samples, investment-grade bonds, and junk bonds. Panels B1–B3 report the regression coefficients for different components for all samples, investment-grade bonds, and junk bonds. Panels B1–B3 report the regression coefficients for different components for all samples, investment-grade bonds, and junk bonds. Panels B1–B3 report the regression coefficients in parentheses are Newey–West adjusted with 12 lags. *, ***, and **** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Summar	y statistics								
			PTV	LA	PW	CC	LAPW	LACC	CCPW
		Mean	-0.73	-0.69	0.08	0.01	-0.83	-0.65	0.05
All samples		Std. Dev.	0.33	0.35	0.09	0.07	0.40	0.30	0.07
Investment grade	bonds	Mean	-0.74	-0.66	0.07	0.01	-0.80	-0.63	0.05
	bollus	Std. Dev.	0.35	0.38	0.07	0.07	0.43	0.33	0.06
Junk bonds		Mean	-0.66	-0.72	0.17	0.10	-0.71	-0.52	0.13
		Std. Dev.	0.31	0.31	0.17	0.12	0.37	0.27	0.14
Panel B: Regressi	on results								
	PTV	LA		PW	CC	LAPW		LACC	CCPW
Panel B1: All sam	ples								
	-0.208***	-0.191****		0.097	0.037	-0.158***		-0.219***	0.108
PT Comp	(-3.85)	(-3.85)		(1.51)	(0.60)	(-3.83)		(-3.87)	(1.40)
Dating	0.108^{***}	0.110****		0.108***	0.104***	0.109***		0.109***	0.108***
Rating	(3.46)	(3.49)		(3.45)	(3.32)	(3.48)		(3.47)	(3.42)
Course	0.171^{***}	0.177^{***}		0.177***	0.183***	0.167***		0.180***	0.180^{***}
Coupon	(3.45)	(3.53)		(3.61)	(3.72)	(3.39)		(3.57)	(3.66)
TM	0.060	0.052		-0.025	0.008	0.050		0.061	-0.018
1 1/1	(0.19)	(0.16)		(-0.08)	(0.02)	(0.16)		(0.19)	(-0.06)
C!	0.003	0.003		0.002	0.003	0.003		0.003	0.003
Size	(0.37)	(0.38)		(0.27)	(0.31)	(0.35)		(0.40)	(0.30)
DEV	-0.074***	-0.075***		-0.074***	-0.076***	-0.074***		-0.075***	-0.075***
REV	(-6.12)	(-6.12)		(-6.15)	(-6.29)	(-6.11)		(-6.15)	(-6.20)
	-0.015^{*}	-0.014^{*}		-0.012	-0.013^{*}	-0.014^{*}		-0.014*	-0.012
LIKEV	(-1.85)	(-1.73)		(-1.52)	(-1.65)	(-1.84)		(-1.75)	(-1.54)
MOM	0.037	0.037		0.023	0.027	0.036		0.040	0.025
MOM	(0.13)	(0.13)		(0.08)	(0.09)	(0.12)		(0.14)	(0.09)
VOI	0.311^{***}	0.312^{***}		0.333***	0.331***	0.305***		0.317***	0.333***
VOL	(2.70)	(2.77)		(3.24)	(3.23)	(2.62)		(2.84)	(3.24)
CV	-0.032	-0.144***		-0.025	-0.183^{***}	-0.006		-0.165***	-0.055
SK	(-0.47)	(-2.55)		(-0.32)	(-3.11)	(-0.09)		(-2.92)	(-0.74)
Indev	-0.019	-0.019		-0.016	-0.018	-0.019		-0.019	-0.017
masic	(-1.08)	(-1.06)		(-0.89)	(-1.01)	(-1.06)		(-1.09)	(-0.93)
R^2	0.32	0.32		0.32	0.32	0.32		0.32	0.32
Panel B2: Investn	nent-grade bond	s							
	-0.124**	-0.131***		0.077	-0.011	-0.151***		-0.152***	0.079
PT Comp	(-2.29)	(-2.50)		(1.00)	(-0.16)	(-3.37)		(-2.54)	(0.87)
	0.124***	0.124***		0.123***	0.113***	0.119***		0.122***	0.120***
Rating	(3.33)	(3.34)		(3.32)	(3.08)	(3.22)		(3.31)	(3.26)
<i>.</i>	0.189***	0.196***		0.201***	0.209***	0.186***		0.199***	0.205***
Coupon	(3.49)	(3.60)		(3.79)	(3.94)	(3.47)		(3.65)	(3.85)
773.4	-0.192	-0.173		-0.100	-0.075	-0.101		-0.163	-0.093
1 M	(-0.59)	(-0.52)		(-0.30)	(-0.23)	(-0.31)		(-0.49)	(-0.28)
0	0.009	0.009		0.007	0.007	0.008		0.009	0.007
5120	(1.08)	(1.07)		(0.88)	(0.86)	(1.05)		(1.09)	(0.89)
DEV	-0.093***	-0.091***		-0.079***	-0.080^{***}	-0.087^{***}		-0.091***	-0.080^{***}
REV	(-8.32)	(-8.16)		(-6.38)	(-6.53)	(-7.70)		(-8.22)	(-6.43)
	-0.009	-0.008		-0.010	-0.011	-0.011		-0.008	-0.010
LIKEV	(-1.08)	(-0.95)		(-1.31)	(-1.37)	(-1.43)		(-0.96)	(-1.30)
MOM	0.089	0.105		0.182	0.179	0.134		0.107	0.185
WOW	(0.27)	(0.32)		(0.56)	(0.56)	(0.42)		(0.33)	(0.57)
VOI	0.047	0.087		0.343***	0.337***	0.194		0.095	0.343***
VOL	(0.44)	(0.82)		(3.12)	(3.06)	(1.63)		(0.91)	(3.10)
CV/	0.053	-0.121^{**}		0.036	-0.189***	0.063		-0.152***	-0.002
5K	(0.76)	(-2.00)		(0.45)	(-3.06)	(0.87)		(-2.51)	(-0.03)
Indev	-0.034*	-0.034^{*}		-0.034*	-0.033^{*}	-0.034^{*}		-0.035*	-0.034^{*}
music	(-1.81)	(-1.82)		(-1.76)	(-1.79)	(-1.83)		(-1.84)	(-1.79)
R^2	0.33	0.33		0.34	0.34	0.33		0.33	0.34

(continued on next page)

X. Zhong, J. Wo	anş
-----------------	-----

Table 8 (continued)

Panel B: Regres	sion results						
	PTV	LA	PW	CC	LAPW	LACC	CCPW
Panel B3: Junk	bonds						
DT Comp	-0.142***	-0.195***	-0.203****	0.160	-0.125***	-0.254***	-0.314***
PΤCONΦ	(-2.51)	(-3.16)	(-2.47)	(1.59)	(-2.52)	(-3.30)	(-2.46)
Datina	0.119	0.219^{*}	0.305***	0.186*	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	0.225^{*}	0.249**
Kaung	(0.94)	(1.77)	(2.40)	(1.68)	(2.39)	(1.82)	(2.22)
Courson	-0.176	0.367	0.382	0.369	0.321	0.408	0.363
Coupon	(-0.78)	(0.85)	(0.91)	(0.79)	(0.80)	(0.93)	(0.84)
TM	0.486	2.548*	0.983	1.769	2.582^{**}	2.381^{*}	1.192
1 1/1	(0.41)	(1.84)	(0.80)	(1.20)	(2.09)	(1.68)	(0.92)
Cina	0.601	-0.163	-0.608	-0.625	0.085	-0.111	-0.655
5120	(0.93)	(-0.20)	(-0.92)	(-0.76)	(0.11)	(-0.13)	(-0.93)
DEV	-0.069***	-0.102^{***}	-0.070^{***}	-0.093***	-0.102^{***}	-0.098***	-0.080^{***}
KEV	(-2.63)	(-3.27)	(-2.70)	(-3.00)	(-3.82)	(-3.19)	(-2.85)
ITDEV	-0.024	0.005	-0.006	-0.016	0.021	-0.002	-0.017
LIKEV	(-0.28)	(0.08)	(-0.12)	(-0.27)	(0.40)	(-0.02)	(-0.31)
MOM	-1.302^{**}	-2.761***	-3.031***	-2.719***	-2.708^{***}	-2.683***	-2.906***
MOM	(-2.18)	(-3.45)	(-2.98)	(-3.23)	(-3.11)	(-3.44)	(-3.08)
VOI	0.371^{*}	-0.078	-0.020	-0.198	-0.040	-0.072	-0.063
VOL	(1.78)	(-0.22)	(-0.05)	(-0.51)	(-0.12)	(-0.20)	(-0.16)
CV/	0.452	0.041	0.460	-0.034	0.497*	-0.043	0.438
5K	(1.38)	(0.15)	(1.20)	(-0.12)	(1.78)	(-0.14)	(1.24)
IndCV	-0.017	0.024	0.027	-0.006	0.058	0.016	0.014
шак	(-0.36)	(0.42)	(0.34)	(-0.10)	(0.80)	(0.28)	(0.19)
R^2	0.40	0.38	0.38	0.38	0.38	0.38	0.38

Panels A and B of Table 9 report the results of the portfolio and regression analyses. All Low–High portfolio returns are significantly positive at the 5% level for all maturity buckets, and the average L–H portfolio return is much larger for junk bonds. This result supports our conclusion that *PTV* has predictive power for various maturity buckets, and the predictive power is much stronger for junk bonds.

5. Robustness tests

In this section, we use five types of additional tests to examine the robustness of our results. First, we reconstruct the *PTV* by using different time windows, different reference points, different parameters for probability weighting and loss aversion, different probability weighting function, skip one month between the *PTV* construction and portfolio return calculation. Second, we test whether the *PTV* is a uniquely informative transformation in predicting future return. Third, we test whether *PTV* retains its predictive power after we include some bond issuer information in the regression. Fourth, we test whether *PTV* has predictive power after accounting for transaction costs. Lastly, we test whether our results hold at the firm level.

5.1. Reconstruction of PTV

5.1.1. Varying Windows for constructing PTV

In the preceding tests, we use the past five years' monthly returns to construct the prospect theory value for each bond. We reconstruct the *PTV* based on past three-, four-, and six-year windows to see whether our main conclusion still holds.

The results in Table 10 show that portfolio returns generally decrease from the lowest to the highest *PTV* portfolio, regardless of the constructing window. The right-most column shows that the returns of the Low–High portfolio are positive and significant for all windows.

In Table 11, we only provide the results of the most comprehensive model specification. Similar conclusions can be drawn from the regression robust checks. We find that prospect theory has significant predictive power regardless of the constructing windows, and the predictive power is much stronger for junk bonds.

5.1.2. Alternative reference points

When calculating the value function in Eq. (2), we need to specify the reference point of the returns. Typically, the reference point is cash (which associates with the raw returns), the risk-free rate (which associates with the return in excess of the risk-free rate), or the market return (which associates with the return in excess of the market return).

When investors evaluate a bond, they observe its past raw returns, as well as overall market performance. Therefore, we use the return in excess of the market return to calculate a bond's prospect theory value and present the results in previous tables. The market return is calculated as the equal-weighted return of the corporate bond market portfolio. In Tables 10 and 11, we also present results when using alternative reference points, such as the raw return or the return in excess of the risk-free rate. Following Barberis et al. (2016), we also use the bond's whole sample period mean return as an alternative reference point because when investors evaluate a bond, they are likely to compare its recent returns with its overall performance.

Different maturity buckets. This table reports portfolio and regression analysis results in various maturity buckets. Bonds with time to maturity less than five years are classified into short buckets, those with time to maturity more than 10 years are classified into long buckets, and other bonds are classified into medium buckets. The sample covers from January 1978 to December 2013. All the *t*-statistics are Newey–West adjusted with 12 lags. ^{*}, ^{**}, and ^{***} indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: P	Panel A: Portfolio analysis											
		Low	PTV2	PTV3	PTV4	PTV5	PTV6	PTV7	PTV8	PTV9	High	L-H
	Chart	0.019	-0.016	-0.106***	-0.103***	-0.138***	-0.157***	-0.174***	-0.168***	-0.155***	-0.112***	0.131**
e	Short	(0.36)	(-0.38)	(-2.99)	(-2.95)	(-4.21)	(-4.87)	(-5.19)	(-4.63)	(-4.51)	(-3.15)	(2.06)
ldu	Madium	0.171^{***}	0.115^{***}	0.046	-0.025	-0.014	-0.067	-0.058	-0.046	-0.029	-0.026	0.198***
sar	Medium	(3.08)	(2.35)	(1.06)	(-0.58)	(-0.32)	(-1.60)	(-1.56)	(-1.14)	(-0.75)	(-0.64)	(3.00)
All		0.259***	0.210^{***}	0.116	0.114	0.047	0.029	0.022	0.073	0.056	0.098	0.161^{**}
	Long	(3.22)	(2.65)	(1.50)	(1.46)	(0.60)	(0.40)	(0.28)	(1.00)	(0.79)	(1.24)	(2.14)
	Chort	0.020	-0.040	-0.060	-0.078**	-0.101***	-0.152^{***}	-0.134***	-0.156***	-0.138***	-0.120***	0.140***
4 L	311011	(0.45)	(-0.94)	(-1.50)	(-2.10)	(-2.97)	(-4.73)	(-4.16)	(-4.00)	(-4.19)	(-3.41)	(2.52)
ono	Modium	0.203***	0.131^{***}	0.070	0.011	-0.003	-0.012	-0.030	-0.020	-0.033	-0.030	0.232^{***}
e b	Medium	(3.60)	(2.61)	(1.58)	(0.24)	(-0.07)	(-0.31)	(-0.80)	(-0.48)	(-0.87)	(-0.72)	(3.64)
rad	Long	0.269***	0.156**	0.167**	0.086	0.119	0.109	0.090	0.083	0.081	0.113	0.157^{**}
Н 60	Long	(3.28)	(2.01)	(2.15)	(1.11)	(1.47)	(1.44)	(1.16)	(1.18)	(1.09)	(1.43)	(1.98)
	Chort	0.545*	-0.148	0.481	-0.196	-0.187	-0.167**	-0.352***	-0.305***	-0.285***	-0.087	0.632***
ds	311011	(1.92)	(-0.99)	(0.80)	(-1.24)	(-1.41)	(-2.29)	(-4.01)	(-3.20)	(-3.41)	(-0.69)	(2.59)
ono	Madium	0.263	0.013	-0.270^{**}	-0.351^{**}	-0.104	-0.211^{**}	-0.021	-0.128	-0.410^{***}	-0.214	0.476**
kЪ	Medium	(1.59)	(0.10)	(-2.11)	(-2.09)	(-1.05)	(-2.18)	(-0.22)	(-1.09)	(-3.28)	(-1.06)	(2.16)
un	Long	0.041	-0.187	-0.143	-0.056	-0.111	-0.108	-0.162	-0.262^{*}	-0.169	-0.189	0.230^{***}
-	Long	(0.32)	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	(-0.59)	(-0.90)	(-1.15)	(-0.77)	(-1.67)	(-1.29)	(-1.24)	(2.55)	
Panel B: Fa	ama–MacBe	th regression										
		PTV	Rating	Coupon	TM	Size	REV	LTREV	МОМ	VOL	SK	IndSK
	01 t	-0.222***	0.089***	0.186***	0.874	0.001	-0.077***	-0.005	0.064	0.459***	-0.131**	-0.017
e	Short	(-3.23)	(3.22)	(3.94)	(1.00)	(0.19)	(-5.71)	(-0.62)	(0.20)	(2.93)	(-2.13)	(-0.91)
lqn	M . 1.	-0.195^{***}	0.172^{***}	0.103	-0.839	0.011	-0.136***	0.057	-0.274	0.198**	0.164	0.006
sar	Medium	(-3.48)	(3.78)	(1.31)	(-0.95)	(0.79)	(-14.75)	(1.06)	(-0.90)	(2.03)	(1.58)	(0.21)
All	Long	-0.151^{***}	0.102^{*}	0.036	-1.247^{**}	0.075^{*}	-0.095***	-0.001	-0.820	0.144	-0.314	0.229
	Long	(-2.75)	(1.87)	(0.26)	(-2.24)	(1.73)	(-5.78)	(-0.01)	(-1.55)	(0.66)	(-1.06)	(-1.45)
	Chort	-0.150**	0.114***	0.195***	0.123	0.003	-0.085***	-0.004	0.179	0.419***	-0.260***	-0.028
4 L	311011	(-2.03)	(3.53)	(3.81)	(0.14)	(0.50)	(-6.23)	(-0.48)	(0.52)	(2.49)	(-3.90)	(-1.57)
ono	Madium	-0.071^{*}	0.160^{***}	0.036	-0.559	0.014	-0.157^{***}	0.065	-0.466	0.245***	-0.401^{***}	0.008
e b	Medium	(-1.75)	(2.75)	(0.48)	(-0.62)	(1.13)	(-15.94)	(1.06)	(-1.44)	(2.64)	(-4.07)	(0.22)
ad		-0.086*	0.492***	-0.201	-0.356	0.056	-0.107^{***}	-0.110	-1.389	0.106	-0.703^{***}	-0.277
ЦБ	Long	(-1.69)	(2.46)	(-1.25)	(-0.64)	(1.30)	(-5.88)	(-0.90)	(-1.50)	(0.58)	(-2.86)	(-1.18)
	Short	-0.229	0.228	0.146	-0.189	2.945***	-0.059***	-0.091	0.685	0.675***	-0.442	0.030
ds	311011	(-3.71)	(1.29)	(0.79)	(-1.54)	(2.48)	(-1.33)	(-0.63)	(0.59)	(3.17)	(-1.51)	(0.59)
one	Modium	-0.123	0.203^{*}	-0.226	-0.208	0.125	-0.154***	-0.124^{*}	-1.512^{***}	0.079	0.613**	0.020
kЪ	wieuruill	(-3.36)	(1.86)	(-0.88)	(-0.13)	(1.04)	(-13.56)	(-1.79)	(-2.75)	(0.65)	(1.96)	(0.44)
Jun	Long	-0.117	0.302^{**}	0.436	-2.195^{**}	0.265	-0.033***	0.056	-1.405^{***}	-0.169	0.090	-0.111
,	LOUG	(-2.12)	(1.97)	(0.68)	(-2.32)	(1.03)	(-1.76)	(0.74)	(-3.54)	(-0.61)	(0.22)	(-1.62)

The portfolio analysis and regression analysis results lead to similar conclusions, which again supports our hypothesis H1 and H2. Prospect theory has significant predictive power regardless of the reference points, and the predictive power is much stronger for junk bonds.

5.1.3. Varying loss aversion and probability weighting parameters

The preceding results show that the loss aversion (*LA*) and probability weighting (*PW*) components play important roles in explaining the predictive power of *PTV*.

We vary the parameters λ and δ to see whether *PTV* retains its predictive power under different magnitudes of loss aversion and probability weighting. We first reconstruct the *PTV* by changing the loss aversion parameter λ from 2 to 2.5, while the probability weighting and concavity/convexity parameters remain the same as before. Parallel tests are also performed to examine when varying the probability weighting parameter δ . The results show that the predictive power of prospect theory remains steady for different λ and δ values. Regardless of the different λ and δ values, prospect theory retains its significant predictive power, and the predictive power is much stronger for junk bonds.

5.1.4. Alternative probability weighting functions

We employ the most commonly used form of the probability weighting function in Eq. (4), which is proposed by Tversky and Kahneman (1992) as a logit function. Several alternative functional forms of the probability weighting function have been proposed, such as a linear form, a power form, and variations of the logit form (e.g., Goldstein and Einhorn, 1987; Wu and Gonzales, 1996). Stott (2006) studies the behavior of these alternative forms and finds that an exponential form offered by Prelec (1998) generally

Robustness through portfolio analysis. This table presents results for robust checks of decile portfolio excess returns sorted by PTV. The rightmost column reports excess returns for the low minus high PTV portfolio. We did six kinds of robustness tests: (1) different construct windows; (2) different reference points; (3) different loss aversion parameters; (4) different probability weighting parameters; (5) probability weighting function; and (6) skip one month. Panels A, B, and C report the results for all samples, investment-grade bonds, and junk bonds, respectively. The sample period is from January 1978 to December 2013. *T*-statistics are reported in the parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		Low	PTV2	PTV3	PTV4	PTV5	PTV6	PTV7	PTV8	PTV9	High	L-H
Panel A: All s	amples											
		0.164***	0.079*	0.014	-0.045*	-0.056**	-0.105***	-0.112***	-0.104***	-0.092***	-0.045	0.210***
	Past 3 years	(2.83)	(1.78)	(0.43)	(-1.68)	(-2.29)	(-4.30)	(-4.26)	(-3.56)	(-2.88)	(-1.22)	(2.72)
w uct	D 14	0.193***	0.106**	0.002	-0.055**	-0.091***	-0.112***	-0.119***	-0.113***	-0.113***	-0.042	0.235***
stri dov	Past 4 years	(3.18)	(2.32)	(0.05)	(-2.10)	(-3.58)	(-4.75)	(-4.57)	(-3.81)	(-3.43)	(-1.23)	(3.14)
Zon vin		0.211***	0.093**	-0.011	-0.032	-0.075***	-0.127***	-0.134***	-0.140***	-0.107***	-0.058*	0.269***
0 1	Past 6 years	(3.35)	(1.99)	(-0.33)	(-1.09)	(-2.84)	(-4.90)	(-4.94)	(-4.41)	(-3.60)	(-1.69)	(3.90)
		0 207***	0.082*	0.016	-0.021	-0.075***	-0.091***	-0.131***	-0.141***	-0.086***	-0.103***	0 310***
0	Cash	(3.44)	(1.92)	(0.47)	(-0.73)	(-2.69)	(-3.67)	(-4.93)	(-4.46)	(-2.33)	(-2.69)	(4 13)
ce tive		0.208***	0.065	0.028	-0.019	-0.066***	-0.124^{***}	-0.112***	-0.126^{***}	-0.080**	-0.092***	0 299***
rna tt	Risk-free rate	(3.49)	(1.54)	(0.77)	(-0.63)	(-2.50)	(-4.88)	(-3.99)	(-4.05)	(-2.20)	(-2.42)	(4.07)
ulte efe: oin		0.265***	0.120***	0.059	0.023	-0.041*	-0.090***	-0.117***	-0.171***	-0.171***	-0.211***	0.476***
A 1 H	Sample mean	(3.98)	(2.53)	(1.51)	(0.75)	(-1.69)	(-3.57)	(-4.24)	(-5.39)	(-4.69)	(-4.97)	(5.35)
		0.176***	0.100***	0.020	0.060**	0.088***	0.108***	0.117***	0.127***	0.105***	0.040	0.216***
uo	$\lambda = 2.0$	(2.01)	(2.41)	(-0.57)	(-2.27)	(-3.49)	(-4.31)	(-4.20)	(-4.25)	(-3.46)	(-1, 20)	(3.01)
ersi		0 108***	(2.41) 0 124***	-0.030	(=2.27) =0.055**	(-3.49) _0.084***	(-4.31) _0.095***	(-4.20) -0.124^{***}	(-4.23) -0.146***	(-3.40) _0.002***	(=1.20) =0.073**	(3.01) 0.272***
Los ave	$\lambda = 2.5$	(3.15)	(2.56)	(-0.030)	(-2.033)	(-3.48)	(-3.90)	(-4.56)	(-4.91)	(-2.052)	(-2.29)	(3.60)
		(0.10)	(2.00)	(0.07)	(2.07)	(0.10)	(0.50)	(1.00)	(1.51)	(2.57)	(2.2)	(0.00)
lity 1g	$\delta = 0.31/0.39$	0.188	0.091	0.008	-0.056	-0.069	-0.095	-0.117	-0.121	-0.125	-0.093	0.281
abil htir		(3.13)	(1.86)	(0.23)	(-1.89)	(-2.75)	(-4.06)	(-4.44)	(-4.38)	(-4.25)	(-3.24)	(3.97)
oba	$\delta = 0.91/0.99$	0.183	0.046	0.008	-0.061	-0.086	-0.095	-0.117	-0.146	-0.112	-0.032	0.216
Pr		(3.05)	(1.03)	(0.24)	(-2.26)	(-3.32)	(-4.07)	(-4.12)	(-4.84)	(-3.52)	(-0.89)	(2.95)
Probability w	eighting function	0.180^{***}	0.037	-0.001	-0.079***	-0.070^{***}	-0.099***	-0.109^{***}	-0.117^{***}	-0.086***	-0.041	0.221^{***}
1100ability v	verginting runction	(3.06)	(0.91)	(-0.04)	(-2.78)	(-2.69)	(-3.78)	(-3.86)	(-4.06)	(-2.86)	(-1.07)	(3.20)
		0.121***	0.058	-0.031	-0.093***	-0.090***	-0.102***	-0.094***	-0.131***	-0.110***	-0.055*	0.176***
Skip one mor	nth	(2.33)	(1.27)	(-0.95)	(-3.63)	(-3.80)	(-3.67)	(-3.26)	(-4.34)	(-3.57)	(-1.71)	(2.85)
D 1 D. I		(,	()	((,	(,		(,	(,	())
Panel B: Inves	stment-grade bonds											
ruct ow	Past 3 years	0.198***	0.076*	0.025	-0.010	-0.068***	-0.075***	-0.079***	-0.097***	-0.084***	-0.037	0.236***
		(3.38)	(1.73)	(0.76)	(-0.36)	(-2.96)	(-3.35)	(-3.12)	(-3.57)	(-2.62)	(-0.99)	(3.07)
	Past 4 years	0.207	0.088	0.037	-0.049	-0.058	-0.097	-0.091	-0.107	-0.089	-0.034	0.241
nde		(3.45)	(1.94)	(1.06)	(-1.80)	(-2.31)	(-4.46)	(-3.63)	(-3.87)	(-2.75)	(-0.99)	(3.31)
Ki Co	Past 6 years	0.219	0.088	0.017	-0.023	-0.066	-0.091	-0.121	-0.110	-0.095	-0.045	0.264
		(3.56)	(1.93)	(0.47)	(-0.77)	(-2.72)	(-3.82)	(-4.59)	(-3.51)	(-3.25)	(-1.31)	(3.86)
	Cach	0.192^{***}	0.088**	0.049	-0.019	-0.051^{*}	-0.065***	-0.118^{***}	-0.118^{***}	-0.066*	-0.092***	0.284***
ve	Gasii	(3.17)	(2.06)	(1.34)	(-0.66)	(-1.85)	(-2.78)	(-4.52)	(-3.78)	(-1.78)	(-2.37)	(3.75)
nce	Pick free rate	0.180^{***}	0.064	0.064*	-0.004	-0.051^{*}	-0.095***	-0.084***	-0.114^{***}	-0.057	-0.066*	0.246***
ere	rusk-nee rate	(3.05)	(1.54)	(1.69)	(-0.12)	(-1.92)	(-4.17)	(-2.97)	(-3.67)	(-1.61)	(-1.71)	(3.37)
Alt ref poi	Sample mean	0.225^{***}	0.152^{***}	0.047	0.038	-0.020	-0.089***	-0.093***	-0.140***	-0.185***	-0.164***	0.389***
	bumple mean	(3.39)	(3.11)	(1.20)	(1.32)	(-0.84)	(-3.56)	(-3.19)	(-4.51)	(-5.23)	(-4.00)	(4.41)
-	1 20	0.193***	0.088^{*}	0.012	-0.032	-0.063***	-0.089***	-0.094***	-0.119***	-0.104***	-0.040	0.233***
sioi	$\lambda = 2.0$	(3.27)	(1.94)	(0.36)	(-1.10)	(-2.80)	(-3.73)	(-3.70)	(-4.02)	(-3.40)	(-1.18)	(3.33)
ver	1 - 25	0.215^{***}	0.093*	0.018	-0.041	-0.051^{**}	-0.084***	-0.097***	-0.137^{***}	-0.081^{***}	-0.063^{*}	0.278^{***}
аГ	$\lambda = 2.3$	(3.50)	(1.94)	(0.51)	(-1.46)	(-2.20)	(-3.59)	(-3.93)	(-4.66)	(-2.66)	(-1.95)	(3.78)
~		0.185***	0.088*	0.024	-0.049*	-0.051**	-0.070***	-0.099***	-0.089***	-0.109***	-0.080***	0.265***
ilit.	$\delta = 0.31/0.39$	(3.18)	(1.85)	(0.70)	(-1.66)	(-2.22)	(-3.03)	(-3.86)	(-3.42)	(-3.90)	(-2.68)	(3.88)
bab ght		0.198***	0.051	0.039	-0.050*	-0.044*	-0.075***	-0.083***	-0.124***	-0.116***	-0.035	0.233***
rol	$\delta = 0.91/0.99$	(3.38)	(1.15)	(1.18)	(-1.72)	(-1.80)	(-3.20)	(-3.20)	(-4.16)	(-3.57)	(-0.96)	(3.34)
		0.191***	0.022	0.014	0.027	0.041*	0.068***	0.000***	0.101***	0.084***	0.054	0.225***
Probability w	veighting function	(3.13)	(0.82)	(0.44)	(-1.01)	(-1.83)	(-2.70)	(-3.34)	(-3.47)	(-2.67)	(-1.44)	(3.48)
		(3.13)	(0.02)	(0.44)	(=1.01)	(-1.00)	(-2.70)	(-3.34)	(-3.47)	(-2.07)	(-1.++)	(3.40)
Skip one mor	nth	0.128***	0.044	0.001	-0.078***	-0.069***	-0.085***	-0.078***	-0.098***	-0.084***	-0.051	0.179***
		(2.48)	(1.03)	(0.03)	(-2.87)	(-2.94)	(-3.19)	(-2.85)	(-3.30)	(-2.68)	(-1.56)	(2.94)
Panel C: Junk	bonds											
		0.227	-0.241***	-0.211***	-0.205***	-0.262***	-0.267***	-0.049	-0.244***	-0.362***	-0.144	0.371**
	Past 3 years	(1.62)	(-2.33)	(-2.36)	(-2.55)	(-2.61)	(-3.06)	(-0.37)	(-3.10)	(-3.75)	(-1.16)	(2.04)
v ict		0.320*	-0.131	-0.337***	-0.201***	-0.273***	-0.301***	-0.050	-0.355***	-0.294***	-0.076	0.396*
stri dov	Past 4 years	(1.81)	(-0.83)	(-3.55)	(-2.38)	(-2.72)	(-3.66)	(-0.37)	(-3.55)	(-3.20)	(-0.61)	(1.80)
Vin											(continued -	n novt nace)
											(communed 0	п нелі ризе)

(continued on next page)

		Low	PTV2	PTV3	PTV4	PTV5	PTV6	PTV7	PTV8	PTV9	High	L-H
	Doct 6 vooro	0.194	-0.219**	0.014	-0.294***	-0.218^{***}	-0.045	-0.189***	-0.245***	-0.321^{***}	-0.169	0.363*
	Fast 0 years	(1.51)	(-2.15)	(0.07)	(-2.45)	(-2.49)	(-0.30)	(-2.38)	(-2.55)	(-3.49)	(-1.12)	(1.92)
()	Cash	0.509***	0.068	-0.154*	-0.429***	-0.317***	-0.338***	-0.365***	-0.148	-0.420***	0.023	0.487*
nt ut	Gasii	(2.65)	(0.62)	(-1.66)	(-4.86)	(-3.75)	(-3.69)	(-5.89)	(-0.91)	(-4.65)	(0.15)	(1.76)
poi	Pick free rate	0.620^{***}	-0.146	-0.224^{***}	-0.328^{***}	-0.415***	-0.248^{***}	-0.256^{***}	-0.233***	-0.247^{***}	-0.116	0.735***
lter sf. J	Risk-free rate	(2.97)	(-1.22)	(-2.69)	(-3.80)	(-4.82)	(-3.32)	(-3.41)	(-3.03)	(-1.99)	(-0.87)	(2.48)
А	Comm10	0.894**	0.097	-0.017	-0.256***	-0.202^{***}	-0.276^{***}	-0.521^{***}	-0.458***	-0.600^{***}	-0.452^{***}	1.346***
	Sample mean	(2.32)	(0.93)	(-0.15)	(-2.79)	(-3.16)	(-3.50)	(-5.80)	(-7.51)	(-8.67)	(-2.99)	(2.83)
sion	$\lambda = 2.0$	0.107	-0.075	-0.054	-0.263***	-0.130	-0.208***	-0.041	-0.295***	-0.381***	-0.139	0.246*
		(0.86)	(-0.35)	(-0.29)	(-2.59)	(-1.28)	(-3.00)	(-0.28)	(-3.48)	(-4.49)	(-1.04)	(1.82)
ver	$\lambda = 2.5$	0.340^{**}	-0.184^{*}	-0.087	-0.270^{***}	-0.213^{*}	-0.150	-0.189^{**}	-0.345***	-0.404***	-0.151	0.491**
ar		(1.95)	(-1.66)	(-0.45)	(-3.06)	(-1.92)	(-1.51)	(-2.06)	(-3.41)	(-4.73)	(-1.12)	(2.24)
È m	\$ 0.21/0.20	0.170	-0.118	-0.197***	-0.423***	-0.105	-0.212	-0.255***	-0.403***	-0.298***	-0.079	0.249*
illio Suit	b = 0.31/0.39	(0.52)	(-1.02)	(-2.50)	(-4.29)	(-0.62)	(-1.53)	(-2.70)	(-4.46)	(-3.77)	(-0.54)	(1.82)
bal ghi	\$ 0.01/0.00	0.148	-0.205^{*}	0.060	-0.285***	-0.060	-0.346***	-0.089	-0.223***	-0.292^{***}	-0.124	0.273**
Prol wei	$\delta = 0.91/0.99$	(0.37)	(-1.67)	(0.17)	(-3.27)	(-0.57)	(-3.58)	(-0.96)	(-3.31)	(-3.47)	(-0.97)	(2.02)
Drobability	waighting function	0.100	0.101	-0.164	-0.321***	-0.228***	-0.155*	-0.160	-0.264***	-0.278***	-0.147	0.247*
Probability weighting function		(0.99)	(0.31)	(-1.30)	(-4.17)	(-2.87)	(-1.65)	(-1.53)	(-2.99)	(-2.95)	(-1.17)	(1.80)
Strin one me	nth	0.373^{*}	-0.251***	-0.312***	-0.362***	-0.439***	-0.227***	-0.058	-0.382***	-0.295***	-0.161	0.534*
Skip one mo	911111	(1.87)	(-2.54)	(-2.98)	(-3.53)	(-4.45)	(-2.99)	(-0.60)	(-4.44)	(-3.28)	(-1.22)	(1.93)

outperforms the others in describing the experimental data of individuals. Therefore, we apply Prelec's (1998) exponential form of the probability weighting function and examine whether our conclusion holds under this specification. Prelec's (1998) probability weighting function is defined as:

$$f(p) = e^{-(-lnp)^d}$$

where the probability weighting parameter, δ , has been estimated by many others (e.g., Bleichrodt and Pinto, 2000; Wu and Gonzales, 1996). We only report results when we set $\delta = 0.94$, following Stott (2006) estimate.¹⁸

The portfolio and regression results in Tables 10 and 11 suggest that prospect theory has significant predictive power under the alternative probability weighting function, and the predictive power is much stronger for junk bonds.

5.1.5. Skipping one month

When calculating the prospect theory value of a bond at month t, we use monthly returns from month t - 60 to t - 1. We then sort bonds into decile portfolios and examine their returns in month t. It is known that a bond's performance and its lagged return are positively correlated. To avoid the confounding effect of the lagged return, we skip one month between the point at which we sort the bonds, and the point at which we calculate the portfolio returns.

The portfolio and regression results in Tables 10 and 11 suggest that prospect theory's predictive power remains intact, and is much stronger for junk bonds. This predictive power of *PTV* is not driven by a possible confounding effect of the lagged returns.

5.2. Expected utility function

One assumption of our study is that investors take a bond as its historical return distribution, and evaluate it according to prospect theory. If investors evaluate a bond according to expected (power) utility instead of prospect theory, then bonds with higher (lower) expected utility would have lower (higher) future returns. To examine whether expected utility has predictive power, we replace *PTV* in our model with expected utility (EU). We perform a portfolio analysis sorted by the expected constant relative risk aversion (CRRA) utility function, which is widely used to approximate real-world behavior. Applying this process to our bond historical returns, the expected utility is defined as:

$$EU = \sum_{i=-n}^{m} \frac{1}{60} \frac{(1+r_i)^{1-\theta}}{1-\theta}$$

where r_i is monthly bond returns for the past 60 months, and θ is the risk aversion parameter. Gandelman and Hernandez-Murillo (2014) estimate the θ parameter at the country level and find that the risk aversion is between 0 and 2 for developed countries, and between 0 and 3 for developing countries. We test a range of θ from 0.5 to 2.5 and present the results in Table 12. We find that the average return of the difference between the highest and lowest portfolios is no longer significant, and the expected utility function does not have predictive power for future returns. Although this result does not provide evidence against the expected utility function, it suggests that prospect theory value transfers the historical returns in a uniquely informative way that can capture investors' evaluation process.

¹⁸ Results based on other estimates lead to similar results.

Robustness through regression. This table presents results for robustness checks of Fama–MacBeth regressions. The right-most column reports excess returns for the low minus high PTV portfolio. We did 6 kinds of robustness tests: (1) different construct windows; (2) different reference points; (3) different loss aversion parameters; (4) different probability weighting parameters; (5) probability weighting function; and (6) skip one month. Panels A, B, and C reports the results for all samples, investment-grade bonds, and junk bonds respectively. The sample period is from January 1978 to December *T*-statistics are reported in the parentheses. All the *t*-statistics are Newey–West adjusted with 12 lags. , *, *, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		PTV	Rating	Coupon	TM	Size	REV	LTREV	MOM	VOL	SK	IndSK
Panel A: All	samples											
	Past 3 years	-0.181 ^{***} (-4.01)	0.099*** (3.19)	0.201 ^{***} (4.25)	-0.040 (-0.13)	0.004 (0.43)	-0.073 ^{***} (-5.98)	-0.011 (-1.44)	0.210 (0.70)	0.334 ^{***} (2.97)	-0.012 (-0.15)	-0.021 (-1.27)
nstruc ndow	Past 4 years	-0.190^{***} (-3.81)	0.103 ^{***} (3.27)	0.197 ^{***} (4.05)	0.034 (0.11)	0.004 (0.44)	-0.074*** (-6.05)	-0.011 (-1.44)	0.175 (0.59)	0.322 ^{***} (2.85)	-0.073 (-1.00)	-0.017 (-0.95)
wi C	Past 6 years	-0.240 ^{***} (-4.27)	0.115 (3.60)	0.172 ^{***} (3.45)	0.031 (0.09)	0.004 (0.41)	$-0.075^{-0.075}$ (-6.13)	-0.012 (-1.48)	-0.070 (-0.24)	0.320	-0.004 (-0.06)	-0.023 (-1.21)
e e	Cash	-0.189*** (-4.34)	0.107**** (3.35)	0.208 ^{****} (4.12)	-0.108 (-0.35)	0.000 (-0.01)	-0.077 ^{***} (-6.84)	-0.011 (-1.44)	0.047 (0.17)	0.243 ^{***} (2.40)	0.092 (0.93)	-0.005 (-0.27)
lternati eferenco oint	Risk-free rate	$-0.141^{-0.00}$ (-4.43) -0.283^{***}	0.106 ^{***} (3.30) 0.102 ^{***}	0.197 ^{***} (3.88) 0.118 ^{***}	-0.022 (-0.07) -0.301	0.002 (0.18) 0.002	$-0.077^{-0.0}$ (-6.79) -0.077^{***}	-0.014 (-1.88) -0.012	0.086 (0.31) 0.068	0.270 (2.63) 0.108	0.025 (0.26) -0.539***	-0.012 (-0.67) -0.008
	Sample mean	(-5.18)	(3.24)	(2.39)	(-1.04)	(0.25)	(-6.94)	(-1.52)	(0.25)	(1.10)	(-5.11)	(-0.42)
s ersion	$\lambda = 2.0$	$-0.214^{-0.00}$ (-3.97)	0.109 ^{***} (3.46)	0.173 ^{***} (3.49)	0.051 (0.16)	0.003 (0.36)	-0.075 ^{***} (-6.14)	-0.014° (-1.81)	0.035 (0.12)	0.314 ^{***} (2.76)	-0.033 (-0.48)	-0.019 (-1.07)
Los ave	$\lambda = 2.5$	(-3.79)	(3.46)	(3.42)	(0.21)	(0.38)	-0.075	(-1.88)	(0.13)	(2.66)	-0.032 (-0.48)	-0.019 (-1.09)
ability hting	$\delta=0.31/0.39$	$-0.197^{\circ\circ\circ}$ (-3.45)	0.105	0.144	0.030 (0.10)	0.003 (0.38)	-0.074 ^{***} (-6.12)	-0.018° (-2.31)	0.039 (0.14)	0.293 ^{**} (2.21)	0.021 (0.18)	-0.020 (-1.09)
Prob	$\delta=0.91/0.99$	-0.212 (-3.91)	(3.48)	(3.57)	(0.18)	(0.40)	-0.075 (-6.14)	-0.014 (-1.73)	(0.14)	(2.86)	-0.156 (-2.76)	-0.019 (-1.08)
Probability	weighting function	-0.238 ^{***} (-3.91)	0.108*** (3.42)	0.170 ^{***} (3.36)	0.082 (0.26)	0.004 (0.43)	-0.075^{***} (-6.20)	-0.018** (-2.22)	0.046 (0.16)	0.323*** (2.92)	-0.222*** (-3.77)	-0.021 (-1.18)
Skip one mo	onth	-0.123 ^{***} (-2.71)	0.102 ^{***} (3.24)	0.148 ^{***} (3.03)	-0.024 (-0.08)	0.003 (0.29)	-0.074 ^{***} (-5.94)	-0.015 ^{**} (-1.97)	0.091 (0.31)	0.326 ^{***} (3.11)	-0.289 ^{***} (-4.48)	-0.014 (-0.75)
Panel B: Inve	estment-grade bonds											
	Past 3 years	-0.108 ^{**} (-2.26)	0.117 ^{***} (3.36)	0.183 ^{***} (3.57)	-0.153 (-0.49)	0.007 (0.91)	-0.077 ^{***} (-5.94)	-0.010 (-1.35)	0.251 (0.78)	0.354 ^{***} (3.04)	-0.347 ^{***} (-4.39)	-0.036 ^{**} (-2.22)
Construct window	Past 4 years	-0.116 ^{**} (-2.27)	0.113 ^{****} (3.17)	0.187 ^{****} (3.61)	-0.144 (-0.45)	0.008 (0.98)	-0.078 ^{***} (-6.00)	-0.010 (-1.32)	0.281 (0.87)	0.327 ^{***} (2.85)	-0.359*** (-4.75)	-0.030 (-1.63)
	Past 6 years	-0.143*** (-2.62)	0.130*** (3.53)	0.144 ^{***} (2.78)	-0.110 (-0.32)	0.009 (1.04)	-0.079*** (-6.06)	-0.015 [*] (-1.82)	0.021 (0.06)	0.318*** (2.78)	-0.311*** (-4.27)	-0.030 (-1.51)
e s	Cash	-0.115 ^{***} (-2.70)	0.128 ^{***} (3.49)	0.166 ^{****} (3.12)	-0.207 (-0.65)	0.007 (0.85)	-0.081 ^{***} (-6.71)	-0.011 (-1.42)	0.176 (0.57)	0.290 ^{***} (2.80)	-0.302 ^{***} (-2.84)	-0.029 (-1.49)
lternati ference vint	Risk-free rate	-0.081^{***} (-2.42)	0.127*** (3.46)	0.159*** (3.00)	-0.149 (-0.46)	0.007 (0.85)	-0.081^{***} (-6.65)	-0.012 (-1.59)	0.161 (0.52)	0.296*** (2.81)	-0.327^{***} (-3.28)	-0.029 (-1.51)
P a pd	Sample mean	(-3.21)	(3.41)	(3.06)	-0.219 (-0.70)	(0.96)	-0.080	(-1.53)	(0.73)	(2.63)	(-1.84)	(-1.49)
ss ersion	$\lambda = 2.0$	-0.138^{***} (-2.48)	0.120*** (3.31)	0.156 ^{***} (2.99)	-0.121 (-0.37)	0.008 (1.03)	-0.079^{***} (-6.09)	-0.016^{**} (-2.02)	0.173 (0.54)	0.317 ^{***} (2.80)	-0.308^{***} (-4.38)	-0.034^{*} (-1.75)
Los ave	$\lambda = 2.5$	-0.123 (-2.49)	(3.30)	(3.00)	(-0.36)	(1.01)	(-6.08)	(-2.00)	(0.54)	(2.83)	(-4.34)	(-1.75)
ability hting	$\delta=0.31/0.39$	-0.123 (-2.42)	0.121 (3.34)	0.160 (3.07)	-0.133 (-0.41)	0.008	-0.079 (-6.12)	-0.015 (-1.87)	0.124 (0.39)	0.327 (2.89)	-0.386 (-4.77)	-0.034 (-1.77)
Prob	$\delta = 0.91/0.99$	(-2.46)	(3.37)	(2.97)	-0.112 (-0.34)	(1.01)	(-6.10)	(-2.01)	(0.58)	(2.75)	-0.271 (-4.07)	-0.034 (-1.76)
Probability v	weighting function	-0.163*** (-2.48)	0.122*** (3.38)	0.159*** (3.02)	-0.114 (-0.35)	0.008 (1.02)	-0.078^{***} (-6.08)	-0.015 [*] (-1.95)	0.207 (0.65)	0.313*** (2.72)	-0.265*** (-3.99)	-0.034^{*} (-1.78)
Skip one mo	onth	-0.126 ^{***} (-2.65)	0.117 ^{***} (3.18)	0.195 ^{***} (3.64)	-0.073 (-0.22)	0.009 (1.07)	-0.083 ^{***} (-6.96)	-0.012 (-1.54)	0.172 (0.53)	0.258 ^{**} (2.09)	-0.218 ^{**} (-2.26)	-0.034 [*] (-1.82)
Panel C: Jun	k bonds											
t	Past 3 years	-0.144 ^{***} (-2.35)	0.483 ^{***} (2.89)	0.621 (1.26)	2.335 [*] (1.68)	-0.174 (-0.18)	-0.070 ^{***} (-2.73)	-0.144 (-0.98)	-2.191 [*] (-1.79)	0.057 (0.18)	-0.046 (-0.99)	0.308 (1.55)
nstruc	Past 4 years	-0.177^{***} (-2.56)	0.289 ^{***} (2.34)	0.359 (0.89)	2.554 ^{**} (2.18)	0.193 (0.25)	-0.082^{***} (-3.43)	0.000 (0.00)	-2.755**** (-3.28)	-0.142 (-0.42)	0.046 (1.61)	0.048 (0.68)
Ϋ́ Ϋ́	Past 6 years	-0.262	0.310	0.461	2.612	0.562	-0.105	0.040	-2.288	0.045	0.048	0.031

(continued on next page)

Table 11 (continued)

		PTV	Rating	Coupon	TM	Size	REV	LTREV	MOM	VOL	SK	IndSK
		(-3.29)	(2.50)	(0.98)	(1.65)	(0.60)	(-3.11)	(0.63)	(-2.97)	(0.14)	(1.53)	(0.51)
	Cash	-0.170^{**}	0.309***	0.455	1.441	-0.087	-0.053^{***}	0.087	-2.893^{***}	-0.108	0.031	0.098
/e	Casii	(-2.24)	(2.66)	(1.10)	(1.39)	(-0.14)	(-2.42)	(1.55)	(-3.24)	(-0.35)	(1.32)	(0.99)
ernativ erence nt	Disk from rate	-0.206^{***}	0.332^{***}	0.477	2.051^{*}	0.050	-0.064***	0.078	-2.827^{***}	-0.027	0.038	0.084
	RISK-ITEE Tale	(-2.43)	(2.75)	(1.12)	(1.86)	(0.08)	(-2.68)	(1.46)	(-3.25)	(-0.09)	(1.50)	(0.88)
Alto refe poi	Comula mean	-0.399***	0.204^{*}	0.048	0.907	1.380	-0.065***	0.081^{*}	-2.180^{***}	0.059	-0.059***	0.042
	Sample mean	(-4.43)	(1.69)	(0.16)	(0.92)	(2.08)	(-3.34)	(1.69)	(-2.62)	(0.21)	(-2.46)	(0.39)
c	1 - 2.0	-0.204***	0.247**	0.344	2.628^{*}	-0.153	-0.108^{***}	0.010	-2.703^{***}	-0.081	-0.047*	0.042
sio	$\lambda = 2.0$	(-2.45)	(2.06)	(0.83)	(1.92)	(-0.18)	(-3.58)	(0.17)	(-3.27)	(-0.23)	(-1.70)	(0.63)
ven	1 25	-0.170^{***}	0.248^{*}	0.320	2.419^{**}	0.041	-0.098***	0.005	-2.720^{***}	-0.080	0.039	0.047
a' L	$\lambda = 2.5$	(-2.91)	(1.95)	(0.80)	(1.96)	(0.05)	(-3.72)	(0.09)	(-3.28)	(-0.23)	(1.58)	(0.72)
È m	$\delta = 0.21/0.20$	-0.094*	0.278^{**}	0.334	1.206	-0.271	-0.065***	-0.005	-2.635***	-0.153	0.053	0.074
ilic ili	b = 0.51/0.59	(-1.82)	(2.27)	(0.91)	(1.09)	(-0.37)	(-2.72)	(-0.08)	(-2.89)	(-0.43)	(1.47)	(0.87)
bal	s = 0.01/0.00	-0.257^{***}	0.235^{**}	0.412	2.212	-0.053	-0.094***	0.001	-2.606***	-0.065	0.027	0.015
Prol	b = 0.91/0.99	(-3.22)	(1.98)	(0.93)	(1.60)	(-0.07)	(-3.17)	(0.01)	(-3.37)	(-0.18)	(0.09)	(0.26)
Drobobility	woighting function	-0.291***	0.231^{*}	0.337	2.593^{*}	-0.104	-0.098***	0.008	-2.799***	-0.083	-0.024	0.002
Probability weighting function		(-3.29)	(1.92)	(0.74)	(1.92)	(-0.14)	(-3.18)	(0.12)	(-3.60)	(-0.23)	(-0.70)	(0.03)
Skip ope m	onth	-0.144*	0.124	-0.185	0.440	0.612	-0.080***	-0.044	-1.317**	0.424**	0.010	-0.062*
Skip one month		(-1.66)	(0.87)	(-0.79)	(0.37)	(0.73)	(-3.00)	(-0.51)	(-2.17)	(2.07)	(0.28)	(-1.79)

Table 12

Expected utility function. This table presents portfolio and regression analysis results with the prospect theory being replaced by the expected utility function. *EU* is the expected constant relative risk aversion (CRRA) utility function, which is calculated based on a bond's historical returns. The sample period is from January 1978 to December 2013. *T*-statistics are reported in the parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolio analysis											
	Low	EU2	EU3	EU4	EU5	EU6	EU7	EU8	EU9	High	L-H
0 - 0 5	0.062	0.005	-0.052^{*}	-0.086***	-0.100^{***}	-0.101***	-0.070^{**}	-0.092***	-0.008	0.039	0.022
$\theta = 0.3$	(1.19)	(0.13)	(-1.68)	(-2.99)	(-3.83)	(-3.30)	(-2.06)	(-2.59)	(-0.19)	(0.75)	(0.32)
0 - 15	0.070	0.018	-0.056^{*}	-0.080^{***}	-0.100^{***}	-0.097***	-0.069**	-0.089***	-0.014	0.027	0.042
$\theta = 1.3$	(1.35)	(0.45)	(-1.78)	(-2.88)	(-3.91)	(-3.25)	(-2.03)	(-2.55)	(-0.35)	(0.54)	(0.62)
0 - 2	0.081	0.019	-0.048	-0.079^{***}	-0.107^{***}	-0.094***	-0.070^{**}	-0.082^{***}	-0.021	0.028	0.053
$\theta = 2$	(1.56)	(0.48)	(-1.52)	(-2.80)	(-4.23)	(-3.07)	(-1.98)	(-2.35)	(-0.51)	(0.56)	(0.78)
0 - 25	0.091*	0.020	-0.043	-0.079^{***}	-0.103^{***}	-0.101^{***}	-0.061^{*}	-0.081^{**}	-0.033	0.031	0.060
$\theta = 2.3$	(1.72)	(0.50)	(-1.37)	(-2.76)	(-3.96)	(-3.42)	(-1.73)	(-2.31)	(-0.81)	(0.63)	(0.88)
Panel B: I	Regression a	nalysis									
	EU	Rating	Coupon	TM	Size	REV	LTREV	МОМ	VOL	SK	IndSK
0-05	0.023	0.105***	0.181***	0.000	0.002	-0.075***	-0.013	0.024	0.328***	-0.163***	-0.018
$\theta = 0.3$	(0.42)	(3.34)	(3.69)	(0.00)	(0.28)	(-6.24)	(-1.63)	(0.08)	(3.20)	(-2.75)	(-0.98)
0 - 15	-0.024	0.105^{***}	0.181^{***}	0.000	0.002	-0.075^{***}	-0.013	0.023	0.325^{***}	-0.163^{***}	-0.018
$\theta = 1.3$	(-0.53)	(3.34)	(3.69)	(0.00)	(0.28)	(-6.24)	(-1.63)	(0.08)	(3.16)	(-2.75)	(-0.98)
0 - 2	-0.048	0.105^{***}	0.181^{***}	0.000	0.002	-0.075^{***}	-0.013	0.023	0.324***	-0.162^{***}	-0.018
$\theta = 2$	(-1.17)	(3.34)	(3.69)	(0.00)	(0.28)	(-6.25)	(-1.63)	(0.08)	(3.14)	(-2.74)	(-0.98)
0 - 25	-0.052	0.105***	0.181^{***}	0.000	0.002	-0.075***	-0.013	0.023	0.323***	-0.162***	-0.018
$\sigma = 2.5$	(-1.28)	(3.34)	(3.68)	(0.00)	(0.28)	(-6.25)	(-1.63)	(0.08)	(3.12)	(-2.73)	(-0.97)

5.3. Fama-MacBeth regression with firm-level characteristics

Chordia et al. (2015) show that bond returns can also be predicted by firm-level variables such as the stock market value, profitability, past stock return, and volatility. We thus include the stock's market value (*MV*), profitability (*PROFIT*), the cumulative stock return during month *t*-12 to *t*-2 (*STKMOM*), the lagged stock return (*STKREV*), and the stock idiosyncratic volatility (*STKIVOL*) as controls. Due to the availability of data, only bonds issued by publicly listed firms are included in the sample.¹⁹

The regression results are in Table 13, where each column corresponds to one model. Model 1 corresponds to Model 7 in Table 7, which serves as the baseline model. In Models 2–6, one or more firm-level control variables are included. The coefficients of *PTV* are negative and significant for all model specifications. The results show that *PTV* has significant predictive power even after including firm-level characteristics in the models.

5.4. Accounting for transaction costs

To examine whether our results remain significant after accounting for transaction costs, we perform portfolio and regression analysis on bond returns adjusted for transaction costs. We estimate the transaction costs following the method used by Bai et al.

¹⁹ The firm-level characteristics are obtained from Compustat and CRSP.

Fama–MacBeth regression with firm-level characteristic included. This table reports Fama–MacBeth regression results with firm-level characteristics included. *MV* is the market value of equity in month *t*-1. *PROFIT* is profitability, which is calculated as the ratio of equity income to book equity. *STKMOM* is stock's momentum, which is calculated as the cumulative stock return (in percent) from month *t*-12 to *t*-2. *STKREV* is stock's short-term reversal, which is the lagged monthly stock return (in percent). *STKIVOL* is stock's idiosyncratic volatility, which is calculated as the volatility of the stock's daily idiosyncratic returns over month *t*-1 as in Ang et al. (2006). The sample covers from January 1978 to December All the *t*-statistics are Newey–West adjusted with 12 lags. *, ** , and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
DTV	-0.088***	-0.094***	-0.086***	-0.095***	-0.088***	-0.097***
PIV	(-3.04)	(-3.41)	(-2.98)	(-3.44)	(-3.05)	(-3.58)
Datina	0.068	0.095*	0.071	0.061	0.074	0.084*
Kuung	(1.36)	(1.85)	(1.45)	(1.21)	(1.55)	(1.72)
Coupon	0.038	0.051	0.026	0.019	0.033	0.005
Coupon	(0.46)	(0.61)	(0.32)	(0.23)	(0.41)	(0.07)
TM	0.762^{***}	0.773***	0.764***	0.744***	0.745***	0.755***
1 111	(4.38)	(4.45)	(4.38)	(4.27)	(4.31)	(4.34)
Sigo	0.041*	0.017	0.041	0.020	0.046*	0.014
5120	(1.65)	(0.72)	(1.59)	(0.95)	(1.80)	(0.61)
REV	-0.147^{***}	-0.147***	-0.149***	-0.152***	-0.149***	-0.154^{***}
ILL V	(-10.40)	(-10.41)	(-10.55)	(-10.64)	(-10.59)	(-10.86)
ITREV	-0.028^{***}	-0.029***	-0.025***	-0.029***	-0.029***	-0.023^{**}
	(-2.74)	(-2.66)	(-2.35)	(-2.77)	(-2.75)	(-1.98)
MOM	-2.070^{***}	-2.143^{***}	-2.093***	-2.521***	-2.091***	-2.651^{***}
mom	(-3.97)	(-4.09)	(-4.03)	(-4.79)	(-4.09)	(-5.06)
VOI	0.185	0.182	0.200	0.199*	0.166	0.192
VOL	(1.50)	(1.49)	(1.63)	(1.67)	(1.35)	(1.62)
SK	0.015	0.061	0.011	0.042	0.004	0.061
bit	(0.13)	(0.54)	(0.09)	(0.37)	(0.03)	(0.54)
IndSK	-0.00	-0.00	-0.01	-0.01	0.00	-0.01
	(-0.36)	(-0.25)	(-0.53)	(-1.10)	(-0.21)	(-1.13)
MV		0.048***				0.017
		(2.48)				(1.03)
PROFIT			0.424***			0.411***
			(2.59)			(2.63)
STKMOM				0.216***		0.224***
				(6.13)		(6.01)
STKREV				0.624***		0.605***
				(7.67)		(7.64)
STRIVOL					-0.529	-0.156
STRIVOL					(-0.33)	(-0.10)
R^2	0.31	0.31	0.31	0.32	0.31	0.33

Table 14

Accounting for transaction costs. This table presents portfolio and regression analysis results for returns adjusted for transaction costs. The transaction cost is estimated by following Bai et al. (2016) and Chordia et al. (2015). The sample period is from January 1994 to December 2013. *T*-statistics are reported in the parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolio analysis

	Low	PTV2	PTV3	PTV4	PTV5	PTV6	PTV7	PTV8	PTV9	High	L-H
All complo	0.275***	0.081	-0.064	-0.036	-0.132***	-0.096	-0.154***	-0.160***	-0.106*	-0.147**	0.422***
All sample	(2.93)	(1.07)	(-0.95)	(-0.62)	(-2.49)	(-1.52)	(-2.58)	(-2.60)	(-1.73)	(-2.15)	(4.00)
Invoctment grade bonds	0.268***	0.065	-0.006	-0.001	-0.105^{*}	-0.124^{***}	-0.099*	-0.193***	-0.150^{**}	-0.118^{*}	0.386***
investment-grade bonds	(3.10)	(0.90)	(-0.08)	(-0.02)	(-1.95)	(-2.71)	(-1.79)	(-3.14)	(-2.19)	(-1.78)	(3.75)
True houde	0.323	0.231	0.101	-0.152	-0.097	-0.184	-0.209^{**}	-0.314^{***}	-0.198^{*}	-0.192	0.515***
Junk Donds	(1.56)	(1.32)	(0.76)	(-1.18)	(-0.76)	(-1.34)	(-1.98)	(-2.70)	(-1.82)	(-1.27)	(5.01)
Panel B: Regression analysis	s										
	PTV	Rating	Coupon	TM	Size	REV	LTREV	MOM	VOL	SK	IndSK
All complo	-0.190***	0.149**	0.344***	1.707***	0.045	-0.165***	0.072***	0.620	-0.007	0.036	0.021
All sample	(-3.84)	(2.30)	(2.75)	(3.72)	(1.26)	(-11.29)	(2.02)	(1.23)	(-0.03)	(0.31)	(0.61)
Invoitment grade bonds	-0.161^{*}	-0.092	0.468***	2.371^{***}	0.043	-0.172^{***}	0.248	0.102	-0.043	0.035	0.076
investment-grade bonds	(-1.94)	(-0.84)	(3.43)	(4.55)	(1.40)	(-11.13)	(1.54)	(0.18)	(-0.17)	(0.30)	(1.57)
Junk bonds	-0.204^{***}	0.292^{**}	-0.274	1.796^{**}	-0.048	-0.191***	-0.274^{***}	-1.547^{***}	-0.022	0.039	-0.078^{***}
Julik Dollus	(-4.69)	(2.41)	(-1.45)	(2.01)	(-0.76)	(-24.86)	(-2.50)	(-4.76)	(-0.37)	(0.19)	(-2.87)

(2016) and Chordia et al. (2015). The results are reported in Table 14. The returns of the Low–High portfolio remain positive and significant, and the regression coefficients for *PTV* remain negative and significant. This again supports our hypothesis H1 and H2 that prospect theory has significant predictive power, which is stronger for junk bonds.

Firm-level analysis. This table presents portfolio and regression analysis results for firm-level. Following Chordia et al. (2015), for firms that have more than one bond issue outstanding, we choose one of the issues by using following four different methods: (1) RAN: randomly choose a bond issue; (2) SMAT: choose an issue with the shortest remaining maturity as long as it is more than one year; (3) RECISS: choose the most recently issued bond; (4) EW: use the equal-weighted average the bond returns across the firm. The sample covers from January 1978 to December 2013. All the *t*-statistics are Newey–West adjusted with 12 lags. ^{*}, ^{**}, and ^{***} indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel	A: Portfolio analysis											
		Low	PTV2	PTV3	PTV4	PTV5	PTV6	PTV7	PTV8	PTV9	High	L-H
		0.253***	0.089***	0.044	-0.003	-0.044*	-0.036	-0.049	-0.067***	-0.067***	-0.026	0.280***
	All sample	(5.02)	(2.34)	(1.46)	(-0.12)	(-1.82)	(-1.63)	(-1.63)	(-2.50)	(-2.56)	(-0.99)	(4.52)
RAN	Investment Crede	0.168^{***}	0.066*	0.054	-0.006	-0.016	-0.050^{*}	-0.102^{***}	-0.082^{***}	-0.084^{***}	-0.056*	0.224***
RA	investment-Grade	(3.37)	(1.75)	(1.55)	(-0.23)	(-0.59)	(-1.86)	(-3.51)	(-2.85)	(-2.84)	(-1.75)	(3.55)
	Junk bonds	0.389***	0.330***	0.283^{***}	0.279^{***}	0.044	0.145***	0.076	0.008	0.023	0.072^{*}	0.317^{***}
	Julik bolius	(5.34)	(4.63)	(4.53)	(4.31)	(0.81)	(2.73)	(1.42)	(0.15)	(0.47)	(1.73)	(3.00)
	All comple	0.173***	0.049*	0.021	-0.049	-0.032	-0.075	-0.102	-0.082^{***}	-0.092^{***}	-0.059*	0.233***
	All salliple	(4.48)	(1.77)	(0.82)	(-2.02)	(-1.29)	(-2.93)	(-3.92)	(-3.02)	(-3.52)	(-1.94)	(3.78)
Τ	Investment Grade	0.136***	0.036	-0.032	-0.055**	-0.058**	-0.099***	-0.113^{***}	-0.126^{***}	-0.113^{***}	-0.074***	0.210^{***}
SM/	investment-Grade	(3.59)	(1.19)	(-1.23)	(-2.08)	(-2.13)	(-3.41)	(-3.96)	(-4.38)	(-3.91)	(-2.68)	(3.94)
0,	Junk bonds	0.404***	0.280^{***}	0.315^{***}	0.192***	0.043	0.096*	0.049	0.051	0.025	0.137^{***}	0.268***
	built bolids	(5.67)	(4.28)	(5.28)	(3.48)	(0.78)	(1.78)	(0.87)	(1.13)	(0.60)	(3.09)	(3.95)
	All comple	0.186***	0.054	0.066*	0.011	-0.011	-0.015	-0.032	-0.067**	-0.033	-0.045	0.231***
	All sample	(3.48)	(1.32)	(1.85)	(0.33)	(-0.40)	(-0.53)	(-1.11)	(-2.20)	(-1.18)	(-1.41)	(3.48)
ISS	Investment Grade	0.137^{***}	0.032	0.040	-0.002	-0.018	-0.033	-0.049	-0.071^{**}	-0.072^{***}	-0.087^{***}	0.224^{***}
EC	investment-Grade	(2.52)	(0.75)	(1.16)	(-0.05)	(-0.59)	(-1.09)	(-1.48)	(-2.25)	(-2.49)	(-2.52)	(3.37)
R	Junk bonde	0.418***	0.390***	0.298^{***}	0.183^{***}	0.091	0.096*	0.051	0.036	0.059	0.131^{***}	0.287^{***}
	Julik bolius	(5.62)	(5.57)	(4.16)	(3.12)	(1.61)	(1.67)	(0.89)	(0.70)	(1.32)	(2.77)	(4.15)
	A 11	0.189***	0.104***	0.021	-0.003	-0.033	-0.035	-0.035	-0.047*	-0.038	-0.035	0.224***
	All sample	(4.46)	(3.25)	(0.72)	(-0.11)	(-1.50)	(-1.58)	(-1.56)	(-1.95)	(-1.56)	(-1.40)	(4.22)
-	In the second second	0.157***	0.059*	-0.016	-0.018	-0.050**	-0.059***	-0.056**	-0.070^{***}	-0.068***	-0.067***	0.224***
EW	Investment-Grade	(3.88)	(1.90)	(-0.52)	(-0.66)	(-2.07)	(-2.47)	(-2.07)	(-2.51)	(-2.54)	(-2.44)	(4.47)
		0.369***	0.392***	0.221^{***}	0.213^{***}	0.112^{**}	0.097^{*}	0.153***	0.026	0.037	0.143***	0.226***
	Junk bonds	(5.33)	(5.67)	(3.30)	(3.96)	(2.27)	(1.71)	(2.80)	(0.55)	(0.90)	(2.95)	(3.21)
Panel	B. Fama–MacBeth reg	ression										
		DTV	Patina	Courson	TM	Sigo	DEV	ITDEV	MOM	VOI	SV.	IndeV
		PIV	Kullig	Coupon	1 1/1	3120	<u>NEV</u>	LIKEV		VOL	<u>эк</u>	musk
	All sample	-0.245	0.135	0.107	0.045	0.008	-0.070	-0.037	-0.112	0.248	0.106	-0.015
	•	(-4.99)	(3.01)	(2.36)	(0.09)	(0.56)	(-5.41)	(-3.96)	(-0.34)	(3.17)	(1.29)	(-0.60)
AN	Investment-Grade	-0.192	(2.02)	(1.01)	-0.1/2	0.010	-0.081	-0.013	-0.578	0.101	0.051	-0.023
Я		(-4.12)	(3.02)	(1.81)	(-0.20)	(0.70)	(-0.02)	(-1.48)	(-1.70)	(1.02)	(0.58)	(-1.25)
	Junk bonds	-0.254	(0.112	(2.21)	(1.00)	(2.20)	-0.075	-0.023	-1.585	0.508	0.074	(1.22)
		(-5.70)	(2.18)	(3.31)	(1.89)	(2.20)	(-/.2/)	(-1.22)	(-5.23)	(4.60)	(0.39)	(1.23)
	All sample	-0.197***	0.131***	0.150***	0.257	-0.007	-0.066***	-0.012	-0.049	0.134	0.052	-0.001
	· · · · · · · · · · · · · · · · · · ·	(-3.76)	(3.72)	(3.58)	(0.47)	(-0.51)	(-4.83)	(-1.55)	(-0.16)	(1.34)	(0.70)	(-0.07)
AT	Investment-Grade	-0.115	0.126	0.117	0.159	-0.014	-0.090	-0.008	-0.142	-0.045	0.040	-0.007
SM		(-2.54)	(3.41)	(2.66)	(0.22)	(-1.09)	(-6.08)	(-0.94)	(-0.40)	(-0.37)	(0.69)	(-0.36)
	Junk bonds	-0.218	0.120	0.208	1.988	0.329	-0.072	-0.016	-1.348	0.458	0.132	0.050
		(-4.70)	(2.38)	(2.12)	(4.00)	(3.66)	(-6.51)	(-0.83)	(-4.45)	(3.65)	(0.93)	(2.70)
	All sample	-0.275^{***}	0.135^{***}	0.133^{***}	-0.347	0.014	-0.085***	-0.039***	-0.345	0.230^{***}	0.019	0.003
	7 in sample	(-5.75)	(3.73)	(2.64)	(-0.67)	(0.84)	(-6.77)	(-3.84)	(-1.13)	(2.79)	(0.22)	(0.14)
ISS	Investment Grade	-0.222^{***}	0.133^{***}	0.108^{**}	-0.017	0.005	-0.083^{***}	-0.027^{***}	-0.281	0.111	0.076	-0.029^{*}
EC	investment-Graue	(-5.16)	(3.29)	(2.26)	(-0.03)	(0.36)	(-5.95)	(-2.41)	(-0.84)	(1.17)	(0.82)	(-1.72)
К	Junk bondo	-0.253^{***}	0.093*	0.147	1.344^{***}	0.151^{*}	-0.074^{***}	-0.016	-1.320^{***}	0.424***	-0.135	0.014
	Julik Dollus	(-4.94)	(1.84)	(1.27)	(2.92)	(1.67)	(-6.81)	(-0.78)	(-4.40)	(3.73)	(-0.75)	(0.76)
							0.004 ***	0.000***		***		
	A11. an.m.n.1 -	-0.238***	0.117^{***}	0.060	-0.040	0.011	-0.081	-0.032	-0.426	0.237	0.080	-0.009
	All sample	-0.238 ^{***} (-4.39)	0.117 ^{***} (3.27)	0.060 (1.18)	-0.040 (-0.08)	0.011 (0.95)	-0.081 (-6.16)	-0.032 (-3.21)	-0.426 (-1.34)	0.237 ^{***} (2.66)	0.080 (0.97)	-0.009 (-0.53)
1	All sample	-0.238 ^{***} (-4.39) -0.203 ^{***}	0.117 ^{***} (3.27) 0.110 ^{***}	0.060 (1.18) 0.119 ^{***}	-0.040 (-0.08) 0.249	0.011 (0.95) 0.000	-0.081 (-6.16) -0.073 ^{***}	-0.032 (-3.21) -0.027***	-0.426 (-1.34) -0.434	0.237 ^{***} (2.66) 0.114	0.080 (0.97) 0.064	-0.009 (-0.53) -0.015
EW	All sample Investment-Grade	-0.238 ^{***} (-4.39) -0.203 ^{***} (-3.71)	0.117 ^{***} (3.27) 0.110 ^{***} (2.92)	0.060 (1.18) 0.119 ^{***} (2.35)	-0.040 (-0.08) 0.249 (0.41)	0.011 (0.95) 0.000 (0.02)	-0.081 (-6.16) -0.073 ^{***} (-5.13)	-0.032 (-3.21) -0.027 ^{***} (-2.48)	-0.426 (-1.34) -0.434 (-1.24)	0.237 ⁻⁴⁴ (2.66) 0.114 (1.00)	0.080 (0.97) 0.064 (0.68)	-0.009 (-0.53) -0.015 (-1.00)
EW	All sample Investment-Grade	-0.238*** (-4.39) -0.203*** (-3.71) -0.285***	0.117*** (3.27) 0.110*** (2.92) 0.073	0.060 (1.18) 0.119 ^{****} (2.35) 0.361 ^{****}	-0.040 (-0.08) 0.249 (0.41) 1.292 ^{***}	0.011 (0.95) 0.000 (0.02) 0.169^*	-0.081 (-6.16) -0.073 ^{***} (-5.13) -0.063 ^{***}	-0.032 (-3.21) -0.027*** (-2.48) -0.036 [*]	-0.426 (-1.34) -0.434 (-1.24) -1.648 ^{***}	0.237 ^{***} (2.66) 0.114 (1.00) 0.519 ^{***}	0.080 (0.97) 0.064 (0.68) -0.135	-0.009 (-0.53) -0.015 (-1.00) 0.035

5.5. Firm-level analysis

Our previous results are obtained at the bond level. In this subsection, we examine whether our results still hold if the analysis is performed at the firm level. Following Chordia et al. (2015), for firms that have more than one bond issue outstanding, we choose one of the issues by using following four different methods: (1) randomly choose a bond issue; (2) choose an issue with the shortest remaining maturity as long as it is more than one year; (3) choose the most recently issued bond; (4) use the equal-weighted average bond returns across the firm.

Table 15 reports the portfolio and regression results at the firm level. The results show that *PTV* has predictive power for future bond returns, regardless of the way we aggregate to firm-level. The predictive power is stronger for junk bonds, which supports our hypothesis H1 and H2.

6. Conclusion

One important implication for prospect theory is that investors evaluate a financial product by the prospect theory value of its historical return distribution. There is evidence that prospect theory has predictive power for stock returns. However, whether it has predictive power in the corporate bond market is still an open question.

In this paper, we examine whether investors evaluate bonds through a mental process that is captured by prospect theory using U.S. corporate bond market data that covers from January 1973 to December 2013. The bonds with higher (lower) prospect theory value are attractive (unattractive) to investors hence be overvalued (undervalued) and earn lower (higher) future returns. This prediction is tested through both portfolio and regression analysis. The results consistently show that bonds with higher (lower) prospect theory values will on average earn lower (higher) future returns. These results are robust for different specifications of the prospect theory value.

Since junk bonds are prohibited to most institutional investors, they are traded more by individual investors. The predictive power of prospect theory is stronger for junk bonds than that for investment-grade bonds. This implies that individual investors tend to rely more on System 1 thinking when making decisions, while institutional investors employ System 2 thinking more to overwrite or revise their decisions made by System 1 thinking. Unlike the findings in stock market, our results show that the loss aversion component contributes the most to prospect theory's predictive power. The probability weighting component plays an important predictive role only for junk bonds.

Acknowledgments

We thank participants at the seminars of the City University of Hong Kong, South China University of Technology, and China Academic Sinica for helpful comments and discussions. Junbo Wang acknowledges financial support from the City University of Hong Kong Strategic Research Grant (Project 7004766 and 7004979).

References

Abdellaoui, M., 2000. Parameter-free elicitation of utility and probability weighting functions. Manage. Sci. 46, 1497-1512. Abdellaoui, M., Bleichrodt, H., Paraschiv, C., 2007. Loss aversion under prospect theory: a parameter-free measurement. Informs 53 (10), 1659–1674. Acciavatti, P., Linares, T., Jantzen, N., Sharma, R., Li, C., 2015. 2015 High-Yield Annual Review. J.P. Morgan North American High Yield Research, p. A134, A135. Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. J. Financ. Mark. 5, 31-56. Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. J. Finance 61, 259-299. Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2007. Momentum and credit rating. J. Finance 62, 2503–2520. Bai, J., Bail, T., Wen, Q., 2016. Do distributional characteristics of corporate bonds predict their future returns? Working paper, Georgetown University. Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. J. Financ. Econ. 99, 427-446. Bao, J., Pan, J., Wang, J., 2011. The illiquidity of corporate bonds. J. Finance 66, 911-946. Barberis, N., Huang, M., 2008. Stocks as lotteries: The implications of probability weighting for security prices. Amer. Econ. Rev. 98, 2066–2100. Barberis, N., Huang, M., Santos, T., 2001. Prospect theory and asset prices. Quart. J. Econ. 116 (1), 1-53. Barberis, N., Mukherjee, A., Wang, B., 2016. Prospect theory and stock returns: An empirical test. Rev. Financ. Stud. 29, 3068–3107. Becker, B., Ivashina, V., 2015. Reaching for yield in the bond market. J. Finance 70 (5), 1863-1901. Benartzi, S., Thaler, R., 1995. Myopic loss aversion and the equity premium puzzle. Quart. J. Econ. 110, 73-92. Bessembinder, H.K., Maxwell, K.W., Xu, D., 2009. Measuring abnormal bond performance. Rev. Financ. Stud. 22, 4219-4258. Bleichrodt, H., Pinto, J.L., 2000. A parameter-free elicitation of the probability weighting function in medical decision analysis. Manage. Sci. 46, 1485–1496. Boyer, B., Mitton, T., Vorkink, K., 2010. Expected idiosyncratic skewness. Rev. Financ. Stud. 23, 169-202. Brachinger, H.W., 2008. A new index of perceived inflation: Assumptions, method, and application to Germany. J. Econ. Psychol. 29, 433-457. Campbell, J.Y., Ammer, J., 1993. What moves the stock and bond markets? A variance decomposition for long term asset returns. J. Finance 48, 3–37. Chiang, I.-H.E., 2016. Skewness and co-skewness in bond returns, J. Financ, Res. 39, 145-178. Chordia, T., Goyal, A., Nozawa, Y., Subrahmanyam, A., Tong, Q., 2015. Is the cross-section of expected bond returns influenced by equity return predictors? Working Paper. Connell, P., Teo, M., 2009. Institutional investors, past performance, and dynamic loss aversion. J. Finan. Quant. Anal. 44, 155-188. Conrad, J., Dittmar, R., Ghysels, E., 2013. Ex-ante skewness and expected stock returns. J. Finance 68, 85-124. Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. J. Finance 52, 1035–1058. Elton, J.E., Gruber, M.J., Agrawal, D., Mann, C., 2001. Explaining the rate spread on corporate bonds. J. Finance 56, 247-277 Erner, C., Klos, A., Langer, T., 2008. Can prospect theory be used to predict an investor's willingness to pay? J. Bank. Finance 37, 1960–1973. Fama, E.F., French, K.R., 1993. Common risk factors in the returns of stocks and bonds. J. Financ. Econ. 33, 3-56. Fama, E.F., French, K.R., 2008. Dissecting anomalies. J. Finance 63, 1653-1678. Frederick, S., 2005. Cognitive reflection and decision making. J. Econ. Perspect. 19, 25-42. Frieder, L., Subrahmanyam, A., 2005. Brand perceptions and the market for common stock. J. Finan. Quant. Anal. 40 (1), 57-85. Gandelman, N., Hernandez-Murillo, R., 2014. Risk aversion at the country level. Working paper. Goldstein, W.M., Einhorn, H.J., 1987, Expression theory and the preference reversal phenomena, Psychol, Rev. 94, 236–254. Goldstein, M., Hotchkiss, E., 2007. Dealer behavior and the trading of newly issued corporate bonds. Working paper, Boston College and Babson College. Gompers, P.A., Metrick, A., 2001. Institutional investors and equity prices. Quart. J. Econ. 116 (1), 229-259. Gonzalez, R., Wu, G., 1999. On the shape of the probability weighting function. Cogn. Psychol. 38, 129–166. Green, R., Odegaard, B., 1997. Are there tax effects in the relative pricing of U.S. government bonds? J. Finance 52, 609-633. Gulko, L., 2002. Decoupling. J. Portf. Manag. 28, 59-66. 47

Gurevich, G., Kliger, D., Levy, O., 2009. Decision-making under uncertainty - a field study of cumulative prospect theory. J. Bank. Finance 33, 1221–1229.

Haigh, M.S., List, J.A., 2005. Do professional traders exhibit myopic loss aversion? An experimental analysis. J. Finance 60, 523-534.

Han, S., Zhou, X., 2013. Informed bond trading, corporate yield spreads, and corporate default prediction. Manage. Sci. 60 (3), 675–694.

Ilmanen, A., 2012. Do financial markets reward buying or selling insurance and lottery tickets? Financ. Anal. J. 68 (5), 26–36.

Kahneman, D., Frederick, S., 2002. Representativeness revisited: Attribute substitution in intuitive judgment. In: Gilovich, D.G.T., Kahneman, D. (Eds.), Heuristics and Biases: The Psychology of Intuitive Judgment. Cambridge University Press, New York, (Chapter).

Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica 47, 263-291.

Kahneman, D., Tversky, A., 1984. Choices values and frames. Am. Psychol. 39, 341-350.

Kumar, A., 2009. Who gambles in the stock market? J. Finance 64 (4), 1889–1993.

Lan, C., 2008. Characterizing the comovement of the stock and bond markets. Working Paper, University of New South Wales.

Lin, H., Wang, J., Wu, C., 2011. Liquidity risk and expected corporate bond returns. J. Financ. Econ. 99, 628-650.

Lin, H., Wang, J., Wu, C., 2013. Liquidity risk and momentum spillover from stocks to bonds. J. Fixed Income 23 (1), 5-42.

Liu, S., Shi, J., Wang, J., Wu, C., 2009. The determinants of corporate bond yields. Quart. Rev. Econ. Finance 49, 85–109.

Longstaff, F., Mithal, S., Neis, E., 2005. Corporate yield spreads: default risk or liquidity? New evidence from the credit default swap market. J. Finance 60, 2213–2253.

Ma, T., Shen, Y., 2003. Prospect theory and the long-run performance of IPO stocks. Working Paper.

Menkhoff, L., Schmeling, M., 2006. A prospect-theoretical interpretation of momentum returns. Econom. Lett. 93, 360-366.

Prelec, D., 1998. The probability weighting function. Econometrica 66, 497–527.

Sarig, O., Warga, A., 1989. Bond price data and bond market liquidity. J. Finan. Quant. Anal. 24, 367-378.

Shapira, Z., Venezia, I., 2001. Patterns of behavior of professionally managed and independent investors. J. Bank. Finance 25, 1573–1587.

Stanovich, K.E., West, R.F., 2000. Individual differences in reasoning: Implications for the rationality debate? Behav. Brain Sci. 22 (5), 645–726.

Stott, H.P., 2006. Cumulative prospect theory's functional menagerie. J. Risk Uncertain. 32, 101–130.

Thaler, R., 1985. Mental accounting and consumer choice. Mark. Sci. 4, 199-214.

Tversky, A., Kahneman, D., 1992. Advances in prospect theory: Cumulative representation of uncertainty. J. Risk Uncertain. 5, 297-323.

Wu, G., Gonzales, R., 1996. Curvature of the probability weighting function. Manage. Sci. 42 (12), 1676–1690.

Zhang, Y., 2006. Individual Skewness and the Cross-Section of Average Stock Returns. Yale University, New Haven, CT.

Zhang, W., Semmler, W., 2009. Prospect theory for stock markets: Empirical evidence with time-series data. J. Econ. Behav. Organ. 72, 835-849.