The Value of Data to Fixed Income Investors*

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Abstract

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Abstract

Using a structural model, we estimate the value of data to fixed income investors and study its main drivers. In the model, data is more valuable for bonds that are volatile and for which price-insensitive liquidity trades are more likely. Empirically, we find that the value of data on corporate bonds increases with yield, time-to-maturity, size, callability, liquidity, and uncertainty during normal times. However, these cross-sectional differences vanish as the value of data falls during financial crises. Using a regression discontinuity based on maturity, we provide causal evidence that investor composition affects the value of data.

1 Introduction

Data is arguably the most valuable resource to an investor. The recent increase in the availability of big data, coupled with an advance in machine learning technology, means that investors today can forecast fundamentals and asset prices with vastly improved precision. Data, however, are not all created equal, with some more valuable than others. The value of data depends on its usefulness for prediction, but also, critically, on the potential gains from prediction. In this paper, we estimate the value of data from the perspective of fixed income investors and study the question: what drives the value of information about corporate bonds?

For a concrete example, suppose you are a bond investor looking to improve your default predictions by acquiring alternative data such as satellite images. How much would you pay? Would you be willing to pay more for information about small or large firms? Does it matter if the bonds are highly-rated or long-dated? One may conjecture that information about small or low-rated firms is more valuable because they are more likely to default, and hence there is more to learn about them. Also, data for bonds with longer duration may be more valuable since it allows more time to exploit informational advantage. However, such bonds also tend to be less liquid. As a result, price impact can overwhelm your trading gains even if you can predict default better than anyone. Thus, what type of data is more valuable is an empirical question, one which we guide with theory.

We answer this question in the context of the corporate bond market using a structural model rich enough to accommodate salient features of fixed income securities (Back and Baruch, 2004a; Glosten and Milgrom, 1985). First, corporate bonds are infrequently traded. On average, corporate bonds traded only six times per month from 2002 to 2021, significantly less than equities. Second, the payoffs of bonds are binary at maturity, and their prices are usually bounded between zero and the face value. Third, bonds are traded over the counter and exhibit large cross-sectional variations in bid-ask spreads. We use a structural model to estimate the value of information for each corporate bond each month based on its yield, duration, bid-ask spread, and trading volume over the month. This model allows us to study even severely illiquid bonds at a relatively high frequency.

The value of data that we measure can be interpreted as the maximum amount an investor would be willing to pay to learn whether a firm will default on a bond before it matures. A signal that a firm intends to default clearly fits this description. Other signals, say alternative data on firm sales, provide more limited, partial information about the likelihood of default. For such partial signals, our measure provides an upper bound on their value to investors.

Our estimates reveal new stylized facts about the value of corporate bond data and its relations to various bond characteristics. First, information about high-yield bonds is more valuable than investment-grade ones. Within high-yield bonds, bonds with a rating of B have greater information value than bonds closer to default (those with a lower rating such as CCC and below). Second, the value of information generally rises with time to maturity but falls sharply at the ten-year mark. Third, larger bonds have higher total information value and higher unit information value per face dollar. Fourth, the value of information increases with bond liquidity as measured by transitory price movements, the gamma measure in Bao, Pan and Wang (2011). Lastly, information values increase on average with return volatility, though this relationship is hump-shaped.

In the time series, bond information values drop sharply during the Great Recession and the Covid-19 pandemic. The mean unit value of information fell from 0.05 per dollar in October 2007 to 0.03 per dollar in December 2008 during the Great Recession, and decreased from 0.06 per dollar in January 2020 to 0.03 in March 2020 during the pandemic crisis. These findings are the opposite of what Kadan and Manela (2020) find for equities. The volatility of both stocks and bonds rises during turbulent times, increasing the value of data. Both markets also become less liquid, which decreases the value of data. However, the volatility effect dominates for stocks, whereas the liquidity effect dominates for corporate bonds, resulting in a lower value of information for corporate bonds.

These stylized facts about bond information values hint at its main drivers. However, such correlations cannot be interpreted as their ultimate causes without strong assumptions about the absence of reverse causality and omitted variables. For example, we find it quite reasonable that an exogenous increase in the value of information would precipitate some investors to acquire more data and trade on it. As the informed fraction rises, characteristics like yield, volatility, and liquidity could all be affected. To identify an ultimate driver of the value of data, we require exogenous variation in this driver.

Fortunately, our analysis reveals a salient discontinuity in the value of information as a function of time to maturity, which provides exogenous variation. This discontinuity is visible in raw data plots (see Figure 1) and arises because mutual funds, influential financial intermediaries for corporate bonds, are segmented across an arbitrary bright line at ten years to maturity, which separates short-term and long-term bonds. We find that around this threshold, the share of the bond amount outstanding held by mutual funds changes discontinuously.

This discontinuity allows us to identify a causal effect of investor composition on the value of information. Using a regression discontinuity design based on maturity, we find that mutual funds increase the value of data about corporate bonds. A one standard deviation increase in the mutual fund share of corporate bond holdings causes a 1.4 to 1.8 standard deviation increase in the value of acquiring information. These increases are driven mainly by an increase in bond liquidity due to a greater mutual fund share. Bond mutual funds apparently play the role of liquidity traders in this market. Their presence allows informed investors to mask their trades and exploit their informational advantage.

Our paper provides the first empirical estimates of the value of data (or information) to fixed income investors. While a large theoretical literature studies the value of information to investors, few papers provide empirical estimates.[1] Manela (2014) studies the value of information to equity investors when information diffuses gradually. Kadan and Manela (2019) estimate the value of macro news using index options and separate between the instrumental and psychic value of information. Farboodi, Matray, Veldkamp and Venkateswaran (2021a) estimates the initial value of a unit of precision and finds that it is greater for large growth stocks. Kadan and Manela (2020) uses the continuous trading Kyle-Back model to estimate the value of information using high-frequency stock trades and quotes data. Farboodi et al. (2021b) pushes the frontier further by allowing for multiple assets and investor heterogeneity.

All of the aforementioned papers focus on the valuation of macro data or equity data. One central input to models exploited in these papers is that securities trade frequently. As we show in the paper, such a stringent prerequisite clearly does not apply to a large portion of corporate bonds. Had we used existing approaches, we would have had to restrict the analysis to select few bonds and periods. For example, calculating the value of data via the Kyle model, one can only

[1] The information economics literature is extensive. See Grossman and Stiglitz (1980), Kyle (1985), Admati (1985), and Back (1992) for early theories, and Cabrales et al. (2013), Epstein et al. (2014), Glode and Opp (2016), and Farboodi and Veldkamp (2020) for more recent theoretical contributions. Veldkamp (2011) provides an excellent survey.

get as low as 15% of the bond-month observations compared to our baseline measure. Beyond the liquidity constraint, existing models also fail to consider unique bond features. For example, the bond's payoff is binary compared to the equity's unbounded payoff. Thus, existing approaches are less suitable for estimating the value of information about fixed income securities.

Our paper also provides the first causal evidence on the drivers of the value of data in any asset market. We show that the composition of bond investors affects the value of data. This finding relates to a small but growing literature that studies the impact of institutional investors on corporate bond pricing. For example, Mahanti, Nashikkar, Subrahmanyam, Chacko and Mallik (2008) show that corporate bonds held by mutual funds with high turnover tend to have lower transaction costs; Anand, Jotikasthira and Venkataraman (2021) emphasize heterogeneous trading styles of corporate bond funds; Chen, Huang, Sun, Yao and Yu (2020) find that corporate bonds with a higher fraction owned by insurance companies have lower liquidity premiums; and more recently, Bretscher, Schmid, Sen and Sharma (2020) estimate demand elasticity of mutual funds and insurance companies on different bond characteristics.

A broader literature on corporate bonds documents the importance of illiquidity and excess volatility in corporate bond pricing, especially in times of stress (to name a few, Bao, Pan and Wang, 2011; Bao and Pan, 2013; Friewald, Jankowitsch and Subrahmanyam, 2012; Dick-Nielsen, Feldhütter and Lando, 2012). Our paper integrates these two important bond trading features and other integral bond characteristics into a single economically meaningful measure of the value of bond data.

In the following sections, we present the structural model to estimate bond information values in Section 2, discuss their stylized facts in Section 3, and examine their drivers in Section 4. A conclusion follows.

2 Estimation

We explain the model and estimation method in this section. We adopt a framework that can capture one unique feature of the corporate bond market, namely, the infrequent trades. Existing methods rely on high-frequency pricing data to calculate return uncertainty, which is not available for most corporate bonds at the monthly frequency since the median number of trades per bond is twice a month. To capture a large sample of corporate bonds, we estimate liquidity and value of information using the Glosten-Milgrom model specified in Back and Baruch (2004a). In this model, liquidity trades arrive in the Poisson process, dealers can observe each trade, and the final asset payoff is binary, all of which make the model more applicable to the corporate bond market.

Model Setup There is one risky bond in the economy with uncertain payoff $\tilde{v} \in \{0, 1\}$, and one risk-free bond with the interest rate set to 0. There are three groups of agents in the economy: liquidity traders, informed traders and competitive market makers. All agents are risk neutral. Liquidity trades arrive exogenously with intensity β, with fixed order size δ. Informed traders know exactly the final payoff of the asset, and decide his trading intensity endogenously. The market makers set bid price and ask price to break even in expectation. In other words, the bid and ask prices reflect the expected payoff given the the information set just before time t and trade direction.

Finally, the risky bond matures with intensity r. Upon maturity, the payoff of the risky bond is immediately observed by the market. Empirically, a given bond have multiple coupon payments and a final principal payment. Hence we match r with the Macaulay duration of the bond, which is the value weighted average of cash-flow maturities.

In equilibrium, if the informed trader deviates from the trading size δ, that will reveal he is informed immediately. Hence all the trades are of size δ in equilibrium. Furthermore, in equilibrium, all the bid and ask prices are between 0 and 1. If the bond payoff is 1, the informed trader will only buy and never sell; if the bond payoff is 0, the informed trader will only sell and never buy.

Following Back and Baruch (2004a), denote p as the market maker's belief about the bond's expected payoff. $a(p; \beta, r)$ and $b(p; \beta, r)$ denote the ask and bid price given the market maker's belief about the bond's payoff $p = E[\tilde{v}]$. We sometimes refer to them as $a(p)$ and $b(p)$, but it is important to keep in mind that both depend on the frequency of liquidity trades (β) and duration r. Furthermore, if the bond pays off 1, denote the informed trader's value function as $V(p; \beta, r)$. We sometimes simply refer to it as $V(p)$. Note that an informed trader who knows the bond will pay off 1 will always buy, as a result, $V(p)$ is a non-decreasing function of p. If the bond pays off 0, denote the informed trader's value function as $J(p; \beta, r)$, or $J(p)$ in short. By similar logic as before, $J(p)$ is a non-increasing function of p. In equilibrium, it must be that if the informed trader knows the final payoff is 1, he should buy, and if the informed trader knows the final payoff is 0, he should sell. Since the price jumps to $a(p)$ when a buy order is executed and jumps to $b(p)$ when a sell order is executed, this implies that the values of the informed trader have the following relationship

$$V(p) = [1 - a(p)]\delta + V(a(p)) \tag{1}$$

$$J(p) = b(p)\delta + J(b(p)) \tag{2}$$

where $[1 - a(p)]\delta$ and $b(p)\delta$ are the profits from executing this trade. $V(a(p))$ and $J(b(p))$ is the continuation value after the price jumps either to $a(p)$ in the buy case or $b(p)$ in the sell case.

Furthermore, it must also be the case that the informed trader is indifferent between trading and not trading. In the case when an informed investor does not trade, his value functions evolve according to the following equations

$$rV(p) = V'(p)f(p) + \beta[V(a) - V(p)] + \beta[V(b) - V(p)] \tag{3}$$

$$rJ(p) = J'(p)f(p) + \beta[J(a) - J(p)] + \beta[J(b) - J(p)] \tag{4}$$

where $f(p) \equiv p(1-p)\beta\left[\frac{p-b}{(1-p)b} - \frac{a-p}{(1-a)p}\right]$ is the drift in the bond's price. When the informed trader does not execute any orders during time dt, several things may happen: the bond may mature with probability rdt, in which case the informed trader's valuation becomes 0. The price also drifts by $f(p)dt$, and the change in informed trader's valuation is $V'(p)f(p)dt$ or $J'(p)f(p)dt$. Finally, with probability βdt, an uninformed buy or sell order arrives, which pushes the market price to either $a(p)$ in the buy case or $b(p)$ in the sell case. As a result, the change in informed trader's value is $V(a) - V(p)$ and $J(a) - J(p)$ if the uninformed order is a buy order, and the change in informed trader's value is $V(b) - V(p)$ and $J(b) - J(p)$ if the uninformed order is a sell order.

Finally, if the final bond payoff is 1 (0), and price is 1(0), then the informed trader has no information advantage, and his value is 0. This implies the boundary condition

$$\lim_{p\to 1} V(p) = \lim_{p\to 0} J(p) = 0 \tag{5}$$

On the other hand, if the final bond payoff is 1 (0), and price is 0(1), then the informed trader's value is ∞. This implies another set of boundary conditions

$$\lim_{p \to 0} V(p) = \lim_{p \to 1} J(p) = \infty. \tag{6}$$

The equilibrium is hence defined by Equation (1), (2), (3) and (4), together with the boundary conditions in (5) and (6).[2] Notice that $V(p)$ and $J(1-p)$ are symmetric around $p = \frac{1}{2}$. This feature helps with the numeric solution as outlined in Appendix B of Back and Baruch (2004a).

Ex-ante, the expected value of information is thus

$$VOI = pV(p;\beta,r) + (1-p)J(p;\beta,r) \tag{7}$$

The more frequently the liquidity trader arrives, the smaller the price impact for any given trade. Hence both $V(p;\beta,r)$ and $J(p;\beta,r)$ increase with β. On the other hand, larger r implies less time for informed traders to trade on their information, as a result, V and J decrease with r.

VOI is the value of information for a bond with a face value of one dollar. To get the value of information for the total issuance of the bond, we need to scale VOI by the bond's amount outstanding. We define the total value of information as

$$TVOI = \text{Amount Outstanding} \times VOI \tag{8}$$

Everything else equal, bonds with larger amount outstanding have larger value of information. Finally, we will measure both VOI and $TVOI$ at the monthly-bond level.

Data We obtain corporate bond trading data from enhanced Trade Reporting and Compliance Engine (TRACE) and information on bond characteristics from WRDS bond return dataset, including amount outstanding, ratings and the average bid-ask spreads of each month. Bonds' issuance information is from Mergent FISD. The sample period runs from November 2002 to September 2020. We only include corporate bonds with ratings higher or equal to CCC. Post-estimation, we further screen our sample to bond-month observations for which the final estimates of β does not

[2] We also verify that in equilibrium, $V(p) \geq [b(p)-1]\delta + V(b(p))$ and $J(p) \geq -a(p)\delta + J(a(p))$, so that it is never better than optimal for an informed investor who knows final payoff is 1 to sell, or for an informed investor who knows the final payoff is 0 to buy.

equal to the starting points. Furthermore, to rule out extreme observations, we winsorize the final sample at the top and bottom 2% for both the β estimated and VOI estimated. In the end, we are left with 875,582 bond-month observations for a unique list of 22,872 bonds.

Estimation Procedure We estimate the model at the bond-month level. There are three unknown parameters that we need to estimate: the average trading size δ, the intensity of public information release r and the arrival rate of liquidity trades β.

For each month m and bond i, we set $\delta_{i,m}$ equal to the average trading size, as a fraction of the amount outstanding. We set $\frac{1}{r_{i,m}}$ equal to the duration of bond i in month m. We then map $yield_{i,m}$ to a risk-neutral price measure $p_{i,m}$ using the following equation

$$p_{i,m} = e^{-\frac{yield_{i,m}}{r_{i,t}}} \tag{9}$$

Finally, we estimate $\beta_{i,m}$ using the following condition,

$$\frac{a(p_{i,m}; \beta_{i,m}, \delta_{i,m}) - b(p_{i,m}; \beta_{i,m}, \delta_{i,m})}{p_{i,m}\,(1 - p_{i,m})} = \frac{BA_{i,m}}{p_{i,m}\,(1 - p_{i,m})} \tag{10}$$

where $a(p; \beta, \delta)$ and $b(p; \beta, \delta)$ are the ask and bid prices from the model given the parameters β, δ and at the price p. $yield_{i,m}$ is the end of the month yield and $BA_{i,m}$ is the average bid-ask price for bond i in month m. The only unknown variable in the equation is $\beta_{i,m}$, so we can solve it by setting the left-hand side (model output) to the right-hand side empirical counterpart. The denominator $p_{i,m}\,(1 - p_{i,m})$ scales both sides so that the left-hand side (model counterpart) remains sensitive to β even for extreme bond prices. Finally, for a given bond, we use the previous month's estimation of β as the initial value for the following month's estimation whenever possible.

3 Bond Information Value: Stylized Facts

Our measure of the value of information, VOI, captures multiple dimensions of corporate bond information in a nonlinear way. Thus it differs from conventional variables in the corporate bond market such as bond illiquidity and bond volatility. In this section, we present the stylized facts of bond information value. First, we check the cross-sectional relationship of VOI and bond characteristics. Then we discuss the time-series evolution of bond information value. Lastly, we compare our baseline measure with the measure from alternative models such as the Kyle model.

3.1 VOI and Bond Characteristics

A corporate bond has many features such as size, ratings, maturity, liquidity, security, seniority, coupon rate, protective covenants, call provision, and convertibility. In this subsection, We examine a bond's value of information and its relationship to six key bond characteristics including rating, maturity, size, callability, illiquidity, and volatility. Each month, we sort corporate bonds by a given feature, calculate each bond's unit value of information per dollar, and then aggregate them within each feature-sorted portfolio using the weight of a bond's outstanding amount. We then plot the time-series average and median values of each portfolio in Figure 1 and summarize the relationships below.

Rating Panel (a) of Figure 1 shows that high-yield (HY) bonds have significantly higher VOI than investment-grade (IG) bonds with the jump happening from BBB− to BB+. Within investment-grade bonds, the unit VOI has similar magnitude from AAA to BBB−. In the high-yield domain, VOI first increases with credit ratings then goes down after the single-B rating. Distressed bonds with lower ratings like CCC− have much lower VOI compared to other high-yield bonds.

Maturity The relationship between VOI and a bond's remaining years to maturity is not monotonic, as shown in Panel (b) of Figure 1. A bond's unit value of information increases with its maturity when the bond has less than ten years to maturity. However, a bond's VOI falls sharply when its maturity is longer than ten years, dropping to a level similar to short-term bonds with less than two years to maturity. Then VOI increases again almost monotonically with a bond's maturity. The sharp change of VOI around the ten-year maturity creates a puzzle which we explore in Section 4.

Size Panel (c) of Figure 1 indicates that a bond's unit value of information increases monotonically with its size which is measured by the outstanding amount. Note that VOI in this plot is for a bond with face value of one dollar. That is, a larger bond not only has a higher total VOI, which is the product of unit VOI and the bond size as shown in Equation (8), but also has a higher unit VOI.

Optionality Panel (d) of Figure 1 shows that bonds that can be redeemed or paid off by the issuer prior to the bonds' maturity date have a higher unit value of information than non-redeemable bonds.

Liquidity We also examine bond trading liquidity and its relationship to bond information value. The literature has proposed multiple empirical measures of bond illiquidity, see Schestag, Schuster and Uhrig-Homburg (2016) for the summary report. One common feature to these proxies of illiquidity is that they require a certain degree of liquidity, otherwise they cannot be calculated. For example, the gamma measure in Bao, Pan and Wang (2011), one of the mostly used measures in the bond literature, is based on the magnitude of transitory price movements. To calculate a bond's monthly illiquidity measured by γ, one needs to have sufficient observations on the daily price change within a month. In our sample, 38.8% of bond-month cannot have valid gamma measures if we require at least five daily price changes observable per month. In contrast, our measure of VOI is designed to capture the infrequent trading feature in the corporate bond market. Thus we can calculate the value of information for all types of bonds including those with severe illiquidity.

As shown in Panel (e) of Figure 1, bonds with high illiquidity under the gamma measure have a lower unit value of information. However, bonds with severe illiquidity whose gamma cannot be calculated, labeled "NA", seem to have slightly higher VOI than bonds with high illiquidity under the gamma measure. The difference between High Illiquid and NA groups is not significant if using the median value.

Volatility Another important feature in corporate bond trading is volatility or uncertainty. Our model implies that the payoff uncertainty is directly related to bond's yield. We sort bonds into four portfolios based on the model implied payoff uncertainty. In the model, the variance of payoff is $\exp(-yield/r)(1-\exp(-yield/r))$. As shown in Panel (f) of Figure 1, generally speaking, bonds with higher uncertain payoff have higher unit value of information.

In sum, bonds with a higher unit value of information are those with higher credit risk, larger size, redeemable provision, and higher liquidity. Investors are willing to pay more for per-dollar information of these bonds.

3.2 Time-series Evolution of Bond Information Value

A bond's value of information is not only related to its characteristics but also varies with economic conditions. In this subsection, we examine the time-series variation of bond information values during our sample period of 2002−2021. Following Figure 1, we construct bond portfolios according to their ratings, time-to-maturity, size, and callable provision, respectively, and plot the median unit value of information over time in Figure 2. Our findings suggest five stylized facts.

First, high-yield bonds, on average, have a higher unit value of information than investment-grade bonds. However, the gap narrows over time mainly due to the increasing VOI of IG bonds. Panel (a) of Figure 2 shows that both IG and HY bonds see their information value falling significantly during the global financial crisis of 2007−2009. Afterward, the VOI of IG bonds steadily increases, whereas the VOI of HY bonds never recovers to their pre-crisis level, instead it presents a volatile movement and is easily affected by negative shocks such as the one in the energy market in 2014Q4. During the COVID crisis, the information value of IG and HY bonds dropped again.

Second, short-term bonds and long-term bonds have a similar unit value of information before the global financial crisis, though their value is significantly lower than mid-term bonds. After the crisis, long-term bonds with remaining maturity longer than ten years had the most salient growth in the unit value of information. The rapid growth makes long-term bonds have almost the same level of information value as mid-term bonds toward the end of our sample period, 2020Q1.

Third, the information value of large-size bonds dominated that of medium-size bonds before the global financial crisis, but the difference markedly reduced in the post-crisis period, and even disappeared during the crisis, both the global financial crisis and the COVID crisis. Small-size bonds have stable and lowest information value throughout the sample period.

Fourth, bonds with redeemable provision have a higher unit value of information than non-redeemable bonds throughout the sample period, echoing the cross-sectional pattern in Panel (d) of Figure 1.

Lastly, all bonds' information values fell during the crises, both the Great Recession of 2007−2009 and the Covid pandemic crisis of 2020.

3.3 Comparison with a Kyle-based Measure

We compare our measure of VOI with the value of information calculated using methods developed for the equity market. Kadan and Manela (2020) uses the Kyle-Back model to estimate the value of information for equities by first calculating the volatility of returns and Kyle-λ, then taking the ratio of the two to infer the value of information. The key insight is that the value of information is determined by both uncertainty as well as the price impact.

There are two main differences between our model and the Kyle model that is used for equity. First, our method accounts for infrequent trading, a key feature of the corporate bond market. The median bond trades about 6 times a month. The model we use does not rely on frequent transaction data to infer the illiquidity of the market. On contrary, the Kyle model assumes continuous trading and relies on high-frequency data to estimate price impact. Second, we account for the fact that the bond's payoff is binary, hence the uncertainty of the asset payoff is bounded. The volatility in returns may not approximate well the final payoff uncertainty. To understand how important these differences are, we apply the Kyle model used in the equity market to estimate the value of information for bond investors and compare the results with our baseline estimates in Table 2.

First, our method is able to calculate VOI for a much larger sample of bonds compared to the measure based on the Kyle model. Estimating Kyle-λ and return volatility need a significant amount of transaction data. If we exclude bonds with fewer than 10 transactions in a given month, we only get 60% of the bond-month observations compared to our baseline measure.[3] That number drops to only 15% if we require the estimated Kyle-λ to be significantly positive (with t-statistics larger than 2). The sub-sample of bonds for which the Kyle-model measure is available tends to be higher rated, larger in size, and shorter in maturity since these are the bonds that tend to be more liquid and are traded the most.

Second, the business cycle pattern using the Kyle-model measure is also different from our baseline case. In particular, the Kyle-model measure indicates higher VOI during crisis periods, as shown in Figure 3. In other words, the measured increase in uncertainty during crisis periods is higher than the measured increase in illiquidity. Since the Kyle model assumes normal payoff distribution instead of binary payoff, it tends to overestimate the uncertainty in the payoff. On

[3] If we only include bonds with more than 20 transactions a month, then we only get less than 10% of the observations.

the other hand, during crisis periods, the sub-sample of bonds with available Kyle-model measure is particularly tilted towards more liquid bonds,[4] hence it tends to under-estimate the increase in illiquidity. Both forces contribute to over-estimation in VOI during crisis periods.

4 Investor Composition and Information Value

In asymmetric information models, asset market participants are usually characterized as informed, uninformed, or liquidity (noise) traders. Investor composition−−the relative proportions of each group−−can have important effects on market prices, volatility, liquidity, and on the focus of our paper, the value of information. For example, an increase in the arrival rate of price-insensitive liquidity trades would all else equal increase bond liquidity and allow a risk-neutral informed investor to profit more from her informational edge. Thus, her willingness to pay for information would tend to rise.

The real world is of course more nuanced. Is a bond mutual fund more like an informed investor or more like a liquidity trader? What about an insurance company? As we show below, these two groups of financial intermediaries hold the lion's share of corporate bonds. Thus understanding how each affects the value of information can substantially advance our understanding of the drivers of the value of information.

In this section, we document a causal effect of investor composition on the value of information. Specifically, we use a regression discontinuity design to identify the treatment effect of the share of a bond that mutual funds hold on the value of information about that bond.

4.1 Investor Composition Summary Statistics

For investor composition analysis, we obtain detailed quarterly holding information at the investor-CUSIP level from the eMaxx dataset for the sample period of 2005Q1 to 2020Q3. At each time point, we group a bond's holdings across two types of primary investors: insurance companies and mutual funds.

Table 3 reports summary statistics for the share of bonds held by mutual funds in our sample.

[4] The number of bonds with available Kyle-model measure drops to 43% of the baseline sample during the global financial crisis.

We can see that the mutual fund share is larger for lower-rated bonds. The mean mutual fund share rises from 8 percent for AAA-rated corporate bonds to 32 percent for CCC−rated ones. It also shows considerable variation within rating groups, with a standard deviation of 8 to 19 percentage points.

In addition to ratings, mutual fund holding shares also vary significantly across bonds with different maturities. Figure 4 provides visual evidence of the maturity discontinuity we exploit for identification. The jump at the threshold measures the first-stage effect of the running variable (time to maturity) on the endogenous variable (the mutual fund share). The figure shows that the mutual fund share drops markedly at 10 years to maturity. Mutual funds hold about 13 percent of the mean bond with just under 10 years to maturity, but only 9 percent for slightly longer-term bonds.[5]

The change in mutual fund shares is likely induced by the investment mandates of intermediate bond funds. Mutual funds often focus on different investment strategies. Along the maturity dimension, there are typically three types of bond mutual funds offered: short-term bond funds, intermediate bond funds, and long-term bond funds. Intermediate bond funds saw the highest AUM growth in the past decade.[6] Intermediate bond funds are restricted to purchase bonds between 5-10 years. For example, Vanguard's intermediate-term corporate bond index fund invests in "U.S. dollar-denominated, investment-grade, fixed-rate, taxable securities issued by industrial, utility, and financial companies, with maturities between 5 and 10 years".[7] Hence as a bond ages and crosses the 10-year threshold, it becomes eligible for purchase from these intermediate bond funds.

4.2 Treatment Effects Based on the Maturity Discontinuity

Figure 5 shows the reduced-form effect on VOI of crossing the 10-year maturity threshold. The value of information drops markedly by 25 percentage points at the cutoff. Because the first-stage effect of crossing this threshold on the mutual fund share is also negative (See Figure 4), together they imply a positive treatment effect of the mutual fund share on the value of information.

[5] A second discontinuity in bond rating is visible in Figure 1. While the discontinuity around investment-grade versus high-yield rating is strong and affects the mutual fund share, we find evidence of bunching around this threshold using (McCrary, 2008) manipulation tests, which violates the assumptions of a regression discontinuity design.

[6] "Breaking Down the Data: A Closer Look at Bond Fund AUM", BlackRock Report June 2016.

[7] https://investor.vanguard.com/investment-products/mutual-funds/profile/vicsx#overview

Why does information become more valuable when the mutual fund share rises? Panel (b) of Figure 5 shows that the arrival rate of liquidity trades, β, jumps at the same cutoff. We find no such discontinuities in the yield. We do find that higher mutual fund shares lead to small average trading sizes, which decreases the value of information. These results suggest that the mechanism by which changes to investor composition affect the value of information is that, all else equal, an increase in the mutual fund share means more price-insensitive liquidity trades and a greater ability for informed investors to profit from their informational advantage.

The identifying assumption is that in the neighborhood of the threshold, the effect of the running variable on the outcomes is smooth. Thus, a discontinuity in the outcome that coincides with the one in the mutual fund share can be attributed to the effect of the mutual fund share on the outcome. Under this identifying assumption, we can estimate the local average treatment effect of the mutual fund share on the value of information (and on β). These estimates depend on choices regarding the degree of the polynomial controlling for smooth variation in the running variable, on the size of the neighborhood around the threshold we focus on (the bandwidth), and on the kernel used. We tried our best to avoid making these decisions and instead rely on the optimal choices suggested by Calonico et al. (2014) and implemented them in the RDrobust package for Stata.

We report the treatment effects of the mutual fund share on the value of information in Table 4. Using the robust estimator suggested by Calonico et al., we estimate a one standard deviation increase in the mutual fund share increases the value of information by 1.5 standard deviations. A 10 percentage point increase in mutual fund shares increases the value of information by 9 cents per dollar of face value invested.

4.3 Robustness

One threat to identification is that issuance of corporate bonds around the 10 years to maturity cutoff changes discontinuously to align with the investment mandates of financial intermediaries like mutual funds. If that was the case, bonds on each side of the cutoff could be quite different and the continuity assumptions sufficient for a valid regression discontinuity design may be violated. McCrary (2008) develops a test for such manipulation of the running variable that essentially tests whether the histogram of bond maturity changes discontinuously around the same cutoff. Figure 6 panel (a) shows that in the full sample of bonds that we study, we find evidence of manipulation around the maturity cutoff. While this does not immediately invalidate the experiment as this condition is sufficient but not necessary, it does suggest that bonds may be issued just below the 10 year mark to target a particular clientele.

For robustness, we also look at a subsample of bonds whose maturity at issuance is larger than 10 years, and which eventually will switch from one side of the threshold to the other. Table 5 presents the results. The sample size is a third of the full sample size. But the treatment effect is quantitatively similar to the full sample ones. Figure 6 panel (b) shows that in this subsample we find no evidence of manipulation, which suggests that the RDD assumptions are likely to hold.

5 Conclusion

We estimate the value of data to an investor about infrequently-traded bonds using a structural model and study its main drivers. In the model, data is more valuable for more volatile high-yield bonds and for ones where information-insensitive liquidity trades are more likely. We find that during normal times the value of data on corporate bonds increases with yield, time-to-maturity, size, callability, liquidity, and uncertainty. But these cross-sectional differences vanish as the value of data falls during financial crises. Using a regression discontinuity design we provide causal evidence that investor composition affects the value of data.

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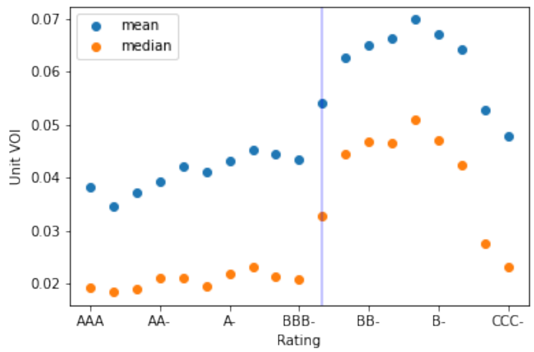
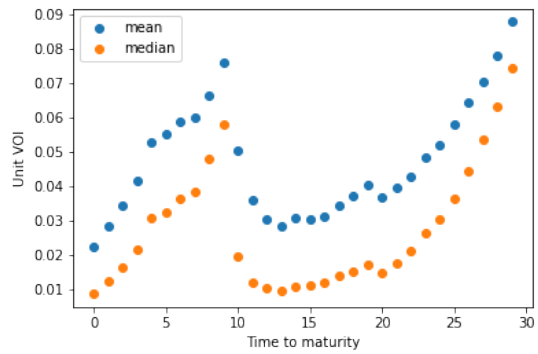
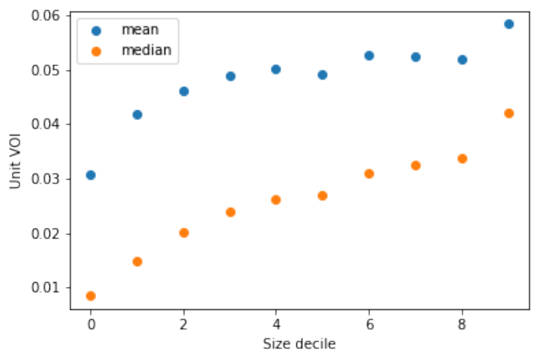
Figure 1: Unit Value of Information and Bond Characteristics



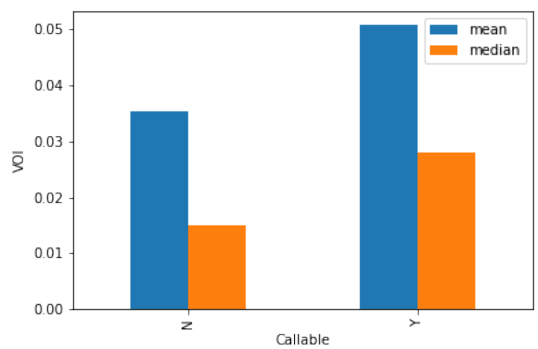
(a) By Rating



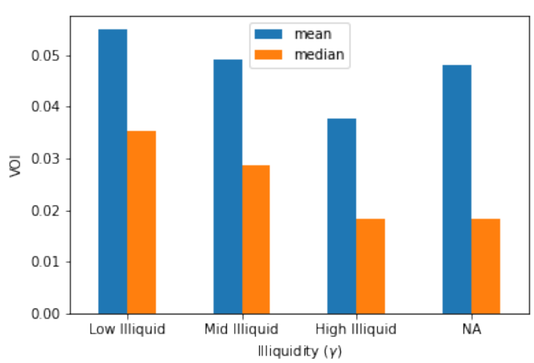
(b) By Time to Maturity



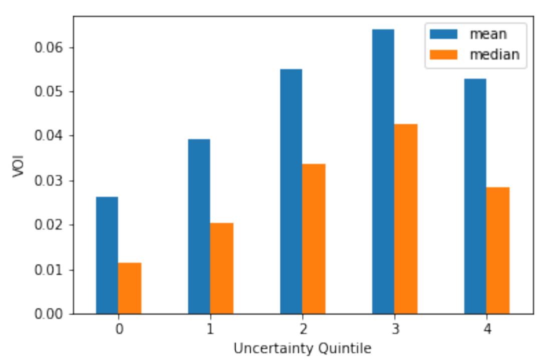
(c) By Size Decile



(d) By Optionality



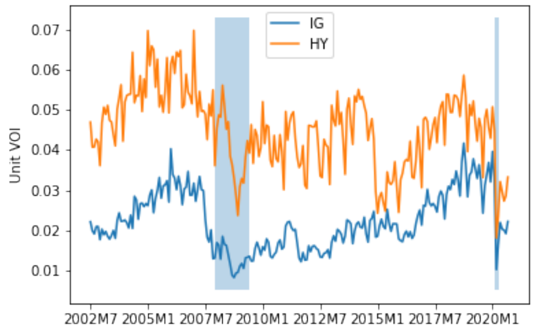
(e) By Illiquidity Tercile



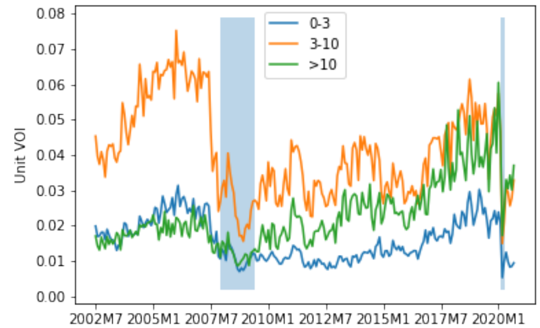
(f) By Uncertainty Quintile

This figure plots the mean and median of VOI by rating group, time to maturity , size decile of amount outstanding, convertibility, illiquidity and uncertainty. We use the gamma measure in Bao et al. (2011) to approximate illiquidity. Uncertainty is measured using model implied payoff variance, which is equal to $\exp(-yield/r)(1-\exp(-yield/r))$.

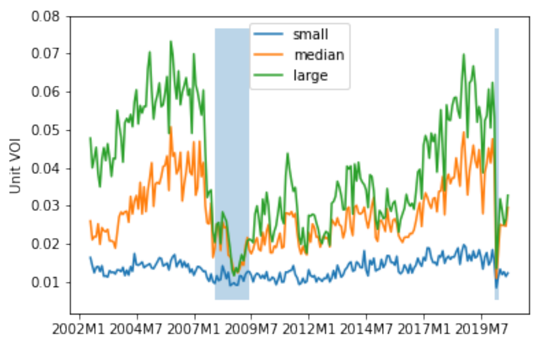
Figure 2: Value of Information Over Time



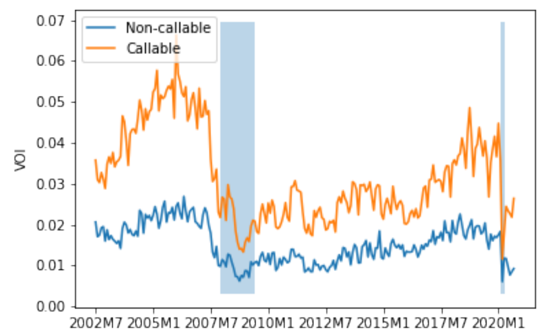
(a) By Rating



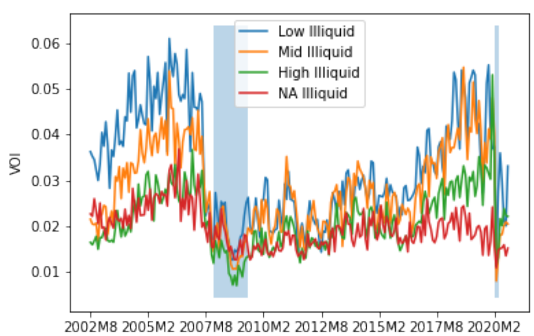
(b) By Time to Maturity



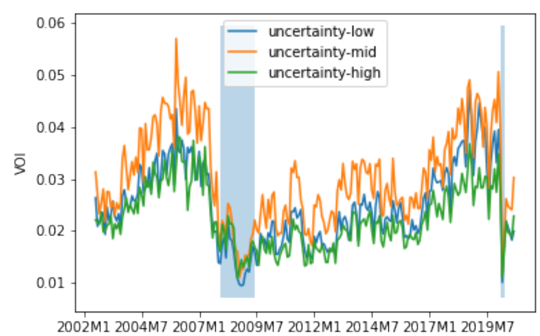
(c) By Size Tercile



(d) By Optionality



(e) By Illiquidity Tercile

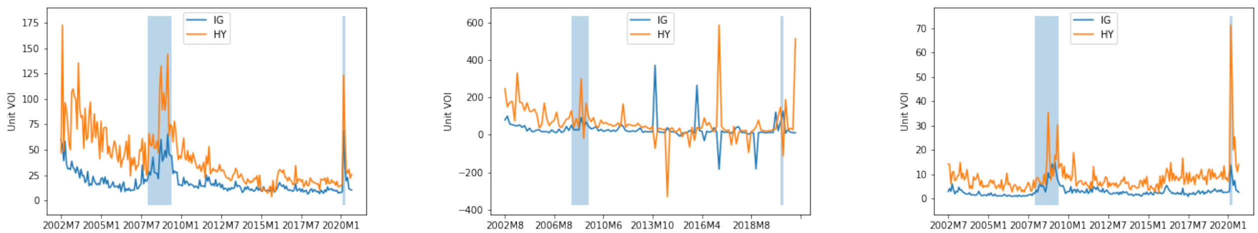


(f) By Uncertainty Tercile

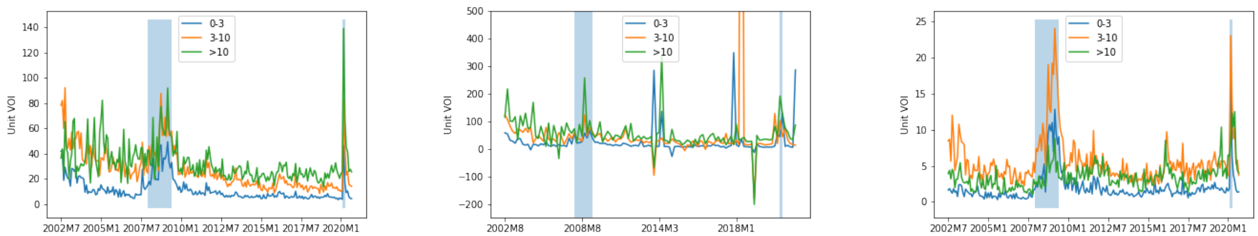
This figure plots the median unit value of information over time by rating group, time to maturity, size decile of amount outstanding and convertibility. We use the gamma measure in Bao et al. (2011) to approximate illiquidity. Uncertainty is measured using model implied payoff variance, which is equal to $\exp(-yield/r)(1 - \exp(-yield/r))$. *Shaded areas are NBER recessions.*

Figure 3: Value of Information Calculated from the Kyle Model

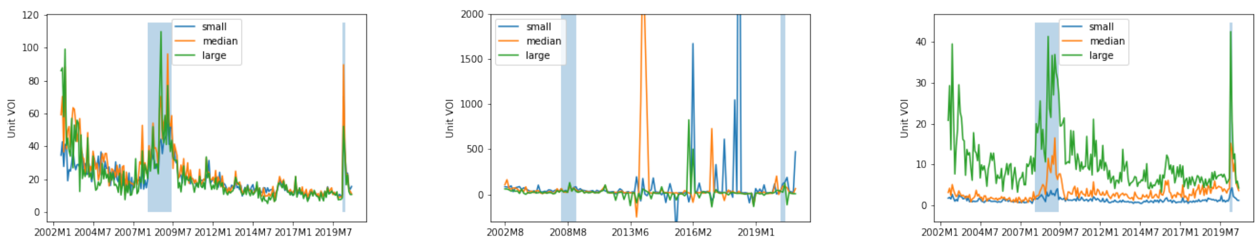
(a) By rating



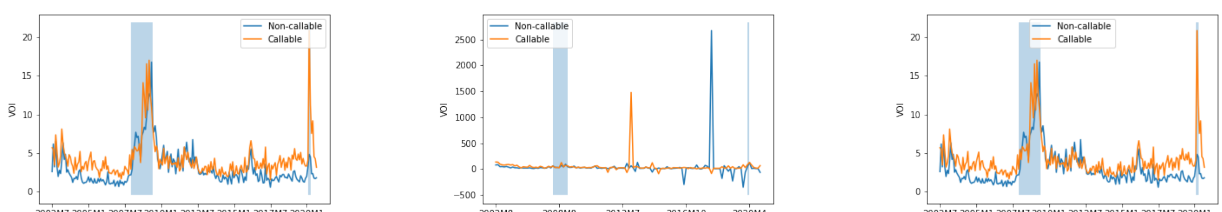
(b) By maturity



(c) By size



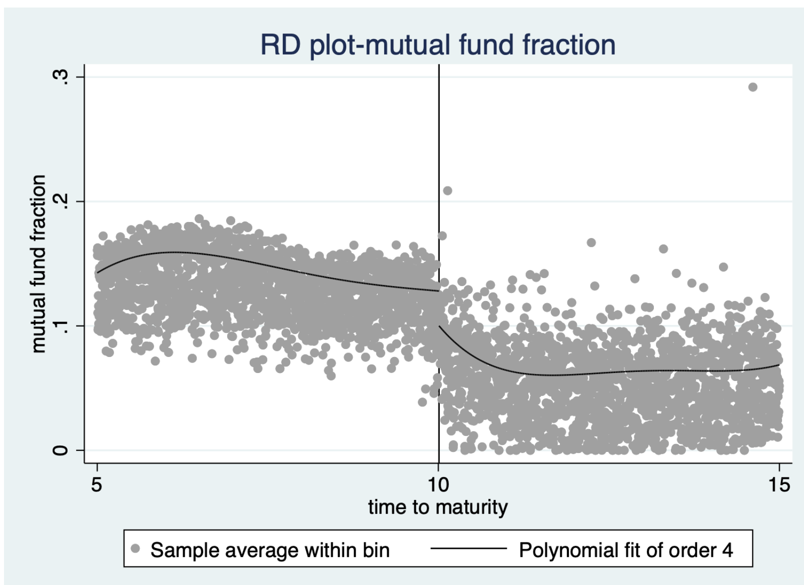
(d) By optionality



A.> 10 obs. B.> 20 obs. C. t-stats >2

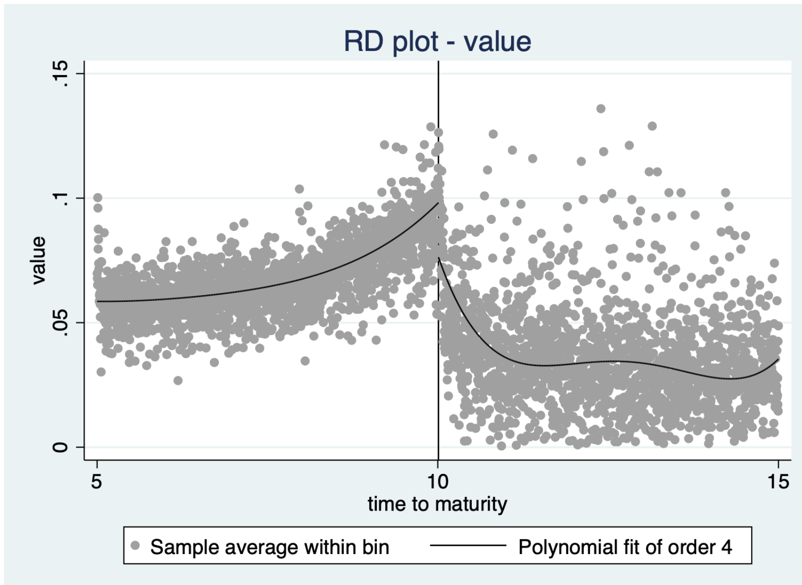
This figure plots the median value of information over time based on the Kyle model. Panel (a) sort bonds into investment grade and high yield portfolios. Panel (b) sort bonds into three maturity categories. Panel (c) sort bonds into different size terciles. Panel (d) sort bonds by optionality. In terms of columns, column A only includes bond-month observations where there are at least 10 transactions; column B only includes bond-month observations where there are at least 20 transactions; column C only includes bond-month observations where the t-statistics for the estimated Kyle-λ is larger than 2.

Figure 4: Discontinuity in the share of corporate bonds held by mutual funds

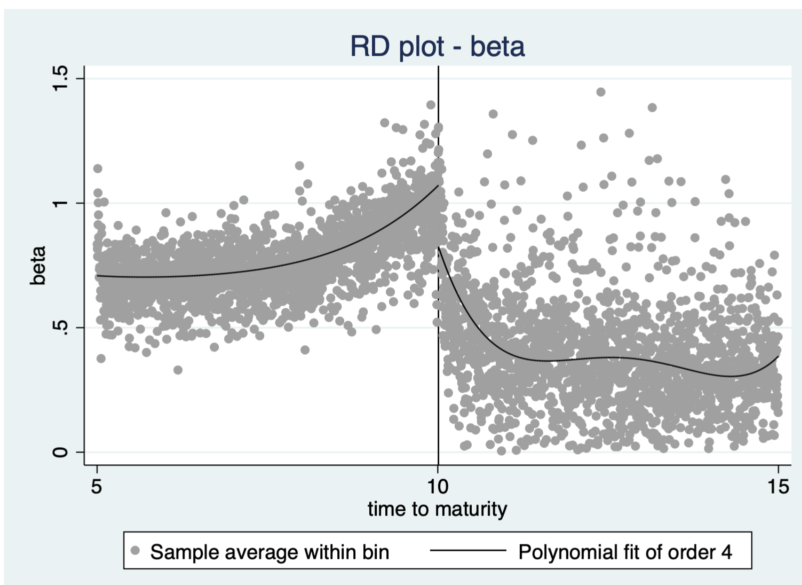


The figure plots the mutual fund share for bonds with different time to maturity in our sample. The time to maturity cutoff is at 10.01 years.

Figure 5: Discontinuities in the value of information and liquidity as a function of maturity



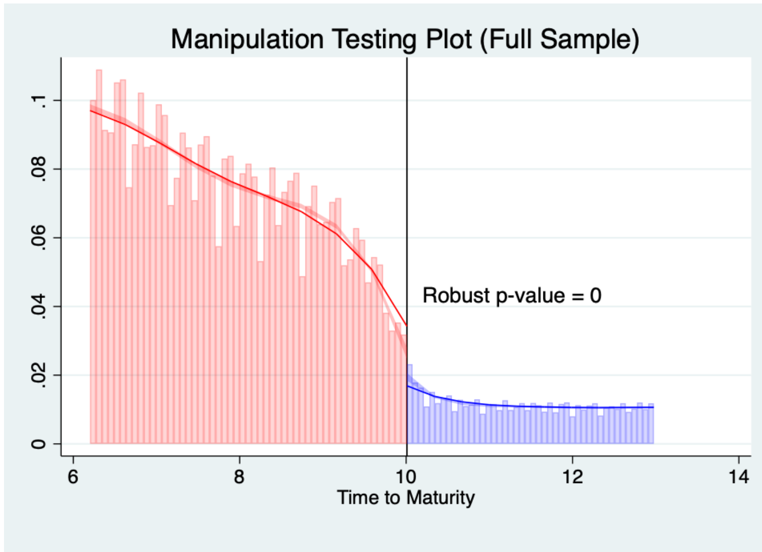
(a) Value of information



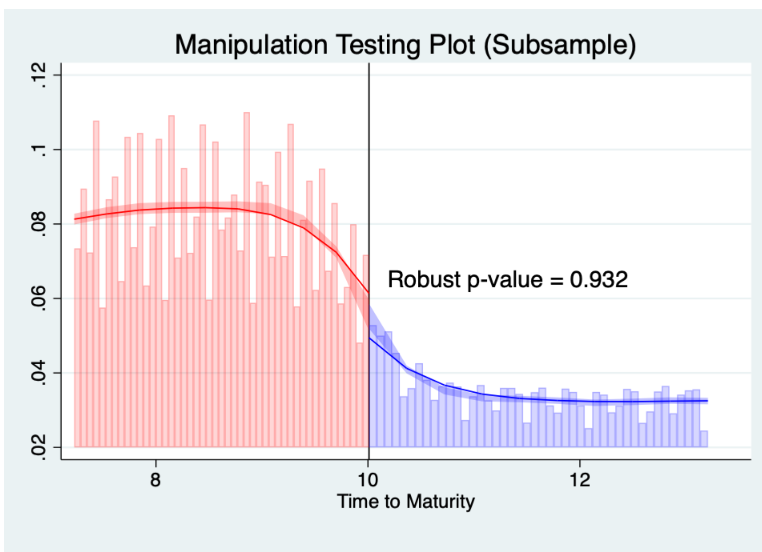
(b) Arrival rate of liquidity trades, β

The top panel plots the average VOI against time-to-maturity for bonds in our sample. The cutoff is set to be 10.01 years. The bottom panel plots the average β *(arrival rate of liquidity trades) estimated for bonds with different time-to-maturity.*

Figure 6: McCrary Tests for Manipulation around Cutoff



(a) Full Sample



(b) Subsample

We plot the density of bonds with different time to maturity to the left and right of the cutoff respectively, estimated using polynomials of order 2. The shaded area is the bias-corrected confidence interval, estimated using polynomial of order 3. Hence, the confidence intervals/bands may not be centered at the point estimates. See Cattaneo et al. (2020) and Cattaneo et al. (2021) for details. We conduct McCrary manipulation tests for both the full sample (panel (a)) and subsample for bonds that have maturity longer than 10 years at issuance (panel (b)). Robust p-values testing the null hypothesis of no manipulation are reported for each subsample.

Table 1: Summary Statistics of Unit VOI (per dollar of face value)

	Rating							Maturity		
	AAA	AA	A	BBB	BB	B	CCC	≤ 10	$(10, 20]$	$(20, 30]$
N	14,294	57,666	291,408	329,212	87,519	70,530	24,953	676,796	85,470	106,265
Mean	0.039	0.039	0.043	0.045	0.061	0.068	0.058	0.047	0.034	0.061
Std	0.047	0.046	0.051	0.054	0.058	0.062	0.061	0.054	0.048	0.059
P25	0.006	0.007	0.007	0.007	0.013	0.016	0.009	0.008	0.004	0.014
P50	0.020	0.020	0.021	0.022	0.041	0.048	0.033	0.025	0.013	0.038
P75	0.053	0.052	0.059	0.063	0.091	0.105	0.089	0.067	0.039	0.090

	Size Deciles										Callable	
	0	1	2	3	4	5	6	7	8	9	N	Y
N	105,097	126,445	80,617	42,489	82,459	104,332	70,679	90,249	89,726	81,802	183,903	686,142
Mean	0.031	0.042	0.046	0.049	0.050	0.049	0.053	0.052	0.052	0.058	0.035	0.051
Std	0.049	0.056	0.057	0.057	0.057	0.054	0.055	0.053	0.051	0.052	0.048	0.056
P25	0.003	0.004	0.006	0.008	0.009	0.010	0.011	0.013	0.014	0.019	0.005	0.009
P50	0.009	0.015	0.020	0.024	0.026	0.027	0.031	0.032	0.034	0.042	0.015	0.028
P75	0.031	0.057	0.065	0.070	0.072	0.070	0.075	0.075	0.074	0.082	0.045	0.074

	Illiquidity				Uncertainty		
	Low Illiquidity	Mid Illiquidity	High Illiquidity	NA	0	1	2
N	209606	209605	209606	246765	291937	291784	291861
Mean	0.055	0.049	0.038	0.048	0.031	0.056	0.056
Std	0.054	0.052	0.047	0.060	0.041	0.057	0.060
P25	0.013	0.010	0.006	0.005	0.005	0.012	0.009
P50	0.035	0.029	0.018	0.018	0.014	0.034	0.032
P75	0.080	0.070	0.050	0.072	0.038	0.081	0.084

This table provides summary statistics for value of information per dollar of face value estimated. The top panel, we sort bonds into different rating categories and maturity groups. For the middle panel, we sort bonds into 10 size deciles and whether they are callable. The last panel sorts the bonds by whether their illiquidity measure based on Bao et al. (2011) and an uncertain measure. The uncertainty measure is modeled implied $p(1-p)$, *where* $p = \exp(-\frac{yield}{r})$.

Table 2: Value of Information: Back-Baruch Baseline vs. the Kyle Model

Panel A: Sample coverage (unit: the number of observations)

	Kyle > 10	Kyle > 20	Kyle t-stat> 2	Baseline
AAA	10686	2283	1871	14294
AA	44114	9692	7458	57666
A	168922	29124	41678	291408
BBB	184887	28472	50330	329212
BB	59359	8984	14088	87519
B	42090	6020	11345	70530
CCC	15398	1878	4142	24953
Redeemable	422187	67927	103703	686142
Total	525456	86453	130912	875582

Panel B: Bond Size (unit: thousands)

	Kyle > 10	Kyle > 20	Kyle t-stat> 2	Baseline
Mean	908,388	1,280,325	570,466	620,509
Std	751,602	943,742	593,909	618,711
P25	475,000	650,000	250,000	250,000
P50	700,000	1,000,000	400,000	450,000
P75	1,035,000	1,650,000	700,000	750,000

Panel C: Bond Maturity (unit: years)

	Kyle > 10	Kyle > 20	Kyle t-stat> 2	Baseline
Mean	7.787	7.192	9.221	8.733
Std	7.972	7.181	9.236	9.182
P25	2.795	2.816	3.173	2.962
P50	5.258	5.044	6.090	5.638
P75	8.712	8.236	11.049	9.586

This table compares our measure of VOI based on Back and Baruch (2004b) with VOI calculated using the Kyle-Back model as in Kadan and Manela (2020). Panel A compares the coverage by rating category and optionality. Panel B compares the coverage for different size bins. Panel C compares coverage for different maturity bins. "Kyle > 10" indicates we only include bond-month observations where there are at least 10 transactions. "Kyle > 20" indicates we only include bond-month observations where there are at least 20 transactions. "Kyle t-stat> 2" indicates we only include bond-month observations where the Kyle-λ estimate has t-statistics larger than 2.

Table 3: Investor Composition Summary Statistics

	Mutual Fund Shares		Life Ins. Shares	
	Mean	Std	Mean	Std
AAA	0.067	0.113	0.184	0.180
AA	0.069	0.089	0.201	0.183
A	0.072	0.080	0.301	0.212
BBB	0.110	0.096	0.313	0.209
BB	0.230	0.146	0.142	0.138
B	0.287	0.165	0.065	0.081
CCC	0.236	0.192	0.035	0.070
Total	0.124	0.128	0.255	0.211

This table shows the mean and standard deviation of mutual fund shares and life insurance company shares for bonds in each rating category.

Table 4: Treatment effects of the mutual fund share: Maturity regression discontinuity

	(1) VOI	(2) VOI	(3) β	(4) β	(5) YTM	(6) YTM	(7) δ	(8) δ
Conventional	1.808***	1.456***	1.792***	1.482***	-0.0296***	0.00395	-1.007**	-0.549**
	(9.02)	(7.20)	(9.52)	(7.67)	(-4.00)	(0.85)	(-2.65)	(-2.71)
Bias-corrected	1.789***	1.549***	1.783***	1.597***	-0.0327***	0.00355	-1.235**	-0.664**
	(8.93)	(7.66)	(9.47)	(8.27)	(-4.43)	(0.76)	(-3.24)	(-3.27)
Robust	1.789***	1.549***	1.783***	1.597***	-0.0327***	0.00355	-1.235**	-0.664**
	(7.89)	(7.44)	(8.33)	(8.15)	(-4.05)	(0.76)	(-3.03)	(-2.92)
Bandwidth	2.105	2.176	2.214	2.269	1.323	3.147	1.225	2.206
Robust (level)	0.907***	0.845***	10.03***	9.893***	-0.265***	0.0278	-0.0530**	-0.0464**
	(6.92)	(9.80)	(7.39)	(11.97)	(-3.67)	(0.76)	(-3.24)	(-2.97)
Bandwidth (level)	1.772	3.306	1.870	4.000	1.166	3.195	1.654	2.019
Obs.	664899	664899	664899	664899	664899	664899	664899	664899
Controls	No	Yes	No	Yes	No	Yes	No	Yes

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents the treatment effects of mutual fund shares on value of information (VOI), liquidity trades arrival rate (β), yield-to-maturity (YTM), and average trading size δ (defined as average trading volume over amount outstanding) using time-to-maturity of 10 years as the discontinuity cutoff. All the variables are normalised by their sample standard deviations for the first three rows. We also report the robust estimate results using the level of the variables on the left hand side (with "level" indicated in the row names). We include the full sample. We report the bandwidth chosen by the RDrobust package for estimation. Controls (if indicated "yes") include rating, coupon rate and amount outstanding. The standard errors are clustered by time.

Table 5: Treatment effects of the mutual fund share: Maturity switchers subsample

	(1) VOI	(2) VOI	(3) β	(4) β	(5) YTM	(6) YTM	(7) δ	(8) δ
Conventional	1.397***	1.387***	1.396***	1.336***	-0.0129*	-0.00197	-0.214	-0.796*
	(6.96)	(3.98)	(7.27)	(3.70)	(-2.40)	(-0.18)	(-1.57)	(-2.24)
Bias-corrected	1.401***	1.391***	1.421***	1.318***	-0.0113*	-0.00406	-0.325*	-0.973**
	(6.97)	(4.00)	(7.40)	(3.65)	(-2.10)	(-0.36)	(-2.38)	(-2.74)
Robust	1.401***	1.391***	1.421***	1.318***	-0.0113*	-0.00406	-0.325*	-0.973*
	(6.32)	(3.62)	(6.74)	(3.33)	(-2.03)	(-0.35)	(-2.07)	(-2.45)
Bandwidth	2.532	2.597	2.625	2.312	2.898	2.482	2.787	2.343
Robust (level)	0.699***	0.664***	7.892***	7.090**	-0.111*	-0.0327	-0.0164*	-0.0611*
	(6.52)	(3.43)	(7.19)	(3.19)	(-1.96)	(-0.36)	(-1.97)	(-2.43)
Bandwidth (level)	2.653	2.416	2.910	2.195	1.847	2.438	3.236	2.199
Obs.	213800	213800	213800	213800	213800	213800	213800	213800
Controls	No	Yes	No	Yes	No	Yes	No	Yes

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents the treatment effects of mutual fund shares on value of information (VOI), liquidity trades arrival rate (β), yield-to-maturity (YTM), and average trading size δ (defined as average trading volume over amount outstanding) using time-to-maturity of 10 years as the discontinuity cutoff. All the variables are normalised by their sample standard deviations. We also report the robust estimate results using the level of the variables on the left hand side (with "level" indicated in the row names). We only include bonds whose maturity at issuance is longer than 10 years. We report the bandwidth chosen by the RDrobust package for estimation. Controls (if indicated "yes") include rating, coupon rate and amount outstanding. The standard errors are clustered by time.