Section 9: Corporate Bonds

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November 21, 2021

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1. Basic structure of the notes

- High-level summary of theoretical frameworks to interpret empirical facts.
- Per asset class, we will discuss:
  1. Key empirical facts in terms of prices (unconditional and conditional risk premia) and asset ownership.
  2. Interpret the facts using the theoretical frameworks.
  3. Facts and theories linking financial markets and the real economy.
  4. Active areas of research and some potentially interesting directions for future research.
- The notes cover the following asset classes:
  1. Equities (weeks 1-5).
     - Discount rates and the term structure of risk (week 1)
     - The Cross-section and the factor zoo (week 2)
     - Intermediary-based Asset Pricing (week 3)
     - Production-based asset pricing (week 4)
     - Demand-based asset pricing (week 5)
  2. Mutual funds and hedge funds (week 6).
  3. Volatility (week 7).
  4. Government bonds (week 8).
  5. Corporate bonds (week 9).
  6. Currencies (week 10).
  7. Commodities (week 11).
  8. Real estate (week 12).

2. Corporate Bonds

2.1. Facts

2.1.1. Types of corporate bonds

- Corporate bonds are differentiated along several dimensions:
  - Maturity.
  - Credit rating.
  - Covenants and seniority.
  - Currency denomination.
  - Callability.
  - ...
- We will discuss some of these characteristics in more detail below.
- Corporate bonds are traded over-the-counter, but transactions are reported in TRACE (introduced in July 2002).
- Note: Many bonds are issued by firms that do not have publicly-listed equity or are privately placed (Rule 144A). These bonds are sometimes ignored in the literature as information about equity prices is required for part of the analysis or because privately-placed bonds are not traded (and hence do not appear in TRACE).

- Important data sources:
  - Datastream: Bond indices by credit rating and maturity from Barclays.
  - Morningstar: Holdings data of bond mutual funds.
  - Schedule D of the NAIC: Bond holdings of insurance companies. These data can be accessed through Mergent FISD in WRDS.
  - TRACE (in WRDS): Transaction level data of corporate bonds.
  - Mergent FISD (in WRDS): Characteristics of corporate bonds.
  - Thomson Reuters eMaxx has additional data on holdings from pension funds, but this is all voluntary disclosure.

- Surprising fact: Number of bonds issued by a single company:

Exhibit 4: BONDS AND SHARES OUTSTANDING OF TOP US INVESTMENT GRADE BOND ISSUERS

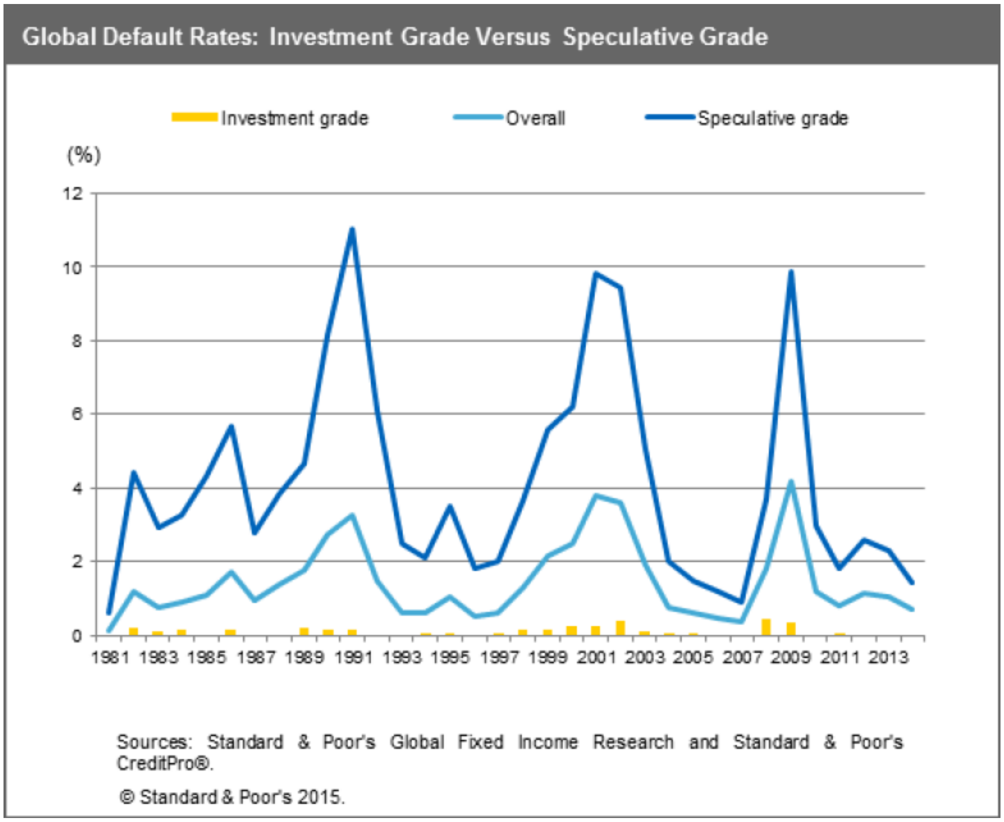
Issuer	Bonds in Barclays US Corporate Index	Share of Dollar Amt Outstanding	Total Bonds Outstanding	Common Equity Securities	Preferred Equity Securities
Bank of America	53	46%	1,295	1	33
General Electric	48	36%	905	1	4
Verizon	42	83%	73	1	0
JP Morgan	45	40%	1,695	1	5
Goldman Sachs	28	44%	1,488	1	8
Citigroup	42	35%	1,865	1	11
Morgan Stanley	27	42%	1,331	1	13
AT&T	43	63%	85	1	0
Wells Fargo	37	39%	304	1	9
Comcast	36	88%	56	1	0

Sources: Barclays and Bloomberg, April 2014. Note: Table shows issuers with the largest notional amount outstanding in the Barclays US Corporate Index. Reference to issuers is for illustrative purposes only, and should not be construed as investment advice or investment recommendation of those companies.

- Why does Verizon need 42 bonds and a single stock and no preferred stocks?
- This fact is even worse for municipal bonds: There are over one million cusips for $3.7 trillion municipal bond market in 2011.
- The municipal bond market is interesting in its own right, and peculiar because of its tax-exempt status for in-state investors:
  - See Babina, Jotikasthira, Lundblad, and Ramadorai (2020) for estimates of the impact of taxes on the municipal bond market yields.

2.1.2. The credit risk premium

- Defaults tend to cluster in bad times.



- Moreover, the loss given default is higher in bad times as well. Consequently, investors need to be compensated to hold risky corporate bonds, giving rise to a **credit risk premium**.

- The credit spread, that is, the difference, between corporate bond yields and Treasuries of the same maturity consists of:

  1. Expected default ("cash flow component").
  2. Risk premium: Compensation for default and liquidity risk.

- Almeida and Philippon (2007) summarize evidence on the *fraction* of the credit spread that is due to expected default:

Table II

Fraction of the Yield Spread Due to Default

This table reports the fractions of yield spreads over benchmark Treasury bonds that are due to default, for each credit rating and different maturities. The first column uses Huang and Huang's (2003) table 7, which reports calibration results from their model under the assumption that market asset risk premia are countercyclically time varying. The second column uses Longstaff, Mittal and Neis's (2005) table IV, which reports model-based ratios of the default component to total corporate spread. The third column uses results from Chen et al. (2005). The fraction reported for BBB bonds is the ratio of the BBB minus AAA spread over the BBB minus Treasury spread. The fourth column uses results from Cremers et al. (2005). The fractions reported are the ratios between the 10-year spreads in Cremers et al.'s table 4 (model with priced jumps), and the corresponding 10-year spreads in Table I of this paper. The fifth and sixth columns report for each rating and maturity the ratio between the default component of the spread and the total spread, where the default component is calculated as the spread minus the one-year AAA spread. The seventh and eighth columns report for each rating and maturity the ratio between the default component of the spread and the total spread, where the default component is calculated as the spread minus the difference between swap and Treasury rates, for the period 2000 to 2004. NA = not available.

Credit Rating	Huang and Huang (2003) 10-Year Spread	Longstaff et al. (2005) 5-Year Spread	Chen et al. (2005) 4-Year Spread	Cremers et al. (2005) 10-Year Spread	Method 1 (AAA Spread) 4-Year Spread	Method 1 (AAA Spread) 10-Year Spread	Method 2 (Spreads over Swaps) 5-Year Spread	Method 2 (Spreads over Swaps) 10-Year Spread
AAA	0.208	NA	0.000	0.603	0.073	0.190	NA	NA
AA	0.200	0.510	NA	0.505	0.215	0.440	NA	NA
A	0.234	0.560	NA	0.512	0.609	0.613	0.511	0.570
BBB	0.336	0.710	0.702	0.627	0.724	0.731	0.732	0.729
BB	0.633	0.830	NA	NA	0.846	0.846	0.872	0.872
B	0.833	NA	NA	NA	0.906	0.906	0.916	0.916

- Share of credit spread that is expected default is much higher for low-grade bonds and higher for longer-maturity bonds (esp. for high-grade ones)

- We can measure the unconditional credit risk premium as the average annual excess return using Barclays indices. From Binsbergen and Koijen (2017):

Intermediate	AAA	AA	A	BAA
Average excess return	2.38%	2.53%	2.76%	3.44%
Standard deviation	5.02%	4.99%	5.28%	5.48%
Sharpe ratio	0.47	0.51	0.52	0.63
Long term	AAA	AA	A	BAA
Average excess return	3.12%	3.80%	3.75%	4.60%
Standard deviation	10.45%	9.74%	9.67%	9.82%
Sharpe ratio	0.30	0.39	0.39	0.47

Table 5: We summarize the annualized average excess return, standard deviation and Sharpe ratios of corporate bond returns. The credit quality is summarized in the first row of each panel. The top panel displays the results for the intermediate maturity (duration around 5 years) and the bottom panel for the long-term maturity (duration around 10 years). The sample period is from January 1973 until August 2014.

- Risk premia and Sharpe ratios are higher for lower-rated bonds.

- The standard deviation and risk premia increase with maturity. However, consistent with the evidence for Treasuries, Sharpe ratios decline with maturity, regardless of the rating.

- Palhares (2012) finds a similar result for CDS returns.

2.1.3. A variance decomposition of credit spreads

- Nozawa (2017) provides a Campbell Shiller-style variance decomposition of the credit spread into expected default and risk premium components.
- Notation:
  - P_{it}: Price per dollar of face value.
  - C_{it}: Coupon rate.
  - The return on the bond

$$R_{i,t+1} = \frac{P_{i,t+1} + C_{i,t+1}}{P_{it}}.$$

  - The return on the matching (=identical coupon rate and repayment schedule as the corporate bond) Treasury bond

$$R^f_{i,t+1} = \frac{P^f_{i,t+1} + C^f_{i,t+1}}{P^f_{it}}.$$

  - A standard log-linear approximation implies

$$r^e_{i,t+1} = \ln R_{i,t+1} - \ln R^f_{i,t+1} = s_{it} - \rho s_{i,t+1} - l_{i,t+1} + \ const.,$$

    where $s_{it} = \ln(P^f_{it}/P_{it})I(t < t_D)$ and $l_{it} = \ln(P^f_{it}/P_{it})I(t = t_D)$, where t_D is the time of default.

    This expression implies that the excess return is low because (i) spreads widen ($s_{it} - \rho s_{i,t+1} < 0$) or (ii) the bond defaults and realizes losses ($-l_{i,t+1}$).

- If we iterate the log-linear approximation forward, we get an expression for price spreads

$$s_{it} = \underbrace{E_t\left(\sum_{j=1}^{T_i-t}\rho^{j-1}r^e_{i,t+j}\right)}_{\text{Expected returns}} + \underbrace{E_t\left(\sum_{j=1}^{T_i-t}\rho^{j-1}l_{i,t+j}\right)}_{\text{Expected credit loss}} + const.$$

- Empirical implementation

  - Define the state vector as

    $$X_{it} = (r^e_{it}, d_{it}s_{it}, \tau_{it}z_{it})',$$

    where d_{it} is a vector of dummy variables for ratings,

    $$d_{it} = (1, d^{Baa}_{it}, d^{Ba}_{it}, d^{B-}_{it})',$$

    τ_{it} is the bond's maturity, and z_{it} are state variables other than returns and price spreads.

  - Estimate a VAR for the state vector, X_{it},

    $$X_{i,t+1} = AX_{it} + W_{i,t+1},$$

    where A is constant across time and bonds. A is assumed to shift in proportion to the rating via d_{it}.

  - Having estimated the VAR, we can compute the long-run expected returns and credit losses.

Table II: Implied Long-Run Regression Coefficients and Volatility Ratios

The sample period is monthly from 1973 to 2011. Panel A shows the VAR-implied long-run coefficient for long-run credit loss, $e_L G(\bar{T})$, and long-run excess returns, $e_1 G(\bar{T})$, where $G(\bar{T}) = A(I-\rho A)^{-1}\left(I-(\rho A)^{\bar{T}-t}\right)$ for a bond with the average maturity. $\sigma(E_t[\cdot])$ shows the sample standard deviation of fitted values of the left-hand side variables. $d^{\theta}_{i,t}$ is a dummy variable for the rating θ. The right-hand side variables are defined in the notes to Table I. Panel B shows the summary statistics of the long-run expected credit loss, $\tilde{s}^l_{i,t} = e_L G(T_i) X_{i,t}$, and the long-run expected returns, $\tilde{s}^r_{i,t} = e_1 G(T_i) X_{i,t}$. $\varrho(\cdot,\cdot)$ shows the sample correlation coefficient. Panel C shows the estimated coefficients for credit loss forecasting regression, $\tilde{l}_{i,t} = b_l X_{i,t} + \varepsilon^l_{i,t}$. $\tilde{l}'_{i,t}$ is the credit loss implied from the identity (3), so that $l'_{i,t} \equiv -\rho s_{i,t} + s_{i,t-1} - r^e_{i,t}$. Panel D shows the summary statistics of the long-run expected credit loss and excess returns, based on the VAR where I replace $\tilde{r}^e_{i,t+1}$ with $\tilde{r}^{e\prime}_{i,t+1} \equiv -\rho\tilde{s}_{i,t+1} + \tilde{s}_{i,t} - \tilde{l}_{i,t+1}$. Panel E shows the estimates based on the VAR, where the state variables include lagged credit spreads times rating dummies, 3 lags of bond excess returns, probability of default, the issuers' stock returns, log book-to-market ratio, log market size of equity and log share price (winsorized at 15 dollars). Standard errors, reported in parentheses under each coefficient, are clustered by time.

Panel A: Long-run regression coefficients, $e_L G(\bar{T})$ and $e_1 G(\bar{T})$

	$\tilde{r}^e_{i,t}$	$\tilde{s}_{i,t}$	$\tilde{s}_{i,t} d^{Baa}_{i,t}$	$\tilde{s}_{i,t} d^{Ba}_{i,t}$	$\tilde{s}_{i,t} d^{B-}_{i,t}$	$\tau \widetilde{PD}_{i,t}$	$\sigma(E_t[\cdot])$
$\sum_{j=1}^{\bar{T}} \rho^{j-1} \tilde{l}_{i,t+j}$	-0.05	0.09	0.09	0.37	0.80	0.12	6.71
	(0.02)	(0.06)	(0.04)	(0.09)	(0.09)	(0.06)	
$\sum_{j=1}^{\bar{T}} \rho^{j-1} \tilde{r}^e_{i,t+j}$	0.05	0.90	-0.09	-0.36	-0.78	-0.12	5.25
	(0.02)	(0.07)	(0.04)	(0.09)	(0.09)	(0.06)	

Panel B: Variation of VAR-implied conditional expectations

	$\frac{\sigma(\tilde{s}^l)}{\sigma(\tilde{s})}$	$\frac{\sigma(\tilde{s}^r)}{\sigma(\tilde{s})}$	$\varrho(\tilde{s}^l, \tilde{s})$	$\varrho(\tilde{s}^r, \tilde{s})$	$\varrho(\tilde{s}^l, \tilde{s}^r)$
Estimates	0.67	0.52	0.76	0.64	0.18
	(0.12)	(0.06)	(0.03)	(0.14)	(0.20)

- In the cross-section, expected returns and expected credit losses contribute about the same amount to overall credit spreads.
- Since most of the expected credit loss variation at the security level is idiosyncratic, the credit loss component is mostly diversified away in the market portfolio.
- At the **aggregate** level, most of the variation in the credit spread reflects expected return variation.
- Credit spread is strong predictor of future excess bond returns.

2.1.4. Time-series predictability of bond returns

- Instead of using data on credit spreads to forecast future bond returns, we can use data on quantities issued.

- Greenwood and Hanson (2013) study issuer quality over time.

- Main idea: When the demand for corporate bonds is high, and hence when the credit risk premium is low, more low-quality firms are able to access bond markets.

- Low-quality firms are most sensitive to changes in financing conditions, either by issuing more debt (intensive margin) or by switching from bank loans to bond markets (extensive margin), see for instance Becker and Ivashina (2014).

- Greenwood and Hanson (2013) compute expected default using the Merton (1974) model (more on this later) for firms that issue a lot of debt compared to firms that issue little (or even retire debt):

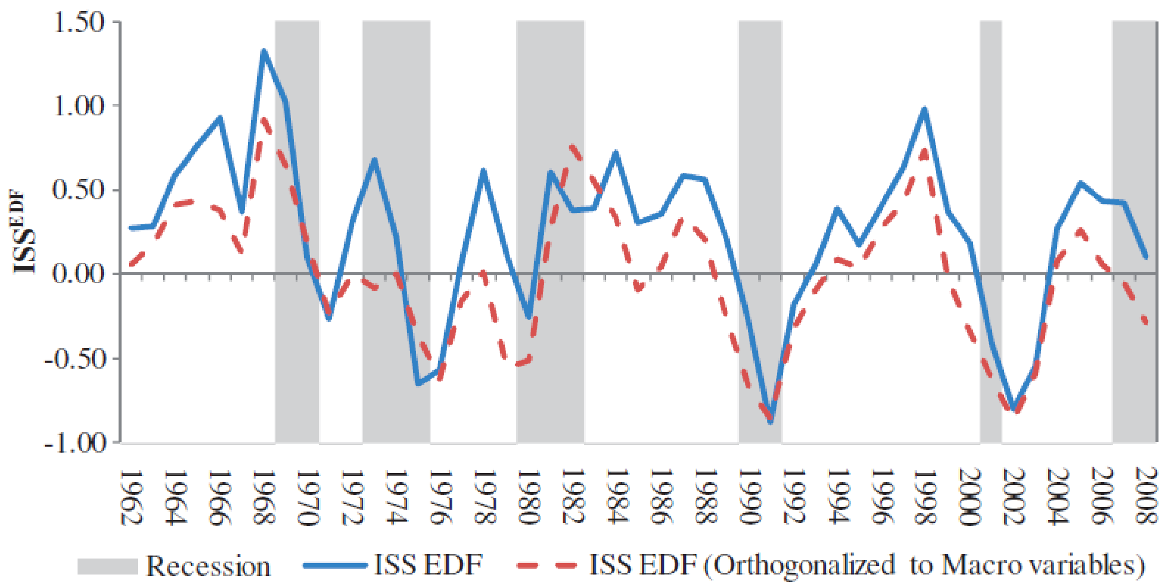


Figure 1
Issuer quality
ISS^{EDF} is the difference between the average *EDF* decile between high- and low-debt issuers. *EDF* is the expected default frequency of Merton (1974). The figure also shows shading for NBER-designated recessions. The dotted line shows a version of ISS^{EDF} that has been orthogonalized with respect to the output gap (Hodrick-Prescott filtered real GDP).

- When this measure is high, low-rated, risky firms are able to issue a lot of debt.
- Obviously, this measure is strongly pro-cyclical. The credit quality of corporate debt issuers deteriorates during credit booms.
- However, removing macro variation doesn't change basic character of series.

- Alternatively, they measure the share of debt issuances by high-yield firms as opposed to investment grade firms, HYS.

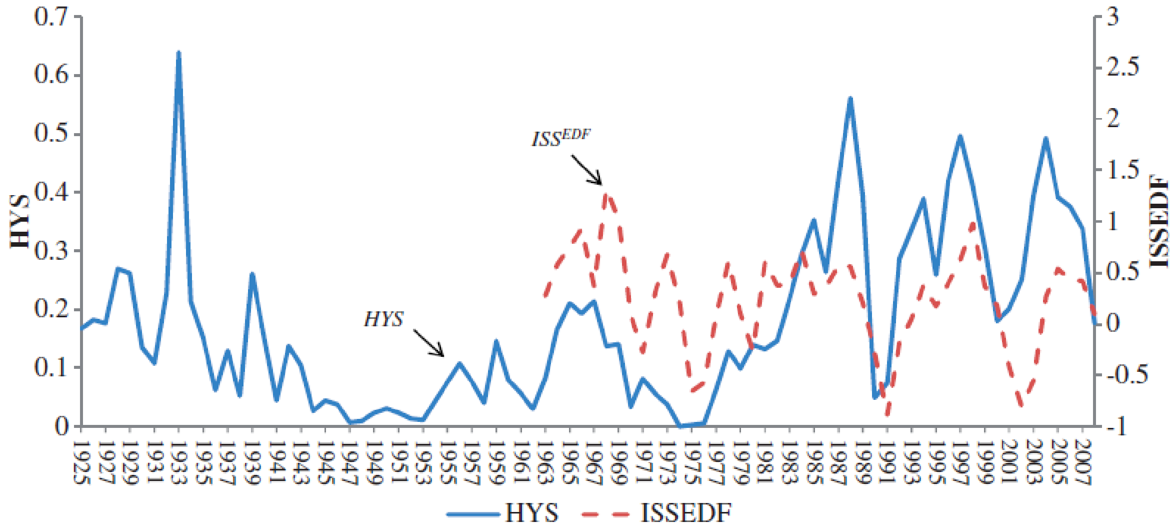


Figure 2
The high-yield share
HYS is the log fraction of nonfinancial corporate bond issuance with a high-yield rating from Moody's. *HYS* is constructed using data from Hickman (1960) and Atkinson (1967) NBER studies from 1926–1965, from hand-collected data from Moody's Bond Surveys from 1966–1982, and from FISD for 1983–2008. For comparison, the figure plots ISS^{EDF} on the right-hand scale.

- The advantage of this measure is that the history is much longer (starts in 1926).

- However, the time-series dynamics is quite similar.

- Link to future bond returns:

$$rx_{t+2}^{HY} = \underbrace{3.62}_{[t=2.02]} \underbrace{-15.24}_{[t=-5.29]} ISS_t^{EDF} + u_{t+2} \qquad R^2 = 26\%$$

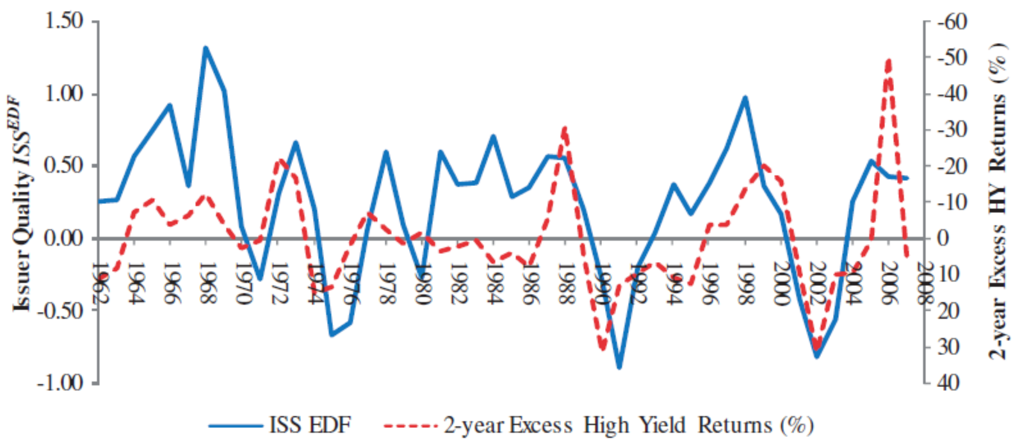


Figure 3
Issuer quality and subsequent high-yield excess returns
Issuer quality (left axis) plotted alongside cumulative excess high-yield bond returns for the following two years (right axis). Returns are plotted in reverse scale, so the negative correlation appears positive visually. Issuer quality is measured with ISS^{EDF}, the difference between the average *EDF* decile of high- and low-debt issuers from 1962–2008.

- A one std.dev. increase in ISS^{EDF} reduces cumulative excess returns over the following 2 years by 7.3% points.

- Results survive controlling for other predictors

Table 4
Multivariate forecasting regressions

	1-yr. returns			2-yr. returns			3-yr. returns		
Panel A: $X_t = ISS^{EDF}$ (1962–2008)									
ISS^{EDF}	−7.636	−8.617	−6.282	−11.022	−18.052	−13.890	−14.214	−21.697	−19.343
	[−3.45]	[−2.97]	[−2.40]	[−3.45]	[−4.60]	[−4.54]	[−2.57]	[−3.83]	[−3.77]
$y^G_{L,t} - y^G_{S,t}$	1.495		2.031	5.025		8.055	4.61		9.477
	[0.62]		[0.67]	[2.25]		[3.36]	[2.49]		[5.68]
$y^G_{S,t}$	−0.442		−0.49	0.487		0.845	1.152		2.102
	[−0.62]		[−0.68]	[1.02]		[1.40]	[1.86]		[3.06]
$y^{BBB}_{L,t} - y^G_{L,t}$		3.836	3.773		−1.498	−5.05		−3.595	−10.624
		[1.29]	[1.21]		[−0.52]	[−1.59]		[0.86]	[−2.44]
rx^{HY}_t		−0.264	−0.29		−0.498	−0.729		−0.667	−0.936
		[−1.77]	[−1.62]		[−2.35]	[−3.46]		[3.45]	[−5.20]
R^2	0.15	0.28	0.32	0.31	0.34	0.45	0.33	0.39	0.51

Time-series forecasting regressions of log excess returns on speculative-grade bonds on measures of debt issuance quality, controlling for the term spread, short-rate, credit spread, and lagged excess returns:

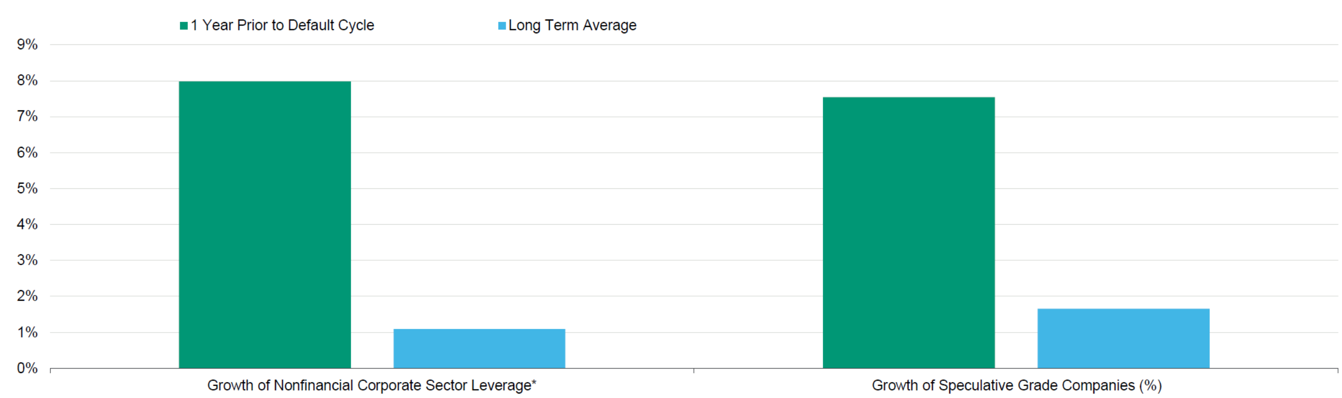
$$rx^{HY}_{t+k} = a + b \cdot X_t + c \cdot \left(y^G_{Lt} - y^G_{St}\right) + d \cdot y^G_{St} + e \cdot \left(y^{BBB}_{Lt} - y^G_{Lt}\right) + f \cdot rx^{HY}_t + u_{t+k}.$$

In Panel A, X_t is ISS^{EDF} from 1962–2008; in Panel B, X_t is ISS^{EDF} from 1983–2008; in Panel C, X_t is $\log(HYS)$ from 1926–2008; and in Panel D, X_t is $\log(HYS)$ from 1983–2008. t-statistics for k-period forecasting regressions (in brackets) are based on Newey-West (1987) standard errors, allowing for serial correlation up to k-lags.

- Summary: When lots of low-quality firms issue debt, the credit risk premium is low, and hence future excess returns are low.

- 2019 Moody's report shows that there tends to be a strong expansion of corporate leverage a year before a recession, and also strong expansion in high yield debt.

Exhibit 2
Deterioration in credit quality has been a warning sign ahead of US default cycles



** Nonfinancial corporate sector leverage is measured by the ratio of aggregate debt to corporate profit after tax. The data covers the US nonfinancial corporate sector as a whole, not only rated issuers.*

Sources: Moody's Investors Service, FRED St. Louis Fed, National Bureau of Economic Research and Haver Analytics

- Earlier work links debt issuance **across maturities** to future bond returns, see Baker, Greenwood, and Wurgler (2003).
- When firms issue a lot of long-term bonds, future bond returns are low.
- This evidence suggests that firms are *timing* the market.

Panel B. Excess corporate bond returns (one-year-ahead returns - solid, cumulative three-year returns - hatch)

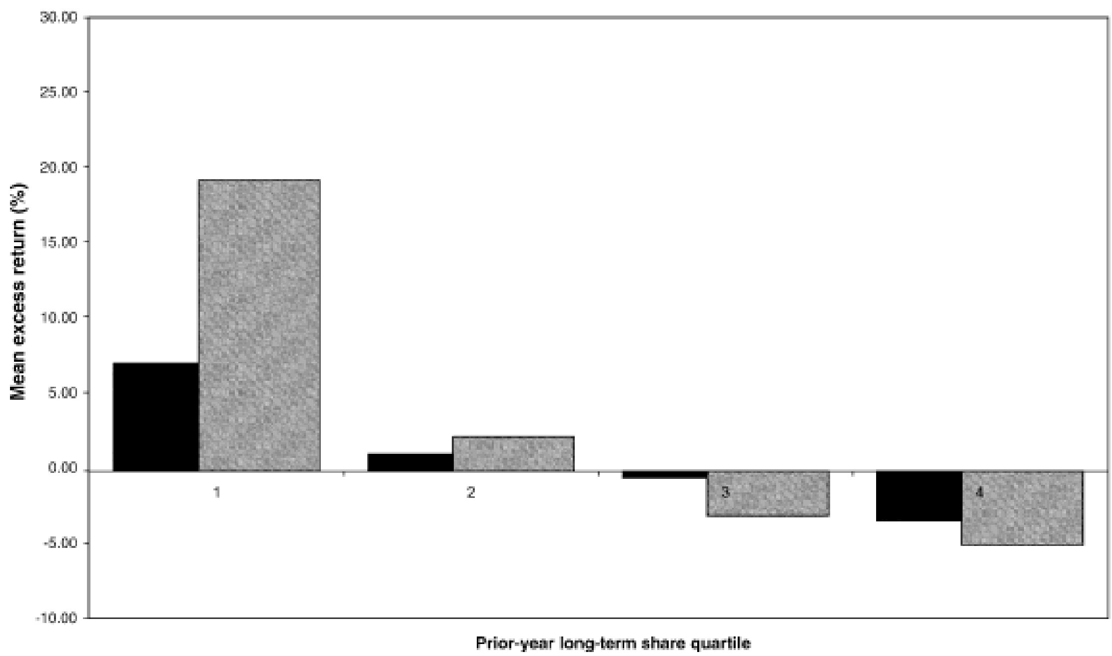
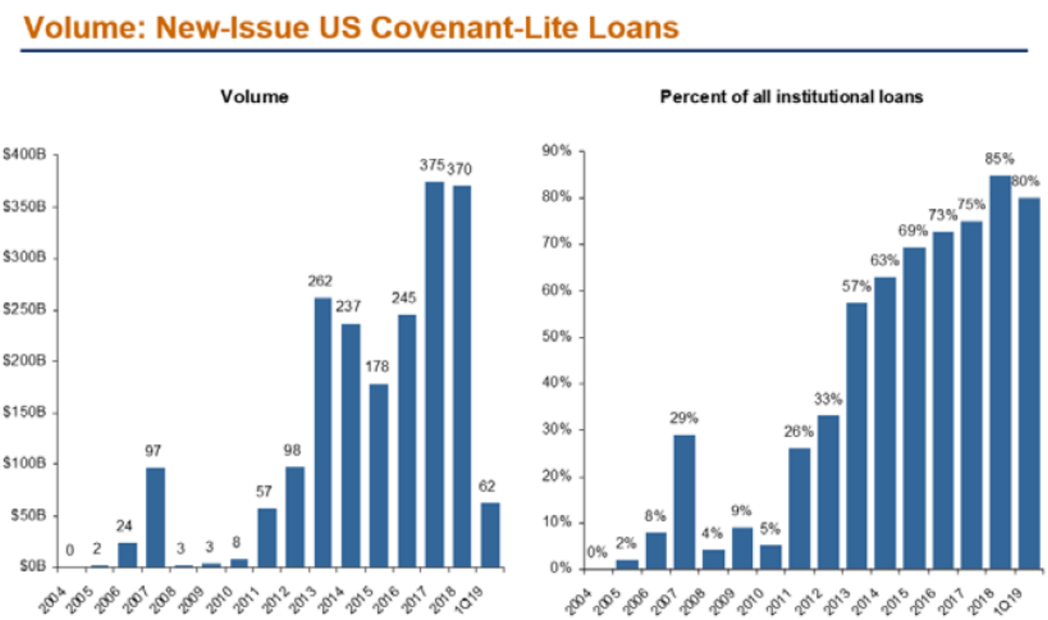


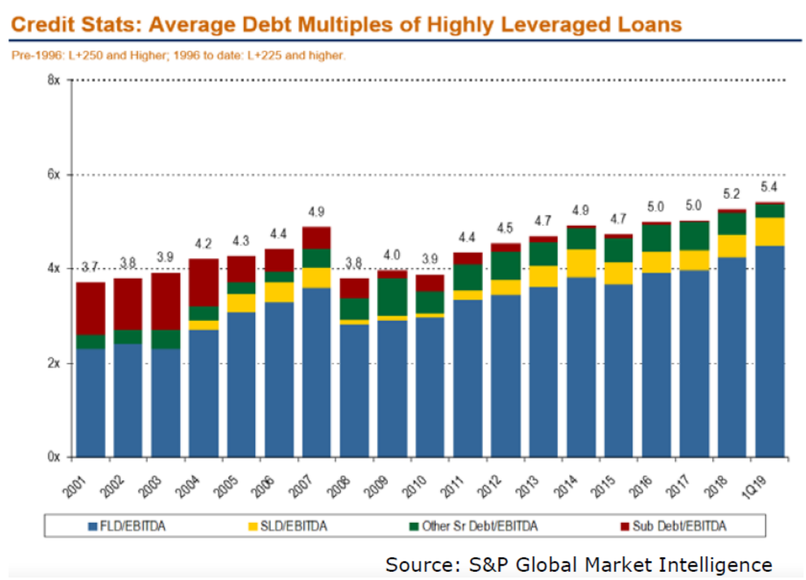
Fig. 3. The maturity of corporate debt issues and subsequent excess bond returns: *Flow of Funds* data. Excess government bond returns as predicted by the historical quartile of the prior year long-term share of total debt issues. Data on the maturity of corporate debt issues come from the Federal Reserve *Flow of Funds*. Panel A shows excess government bond returns. Panel B shows excess corporate bond returns. Excess bond returns are calculated for one-year-ahead (solid) and cumulative three-year-ahead (hatch) periods.

- Related evidence at the household level in terms of mortgage choice, see Koijen, Van Hemert, and Van Nieuwerburgh (2009).

- Where is the credit cycle today? Expansion from 2009-2019 witnessed lots of high-yield debt issuance. Lots of "covenant-lite" debt issuance.



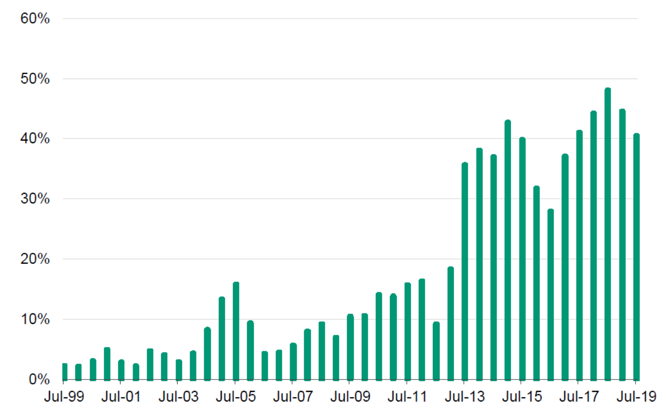
- Debt service coverage of high-leverage loans is deteriorating



- Tons of high-yield debt issuance in 2014-19 and large and rising share of them with credit ratings below Caa2 (40% in 2019).

Exhibit 8

Share of newly rated speculative-grade issuers with a rating of Caa2 or below

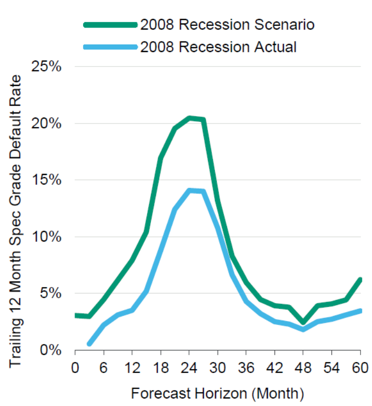


Rating refers to the SU rating, as mentioned in the box on page 2. On average, a US company with an SU rating of Caa2 has corresponded to a corporate family rating between Caa1 and B3 over the past 10 years.
Source: Moody's Investors Service

- This could lead to large wave of corporate defaults. This graph explores what the defaults would look like if the recession was like one of the previous three (analysis pre-dates covid)

Exhibit 10

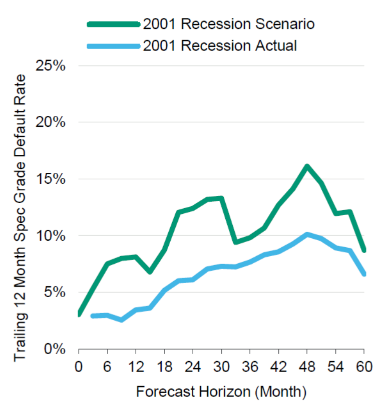
Trailing 12-month default forecasts given the 2008 recession scenario



The 2008 scenario uses the default path of the cohort of issuers on 10/1/2007.
Source: Moody's Investors Service

Exhibit 11

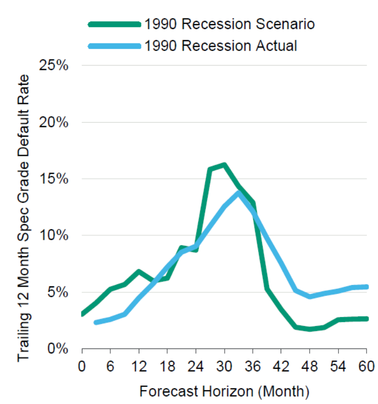
Trailing 12 month default forecasts given the 2001 recession scenario



The 2001 scenario uses the default path of the cohort of issuers on 1/1/1998.
Source: Moody's Investors Service

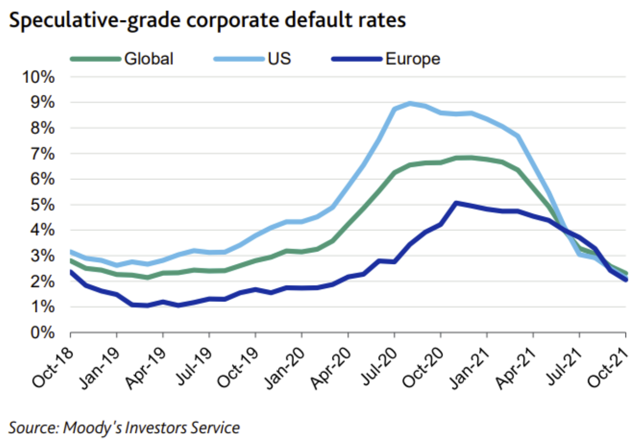
Exhibit 12

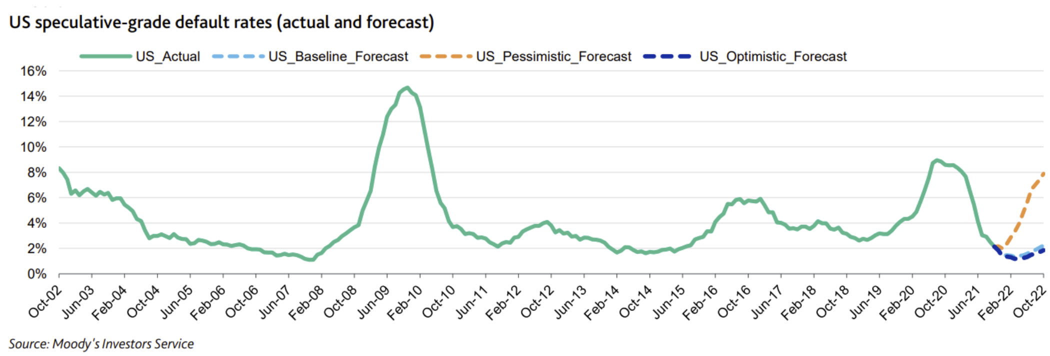
Trailing 12 month default forecasts given the 1990 recession scenario



The 1990 scenario uses the default path of the cohort of issuers on 10/1/1988.
Source: Moody's Investors Service

- Defaults increased during covid-19. High yield default rates peaked at 6.8% globally (9% in U.S.), compared to a long-run average of 4.1%.





- Greatly aided by massive indirect and direct government support during covid: ultra-low interest rates facilitated corporate refinancings + PPP/SMCCF/PMCCF programs directly subsidized corporate credit

2.1.5. Liquidity premium

- As the bond market is quite fragmented, and many bonds trade infrequently, there is a substantial literature studying the liquidity premium in corporate bonds.
- Dick-Nielsen, Feldhütter, and Lando (2012) measure liquidity in the corporate bond market around the financial crisis.
- Main regression:

$$\begin{aligned}\text{Spread}_{it} = {} & \alpha + \gamma \text{ Liquidity}_{it} + \beta_1 \text{ Bond age}_{it} \\ & + \beta_2 \text{ Amount issued}_{it} + \beta_3 \text{ Coupon}_{it} \\ & + \beta_4 \text{ Time-to-maturity}_{it} + \beta_5 \text{ Eq.vol}_{it} \\ & + \beta_6 \text{ Operating}_{it} + \beta_7 \text{ Leverage}_{it} + \beta_8 \text{ Long debt}_{it} \\ & + \beta_{9,pretax} \text{ Pretax dummies}_{it} + \beta_{10} \text{10y Swap}_t \\ & + \beta_{11} \text{10y} - \text{1y Swap}_t \\ & + \beta_{12} \text{ Forecast dispersion}_{it} + \epsilon_{it}, \qquad (1)\end{aligned}$$

- A key challenge is how to measure (and identify) liquidity in corporate bond markets.

- Measures of liquidity:
  - Amihud (2002) illiquidity for asset i in year y:

$$ILLIQ_{iy} = \frac{1}{D_{iy}} \sum_{d=1}^{D_{iy}} \frac{\mid R_{iyd} \mid}{VOLD_{iyd}},$$

    where R_{iyd} is the return on day d and $VOLD_{iyd}$ is the dollar volume on day d. Hence, a security is illiquid if, on average, we see *large absolute price changes without much trade*.
  - Bid-ask spread, based on the imputed round-trip trades (IRT), see Feldhütter (2012):
    - A bond does not trade for hours and then suddenly trades two times with the same volume in a matter of minutes. This is an imputed round-trip trade.
    - Assumption: The highest (lowest) price is an investor buying from (selling to) a dealer.
    - The Imputed Round-trip trade Cost (IRC) is the difference in buying and selling prices.
  - Turnover.
  - The number of zero-trading days (both at the bond and the firm level).
  - Liquidity *risk* based on the Amihud and IRC measures by computing the standard deviation of daily observations.

- Comovement of liquidity measures:

Table 1
Principal component loadings on the liquidity variables.
This table shows the principal component analysis loadings on each of the eight liquidity variables along with the cumulative explanatory power of the components. The liquidity variables are measured quarterly for each bond in the data sample. The data are U.S. corporate bond transactions data from TRACE and the sample period is from 2005:Q1 to 2009:Q2.

Panel A: Principal component loadings, pre-subprime (2005:Q1–2007:Q1)								
	1PC	2PC	3PC	4PC	5PC	6PC	7PC	8PC
Amihud	0.45	0.05	−0.12	−0.05	0.44	0.70	−0.12	0.28
Roll	0.26	0.33	0.08	−0.86	−0.27	−0.06	0.06	0.02
Firm zero	−0.04	0.64	−0.02	0.39	−0.56	0.36	0.07	0.02
Bond zero	−0.00	0.67	−0.10	0.10	0.56	−0.45	0.05	0.11
Turnover	−0.02	0.07	0.98	0.07	0.15	0.08	0.01	0.03
IRC	0.52	0.06	0.03	0.15	0.00	−0.10	−0.39	−0.73
Amihud risk	0.47	−0.11	0.01	0.16	−0.01	−0.09	0.85	−0.09
IRC risk	0.49	−0.12	0.06	0.21	−0.29	−0.40	−0.31	0.60
Cum. % explained	39%	59%	72%	81%	89%	94%	99%	100%
Panel B: Principal component loadings, post-subprime (2007:Q2–2009:Q2)								
	1PC	2PC	3PC	4PC	5PC	6PC	7PC	8PC
Amihud	0.46	0.04	−0.10	−0.10	−0.07	0.73	0.43	0.21
Roll	0.06	0.47	0.35	−0.78	0.10	−0.02	−0.17	0.02
Firm zero	−0.11	0.59	−0.28	0.33	0.62	0.20	−0.17	0.00
Bond zero	−0.12	0.64	−0.07	0.21	−0.67	−0.16	0.21	0.12
Turnover	−0.14	0.05	0.88	0.39	0.08	0.20	0.12	0.01
IRC	0.52	0.15	0.06	0.09	0.09	−0.26	0.28	−0.73
Amihud risk	0.46	0.03	0.07	0.21	−0.30	0.19	−0.78	−0.04
IRC risk	0.51	0.02	0.09	0.13	0.23	−0.51	0.10	0.63
Cum. % explained	39%	58%	71%	81%	88%	94%	99%	100%

- The first PC is almost an equally-weighted average of the Amihud, IRC, Amihud Risk, and IRC risk measures. Refer to this factor, which is close to the first principal component, as λ.

- Regression results:

Table 3
Liquidity regressions.

For each rating class R and each liquidity variable L a pooled regression is run with credit risk controls

$$Spread_{it}^{R} = \alpha^{R} + \gamma^{R} L_{it} + \text{Credit risk controls}_{it} + \epsilon_{it},$$

where i is for bond in rating R and t is time measured in quarters. In total, 45 regressions are run (nine liquidity variables × five rating classes). This table shows for each regression the coefficient and t-statistics in parentheses for the liquidity variable. The proxies are described in detail in Section 3 and are calculated quarterly from 2005:Q1 to 2009:Q2. The data are U.S. corporate bond transactions from TRACE. Panel A shows the coefficients using data before the subprime crisis, while Panel B shows the coefficients using data after the onset of the subprime crisis. Standard errors are corrected for time series effects, firm fixed effects, and heteroskedasticity, and significance at 10% level is marked *, at 5% marked **, and at 1% marked ***.

Panel A: Pre-subprime (2005:Q1–2007:Q1)

	AAA	AA	A	BBB	Spec
λ	0.0038*** (2.97)	0.0056*** (2.95)	0.0131*** (2.61)	0.0260*** (3.69)	0.1726*** (5.34)

Panel B: Post-subprime (2007:Q2–2009:Q2)

	AAA	AA	A	BBB	Spec
λ	0.0281** (2.12)	0.2495*** (3.64)	0.2500*** (4.08)	0.3333*** (3.57)	0.6746*** (6.73)

- Liquidity much more important during the financial crisis. The slope coefficients for all ratings classes are an order of magnitude larger.

- Define the liquidity component of bond spreads as the difference in bond yields between a bond with average liquidity and a very liquid bond.

- By rating, bonds are sorted by λ_{it} and call the 5% percentile λ_5. Then estimate a regression of the spread on the liquidity measure $\lambda_{it} - \lambda_5$ (incl. controls). Compute the "liquidity fraction" of the credit spread: $\beta^R(\lambda_{it} - \lambda_5)/Spread^R_{it}$.
  The table reports the median of this statistic.

Table 5
Liquidity component in fraction of spread.
For each rating R, we run the pooled regression

$$Spread^R_{it} = \alpha^R + \beta^R \lambda_{it} + \text{Credit risk controls}_{it} + \epsilon_{it},$$

where i refers to bond, t to time, and λ_{it} is our liquidity measure. Within each rating we sort increasingly all values of λ_{it} and find the 5% value λ_5. For each bond we define the liquidity fraction of the total spread as $\beta^R(\lambda_{it}-\lambda_5)/Spread^R_{it}$. The estimated fractions in the table are for each entry the median fraction. Confidence bands are found by a wild cluster bootstrap. The data are U.S. corporate bond transactions from TRACE and the sample period is from 2005:Q1 to 2009:Q2.

Panel A: Liquidity component in fraction of spread, pre-subprime (2005:Q1–2007:Q1)

Maturity	0–1y	1–2y	2–3y	3–4y	4–5y	5–8y	8–10y	10–30y
Fraction in pct	3 (2;4)	7 (4;9)	13 (8;17)	13 (8;18)	13 (8;17)	11 (7;15)	8 (5;11)	10 (7;14)
Number of observations	1596	1613	1241	891	641	1187	578	1218
Rating	AAA	AA	A	BBB	Spec			
Fraction in pct	3 (2;5)	4 (2;7)	11 (5;18)	8 (3;12)	24 (18;30)			
Number of observations	533	1869	4148	1340	1075			

Panel B: Liquidity component in fraction of spread, post-subprime (2007:Q2–2009:Q2)

Maturity	0–1y	1–2y	2–3y	3–4y	4–5y	5–8y	8–10y	10–30y
Fraction in pct	11 (7;14)	20 (13;27)	23 (15;31)	27 (18;38)	31 (20;42)	44 (28;60)	33 (21;44)	43 (28;53)
Number of observations	809	819	675	657	556	817	568	598
Rating	AAA	AA	A	BBB	Spec			
Fraction in pct	7 (1;12)	42 (23;60)	26 (14;39)	29 (16;41)	23 (16;30)			
Number of observations	414	1549	2533	539	464			

- Before the financial crisis, liquidity averages to about 10% of the spread. Lower for investment-grade bonds.

- During the financial crisis, 20-40% of the spread is due to illiquidity (except for AAA).

- Graphically:

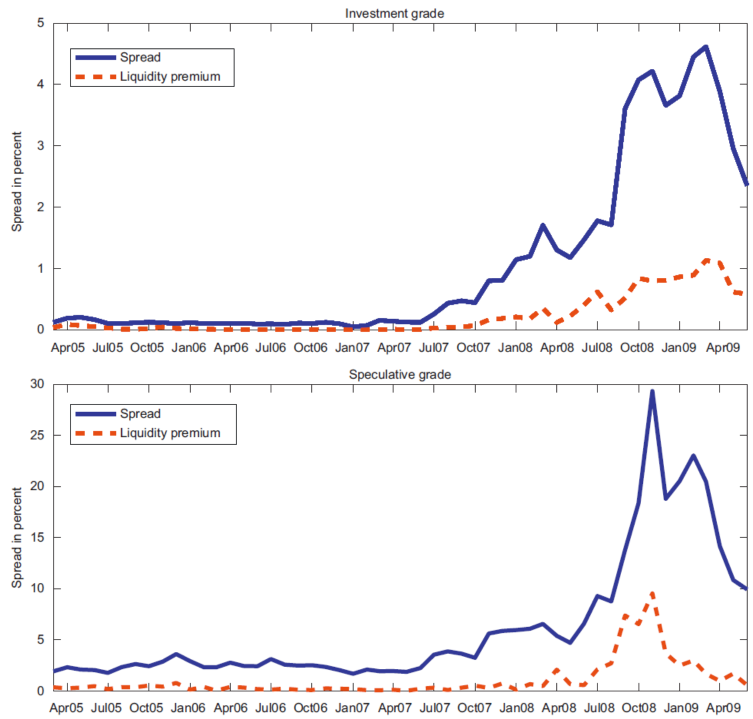


Fig. 3. Liquidity premium and total spread for investment grade and speculative grade bonds. This graph shows for investment grade and speculative grade yield spreads the variation over time in the amount of the spread that is due to illiquidity and the total yield spread. On a monthly basis, the fraction of the yield spread that is due to illiquidity is calculated as explained in Section 4.3. This fraction multiplied by the median yield spread is the amount of the spread due to illiquidity and plotted along with the median yield spread. The data are U.S. corporate bond transactions from TRACE and the sample period is from 2005:Q1 to 2009:Q2.

- The liquidity premium picks up quickly for speculative-grade bonds, but also declines quickly thereafter.

- For investment-grade bonds, by contrast, the liquidity premium increases more gradually, but it is also much more persistent.

- Determinants of the liquidity premium:

  - Is the lead underwriter in financial distress (Bear Sterns, Lehman Brothers).

  - Industry effects (issuer is financial versus industrial firm).

- For more on bond liquidity, see also Longstaff, Mithal, and Neis (2005) who compare CDS and credit spreads to measure liquidity effects.

2.1.6. Cross-sectional Predictability

- Chordia, Goyal, Nozawa, Subrahmanyam, and Tong (2017) study the cross-section of bond returns.
- Empirical work is more challenging due to infrequent trading.

Table 4: Monthly Cross-Sectional Regressions for Bond Returns

We run the following cross-sectional regression each month:

$$R_{it} = \gamma_{0t} + \gamma'_{1t} Zeq_{it-1} + \gamma_{2t} R_{it-1} + \gamma_{3t} R_{it-2:t-12} + \gamma_{4t} DD_{it-1} + \gamma_{5t} L^{eAmihud}_{it-1} + \epsilon_{it},$$

where R_{it} is the excess bond return, Zeq_{it-1} are lagged equity return predictors (the momentum returns are lagged by an additional month), DD is the distance-to-default, and $L^{eAmihud}$ is the negative of the Amihud illiquidity measure's logarithm. All returns are in basis points per month. Equity return predictors are described in Table 2. Panel A presents the OLS results using subsets of variables for the sample of all bonds. Panel B presents further results using all variables. EW and VW represent OLS and value-weighted regressions, respectively. To value-weight, we multiply the square root of the market value of a bond in month $t-1$ with both its excess return in month t and the independent variables in month $t-1$. We also present EW estimates on subsamples of investment grade (IG) and speculative grade (junk) bonds. Newey-West (19987) corrected (using 12 lags) t-statistics are given in parentheses. We denote statistical significance at the 10% and 5% level with one and two asterisks, respectively. The sample period is 1973 to 2011.

Panel B: All variables

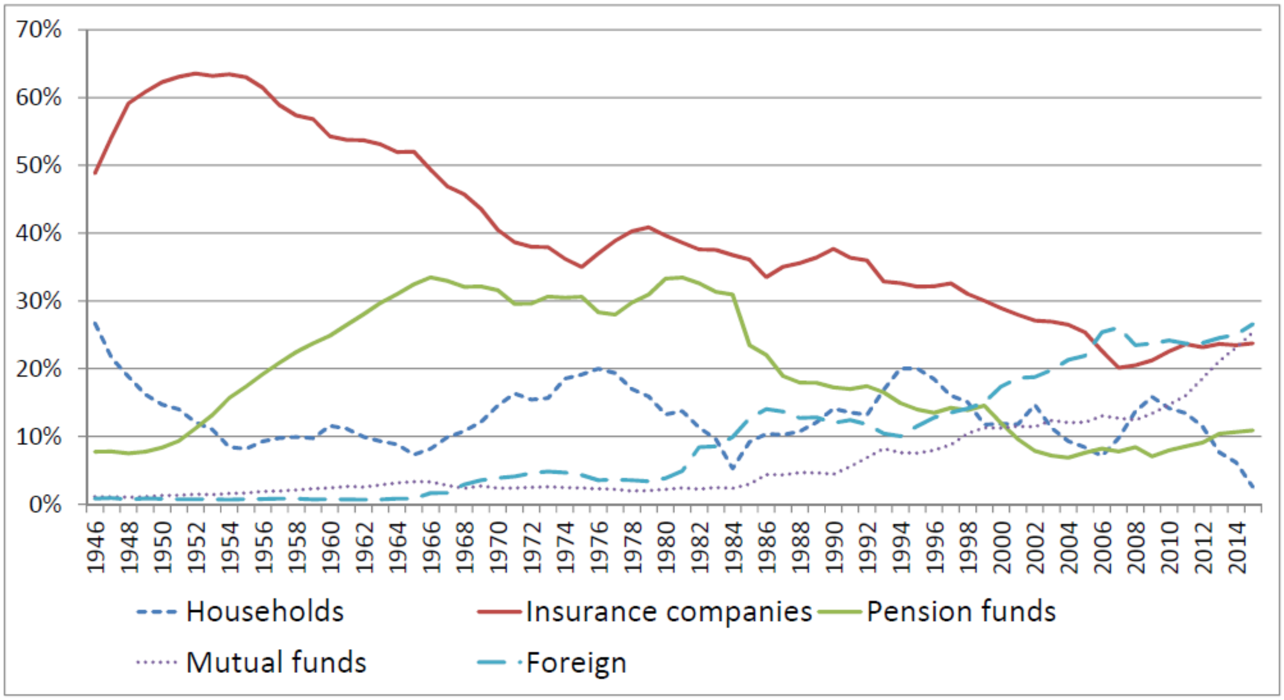
	All		IG	Junk	IG−Junk
	EW	VW	EW	EW	EW
$\log MC$	−6.07**	−3.85*	−3.94**	−11.01**	7.07
	(−3.09)	(−1.93)	(−2.44)	(−2.23)	(1.32)
$\log B/M$	0.12	−0.53	−0.80	2.97	−3.77*
	(0.15)	(−0.64)	(−1.13)	(1.45)	(−1.82)
$R_{eq}(2,12)$	3.72**	3.86**	3.50**	5.47**	−1.97
	(4.33)	(4.64)	(6.07)	(2.20)	(−0.75)
$R_{eq}(1)$	8.48**	8.93**	3.89**	18.26**	−14.37**
	(6.32)	(6.68)	(5.06)	(6.69)	(−5.85)
Y/B	−4.71**	−5.20**	0.20	−8.44**	8.64**
	(−4.18)	(−4.62)	(0.32)	(−3.09)	(3.11)
NS	1.07	1.19*	−0.10	2.81	−2.91
	(1.36)	(1.76)	(−0.14)	(1.48)	(−1.54)
Ac/A	0.31	0.12	−0.59	−0.87	0.28
	(0.57)	(0.20)	(−1.43)	(−0.55)	(0.17)
dA/A	−0.81	−0.76	−0.19	−0.38	0.19
	(−0.87)	(−0.87)	(−0.24)	(−0.22)	(0.11)
SUE	−0.37	0.07	−0.37	−1.20	0.83
	(−0.44)	(0.07)	(−0.42)	(−0.57)	(0.38)
$IdioVol$	3.97**	2.82**	−0.66	3.28	−3.94*
	(3.32)	(2.26)	(−1.14)	(1.39)	(−1.72)
$R_{bd}(2,12)$	−4.99**	−6.87**	−9.19**	−5.03	−4.16
	(−2.05)	(−2.72)	(−4.29)	(−1.37)	(−1.28)
$R_{bd}(1)$	−30.44**	−36.28**	−36.66**	−28.02**	−8.64
	(−7.60)	(−10.38)	(−11.14)	(−4.33)	(−1.31)
DD	−2.37**	−2.25**	−1.81*	−6.55**	4.74**
	(−2.45)	(−2.12)	(−1.80)	(−3.27)	(2.11)
$L^{eAmihud}$	1.36	−0.38	1.52	6.08	−4.56
	(0.81)	(−0.24)	(1.15)	(1.16)	(−0.82)

- Main takeaways:
  - Strong size effect, which is more pronounced for junk bonds (although the difference is statistically insignificant).
  - Equity momentum also predicts bond returns.
  - Lagged 1-month equity returns has the strongest predictive power, and in particular for junk bonds (difference is significant).
  - Profitability is significant, that is, profitable firms have low bond returns (recall, such firms have abnormally *high* equity returns).
  - Other accounting variables do not matter.
  - Note the strong negative coefficient on lagged bond returns (reversals), which is consistent with liquidity concerns.
  - The distance to default (DD) predicts bonds negatively, consistent with a credit risk premium.

2.2. Market Structure

- Based on data of the flow of funds (note: the FoF reports holdings of corporate and *foreign* bonds jointly): Table L.213
- $14.7 tr market in 2021.Q2, $3.6 trillion of which is foreign bonds, hence $11.1 tr corporate bond market in U.S.
- Lots of new issuance of IG bonds in 2020 and HY in 2021 due to the low interest rate environment. Refinancing and new borrowers.
- Major holders of corporate and foreign bonds:
  - Foreigners: $4.4 tr
  - Life Insurers: $2.9 tr
  - Mutual funds: $2.8 tr
  - Private pension funds: $0.8 tr
  - P&C insurers: $0.7 tr
  - Banks: $0.6 tr
  - Households: $0.3 tr

- Insurance companies are major investors in corporate bond markets, but their share has been declining:



- The large groups that have been growing are mutual funds and the foreign sector.

- An interesting question is how their demand is different, and in particular the demand for liquidity (e.g., insurance companies versus mutual funds).

2.3. *Interpreting the Facts*

2.3.1. Structural models and the credit spread puzzle

- Classic model to understand corporate bond prices: Merton (1974).
- Merton model outline:
  - Firm value (assets) is modeled exogenously:
  $$\frac{dV_t}{V_t} = (r - \delta)dt + \sigma dW_t,$$
  where δ is the payout rate to debt- and equity holders.
  - The firm is financed by equity and a zero-coupon bond with face value F.
  - If the asset value is below the face value when the bond matures, the firm cannot repay its debt holders and is assumed to default.
  - This is an application of the Black-Scholes model: Corporate debt can be seen as a risk-free bond plus a short put option.
- Note that this is a relative pricing model. **Given** the dynamics of the firm value, we compute the price of the bond.
- The famous Leland (1994) paper extends the Merton model with capital structure choice, breaking Modigliani-Miller by introducing taxes and bankruptcy costs.

- The credit spread puzzle: It is hard to reconcile the observed credit spreads with structural models.

- Puzzle documented in Huang and Huang (2012).

- Note: This is an old paper that never got published until recently. The sample is January 1973 - December 1993.

- Summary of the problem, after calibrating the model:

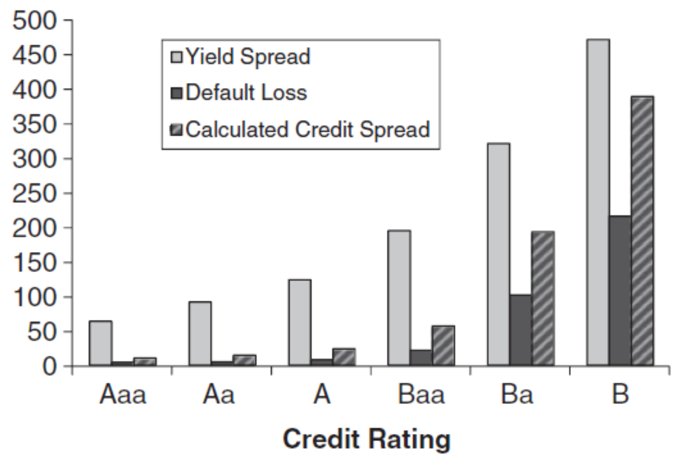


Figure 2
Historical average yield spreads and default loss rates, and predicted credit spreads for ten-year bonds
This figure plots the historical average yield spread (in basis points) and calculated credit spreads of ten-year corporate bonds, and the average default loss rate (in basis points) over a ten-year time interval, for each rating category. Average yield spreads for investment-grade bonds are based on monthly Lehman bond index data over January 1973–December 1993. Average spreads for junk bonds are from Caouette, Altman, and Narayanan (1998). Default loss rates are estimated using historical default rates and average recovery rates from the Moody's that are reported in Table 1. Predicted (or calculated) credit spreads are obtained using the one-factor Longstaff and Schwartz (1995) model under the base case, as reported in column 7 of Table 2.

- The model-implied credit spreads appear to be too low, more so for the high-grade bonds.

- There exists a large literature that tries to fix the models.

- Feldhütter and Schaefer (2018) argue that there is no credit spread puzzle to begin with. Main insight:
  - Defaults are rare events.
  - Hence, we need a long sample to measure expected default.
  - Feldhütter and Schaefer (2018) use 82 years of data (1920-2001). The previous literature only uses 30 years of data...

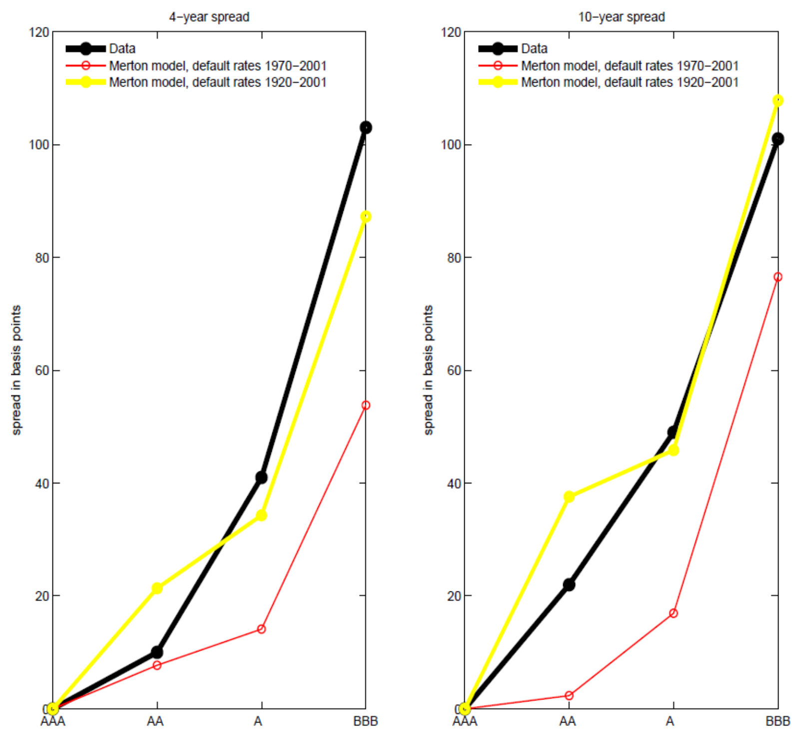


Fig. 2 *Corporate spreads to AAA-bond yields in the Merton model using default rates from different periods.* This figure shows actual and model-implied spreads to AAA yields. The thin red line shows spreads in the Merton model based on Moody's default rates from the period 1970-2001 and corresponds exactly to the calculations in Chen, Collin-Dufresne, and Goldstein(2009). The thick yellow line shows spreads in the Merton model where Moody's default rates from the period 1920-2001 are used. Actual spreads are from Duffee(1998).

- This is all relative to AAA yields. AAA-Treasury spread is assumed to reflect the demand for safety/liquidity.

- Instead of looking at the *level* of credit spreads, Collin-Dufresne, Goldstein, and Martin (2001) study the *changes* in credit spreads.

- In structural models, these changes are related to changes in Treasury yield factors (level and slope), changes in leverage, changes in risk (volatility or disaster risk), or macro-economic conditions.

- Main regression and predictions according to the theory:

Table I

Explanatory Variables and Expected Signs on the Coefficients of the Regression:

$$\Delta CS_t^i = \alpha + \beta_1^i \,\Delta lev_t^i + \beta_2^i \,\Delta r_t^{10} + \beta_3^i \,(\Delta r_t^{10})^2 + \beta_4^i \,\Delta slope_t + \beta_5^i \,\Delta VIX_t + \beta_6^i \,S\&P_t + \beta_7^i \,\Delta jump_t + \epsilon_t^i.$$

Variable	Description	Predicted Sign
Δlev_t^i	Change in firm leverage ratio	+
Δr_t^{10}	Change in yield on 10-year Treasury	−
$\Delta slope_t$	Change in 10-year minus 2-year Treasury yields	−
ΔVIX_t	Change in implied volatility of S&P 500	+
$S\&P_t$	Return on S&P 500	−
$\Delta jump$	Change in slope of Volatility Smirk	+

- The regression results by leverage group:

Table II

Structural Model Determinants of Credit Spread Changes by Leverage Group

For each industrial bond i having at least 25 monthly quotes CS_t^i over the period July 1988 to December 1997, we estimate the following regression: $\Delta CS_t^i = \alpha + \beta_1^i\, \Delta lev_t^i + \beta_2^i\, \Delta r_t^{10} + \beta_3^i\,(\Delta r_t^{10})^2 + \beta_4^i\, \Delta slope_t + \beta_5^i\, \Delta VIX_t + \beta_6^i\, S\&P_t + \beta_7^i\, \Delta jump_t + \epsilon_t^i$. Quotes are discarded whenever a bond has less than 4 years to maturity. Average OLS parameter estimates are reported in Panel A. Panel B shows averages for a short maturity subsample where quotes are discarded whenever a bond has more than 9 years to maturity. Panel C shows averages for a long maturity subsample where quotes are discarded whenever a bond has less than 12 years to maturity. Associated t-statistics for each average appear immediately beneath.

	Leverage Groups					
	<15%	15–25%	25–35%	35–45%	45–55%	>55%
			Panel A: All Maturities			
Intercept	0.022	0.016	0.013	0.013	0.010	−0.002
t	8.76	10.00	6.57	4.59	2.73	−0.20
Δlev_t^i	−0.005	0.007	0.003	0.004	0.008	0.033
	−1.74	4.89	1.86	2.02	3.35	3.75
Δr_t^{10}	−0.124	−0.140	−0.181	−0.215	−0.215	−0.342
	−17.84	−30.23	−18.93	−17.63	−11.93	−6.15
$(\Delta r_t^{10})^2$	−0.010	−0.001	0.009	0.048	0.004	0.164
	−0.54	−0.05	0.67	2.40	0.10	2.31
$\Delta slope_t$	0.006	0.001	−0.028	0.008	0.004	−0.033
	0.30	0.07	−2.29	0.48	0.15	−0.73
ΔVIX_t	0.001	0.002	0.003	−0.001	0.005	0.001
	0.82	3.44	2.85	−0.94	2.65	0.11
$S\&P_t$	−0.016	−0.015	−0.016	−0.017	−0.016	−0.019
	−21.00	−29.56	−22.68	−15.60	−10.65	−6.85
$\Delta jump_t$	0.004	0.004	0.003	0.002	0.004	0.003
	16.86	18.50	7.76	5.83	7.87	1.88
Adjusted R^2	0.244	0.23	0.211	0.216	0.197	0.192
N	100	162	138	123	91	74

- The determinants as predicted by the theoretical models only explain 20-25% of the variation.

- Interestingly, the regression residuals are driven by a single common factor.

- If this is not related to credit risk or liquidity, this common component must be related to risk premia.

- Hence, this suggests that there is a common risk premium component in credit markets.

- Equilibrium models of corporate bond markets:
  - Chen, Collin-Dufresne, and Goldstein (2009): Introduce a counter-cyclical price of risk (via habit formation) and default boundary, so that credit spreads and default rates are both counter-cyclical. The model can replicate the Baa-Aaa spread, but fails on the Aaa-Treasuries spread. This may be because Treasuries are special, see Krishnamurthy and Vissing-Jorgensen (2012).
  - Gomes and Schmid (2011): Macro-finance model with recursive preferences, where firms make optimal investment and capital structure choices.
  - He and Milbradt (2014): A search model of corporate bonds to understand the interaction between liquidity and default. See also Chen, Cui, He, and Milbradt (2018).
  - Elenev, Landvoigt, and Van Nieuwerburgh (2021) solve an intermediary-based asset pricing model with long-term defaultable corporate debt, and optimal capital structure choice on the firm and the intermediary side. The model generates large and counter-cyclical credit risk premia while being consistent with observed quantity of credit risk.

- Culp, Nozawa, and Veronesi (2018) propose a creative way to:
  - Test theories of credit risk.
  - Ask counterfactual questions

  without the need to write down a fully structural model.

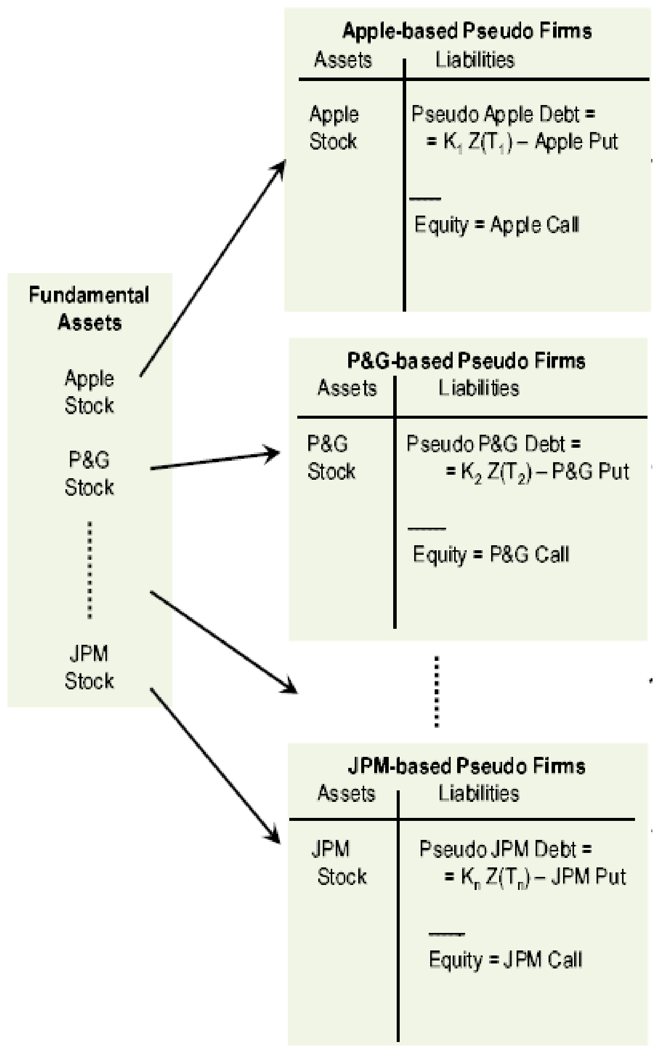
- Simple insight from Merton (1974): Equity is a call option on the firm. Debt is a risk-free bond plus a short put.

- Create "pseudo-firms," where we know the underlying assets and create **pseudo bonds** using options data.

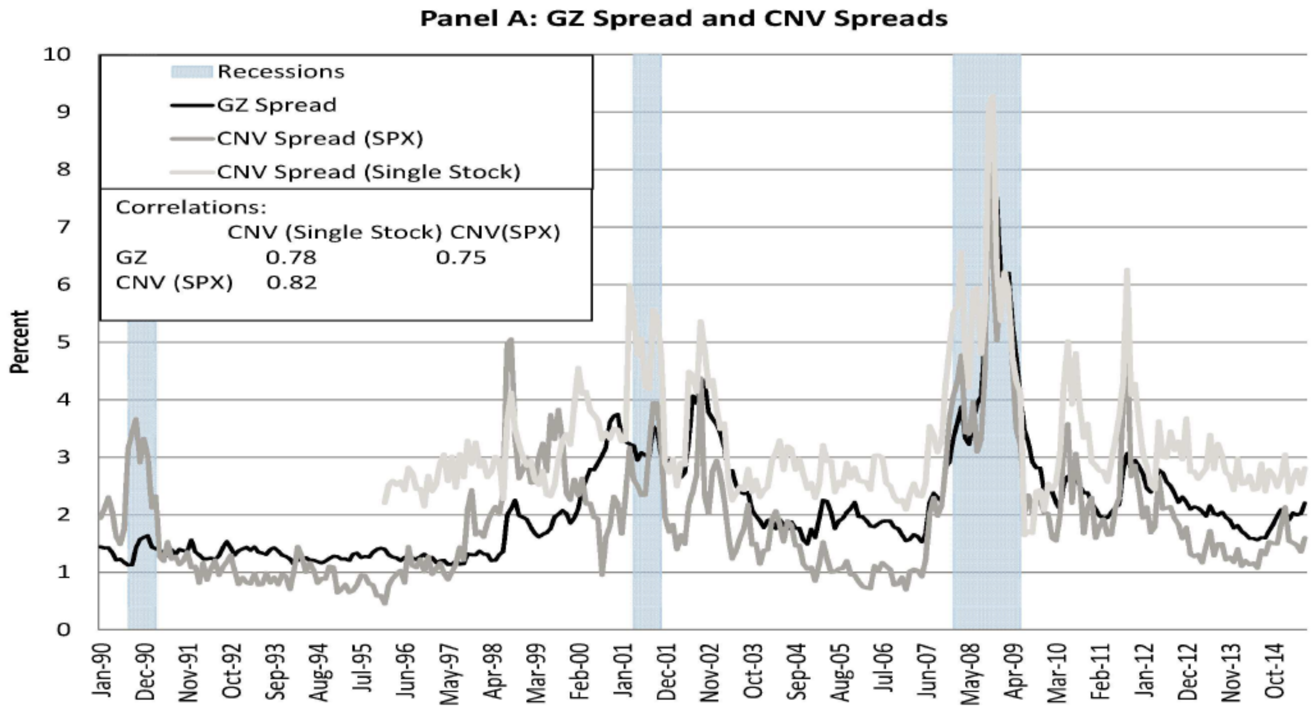
- Mechanics of constructing a pseudo firm: Assets A_t= Apple stock. Liabilities are equity and zero coupon debt with face value K_1 and maturity T_1. At maturity, bond holders of the pseudo firm receive $min\{K_1, A_{T_1}\} = K_1 - max\{K_1 - A_{T_1}, 0\}$, which is payoff of risk-free debt K_1 minus payoff on a put option on Apple stock. Thus, the no arbitrage value of the pseudo bond at t is: $K_1 Z_t(T_1) - P_t(K_1, T_1)$, where Z_t is risk-free discount factor between t and T_1.

- By using pseudo bonds, we do not have to think about liquidity issues specific to bond markets, covenants, search frictions, broker-dealer regulation, etc. We also side-step the issue that the market value of the firm is not observable.

- They find that the credit spreads are large and counter-cyclical. Interestingly, they also find large credit spreads for short-maturity, and high-grade bonds!


Fundamental Assets
Apple Stock
P&G Stock
JPM Stock
Apple-based Pseudo Firms
Assets
Liabilities
Apple Stock
Pseudo Apple Debt = = $K_1 Z(T_1)$ – Apple Put
Equity = Apple Call
P&G-based Pseudo Firms
Assets
Liabilities
P&G Stock
Pseudo P&G Debt = = $K_2 Z(T_2)$ – P&G Put
Equity = P&G Call
JPM-based Pseudo Firms
Assets
Liabilities
JPM Stock
Pseudo JPM Debt = = $K_n Z(T_n)$ – JPM Put
Equity = JPM Call

- The GZ spread is the average credit spread from Gilchrist and Zakrajsek (2012).



⇒ Illiquidity, investors' over-estimation of default risks, corporate frictions, and constraints on aggregate credit supply do not seem to explain observed credit spreads.

- Instead, variation in credit spreads appears more related to variation in (tail) risk premia.

2.3.2. Model of "A" Marginal Investor

- There are no models of the demand of major investors in corporate bonds (insurance companies, mutual funds, and foreign investors).
- Given their historical importance, it seems natural to model the demand of insurance companies.
- A key friction is that insurance companies care about the regulatory risk weights (capital charge) of the assets.
- Risk weights of insurance companies (Becker and Ivashina, 2015):

Table II
NAIC Risk-Based Capital Requirement

This summarizes National Association of Insurance Companies (NAIC) post-tax capital requirement factors (NAIC Risk-Based Capital Newsletter, 10/12/2001). Default rates are from Fitch Ratings Global Corporate Finance 2010 Transition and Default Study.

NAIC categories	Credit ratings		Capital charge	5-year cumulative default rates (1990-2010)
Federal government			Exempt	
NAIC 1 (highest)	AAA, AA, A	Investment Grade	0.3%	0.00%, 0.09%, 0.69%
NAIC 2	BBB	Investment Grade	0.96%	2.62%
NAIC 3	BB	High Yield/Speculative Grade	3.39%	6.76%
NAIC 4	B	High Yield/Speculative Grade	7.38%	8.99%
NAIC 5	CCC	High Yield/Speculative Grade	16.96%	34.38%
NAIC 6 (lowest)	CC or below	High Yield/Speculative Grade	19.50%	

- The risk-based capital (RBC) ratio of an insurance company is computed as

$$\text{RBC ratio} = \frac{\text{Assets - Liabilities}}{\text{Required Capital}},$$

where the risk weights appear in the required capital.

- This framework was introduced in the early 1990s.

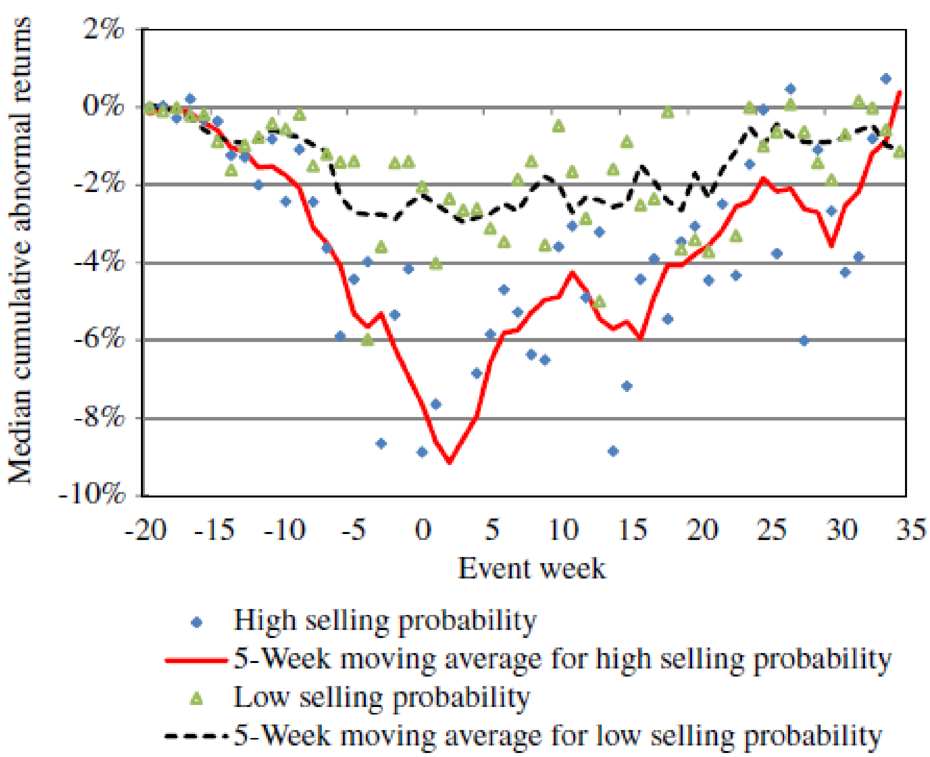
- To illustrate the importance of risk weights for insurance companies, and the importance of insurance companies for the corporate bond markets, we can look at rating downgrades, see Ellul, Jotikasthira, and Lundblad (2011).

- Consider two bonds:

  - Bond A is primarily held by constrained insurance companies.

  - Bond B is primarily held by unconstrained insurance companies.

  If bond A is downgraded, this puts significant pressure on the insurance companies to sell the bond. In case of bond B, insurance companies can hold on to the bond and there are no "fire sales:"



- It turns out that the risk regulation also interacts with the accounting framework.
- The incentive to sell is stronger for insurers that have to use mark-to-market accounting compared to historical cost accounting, see Ellul, Jotikasthira, Lundblad, and Wang (2015).

2.3.3. Corporate Bonds and the Real Economy

- Credit spreads tend to predict economic activity, see Gilchrist and Zakrajsek (2012).

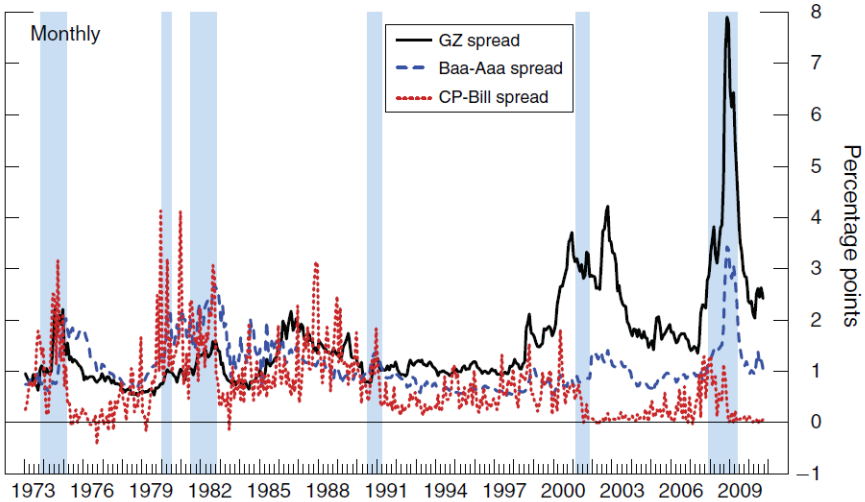


FIGURE 1. SELECTED CORPORATE CREDIT SPREADS

Notes: Sample period: 1973:1–2010:9. The figure depicts the following credit spreads: GZ spread = the average credit spread on senior unsecured bonds issued by nonfinancial firms in our sample (the solid line); Baa–Aaa = the spread between yields on Baa- and Aaa-rated long-term industrial corporate bonds (the dashed line); and CP–Bill = the spread between the yield on one-month A1/P1 nonfinancial commercial paper and the one-month Treasury yield (the dotted line). The shaded vertical bars represent the NBER-dated recessions.

TABLE 3—FINANCIAL INDICATORS AND REAL GDP

Financial indicator	Forecast horizon: 1 quarter				Forecast horizon: 4 quarters			
Term spread	−0.198 [1.77]	−0.217 [1.92]	−0.250 [2.07]	−0.247 [2.26]	−0.398 [2.79]	−0.406 [2.81]	−0.413 [2.70]	−0.460 [3.22]
Real FFR	−0.016 [0.12]	0.175 [1.12]	0.020 [0.15]	−0.123 [0.95]	−0.036 [0.24]	0.042 [0.22]	−0.026 [0.17]	−0.131 [0.87]
CP–bill spread	—	−0.254 [2.16]	—	—	—	−0.105 [0.82]	—	—
Baa–Aaa spread	—	—	−0.229 [1.95]	—	—	—	−0.066 [0.52]	—
GZ spread	—	—	—	−0.437 [4.96]	—	—	—	−0.482 [5.74]
Adjusted R^2	0.170	0.197	0.209	0.313	0.215	0.215	0.213	0.369

Notes: Sample period: 1973:I–2010:III. Dependent variable is $\nabla^h Y_{t+h}$, where Y_t denotes the real GDP in quarter t and h is the forecast horizon. In addition to the specified financial indicator in quarter t, each specification also includes a constant and p lags of ∇Y_{t-1} (not reported), where p is determined by the AIC. Entries in the table denote the standardized estimates of the OLS coefficients associated with each financial indicator; absolute asymptotic t-statistics reported in brackets are computed according to Hodrick (1992) (see text for details).

- Furthermore, we have seen (in week 4) that Q-theory does not work that well for equity markets. Market-to-book does not strongly predict future investment (in levels or in changes).
- However, we can also test Q-theory on bond markets.
- Philippon (2009) develops this idea. Most evidence seems to suggest a much stronger link between corporate bond markets and investment.
- Bond versus stock Q (left) and the failure of standard Q theory (right):

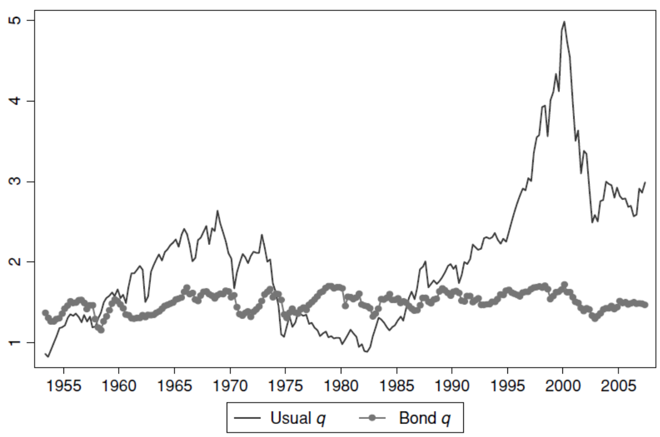


FIGURE IV
Usual Measure of q and Bond Market's q
Tobin's q is constructed from the flow of funds, as in Hall (2001). Bond q is constructed from Moody's yield on Baa bonds, using the structural model calibrated to the observed evolutions of book leverage and firm volatility, expected inflation from the Livingston survey, and the yield on 10-year Treasury bonds.

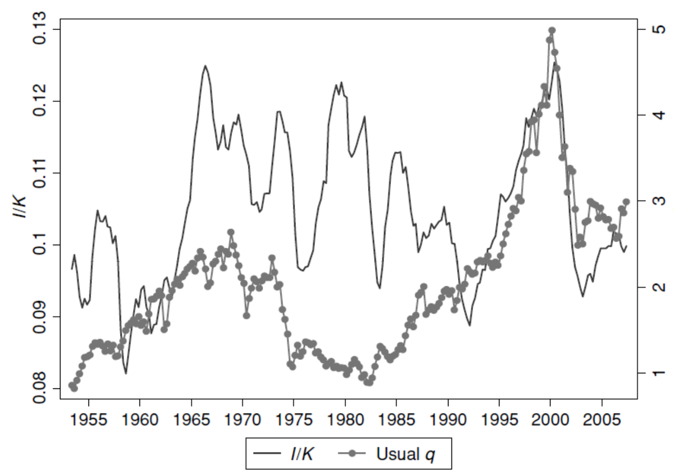


FIGURE V
Usual Measure of q and Investment Rate
I/K is corporate fixed investment over the replacement cost of equipment and structure. Usual q is constructed from the flow of funds, as in Hall (2001).

- The bond market Q and the investment rate:

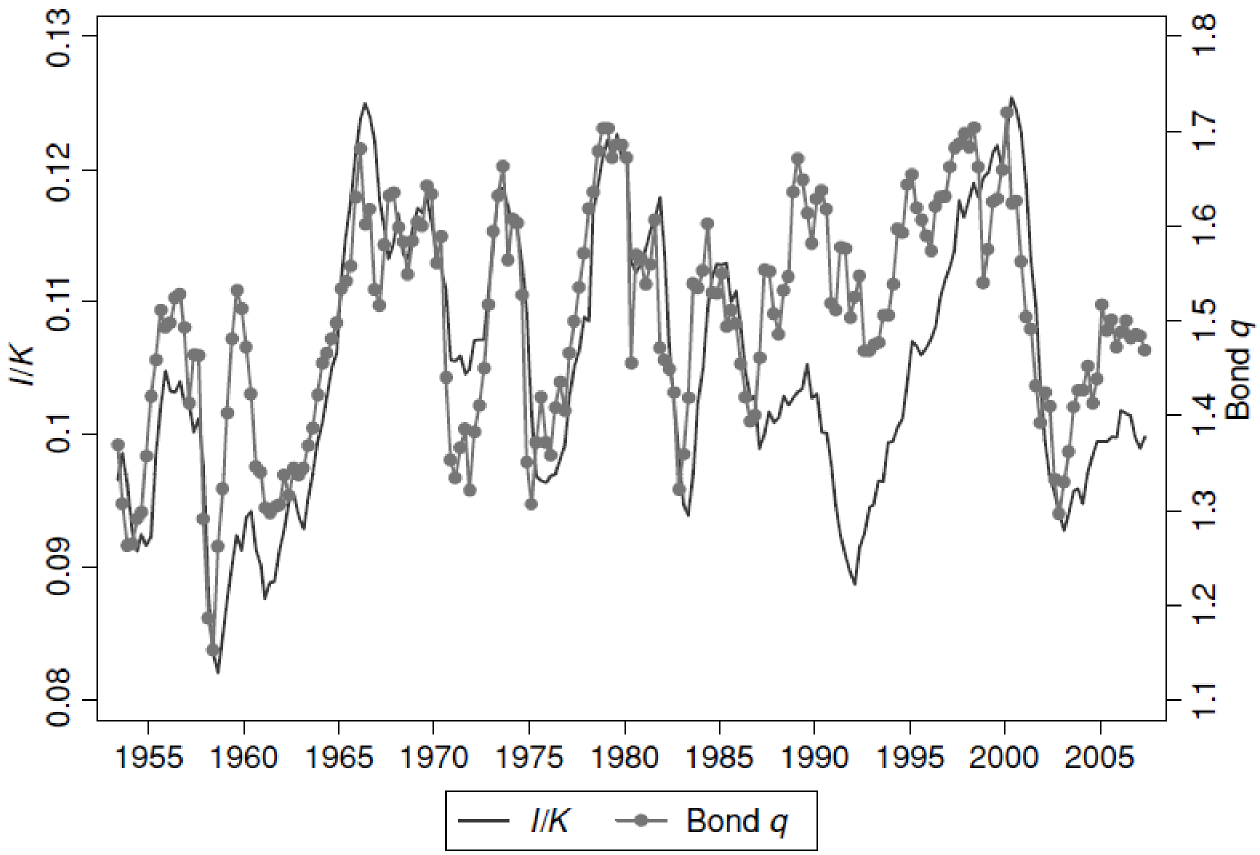


FIGURE VI
Bond Market's q and Investment Rate

I/K is corporate fixed investment over the replacement cost of equipment and structure. Bond q is constructed from Moody's yield on Baa bonds, using the structural model calibrated to the observed evolutions of book leverage and firm volatility, expected inflation from the Livingston survey, and the yield on 10-year Treasury bonds.

- See Gilchrist and Zakrajsek (2007) for firm-level evidence relating credit spreads to corporate investment.

2.4. Active areas

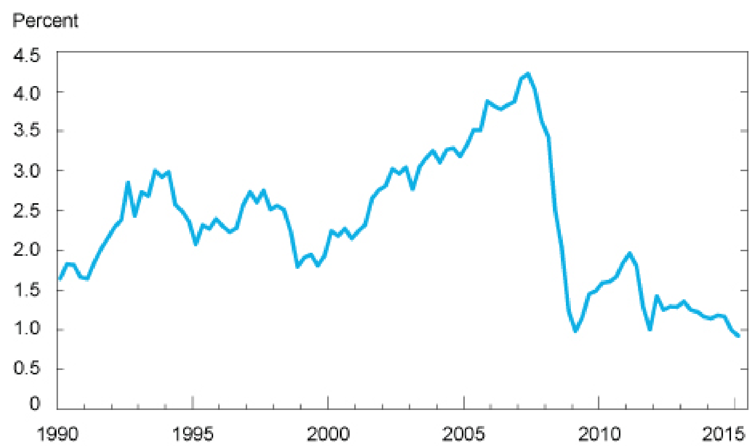
2.4.1. Liquidity in bond markets

- Ongoing debate on the impact of new banking regulation, and the financial sector more broadly, on financial markets.
- In corporate bond markets, the narrative seems to be that small trades moved to online platforms, thereby improving liquidity, but people argue that the liquidity for large trades deteriorated.
- Empirical challenge: We have not seen a large liquidity event, so we do not quite know.
- Duffie (2016) in the media.
- The NY FED has a series of articles on bond market liquidity, see for instance here and here.

- Some facts:

  1. Dealer inventories went down:

Dealers' ownership share of corporate bonds has declined in recent years



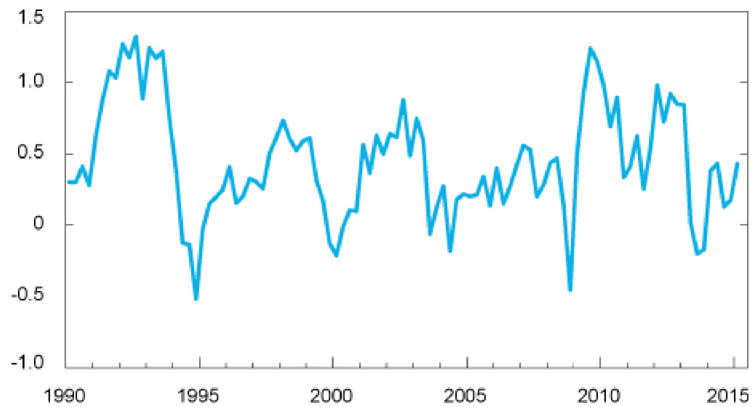
Source: Federal Reserve Board, "Financial Accounts of the United States."

Note: The chart plots the share of corporate and foreign bonds owned by security brokers and dealers as a fraction of the total amount of corporate and foreign bonds outstanding.

2. We have seen that share of corporate bonds in the hands of mutual funds went up. However, mutual funds experience volatile flows, in part in response to past performance:

Net flow volatility of bond funds is stable

Net bond flows as percentage of corporate bonds outstanding

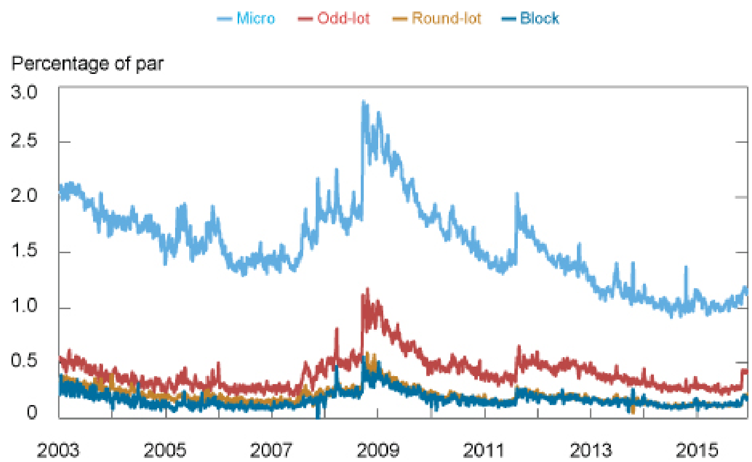


Sources: For net bond mutual fund flows, Investment Company Institute; for corporate bonds outstanding, Federal Reserve Board, "Financial Accounts of the United States."

Note: The chart plots net bond flows as a percentage of outstanding corporate and foreign bonds (held in the United States).

3. Bid-ask spreads have narrowed following the financial crisis, and are back to pre-crisis levels:

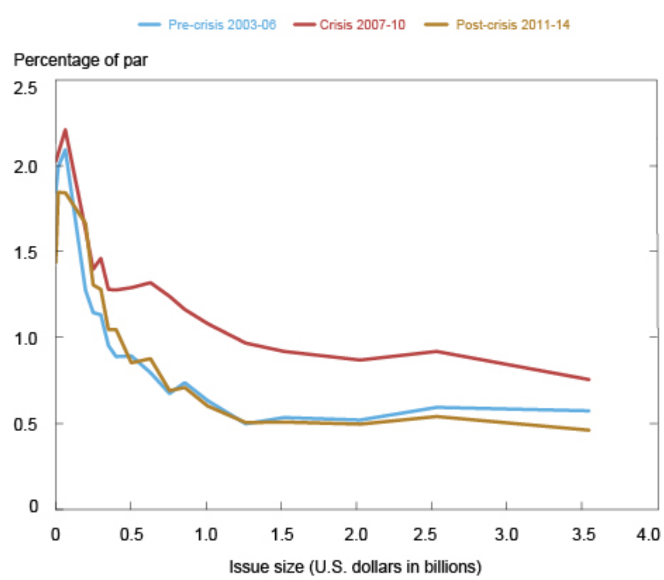
Bid-Ask Spreads Are Narrower for Larger Trades



Source: Authors' calculations, based on Trade Reporting and Compliance Engine (TRACE) data from the Financial Industry Regulatory Authority (FINRA).

Notes: The chart plots the five-day moving averages of realized bid-ask spreads. The spreads are computed daily for each bond and trade size category as the difference between the average (volume-weighted) dealer-to-client buy price and the average (volume-weighted) dealer-to-client sell price, and then averaged (on an equal-weighted basis) across bonds.

Bid-Ask Spreads Are Comparable to Pre-Crisis Levels Across Issue Sizes

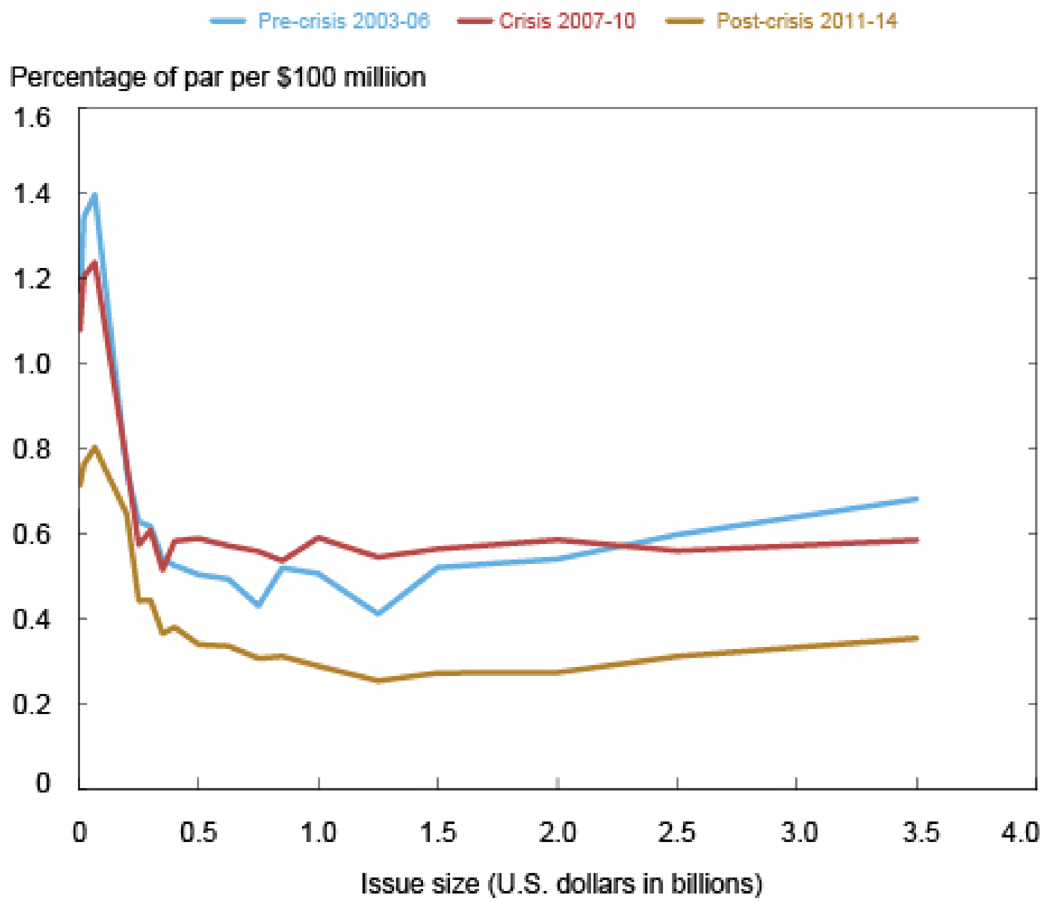


Source: Authors' calculations, based on Trade Reporting and Compliance Engine (TRACE) data from the Financial Industry Regulatory Authority.

Notes: The chart shows realized bid-ask spreads for bonds within one of twenty issue size buckets for the 2003-06, 2007-10, and 2011-14 time periods. The spreads are computed daily for each bond as the difference between the average dealer-to-client buy price and the average dealer-to-client sell price, and then averaged across days and then bonds.

4. Price impact measures also do not have changed much though:

Price Impact Has Declined Across All Issue Sizes



Source: Authors' calculations, based on Trade Reporting and Compliance Engine (TRACE) data from the Financial Industry Regulatory Authority.

Notes: The chart shows price impact for bonds within one of twenty issue size buckets for the 2003-06, 2007-10, and 2011-14 time periods. Price impact is computed for each trade as the absolute price return divided by trade size, then averaged to a daily level for each bond, and then averaged across days and then bonds.

However, there may be selection and large trades that would have moved prices were not executed

2.4.2. Crises and credit markets

- A fast-growing literature tries to understand the nature of financial crises. Key challenge as emphasized by Bernanke:

  "Indeed, the 30 percent or so aggregate decline in house prices since their peak has by now eliminated nearly $7 trillion in paper wealth. [. . .] any theory of the crisis that ties its magnitude to the size of the housing bust must also explain why the fall of dot-com stock prices just a few years earlier, which destroyed as much or more paper wealth–more than $8 trillion–resulted in a relatively short and mild recession and no major financial instability."

- Some key background papers:
  - Schularick and Taylor (2012):
    - Lagged credit growth highly significant predictor of financial crises; other variables add little explanatory power.
  - Jorda, Schularick, and Taylor (2013):
    - After 5 years, the financial-crisis recession path of real GDP per capita is about 5% lower than the normal-recession path.
    - More credit-intensive expansions tend to be followed by deeper recessions (in financial crises or otherwise) and slower recoveries.

- Mian, Sufi, and Verner (2017):
    * An increase in household debt-to-GDP predicts low future GDP growth and higher unemployment; 30 countries, data from 1960-2012.
    * Household debt-to-GDP has a common global component: Global household debt cycle.
    * Countries with a household debt cycle more correlated with the global household debt cycle experience a sharper decline in growth after an increase in domestic household debt.

- Krishnamurthy and Muir (2017) bring in information from credit spreads.

- A financial crisis is defined as "bank runs, sharp increases in default rates accompanied by large losses of capital that result in public intervention, bankruptcy, or forced merger of financial institutions."

- The precise dates are in Jorda, Schularick, and Taylor (2013).

- Main evidence:
  - Before a financial crisis: Unconditionally, credit spreads and credit growth are positively correlated. However, in the 5 years before a financial crisis, spreads and credit growth are negatively correlated.
    $\Rightarrow$ This suggests that expansions of credit supply are an important precursor of crises.

    Mian, Suf, and Verner (2017) also make this point by looking at mortgage spreads.

– Transition into a financial crisis: Many theories suggest that the crisis is a "surprise," for instance due to the losses that the bank experiences on its assets.
The change in spreads measures the shock and predicts the subsequent severity of financial crises.

– Following a financial crisis: There is a lot of heterogeneity in the severity of financial crises

Distribution of declines in GDP across episodes

Financial Crises (ST dates)						
	Mean	Median	Std Dev	P 10th	P 90th	N
Trough	-6.8	-4.1	7.6	-14.2	-0.7	44
3 year	-2.6	-0.8	8.5	-12.9	5.5	39

– The severity is in part explained by spreads. The main regression

$$\ln(y^i_{t+k}/y^i_t) = a_i + a_t + b\ s_{it}\ I(Crisis_{it}) + c\ s_{it}\ I(NoCrisis_{it}) + d' x_{it} + \epsilon^i_{t+k},$$

where $\ln(y^i_{t+k}/y^i_t)$ is $k-$period output growth and s_{it} is the credit spread in country i. They also include the lag of the credit spread ($s_{i,t-1}$) and two lags of GDP as controls.

Panel B: 5 year GDP growth

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\widehat{s}_{i,t}$	-1.16						
	(0.40)						
$\widehat{s}_{i,t-1}$	1.64						
	(0.79)						
$\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-1.87	-0.05				
		(1.24)	(1.13)				
$\Delta\widehat{s}_{i,t} \times 1_{crisisST,i,t}$			-8.13				
			(1.60)				
$\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$				-0.47			
				(0.28)			
$\Delta\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$					-0.18		
					(0.23)		
$\widehat{s}_{i,t} \times 1_{recess,i,t}$						-2.06	-1.30
						(1.41)	(0.92)
$\Delta\widehat{s}_{i,t} \times 1_{recess,i,t}$							-2.35
							(3.22)
Observations	634	634	634	634	634	634	634
R-squared	0.53	0.52	0.54	0.55	0.55	0.52	0.54

- A one-standard deviation increase in spreads is associated with a 5-year cumulative decline in GDP of 8.13% in a financial recession, while a one-standard deviation increase in spreads is "only" associated with a cumulative decline of 2.35% in GDP in a non-financial recession.

2.4.3. Covid-19 and Central Bank interventions

- Central Banks intervened directly into corporate credit markets
- Elenev, Landvoigt, and Van Nieuwerburgh (2021) provide an overview of the various programs in the U.S. supported by the Fed's lending facilities and the Treasury
  - Paycheck Protection Program (PPP):
    - $671 billion or 3.1% of 2019 GDP
    - Two-year loans with 1% interest
    - Principal up to 2.5 months payroll, max $10 million
    - Up to 100% of principal forgiven (if used for payroll)
    - Banks originate, Fed provides terms financing, Treasury guarantees losses
  - Main Street Lending Program (MSLP)
    - $600 billion or 2.8% of 2019 GDP
    - Consists of different facilities aimed at medium-size firms
    - Banks originate, retain 5-15% share (85-95% guaranteed)
    - LIBOR + 3% interest rate
    - Loan size tied to firm EBITDA
    - No principal forgiveness
  - Corporate Credit Facilities
    - $850 billion or 3.9% of 2019 GDP
    - Consists of different facilities aimed at the largest firms: PMCCF, SMCCF, and TALF

    * Mainly purchases of investment-grade corporate bonds in primary and secondary markets
    * Also syndicated loans, CLOs, and other types of ABS if necessary
    * Market interest rates

- Elenev, Landvoigt, and Van Nieuwerburgh (2021) analyze how these facilities have avoided a substantial share of corporate bankruptcies by providing firms with bridge loans, thereby averting also a financial crisis.
- Cox, Greenwald, Ludvigson (2020) also analyze these facilities and emphasize they lowered risk aversion.
- Growing empirical literature studies (mis)allocation of PPP loans to firms and program effectiveness.