Crowded Ratings: Clientele Effects in the Corporate Bond Market

Francisco Gomes* Ryan Lewis† Jordan Nickerson‡

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*London Business School. Email: fgomes@london.edu.
†University of Colorado-Boulder. Email: ryan.c.lewis@colorado.edu.
‡Sloan School of Management, MIT. Email: jordo@mit.edu.

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Abstract Consistent with a simple model of market segmentation, we document rating-based clientele effects in the corporate bond market. Net capital flows that arise due to idiosyncratic firm upgrades and downgrades cause significant price movements for the other bonds in the effected rating bucket. A one-standard-deviation flow into a rating bucket generates a 5 bp bond price reduction, equivalent to 4.1% of the monthly price variation driven by macro variables. This effect is highly persistent, with an approximate half-life of five months. Guided by the model, we also document a significant decaying spillover pattern to bond prices in adjacent buckets.

1. Introduction

Perhaps the two most prominent characteristics of fixed income securities, not shared by their equity counterparts, are fixed maturity dates and credit ratings. The salience of each feature has brought about a pair of robust, yet quite distinct, strands of literature exploring their bond pricing implications. Typically motivated from the perspective of heterogeneous preferences, a whole host of works has previously explored the ensuing clientele effects that arise from the issuance of bonds with different maturities.[1] In contrast, the extent credit rating literature has generally approached the subject from an information production perspective, seeking evidence that credit ratings contain additional information relevant in bond pricing.[2] Although the discrete nature of credit ratings easily lends itself to the manifestation of clientele effects, this feature has been largely ignored by prior literature. We fill this gap by presenting evidence of large scale rating-based clientele effects in the corporate bond market with significant pricing implications.

Credit rating buckets provide an important new setting to test the impact of clientele effects for two primary reasons. First, unlike variation across maturity and bond duration, the influx of supply into a particular rating bucket is stochastic and highly variable. Second, the most common constraints faced by bond market investors are on quantities within rating buckets (e.g. insurance company risk ratings examined in Becker and Ivashina (2015)). These constraints allow plausibly exogenous, idiosyncratic shocks to spillover to similarly rated bonds by straining the capital available within a rating bucket. The setting allows a simple research design: we relate the price of bonds with unchanged ratings within a particular bucket on the net capital flows into that bucket from bonds with fluctuating ratings. We find that a one standard deviation increase in net flows reduces bond prices in that bucket by 5 basis points.

1. See, for example, Vayanos and Vila (2009), Krishnamurthy and Vissing-Jorgensen (2011), D'Amico and King (2013), Greenwood and Vayanos (2010), Greenwood and Vayanos (2014) and Guibaud, Nosbusch, and Vayanos (2013).

2. For example, Hand, Holthausen, and Leftwich (1992), Kliger and Sarig (2000), and Tang (2009).

To discipline our analysis, we begin by presenting a parsimonious model of the bond market with heterogeneous investors and bonds that vary in their discrete credit ratings. Investors specialize in different segments of the credit rating spectrum, in the spirit of Vayanos and Vila (2009). However, unlike the former work, while an investor in our setting has strong preferences for a particular credit rating, their tastes also extend to nearby ratings. From this setup, we analyze the price impact of a reallocation of bonds across credit ratings. Following a sudden inflow of bonds into a particular rating bucket, the downward-sloping demand curve of investors naturally results in a negative price effect for all bonds in the rating bucket. A second, more novel, prediction of our model is that this pricing effect is not confined solely to the rating category experiencing the supply shock. Instead, since investor preferences also span nearby rating categories, there is a significant spillover effect reducing the price of bonds in adjacent buckets, with a gradual decay as the distance between bond rating increases.

To test the model's predictions, we first construct a monthly measure of the relative net flow of bonds into each rating category using the Mergent FISD. To avoid capturing strategic issuance by firms, the measure only includes flows due to rating transitions and not new issuance. We then combine our empirical proxy with monthly issue-level bond prices and yields over the period from 2002 to 2019 from the WRDS Bond Returns data, yielding three primary findings.

Confirming the model's prediction, we find a negative relation between monthly net flows into a rating category (e.g., *BB-*) and bond prices belonging to that rating bucket. Specifically, a one-standard deviation inflow of capital is associated with a \$0.055 decrease in bond prices. For context, the monthly standard deviation of macroeconomic-induced bond price changes is \$1.33, implying a 0.041σ relative effect of our finding.[3] Importantly, this analysis excludes bonds with a rating action and instead considers the price impact of other bonds in the rating bucket. This estimate accounts for both time-invariant issue

3. To estimate the macro pricing effect, we regress bond prices on bond and month fixed effects. The first difference of monthly fixed effect estimates has a standard deviation of \$1.33

heterogeneity and macro-economic trends with the inclusion of issue and month fixed effects, respectively. Moreover, to ensure we are not picking up time-varying risk-premia, we also include a BBB-AAA yield spread beta that varies at the rating level. An examination of bond yields offers similar inferences.

We ensure our result is not due to changing economic conditions or other potential risk factors correlated with rating changes in two ways. First, we perform a litany of robustness checks to eliminate risk hypotheses and incorporate as controls a wide spectrum of economic variables. We include as regressors the time varying beta exposure to three prominent sets of risk factors documented in prior literature (Fama and French (2015), He, Kelly, and Manela (2017), and Bai, Bali, and Wen (2019), hereafter FF5, HKM and BBW). Despite the factor betas loading in many cases, point estimates are virtually unchanged with the inclusion of each. We find the effect remains when excluding months eclipsed by the financial crisis (as measured by the NBER recession dates). Additionally, we allow for bond-specific risk-premia exposure by interacting the BBB-AAA spread with an issue-fixed effect. Finally, we ensure our measure is not capturing time-series variation in the slope of the "credit yield curve," measuring the cross-sectional relation between prices/yields and ordinal credit ratings. The effect of net flows into a rating bucket continues to persist following each addition.

Second, we perform a placebo test using pseudo bonds constructed using equity options from Culp, Nozawa, and Veronesi (2018). Leveraging the insight that the payout structure of a bond can be replicated using equity options, they create synthetic—pseudo—bonds where the equity of a firm represents the synthetic assets and a combination of long equity and a sold, in the money call option, reflects a "pseudo" bond. They map these individual name synthetic bonds to ratings based on implied default probabilities and find that pseudo bonds exhibit cross sectional and time series similarities with their vanilla counterparts of the same rating. Thus pseudo bonds provide an ideal placebo: they are subject to similar economic shocks but do not experience rating bucket flow effects. We run the same empirical specifications relating inflows into a rating bucket on the yields of synthetic bonds within that bucket and find no relation.

Next, we consider the second prediction from our model regarding the spillover effect of a supply shock to adjacent buckets. Consistent with the model, when including net flows into adjacent rating buckets, we find a negative (albeit smaller) pricing effect of neighboring rating buckets that diminishes as the distance between ordinal rating increases. A simple calibration of our model suggests model-implied pricing effects that are comparable in magnitude and decay rate.

Finally, we go beyond our static model and examine the persistence of the direct pricing effect. Lagged values of our flow measure indicate a gradual decrease in the pricing impact of prior flows. Approximately one-half of the original effect is still present five months after the inflow is realized, with additional lags that are statistically indistinguishable from zero.

In sum, our findings suggest a non-trivial price impact of rating-based clientele effects. In contrast to characteristics generally associated with clientele effects (e.g., debt maturity), our setting is driven by unanticipated variation due to the rating actions taken on other firms. As such, our findings provide another means by which a firm's financial and operating choices impose externalities on other firms. Interestingly, this effect stems from a time-varying bond characteristic, thereby exposing a given issue to the choices of an evolving set of peer firms as credit ratings change.

Our paper is related to two distinct strands of literature, centering on credit ratings and clientele effects. With respect to the former, our paper contributes to the literature studying the pricing implications of credit ratings. From an informational standpoint, Hand, Holthausen, and Leftwich (1992) and Goh and Ederington (1993), among others, examine the abnormal returns of rating announcements on equity and bond returns, respectively. More recently, Tang (2009) and Cornaggia, Cornaggia, and Israelsen (2018) study the price effect of two distinct credit rating refinements enacted by Moody's, while Xia (2014) shows an increase in rating information content and pricing effects following more competition. In contrast, prior literature also considers non-information channels, finding general support for regulatory pricing effects of ratings (see Bongaerts, Cremers, and Goetzmann (2012) and Kisgen and Strahan (2010), among others). While the specific mechanism varies, the extent literature generally studies the direct impact of a firm's credit rating, or a change there of, on bond prices. We compliment this literature, instead considering the pricing implications caused by a change in the credit ratings of other firms. Our results highlight the externality imposed on a firm by the rating actions realized by others, by way of a clientele effect. This is consistent with the coordination mechanism provided proposed by Boot, Milbourn, and Schmeits (2006), where coarse credit ratings serve as a focal point for investors.

Clientele effects have been documented several markets, starting with the work of Harris and Gurel (1986) and Shleifer (1986) who first documented that S&P 500 inclusions are associated with a stock price increase. A growing literature has documented clientele effects in the government bond market, building on the preferred habit hypothesis of Culbertson (1957) and Modigliani and Sutch (1966). Vayanos and Vila (2009), Guibaud, Nosbusch, and Vayanos (2013) and Greenwood and Vayanos (2014) develop models of the term structure of interest rates where certain investors have preferences for specific maturities, i.e. a "preferred habit", resulting in a partially segmented equilibrium of the treasury bond market. Greenwood and Vayanos (2010), Greenwood and Vayanos (2014), Krishnamurthy and Vissing-Jorgensen (2011) and D'Amico and King (2013) provide supporting evidence for this mechanism.

In the corporate bond market, Schaefer (1982), Dermody and Prisman (1988) and Hochman and Palmon (1988) show how tax clientele effects arise in equilibrium when investors face different tax brackets and transaction costs or short-selling constraints. Chen, Huang, Sun, Yao, and Yu (2020) document a liquidity clientele effect, driven by insurers' investment horizon and funding constraint, while Kim and Stulz (1988) find evidence for partial segmentation in international bond markets and Butler, Gao, and Uzmanoglu (2019) find evidence that firms adjust bond maturities in response to clientele effects. Greenwood, Hanson, and Stein (2010) argue that highly-rated corporate bonds are substitutes for government bonds and therefore the maturity-based clienteles in the government bond market spillover to the corporate bond market. This in turn has an impact on the financing decisions of highly-rated corporations, and Badoer and James (2016) provide supporting evidence for this behavior.[4]

More generally, our paper is connected to the broader literature studying the determinants of bond prices. Motivating our results, Collin-Dufresn, Goldstein, and Martin (2001) argue that a large portion of credit spread changes appear to be driven by local supply and demand shocks that are unrelated to credit risk factors or liquidity. He, Khorrami, and Song (2019) further explores this variation and shows that dealer inventories are responsible for a large part of the variation in credit spread changes. Perhaps closer in spirit, Ellul, Jotikasthira, and Lundblad (2011) show that insurance companies tend to sell bonds after they have been downgraded below investment grade, temporarily pushing prices lower around the downgrade event. Finally, our paper is related to the growing literature on slow moving capital and limited arbitrage (e.g. De Long, Shleifer, Summers, and Waldmann (1990), Shleifer and Vishny (1997), Mitchell, Pedersen, and Pulvino (2007), Gabaix, Krishnamurthy, and Vigneron (2007), Duffie (2010), Acharya, Shin, and Yorulmazer (2013), Greenwood and Vayanos (2014), Lewis (2016) or Greenwood, Hanson, and Liao (2018)).

The remainder of the paper is organized as follows: Section 2 presents a model and derives a set of empirical predictions. Next, we describe the data used and present summary statistics in Section 3. We follow this with a description of our empirical strategy and a presentation of our main findings in Section 4. We then consider alternative explanations and other robustness in Section 5, before concluding in Section 6.

2 Model

We consider an economy where investors specialize in particular segments of the market, as in the preferred habit model of Vayanos and Vila (2009). Unlike in their model our

4. Kashyap, Kovrijnykh, Li, and Pavlova (2018) document that corporations respond to price pressures induced by clienteles in the equity market.

investor are also willing to invest in bonds in "related segments", although that is not their main preference. This will allow us to match important features of our empirical results, and removes the need to include an arbitrageur in the model.

2.1 Set-Up

Each bond has an expected payoff D and an initial price p. These are identical for bonds within the same credit rating. We have N credit ratings, and the supply of bonds in each rating is denoted by S^i, with $i = 1, ..., N$.

Each investor has a strong preference for a particular credit rating, so we have N investors and often use the same identifier for both bonds and investors, i.e. investor i has a strong preference for bonds of rating i. In addition to bonds in "her credit rating", each investor also considers bonds in the rating immediately above $(i + 1)$, and the rating immediately below $(i - 1)$, but with a lower preference.[5]

More precisely investor i has the following demand functions

$$B_i^j = \begin{cases} \theta k_i \left(\frac{D_j}{p_j}\right)^\alpha & \text{if } j = i + 1 \\ k_i \left(\frac{D_j}{p_j}\right)^\alpha & \text{if } j = i \\ \theta k_i \left(\frac{D_j}{p_j}\right)^\alpha & \text{if } j = i - 1 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where α is a positive number which determines the demand-price elasticity, and θ is a positive number smaller than 1, which captures the investor's (positive but) lower preference for bonds in nearby credit ratings. Finally, the constant k^i is not a free parameter. It is

5. With the natural exception of investor 1 and N, which only consider bonds in the ratings immediately above and immediately below, respectively.

determined by the investor's budget constraint:

$$p_{i+1}\theta k_i\left(\frac{D_{i+1}}{p_{i+1}}\right)^{\alpha}+p_ik_i\left(\frac{D_i}{p_i}\right)^{\alpha}+p_{i-1}\theta k_i\left(\frac{D_{i-1}}{p_{i-1}}\right)^{\alpha}=W_i \tag{2}$$

which yields the following solution

$$k_i=\frac{W_i}{\theta p_{i+1}\left(\frac{D_{i+1}}{p_{i+1}}\right)^{\alpha}+p_i\left(\frac{D_i}{p_i}\right)^{\alpha}+\theta p_{i-1}\left(\frac{D_{i-1}}{p_{i-1}}\right)^{\alpha}} \tag{3}$$

2.2 Equilibrium prices

2.2.1 General case

Equilibrium prices for bonds in any intermediate credit rating (i.e. $1<i<N$) are given by[6]

$$\theta k_{i-1}\left(\frac{D_i}{p_i}\right)^{\alpha}+\theta k_i\left(\frac{D_i}{p_i}\right)^{\alpha}+\theta k_{i+1}\left(\frac{D_i}{p_i}\right)^{\alpha}=S_i\iff \tag{4}$$

$$(k_i+\theta k_{i-1}+\theta k_{i+1})\left(\frac{D_i}{p_i}\right)^{\alpha}=S_i\iff p_i=D_i\left(\frac{k_i+\theta k_{i-1}+\theta k_{i+1}}{S_i}\right)^{\frac{1}{\alpha}} \tag{5}$$

Substituting equation ((3)) in ((5)) we obtain the final solution. Since p_i is also in equation ((3)) we don't have a full closed-form solution for prices. We next present closed-form solutions for two special cases ($\alpha=1$ and $\theta=0$). Building on the intuition from those results we return to discuss the general case.

6. For the special case of $i=1$ this becomes

$$\theta k_1\left(\frac{D_1}{p_1}\right)^{\alpha}+\theta k_2\left(\frac{D_1}{p_1}\right)^{\alpha}=S_1$$

while for $i=N$ we have

$$\theta k_N\left(\frac{D_N}{p_N}\right)^{\alpha}+\theta k_{N-1}\left(\frac{D_N}{p_N}\right)^{\alpha}=S_N$$

2.2.2 Full market segmentation

It is instructive to consider the special case with $\theta = 0$, i.e. full market segmentation. In this case equation ((3)) becomes

$$k_i = \frac{W_i}{(p_i)^{1-\alpha}\,(D_i)^{\alpha}} \tag{6}$$

while equation ((5)) is now

$$p_i = D_i \left(\frac{k_i}{S_i}\right)^{\frac{1}{\alpha}} \tag{7}$$

Combining these two equations we have

$$\begin{aligned}
p_i &= D_i \left(\frac{W_i}{S_i(p_i)^{1-\alpha}\,(D_i)^{\alpha}}\right)^{\frac{1}{\alpha}} \iff && (8)\\
(p_i)^{\alpha} &= (D_i)^{\alpha}\frac{W_i}{S_i(p_i)^{1-\alpha}\,(D_i)^{\alpha}} \iff && (9)\\
p_i &= \frac{W_i}{S_i} && (10)
\end{aligned}$$

If markets are fully segmented then prices are purely determined by the ratio of the wealth of the investors in each rating to the total supply of bonds in that particular rating. This is an extreme version of Vayanos and Vila (2009) since we don't have arbitrageurs in our model.

2.2.3 Unit price elasticity

Next we consider the case where the direct demand own price elasticity (α) is 1. Equation ((3)) becomes

$$p_{i+1}\theta k_i \frac{D_{i+1}}{p_{i+1}} + p_i k_i \frac{D_i}{p_i} + p_{i-1}\theta k \frac{D_{i-1}}{p_{i-1}} = W_i \tag{11}$$

This is no longer a function of prices, and therefore we can solve for k_i explicitly:

$$k_i = \frac{W_i}{\theta D_{i+1} + D_i + \theta D_{i-1}} \tag{12}$$

Substituting ((12)) in equation ((5)) and imposing again $\alpha = 1$ we obtain[7]

$$p_i = \frac{D_i}{S_i}\left(\frac{W_i}{\theta D_{i+1} + D_i + \theta D_{i-1}} + \frac{\theta W_{i+1}}{\theta D_{i+2} + D_{i+1} + \theta D_i} + \frac{\theta W_{i-1}}{\theta D_i + D_{i-1} + \theta D_{i-2}}\right) \tag{13}$$

From equation ((13)) we see that the bond price in credit rating i will depend on:

- Its expected payoff (D_i)

- Its supply (S_i)

- The wealth of all investors in that rating (W_{i-1}, W_i, and W_{i+1}), particularly the wealth of the investors that have a stronger preference for those bonds (W_i).

- The expected payoff of bonds in the nearby credit ratings (D_{i-2}, D_{i-1}, D_{i+1} and D_{i+2}).

In this version of the model the price of a bond in credit rating i does not depend on the supply of bonds on other credit ratings. This happens for two reasons. First because we have constant bond supply and second because we have imposed $\alpha = 1$.

With α equal to 1 an increase in supply in one particular bucket is reflected in a proportional change in the price of bonds in the same bucket so that the total value of the securities ($p_i \times S_i$) remains unchanged. This rules out spillover effects since, in general equilibrium, total investor wealth must equal the total value of securities in all buckets. Therefore, with regards to supply shocks the α equal to 1 case is essentially identical to the full segmentation equilibrium, where prices times supply are always equal to a constant. The main differences

7. With the special cases for

$$\begin{aligned} p_1 &= \frac{D_1}{S_1}\left(\frac{W_1}{\theta D_2 + D_1} + \frac{\theta W_2}{\theta D_3 + D_2 + \theta D_1}\right) \\ p_N &= \frac{D_N}{S_N}\left(\frac{W_N}{\theta D_{N-1} + D_N} + \frac{\theta W_{N-1}}{\theta D_N + D_{N-1} + \theta D_{N-2}}\right) \end{aligned}$$

and also p_2 and p_{N-1}.

are that wealth shocks from investors in adjacent buckets also matter, and the same for shocks to the expected payoffs of securities in adjacent buckets. Since the focus of our paper is on supply shocks, the α equal to 1 case and the full segmentation case are essentially equivalent for our purposes. [8]

2.2.4 Discussion of the general case

Considering the solution for the general case (equations ((3)) in ((5))) we can see that, as long as $\alpha \neq 1$ and $\theta \neq 0$, then p_i depends on the prices in adjacent buckets (p_{i-2}, p_{i-1}, p_{i+1} and p_{i+2}). Since those prices depend on the supply of bonds in those credit buckets that generates an impact of S_{i-2}, S_{i-1}, S_{i+1} and S_{i+2} on p_i. Furthermore, since p_{i+1} will then depend on S_{i-1}, S_i, S_{i+2} and S_{i+3} (in addition to its own supply), then S_{i+3} also has an (indirect) impact on p_i. And, following this logic further, even the supply of "more distant" credit ratings will matter, generating a decaying pattern of spillover effects. We document these effects in the next subsection using numerical examples.

2.3 Numerical Example

To illustrate the previous conclusions we consider a numerical example where for simplicity both the expected payoffs and the baseline supply in all ratings are normalized to 1.[9]

$$
\begin{aligned}
D_i &= 1,\ i = 1, ..., N \\
S_i &= 1,\ i = 1, ..., N
\end{aligned}
$$

8. As we can see from equation ((13)) the quantitative magnitude of the wealth and dividend channels is determined by theta. In this case that is the only role of theta, since there are no price spillover effects.

9. The first assumption is made merely for simplicity. In equilibrium, bonds in lower credit ratings should have higher expected risk premium so potentially higher expected payoffs, but these differences do not play a role in our model.

Likewise we also normalize the wealth of all investors to 1, so

$$W_i = 1,\ i = 1, ..., N$$

For a given choice of α and θ we can then jointly solve equations ((3)) and ((5)) for an arbitrary value of N.

Using this solution we can then compute the impact of a change in supply in one credit rating. More precisely we increase the supply in the middle rating ($i = (N + 1)/2$) by 10%, i.e. from 1 to 1.1. In order to match the set-up in our empirical analysis, in which we keep total bond supply unchanged, we decrease the supply in the other ratings proportionally, i.e. by $1.1/(N - 1)$.[10]

2.3.1 Direct price effects

Figure 1 plots the percentage price change following a 10% increase in the supply of bonds in that bucket, for different values of α (on the horizontal axis) and of θ (different curves). α controls the demand price elasticity so, as we increase α, the price response to a given change in supply is reduced. As α approaches zero demand becomes fully inelastic and price change would converge to -100%, while as α converges to infinity the price change converges to zero. In the figure we restrict the range of α to be between 0.5 and 50 so that the profiles are easily visible.

θ impacts the direct price response because it determines how much wealth is allocated to the bucket in the first place, but the effect is not quantitatively large as we can see from Figure 1.[11]. When α is equal to 1 the value of θ is irrelevant, as previously discussed, so the two lines ($\theta = 0.5$ and $\theta = 0.25$) cross exactly at this point.

10. In this example we consider 19 credit rating buckets.

11. This effect could be larger for specific buckets, for instance, if we had a substantially asymmetric distribution of wealth across investors

2.3.2 Spillover price effects

One interesting implication of the partial segmentation set-up is that it generates price spillover effects. With full market segmentation we would actually observe exactly the opposite result. As we increase the supply in the middle bucket we decrease supply in all others proportionally, so that the total number of bonds in the economy remains the same. Therefore, with full market segmentation (i.e. $\theta = 0$), we would simply observe a (small) decrease in prices in all other categories, which would be exactly identical for all of them.

When θ is different from zero, and α is not equal to 1, we have price spillover effects as documented in Figure 2. These figures plot the price response in the different buckets for different values of α and θ.[12]

In Panel A of Figure 2 we set θ equal to 0.5 and consider different values of α. As previously discussed, for α equal to 1 we have the same results as with full market segmentation. The price in the middle bucket (10) decreases, while all others increase by a small amount, reflecting the (modest) increase in supply in these other categories. When α is different from 1 the patterns become more interesting, though, as we have price spillover effects. Since prices in the middle bucket don't adjust one-for-one with the change in supply, investors reallocate part of their wealth to/from the other rating buckets. This effect first takes place in the adjacent buckets, which are the ones where these investors are also active market participants, and from these it propagates to all others.

For α less than 1 the prices of bonds in nearby ratings actually increase since the price in the middle bucket has decreased by more than 10%, while for α greater than 1 we observe a monotonically decreasing pattern of price changes as we move away from the middle.

In Panel B of Figure 2 we fix the value of α at 50 since it delivers a pronounced spillover effect and vary θ. As shown in Figure 1 a high value of θ leads to a small price response in the middle bucket. Panel B of Figure 2 shows that a high θ also produces a strong spillover

12. In our numerical example we consider 19 buckets. The equations for buckets 1, 2, 18, and 19 are slightly different because of the boundary conditions, and consequently these conditions generate their own price patterns. Therefore, we omit these four buckets from the comparative statics reported in the paper.

effect to nearby credit ratings, with the price response decaying more gradually as we move away from the middle bucket. Note that, for bonds in distant buckets the net change is positive, i.e. the spillover effect is dominated by the direct effect of the change in supply. This is more likely to happen for a low value of θ since the spillovers are less pronounced.

3. Data

This section describes the data used in the analyses, discusses our sample selection process, outlines the construction of the empirical proxy consider, and describes our final sample. The bulk of our empirical tests rely on the intersection of two relatively standard data sets: 1) monthly bond pricing data from WRDS Bond Returns, and 2) bond issuance characteristics and rating action data from the Mergent Fixed Income Securities Database (FISD).

3.1. Data and Sample Selection

We first turn to Mergent FISD for credit rating actions. For each bond issue, the data set includes historical information on both rating changes and credit watches issued by Standard and Poor's (S&P), Moody's, and Fitch. Moreover, the data set includes information on the bond issuer, industry classification, as well as offering and maturity dates. From this information, we construct an unbalanced panel of monthly credit ratings and watches for each combination of rating agency and bond issue from offering date to maturity. However, our analysis focuses on the effects of S&P and Moody's credit ratings, omitting Fitch in light of its reduced market share among corporate bonds.

We obtain data on monthly bond prices and accompanying yields from the WRDS Bond Returns. Sourced from TRACE and cleaned by WRDS, the sample runs from July 2002 to December 2019. The initial sample includes 1.73M issue-month observations from 80k unique issues and 4.78k issuers. The data set includes information on the estimated end of month bond price, yield to maturity, and par volume traded, among others.

To construct our final bond pricing sample, we begin by merging the Bond Returns data with the panel of rating histories from Mergent's FISD. We retain all issue-months with a rating by either S&P or Moody's. Next, we remove all government issued debt and callable bonds. We also eliminate medium-term notes (MTNs). Next, we drop all issue-months within 12 months of maturity. In addition, we exclude all issue-months with a yield that is negative, or above 25% (roughly corresponding to the 99th percentile of yields), which likely reflects a distressed issue or other pricing outliers. Finally, in the bond pricing sample we do not consider bonds-months in which the issue is on credit watch or in the month of a credit rating change. The resulting sample consists of roughly 1.05M issue-month observations, spanning 20.5k unique bond issues.

3.2. Construction of Empirical Proxy

The model in Section 2 illustrates the potential impact that investing constraints among a subset of investors may have on bond prices. One particularly salient feature in the fixed income setting which may impact prices through a clientele effect is a bond's credit rating. To examine this possibility, we construct an empirical proxy to capture time-series changes in the supply of bonds of a particular rating classification. More precisely, we define *Rating Bucket Flow* as follows:

$$RatingBucketFlow_{R,t} = \frac{\sum s_i \times 1(r_{i,t} = R) \times 1(r_{i,t-1} \neq R) - \sum s_i \times 1(r_{i,t} \neq R) \times 1(r_{i,t-1} = R)}{\sum s_i \times 1(r_{i,t} = R)} \tag{14}$$

where bond i has par amount outstanding of s_i with credit rating $r_{i,t}$ at the end of month t. Thus, *Rating Bucket Flow* represents the par-weighted net flow of bonds into (or out of) credit rating partition R, as measured on the final day of month t. Note, while our primary measure partitions bonds by fine rating notches (e.g., BB+ vs. BB), we consider alternate segmentations based on coarser rating classifications in some tests. Importantly, in computing net flows we only consider the effects due to rating changes. In contrast, we do not consider the effects due to new bond issuance or retirements, as the financing decisions of a firm are plausibly correlated with our ultimate outcome of interest: bond prices. Finally, to capture the relative change due to bond's changing ratings, we scale this net flow by the total par amount outstanding of all bonds in the rating classification.[13]

3.3. Summary Statistics

Table 1 presents summary statistics for the final bond pricing sample and our empirical proxy. Among bonds rated by Moody's, the average offering amount is \$584M, of which approximately \$42M changes hands in months where the bond trades. Traded bonds have an average yield of 5%, consequently trade above par at \$105.5, and are relatively long-lived with approximately 9.5 years left until maturity. Finally, the median traded bond is right at the IG/HY threshold with regards to both Moody's and S&P, as an ordinal rating of 9 corresponds to a BBB/Baa rated bond. Additionally, S&P rated bonds carry an average rating that is 0.4 notches more favorable.

[Insert Table 1 Near Here]

The latter half of the table presents summary statistics for the empirical proxy. We report statistics for *Rating Bucket Flow* under the different rating partitions we consider. Specifically, *Rating Bucket Flow* partitions bonds by fine credit rating. In contrast, *Coarse Rating Flow* does not consider rating modifiers, thus comparing bonds rated BBB to those rated BB. Two patterns emerge from the summary statistics. First, each proxy is centered at approximately zero. This is not unexpected, as the numerator across all rating partitions (the net flow into or out of a rating bucket) sums to zero in each period. Second, the standard deviation of the empirical proxy is positively correlated with the granularity of credit ratings considered. This is also expected, as any rating changes that remain in a coarse rating bucket will net out. For example, bonds being upgraded from BB to BB+ will increase the

13. Note, we obtain consistent results when using a lagged version of the par amount outstanding among bonds with a given credit rating.

numerator for the fine-based proxy but not the coarse-based proxy. Figure 3 exhibits the time series pattern of the *Rating Bucket Flow* measure and credit spreads for three particular rating buckets, AA, BBB and B. The measure does not follow any obvious time treads nor is it clearly correlated with economic conditions.

[Insert Figure 3 Near Here]

4. Main Result

This section outlines our empirical approach and formally tests the asset pricing implications outlined in our theoretical model from Section 2 above. In doing so, we first examine the direct effect of an inflow or outflow of corporate debt into a rating-defined partition. We follow this up by testing a second key prediction from our theoretical model involving adjacent credit rating partitions. We delay the consideration of alternative explanations until Section 5 below.

4.1. Empirical Approach

We test the model's predictions using panel regressions where the key variable of interest is the empirical proxy described in Section 3.2. More precisely, we estimate OLS regressions of the following form:

$$y_{irt} = \beta RatingBucketFlow_{r,t-1} + \gamma \mathbf{X}_{irt} + \phi_i + \eta_r + \delta_{(m)t} + \varepsilon_{irt}, \tag{15}$$

where the dependent variable, y_{irt}, is either the end-of-month price or yield of bond i with credit rating r in month t. The primary variable of interest, $RatingBucketFlow_{r,t-1}$, captures the relative change in the supply of bonds with credit rating of r. Given the infrequent nature of bond trades, we lag *Rating Bucket Flow* by one month to ensure that all credit rating changes reflected in the proxy happen prior to a bond's last trade. $\mathbf{X}$

includes previously documented bond pricing factors (e.g., FF5, HKM or BBW). We include a bond fixed effect, ϕ_i, to capture bond-specific features (e.g. callable) correlated with prices. Similarly, we include a rating fixed effect, η_r, to capture the average differences in prices or yields across different credit ratings.[14] Finally, we include a month fixed effect, δ, to allow for macro-economic effects. Alternatively, we consider a maturity-month fixed effect (where maturity is measured at the yearly level) in some specifications to allow for time-series variation in both the slope and the level of the yield curve. It is important to note that Moody's and S&P do not always assign the same rating to a given issue. For all bond-months that have a credit rating from Moody's and S&P, we include a bond-month observation for each rating agency and assign a weight of 0.5 to each observation. Thus, our regressions are equal-weighted across all bond-months, regardless of being single or dual-rated.

Before presenting the main results, we briefly highlight a feature of our primary variable of interest, *Rating Bucket Flow.* One possible concern when examining the relation between this empirical proxy and bond prices is that the effect of *Rating Bucket Flow* is being driven by changing macro-economic conditions that differentially impact bonds of varying credit qualities. In other words, our proxy is capturing a "laddering down" of credit ratings in bad times and "laddering up" of ratings in good times. However, this scenario is made less likely when considering that the proxy is based on *net* flows, where an inflow of bonds into a bucket is likely due to an exodus from an adjacent bucket. To examine this possibility, Figure 4 illustrates the pair-wise correlation of *Rating Bucket Flow* across credit ratings. Consistent with the reallocation of bonds from one rating bucket to an adjacent rating, *Rating Bucket Flow* is negatively correlated for each credit rating and its two adjacent credit ratings. Thus, it is unlikely that the proxy is picking up variation in macro-economic cycles. Nevertheless, we consider this possibility with more depth in our formal empirical approach.

[Insert Figure 4 Near Here]

14. Note, while we consider coarse credit rating partitions in some tests, η is always defined using the granular rating notch scale.

4.2. Rating Buckets & Bond Prices

We begin by examining the effect of a change in the relative size of a rating category on bond prices and yields. For ease of exposition, throughout the discussion we colloquially refer to a rating-defined partition as a "rating bucket." Table 2 presents OLS regressions of the form described in Equation (15) when considering granular credit rating buckets (e.g., Aa1 vs. Aa2). The sample includes bond-month-agency observations for both Moody's and S&P. Standard errors are double-clustered by issue and month.

Consistent with our theoretical predictions, the first specification of the panel demonstrates a negative relation between the net flow of bonds into a rating bucket and the price of other bonds in the rating bucket. As we standardize *Rating Bucket Flow*, the coefficient of -0.086 (t-stat=-4.02) indicates that a one-standard-deviation increase in the par value of corporate debt with a particular credit rating is associated with a \$0.09 price decrease for other bonds with the same credit rating. In addition to both issue and rating fixed effects, the inclusion of a time (month) fixed effect ensures that *Rating Bucket Flow* is not picking up time-series variation in prices due to the business cycle. In the second specification, we ensure that our variable of interest is not capturing time-series variation in the slope of the yield curve that flows through to prices. Specifically, we include a vector of indicators corresponding to all bond maturities, rounded to the nearest year, which we interact with the monthly time fixed effect. The point estimate on *Rating Bucket Flow* remains relatively unchanged with a slight increase in the coefficient's standard error following the addition of this control. Importantly, while providing intuition for the asset pricing implications of investor constraints tied to a salient feature of the bond market (e.g., bond ratings), the simplicity of our model does not speak to the duration of possible effects. We will revisit this point and examine the duration of the effect shortly.

[Insert Table 2 Near Here]

These initial specifications are consistent with the model we develop in Section 2. Yet, as our primary measure is based on rating changes, the relation between our proxy and macroeconomic conditions may be a cause of concern for the reader. More precisely, if bonds with a riskier credit rating are more sensitive to macro shocks, then our result might manifest if these rating buckets are also likely to experience an inflow in bad times. However, this latter assumption is at odds with the results presented in Figure 4 which shows a negative correlation in the flows to adjacent buckets. Nevertheless, before continuing we specifically address this concern in the third specification of Table 2, in which we allow for a general form of business cycle exposure that is heterogeneous across rating buckets. More precisely, we begin by computing the yield spread between BBB and AAA rated corporate debt from FRED economic data. We then include as an additional covariate the interaction of the BBB yield spread with a vector of indicators which map to each rating bucket. Following the inclusion of this rating-specific BBB spread beta in the final specification, we see a slight reduction in the magnitude of the effect, with the coefficient on *Rating Bucket Flow* increasing to -0.055. At the same time, we see a greater reduction in standard errors, leading to a t-stat of -4.67. To provide economic perspective, we approximate the effects of macroeconomic conditions by regressing bond prices in our sample on a bond fixed effect and month fixed effect. This exercise yields a month-over-month change in time fixed effects with a standard deviation of \$1.33, implying a one-sigma effect of bond flows into a rating bucket is equivalent to a 0.041-sigma effect due to macroeconomic conditions. Note, the reduction in estimated magnitude is not entirely surprising, as the additional control is certainly correlated with part of our sample (i.e., AAA- and BBB-rated debt), thereby attenuating the point estimate on our variable of interest. Nevertheless, this result suggests that our main finding is not explained by heterogeneous exposure to business cycles across rating categories, at least as proxied for by BBB yield spreads.

Next, we examine the robustness of the prior result when considering a closely related outcome of interest, bond yields. Note, it is theoretically unclear if clientele effects due to a sudden inflow or outflow to a rating bucket would result in uniformly lower yields or instead result in a nominal pricing effect for all bonds. In light of this, we briefly validate the previous results in the remaining specifications, which substitute bond yields for prices and re-estimates the first three empirical models. When repeating the initial specification in the fourth column, the coefficient on *Rating Bucket Flow* of 0.017 (t-stat=3.11) indicates that a one-sigma increase in the relative size of a rating bucket is associated with a 1.7bp increase in bond yields. This point estimate remains unchanged with a slight decrease in standard errors in the fifth specification, which includes time-varying controls for a bond's yield to maturity. Similarly, when including rating-specific BBB yield spread betas in the final specification we see a slight reduction in both the point estimate and associated standard error, consistent with the result presented in Column 3. In un-tabulated results we repeat the previous analysis when separately considering an empirical proxy based on Moody's or S&P's credit ratings. The results are largely consistent and statistically significant when considering each rating agency individually.

The results in Table 2 present the first empirical evidence consistent with our model's predictions. At the same time, the model takes a strong stance regarding the granularity with which any such clientele effects exist, with demand functions defined over a 3-notch range. If investors have correspondingly narrowly defined risk appetites informed by credit ratings, pricing effects might operate most strongly at a granular level. At the same time, if our empirical proxy is a noisy measure of clientele effects, it is plausible that a more coarsely defined proxy suffers from less measurement error. To this end, we briefly consider an alternative rating partition when constructing *Rating Bucket Flow*. Table 3 repeats the previous analysis when defining credit buckets based on coarse, non-notched, credit ratings (e.g., AA vs. A rated debt). When considering the effect on bond prices in the first two specifications, the point estimates on *Rating Bucket Flow* are larger in magnitude relative to their Table 2 counterparts. Moreover, while they are generally estimated with less precision based on the reported test-statistics, they are still strongly statistically significant at traditional levels. Again, following the inclusion of BBB yield spread betas which vary by credit rating, we see a decrease in the economic magnitude of the effect, with a commensurate increase in estimated precision. These patterns are confirmed when considering yields in the latter triplet of specifications. Point estimates on *Rating Bucket Flow* continue to be larger in magnitude, with increased standard errors. To provide economic content, in the final specification a one standard deviation increase in the relative size of a coarse rating bucket is associated with a 2.4bp increase in the yield of bonds within the bucket (as opposed to a 1.3bp effect from the corresponding specification in Table 2).

[Insert Table 3 Near Here]

4.3 Adjacent Rating Buckets

The intuitive prediction of the model, that a shock to the supply of bonds in a rating bucket affects prices in that bucket when capital cannot move freely to absorb the shock, arises directly from the capital constraints and is consistent with prior literature on limits to arbitrage. A second, slightly more nuanced prediction of the model arises when investors have preferences that span multiple credit rating partitions. In this case, a shock to the size of one rating bucket has implications for the pricing of bonds in surrounding buckets, as investors attempt to allocate funds across their preferred interval of credit risk. Moreover, in the model this "spillover" effect is not confined to the width of the investors credit risk interval, instead cascading to rating buckets further away from the supply shock.

We now examine the empirical validity of this additional model prediction, both in a qualitative sense and in terms of economic magnitudes. To do this, we begin with the final price-related specification from Table 2. We augment this base model with an additional set of covariates designed to capture the effect of spillovers. Specifically, for a bond with current rating r, we define a set of covariates $\textit{Rating Bucket Flow}_k$ for $k \in [-3, 3]$, where each covariate captures the net flow of bonds into a rating bucket k notches from r. For example, for bonds with a current credit rating of AA-, $\textit{Rating Bucket Flow}_{+1}$ will equal the net flow of bonds into the AA rating bucket.[15]

To test the model's prediction from a quantitative standpoint involves not only constructing a new empirical test, but also producing a theoretical analog. To achieve this latter requirement, we modify the pricing-effect exercise performed in Section 2.3 above, and simulate an inflow equal to one standard deviation of inflows observed in our sample.

Figure 5 illustrates the spillover effect of a sudden bond inflow, both empirically and from a model-implied viewpoint. The figure reports the coefficients (hollow diamonds) and corresponding 95% confidence intervals from our augmented OLS regression, with two patterns emerging. First, the negative coefficients on the adjacent rating buckets is consistent with a "pricing spillover", where a positive inflow into a neighboring rating bucket is associated with a negative pricing effect. Second, the coefficient on *Rating Bucket Flow* also increases in magnitude compared to the corresponding specification from Table 2. This second finding is not surprising in the presence of a pricing spillover. As these adjacent bins make up the control group in Table 2, failing to account for a negative pricing effect on adjacent rating bins, thereby attenuating the point estimate on *Rating Bucket Flow*.

[Insert Figure 5 Near Here]

Recall that in the context of the model, the variable θ determines the magnitude of the spillover effects, while the coefficient α primarily affects the direct price response to a change in supply, i.e. the response of prices for bonds in a rating bucket following a change in the bucket's supply. In our calibration we set $\theta = 1/2$ and then choose the value of α such that the model-implied direct pricing effect of a flow into a rating bucket loosely matches our empirical estimate. Following this calibration, in which we ultimately set α equal to 80, we plot the model-implied pricing effects on surrounding rating buckets. Note, rather than attempting to precisely tune model parameters to perfectly match model-implied effects to their empirical analogs, we instead gauge the sensibility of the model by (ex-ante) picking

15. Note, the inclusion of *Rating Bucket Flow* for the net flow in adjacent rating buckets necessitates restricting the sample to bonds with a credit rating between AA- and CCC

a value for θ that seems reasonable (i.e., 0.5). After solving for prices, Figure 5 reports the model-implied pricing effect as solid triangles. Overall, the model-implied pricing effects track their empirical analogs quite well, although slightly understating the average spillover effect. Of note, while there appears to be a small asymmetry in pricing effects in our empirical estimates, the simplicity of our model dictates a symmetric effect for the median credit rating. Overall, Figure 5 presents evidence consistent with a second prediction from our model, both qualitatively and in terms of economic magnitudes.

4.4 Effect Permanence

The results thus far provide evidence consistent with our theoretical model. However, properly interpreting the results above requires an understanding of the persistence of the effect. To do so, we repeat the regression specification from Column 3 of Table 2 but add lags of *Rating Bucket Flow* for the previous 11 months as additional dependent variables of interest. Figure 6 plots each coefficient, illustrating two important points. First, the effect of flows on prices decays smoothly over time. The flow six months prior to when we measure prices (lag 5) has a statistically insignificant impact on prices, while the estimated effect for flows a year preceding the observation date is approximately zero. Second, the point estimate for the first lag of *Rating Bucket Flow* is nearly identical to the estimated coefficient from Column 3 of Table 2 indicating that the effect of flows on prices in each period is orthogonal to the effect from previous period flows.

[Insert Table 6 Near Here]

This figure indicates a transient effect of rating bucket flows on prices. While outside the scope of the model we present, this effect is consistent with a slow moving capital narrative: a particular rating bucket receives an inflow of bonds, pushing down prices for all bonds in that bucket. Over time the price effect reverts as capital accumulates to absorb the shock. Consistent with the transient, “clientele” nature of the shocks, we find little evidence that prices move differentially across time to maturity. Figure 7 plots the estimated coefficient of rating bucket flows on prices for various time to maturity categories. The coefficient is stable for all medium maturity bonds (e.g. between 3 and 11 years) and, excluding the near term maturities, is statistically indistinguishable across maturity buckets.

[Insert Figure 7 Near Here]

5. Alternative Explanations

The results to this point provide empirical support for rating-based clientele effects, as outlined in our theoretical model. We now consider alternative theories which both impact bond prices and are plausibly correlated with our empirical proxy. We begin by examining risk factors proposed by the existing literature. We then consider the robustness of our main result to different treatments of possible business cycle effects.

5.1 Risk Factors

First we examine the possibility that time varying exposure to risk factors drives our result. Our concerns are twofold. First, as the model we propose shares common themes with the extant intermediary asset pricing literature, the ratings flow effect may overlap with the standard intermediary pricing channel. Second, existing studies offer factor models that explain a significant portion of expected returns in the bond market, so one might worry that our effect is spanned by those risk factors.

One aspect of our existing analysis helps to alleviate such concerns: we include an issue level fixed effect which absorbs any time invariant bond level exposure to risk. Thus for the risk factor narrative to explain our results, it must be that priced changes in betas are correlated with the net ratings bucket flow measure. We test this possible channel by estimating time varying, bond specific betas over 2 year windows (+- 12 months) for each bond month with respect to three different factor models, the Fama-French 6 factor, the He, Kelly and Manela (HKM) intermediary model and the Bai, Bali, and Wen (BBW) model of bond returns. We then include these beta estimates as regressors in our main specification.

[Insert Table 4 Near Here]

If our effect is spanned by existing models, including these time varying betas should diminish the coefficient on our variable of interest. As shown in Table 4, the coefficient on *Rating Bucket Flow* for both prices (Columns 1-3) and yields (Columns 4-6) is stable across all risk factors and similar to the coefficient excluding the factor betas as regressors. Importantly, realized betas do appear to have an impact on bond yields. We find substantial evidence, particularly in the HKM model, that time variation in betas drive bond prices. Thus the estimates themselves are not overly noisy or irrelevant, their effect is simply orthogonal to the flow effect we document.

5.2. Economic Conditions

We now turn our attention back to the effect of business cycles on bond prices and the possible interaction with our variable of interest, *Rating Bucket Flow*. As we discuss above, one plausible concern is that our empirical proxy is being driven by economic downturns which are also associated with higher bond yields. As our results are cross-sectional within a given month, this concern would require that economic recessions are positively correlated with our proxy in the set of credit ratings more sensitive to macro-economic shocks (e.g., speculative grade ratings). While our specifications in Table 2 explicitly consider this possibility, we now examine this alternative in more detail.

Table 5 attempts to address the previous concern in three distinct ways. First, we remove from the sample the set of months classified as a contraction by the NBER. For comparability, we re-report our baseline specification which does not exclude such months. Following the exclusion of months coinciding with an economic contraction, the coefficient on *Rating Bucket Flow* only decreases slightly in magnitude, remaining an economically important factor in the determination of bond prices. The point estimate indicates that a one-standard-deviation relative increase in the size of a rating bucket is associated with a \$0.043 decrease in prices. Next, we extend our baseline model even further by allowing for issue-specific sensitivity to business cycles. More precisely, to our baseline regression we include as an additional covariate the interaction of a bond fixed effect with the BBB yield spread. Following the inclusion of this bond-specific BBB spread beta in the third specification, we see a slight decrease in the magnitude of the point estimate on *Rating Bucket Flow*, to -0.038 (t-stat=-3.67). The decrease in the point estimate following this inclusion is not entirely unsurprising, as this specification includes an additional regressor for each issue in our sample. As the BBB yield spread is certainly correlated with time-series changes in yields for other bonds with a rating near either AAA or BBB, this inclusion likely absorbs variation useful in identifying our primary effect. As such, it isn't surprising to see a decrease in point estimates when extending the model to this point.

While the previous specifications suggest that our primary results are not being driven by a correlation with macroeconomic effects, before continuing we consider an even more rigorous version of the previous concern. Specifically, a remaining alternative explanation might be that our empirical proxy is in some way correlated with an economy wide factor that has a differential effect across bonds. However, the previous specifications address concerns that the effect materializes as a heterogeneous but time-invariant sensitivity to the risk premium associated with risky debt (proxied for by BBB yield spreads). We now take an additional step to ensure that our findings are not picking up a change in the slope (e.g. steepening) of bond prices across credit ratings that is correlated with *Rating Flow*. Intuitively, to address this concern we fit an n-degree polynomial (w.r.t. ordinal bond ratings) to bond prices and allow the slope of this polynomial to vary across time. To be conservative we allow the slope to vary at a monthly frequency by interacting a time fixed effect with each polynomial coefficient.

The final two columns of Table 5 present the results for prices when considering various functional forms for the polynomial. The inclusion of a linear polynomial in the fourth specification does lead to a noticeable decrease in the coefficient on *Rating Bucket Flow*. The drop in estimated magnitude is approximately the same as when including issue-specific BBB yield spread betas in Column 3. Again, it should be noted that by including a term to capture the slope of yields with respect to credit ratings and allowing this slope to vary at the *monthly* level, we are likely absorbing a large amount of variation used to identify our primary effect, thereby attenuating the coefficient towards zero. As a final step, we go further and consider a quadratic polynomial in the final specification, with little change to the coefficient on *Rating Bucket Flow*. Taken together, the results presented in Table 5 suggest that our primary results are not being driven by a correlation with macroeconomic effects.

5.3 . Placebo Test

As a second robustness strategy, we identify a set of assets that is subject to the same business cycle effects as bonds but is unaffected by capital flows into and out of rating buckets: pseudo bonds from Culp, Nozawa, and Veronesi (2018). Pseudo bonds are constructed synthetically using the equity value of a firm as the "pseudo" assets and a combination of long equity and a short in the money call position as the "pseudo" bond. As the authors show, spreads across synthetic rating buckets display similar time series properties to vanilla bonds. For example, AAA-BBB synthetic bond spreads expand and contract in similar magnitudes as the vanilla BBB bond spread across the business cycle.

Pseudo bonds mimic regular bonds when it comes to economic fluctuations. However, the options utilized to create synthetic bonds are not subject to discrete ratings so their yields should be unrelated to capital flows generated by the upgrades and downgrades of vanilla bonds. Thus they provide an ideal placebo test for our mechanism: if net rating flows also drive spreads in pseudo bonds, then the effect we document could likely be attributed to an omitted variable that correlates with upgrade and downgrade activity.

[Insert Table 6 Near Here]

Table 6 illustrates that rating bucket net flows are unrelated to pseudo bond yields. These columns mimic the specifications (1-3) from Table 2. Here, the estimated coefficient is positive and insignificant in the first two specifications that do not include any economic controls and it flips signs to become negative but remains insignificant after including these controls. In contrast to the idea that our result is driven by economic conditions, we find no evidence that rating bucket flows impact the prices of synthetic bonds with similar implied creditworthiness.

6. Conclusion

Both the prominence and discrete nature of credit ratings lend themselves to the manifestation of a clientele effect, whereby investors have heterogeneous preferences for corporate debt with respect to credit ratings. We formalize this idea in a theoretical model that demonstrates the direct pricing effect caused by a supply shock to a specific rating bucket. Moreover, the model generates a second prediction that the supply shock effect need not be confined to bonds of that bucket, instead spilling over to adjacent credit rating buckets in a gradual fashion.

Using monthly-level bond pricing data and credit rating histories of corporate debt issues, we validate both predictions of the model. We find that a one-standard deviation increase in the flow of bonds into a rating category is associated with a $0.055 decrease in the traded price of bonds in that bucket. This effect is not driven by changing economic conditions or heterogeneous bond exposure to previously documented risk factors. Moreover, the supply shock effect is not restricted to a single rating bucket, instead spilling over to bonds in neighboring credit ratings. Finally, we find the effect is relatively transient, dissipating after approximately five months.

Taken together, these findings highlight another dimension by which investors develop specific tastes, generating a clientele effect. In contrast to many previously documented instances, in our setting a firm is exposed to a shifting clientele base as its credit rating evolves, realizing a series of unanticipated shocks as other firms experience credit rating actions. Thus, our results underscore the importance of credit ratings, demonstrating an additional facet by which they impact bond prices. Interestingly, our setting is one in which firms are inter-connected in a time-varying fashion, as determined by contemporaneous credit ratings. As such, to the extent that the financing and operational choices of a firm result in a rating change, this imposes an externality on connected firms that share a common credit rating.

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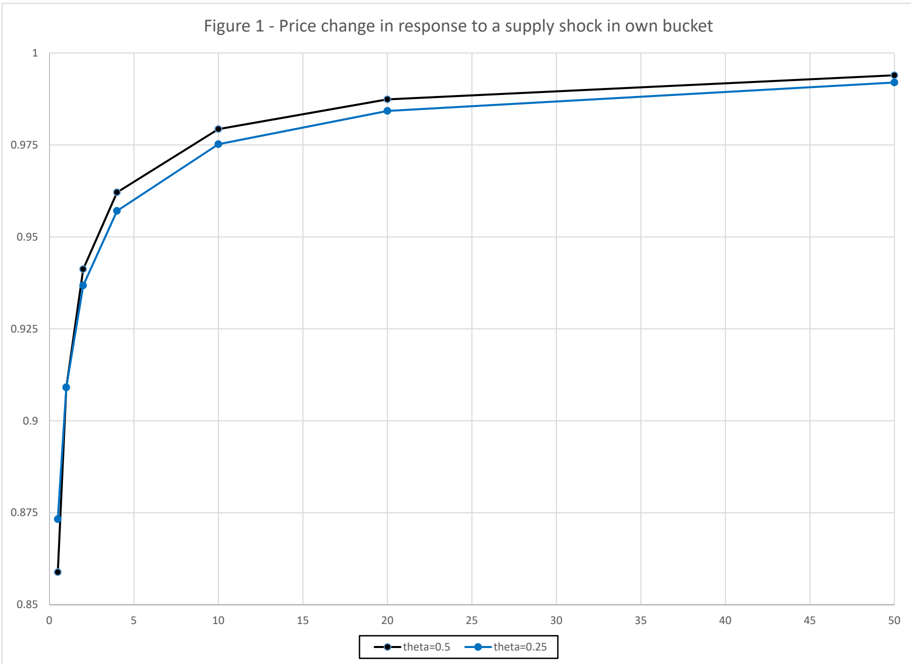
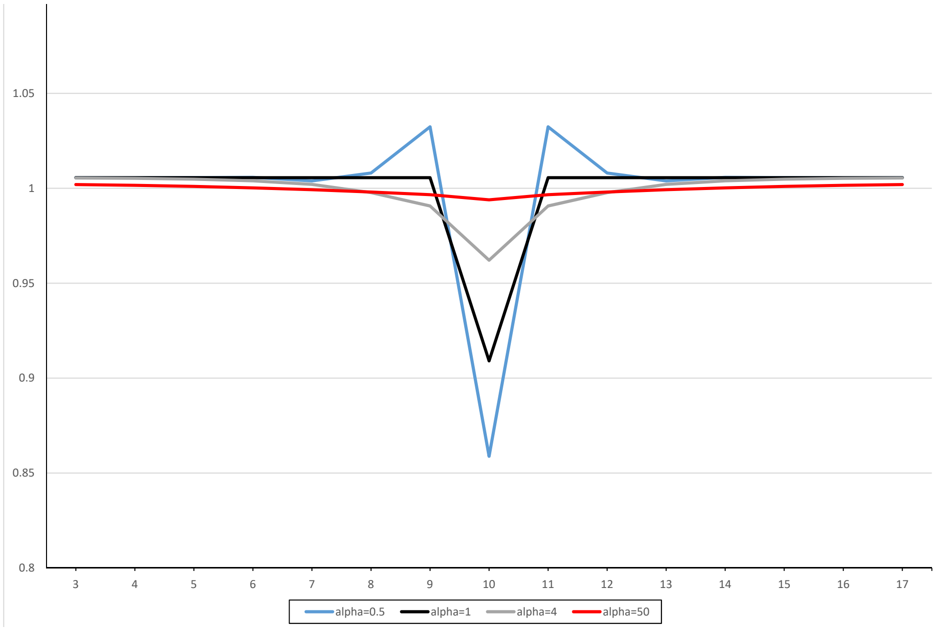
Fig. 1. Illustration of Direct Pricing Effect



Note: This figure plots the model-predicted direct pricing effect for different values of α (x-axis) for $\theta = 0.25, 0.5$. Prices are computed by numerical approximation, solving the system of non-linear equations presented in Section 2.

Panel A: Illustration of Effect of α on Indirect Pricing (Spillover) Effect



Panel B: Illustration of Effect of θ on Indirect Pricing (Spillover) Effect

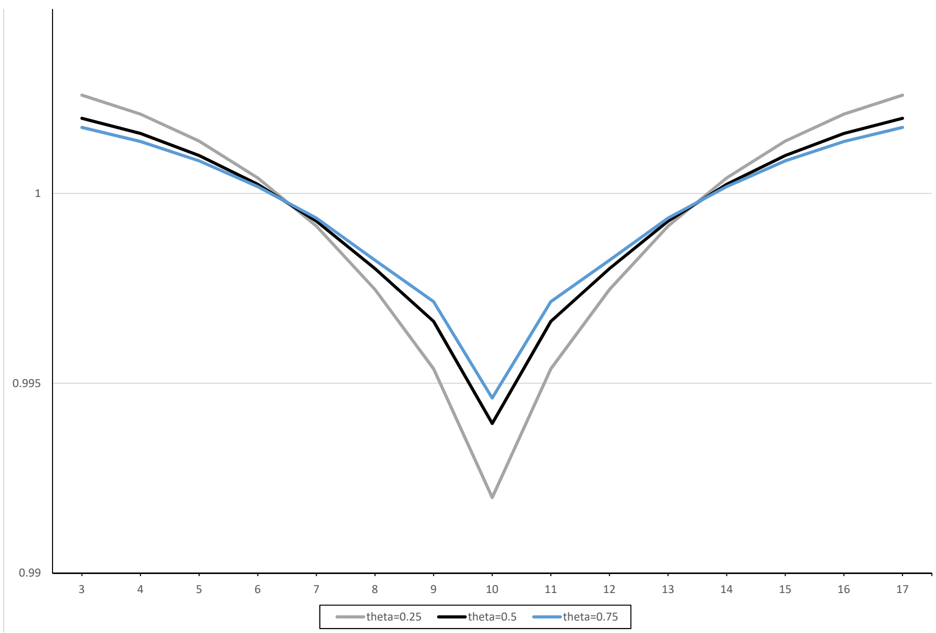
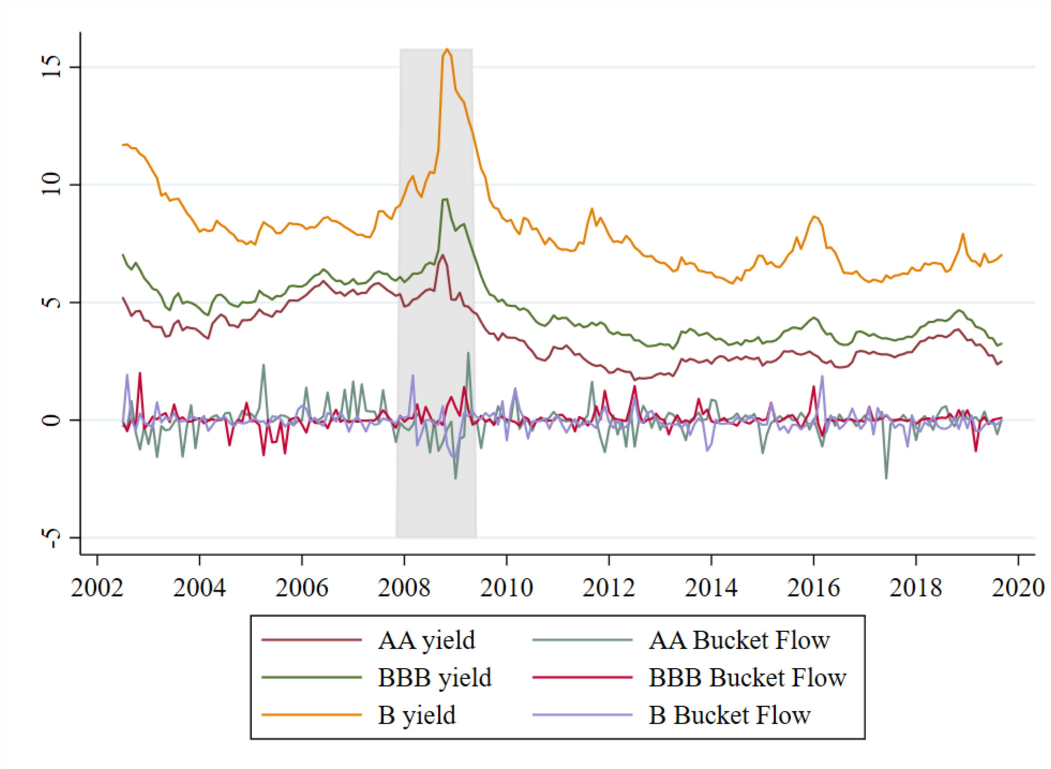


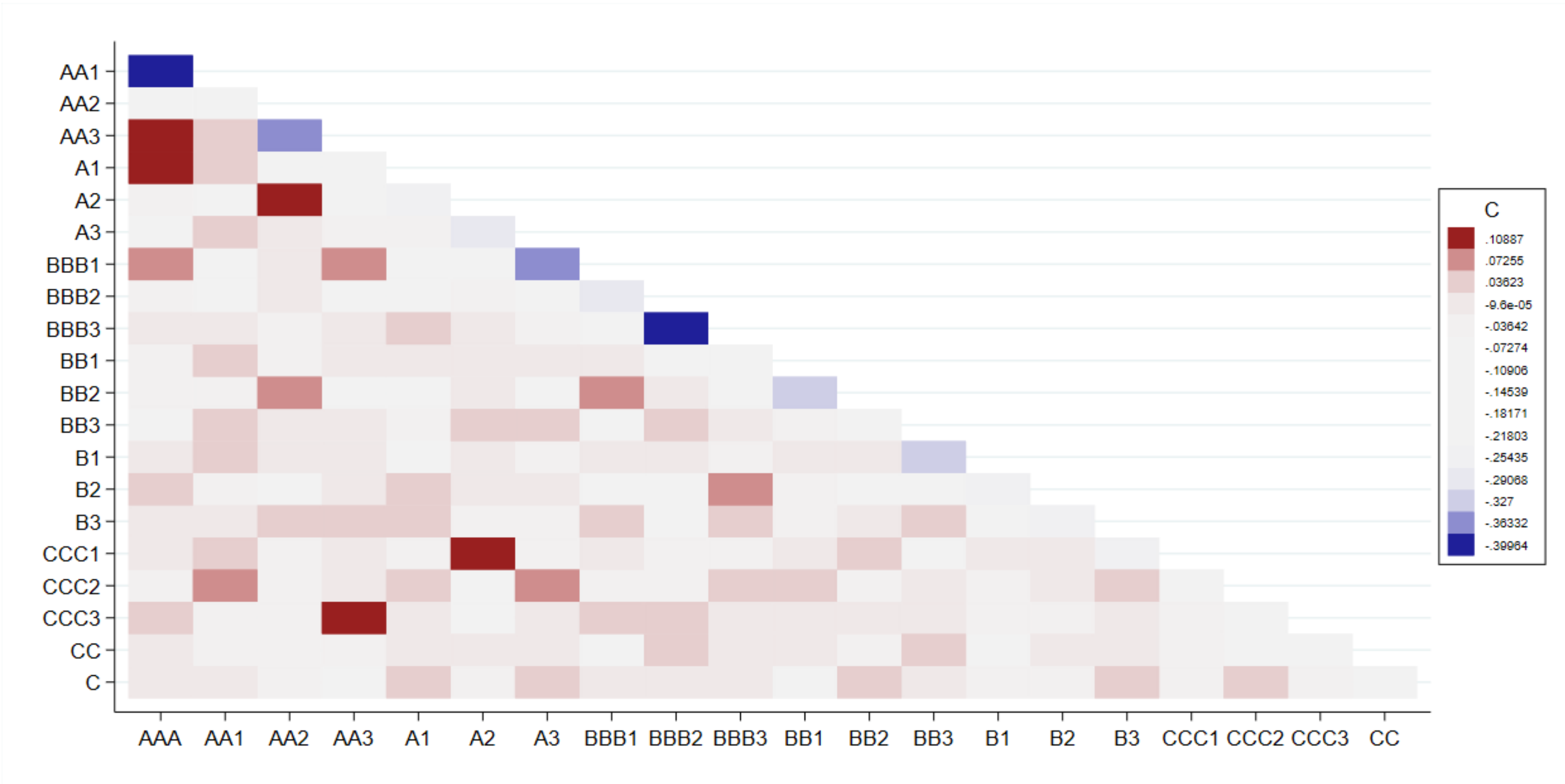
Fig. 2. This figure illustrates the spillover effect present in the model. Panel A reports the effect of a 10% inflow for different values of *alpha* when fixing $\theta = 0.5$. Panel B reports the estimated pricing effects when setting $\alpha = 50$ for different values of θ.

Fig. 3. Net Flows and Credit Spreads



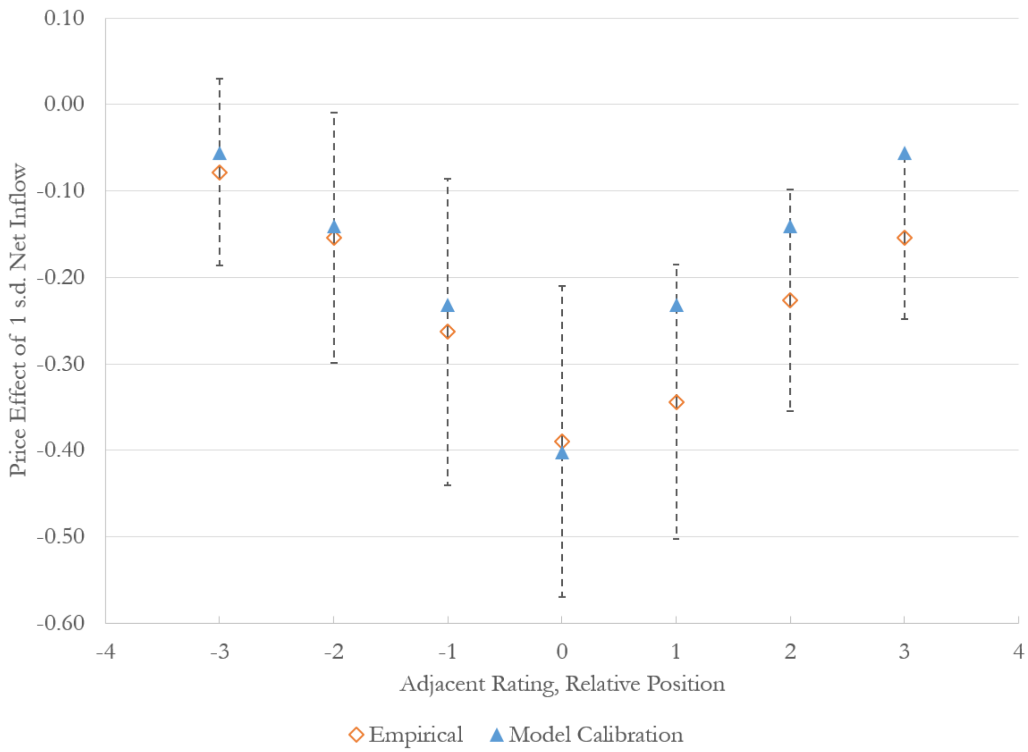
Note: This figure illustrates the time series of bond yields and the time series of our primary variable of interest, net flows to a rating bucket. We collapse buckets to coarse ratings and plot the yields and flows to AA, BBB, and B ratings. The shaded region indicates NBER recession.

Fig. 4. Net Flows Correlations



Note: This figure displays the timeseries correlations for the net flow measure between all pairs of rating buckets. Blue indicates negative correlations, red, positive correlations and grey boxes are correlations close to zero.

Fig. 5. Price Effect Spillover

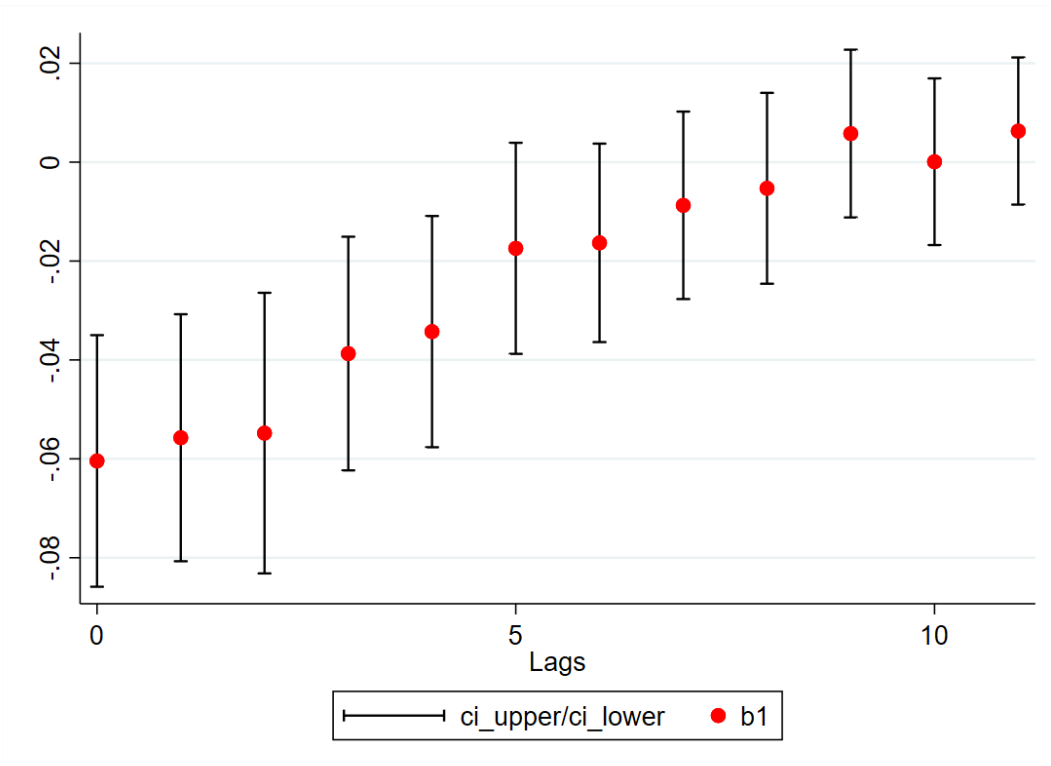


Note: This figure plots the model implied adjacent bucket effects against estimated β coefficients (orange circles) with associated 95% confidence intervals from the following regression:

$$y_{irt} = \sum_{j=-3}^{3} \beta_j RatingBucketFlow_{r-j,t-1} + \gamma \mathbf{X}_{irt} + \phi_i + \eta_r + \delta_{(m)t} + \varepsilon_{irt},$$

where j indexes across adjacent granular rating buckets with negative values indicating higher ratings and positive values indicating lower ratings. The specification is consistent with model from Column (3) of Table 2. The plotted coefficients capture the spillover effect from the indexed rating bucket to the "0" bucket. Standard errors are heteroscedasticity-robust and double clustered by issue and month.

Fig. 6. Price Effect Lags

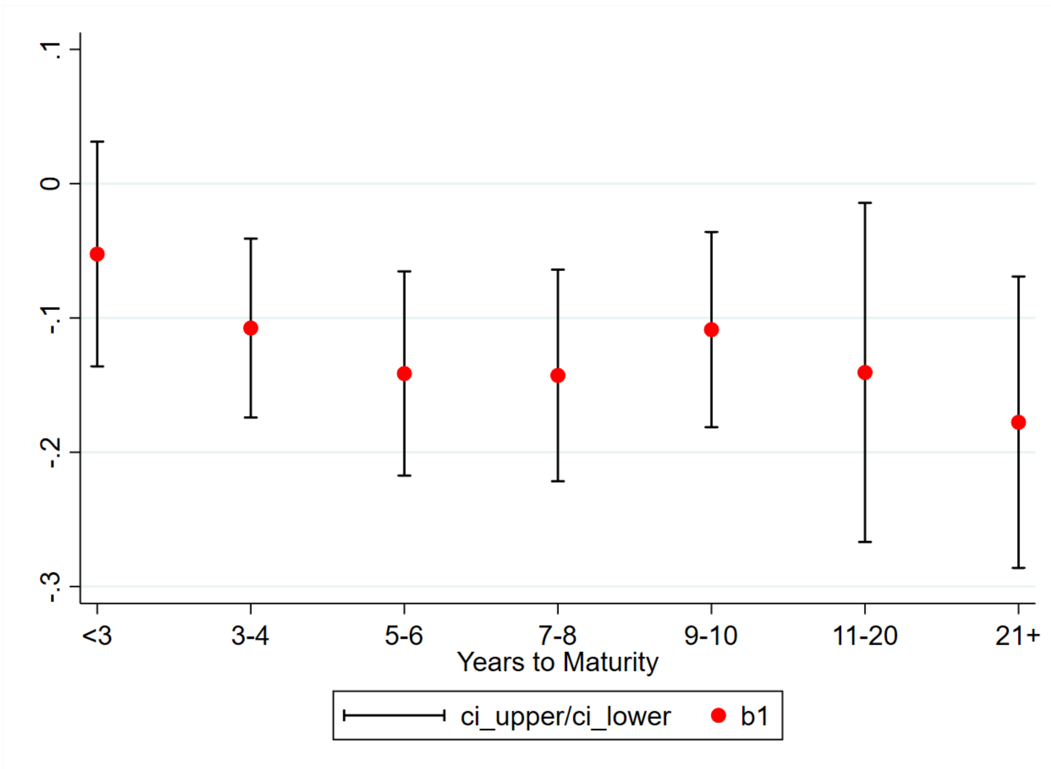


Note: This figure plots the estimated β coefficients (red dots) and their associated 95% confidence bands of a regression that takes the following form:

$$y_{irt} = \sum_{j=1}^{-} 12\beta_j RatingBucketFlow_{r,t-j} + \gamma \mathbf{X}_{irt} + \phi_i + \eta_r + \delta_{(m)t} + \varepsilon_{irt},$$

where j indexes the previous 12 months of rating bucket flows. The specification is consistent with model from Column (3) of Table 2. Standard errors are heteroscedasticity-robust and double clustered by issue and month.

Fig. 7. Price Effect by Time to Maturity



Note: This figure plots the estimated β coefficients (red dots) and their associated 95% confidence bands of a regression that takes the following form:

$$y_{irt} = \sum_j \beta_j RatingBucketFlow_{r,t} X \mathbb{1}_j + \gamma \mathbf{X}_{irt} + \phi_i + \eta_r + \delta_{(m)t} + \varepsilon_{irt},$$

where j indexes across 7 different maturity buckets. The specification is consistent with model from Column (3) of Table 2. Standard errors are heteroscedasticity-robust and double clustered by issue and month.

Table 1. Summary Statistics

	Moodys			S&P		
	Mean	Median	StDev	Mean	Median	StDev
Bond Characteristics						
Numeric Rating	9.18	9.00	3.71	8.77	8.00	3.31
Years to Maturity	9.45	6.00	9.75	9.41	6.00	9.63
Yield (%)	4.98	4.48	2.85	4.84	4.49	2.58
Price	105.53	104.30	11.92	105.99	104.60	11.39
Volume ($ mil, Par)	42.05	13.70	80.71	38.94	12.44	76.19
Offering Amount ($ mil)	584.81	400.00	566.27	566.58	400.00	560.20
Bucket Flow Measures						
Rating Bucket Flow (%)	0.05	0.00	3.31	0.05	0.00	3.32
Coarse Bucket Flow (%)	0.06	0.00	1.50	0.06	0.01	1.46
Three Bucket Flow (%)	-0.03	-0.03	0.78	-0.04	-0.03	0.75
Observations	879266			848868		

Note: This table describes the final sample. The left set of three columns reports summary statistics for issue-months with a Moody's credit rating, while the right set of columns describes issue-month observations with an S&P credit rating. We define *Numeric Rating* as the ordinal mapping of each rating agency's granular rating scheme, where a value of one represents a AAA/Aaa credit rating.

Table 2. Rating Bucket Inflows

	Price			Yield		
	(1)	(2)	(3)	(4)	(5)	(6)
Rating Bucket Flow	-0.086***	-0.084***	-0.055***	0.017***	0.017***	0.013***
	(-4.02)	(-3.91)	(-4.67)	(3.11)	(3.43)	(4.63)
Issue FE	Y	Y	Y	Y	Y	Y
Time FE	Y	N	N	Y	N	N
Rating FE	Y	Y	Y	Y	Y	Y
Time X Yr to Mat FE	N	Y	Y	N	Y	Y
Rating X AAA-BBB Betas	N	N	Y	N	N	Y
R^2	0.785	0.840	0.853	0.840	0.862	0.878
Observations	1,727,994	1,727,596	1,727,596	1,717,543	1,717,153	1,717,153

Note: This table shows OLS regressions for different variants of Equation (15). The dependent variable is the end-of-month traded price in Columns 1 - 3, and is the corresponding yield-to-maturity in Columns 4 - 6. The main variable of interest is *Rating Bucket Flow*, the relative change in par outstanding in a credit rating bucket, measured at a monthly frequency. *Rating Bucket Flow* is first winsorized at the 1% level, and then standardized. When constructing fixed effects, *Time* refers to the monthly level and *Rating* refers to granular credit ratings. *Yr to Mat* equals the remaining years to maturity, rounded to the nearest yearly value. *BBB-AAA* is the monthly difference in BBB yields relative to AAA corporate yields, collected from FRED. Reported t-statistics in parentheses are heteroscedasticity-robust and double clustered by issue and month. ***p<0.01, **p<0.05, *p<0.1.

Table 3. Coarse Rating Buckets

	Price			Yield		
	(1)	(2)	(3)	(4)	(5)	(6)
Coarse Bucket Flow	-0.197***	-0.196***	-0.133***	0.035*	0.033**	0.024***
	(-3.04)	(-2.99)	(-3.27)	(1.84)	(1.98)	(2.75)
Issue FE	Y	Y	Y	Y	Y	Y
Time FE	Y	N	N	Y	N	N
Rating FE	Y	Y	Y	Y	Y	Y
Time X Yr to Mat FE	N	Y	Y	N	Y	Y
Rating X AAA-BBB Betas	N	N	Y	N	N	Y
R^2	0.785	0.840	0.853	0.840	0.862	0.878
Observations	1,727,994	1,727,596	1,727,596	1,717,543	1,717,153	1,717,153

Note: This table shows OLS regressions similar to those estimated in Table 2. Here, the main variable of interest is *Coarse Bucket Flow*, which measures the relative change in par outstanding in a coarse credit rating bucket (e.g., BBB vs. BB), measured at a monthly frequency. *Coarse Bucket Flow* is first winsorized at the 1% level, and then standardized. Note, in the construction of fixed effects, *Rating* corresponds to granular credit ratings. All other variables are defined in Table 2. Reported t-statistics in parentheses are heteroscedasticity-robust and double clustered by issue and month. ***p<0.01, **p<0.05, *p<0.1.

Table 4. Adjusting For Risk

	Price			Yield		
	(1)	(2)	(3)	(4)	(5)	(6)
Rating Bucket Flow	-0.054***	-0.051***	-0.056***	0.014***	0.013***	0.014***
	(-4.18)	(-3.97)	(-4.21)	(4.52)	(4.37)	(4.52)
Beta Market	-3.643***			0.635***		
	(-11.14)			(10.70)		
Beta SMB	-1.070***			0.199***		
	(-6.10)			(6.26)		
Beta HML	-0.979***			0.174***		
	(-6.28)			(5.76)		
Beta MOM	1.295***			-0.249***		
	(5.23)			(-5.16)		
Beta LTREV	-1.540***			0.213***		
	(-6.93)			(5.12)		
Beta STREV	-0.860***			0.136***		
	(-4.46)			(3.97)		
Beta Market		-5.404***			0.922***	
		(-12.01)			(11.43)	
Beta HKM		-7.645***			1.335***	
		(-12.10)			(10.96)	
Beta BMKT			-0.000***			0.000***
			(-5.06)			(2.89)
Beta DRF			-0.004			0.001
			(-1.48)			(1.09)
Beta CRF			-0.003			0.001
			(-1.17)			(0.99)
Beta LRF			-0.001			0.000
			(-0.77)			(0.68)
Beta REV			-0.000			0.000
			(-0.18)			(0.07)
Issue FE	Y	Y	Y	Y	Y	Y
Rating FE	Y	Y	Y	Y	Y	Y
Time X Yr to Mat FE	Y	Y	Y	Y	Y	Y
Rating X AAA-BBB Betas	Y	Y	Y	Y	Y	Y
R^2	0.861	0.864	0.857	0.883	0.884	0.881
Observations	1,424,360	1,424,360	1,424,360	1,416,424	1,416,424	1,416,424

Note: This table shows OLS regressions similar to those estimated in Table 2. Here, we augment the final specification of Table 2 with additional explanatory variables. Specifically, we estimate time varying, issue specific betas utilizing the Fama-French 5 factor, the He, Kelly and Manela intermediary and the Bai, Bali, and Wen bond factor models. All other variables are defined in Table 2. Reported t-statistics in parentheses are heteroscedasticity-robust and double clustered by issue and month. ***p<0.01, **p<0.05, *p<0.1.

Table 5. Economic Conditions

	Price				
	(1)	(2)	(3)	(4)	(5)
Rating Bucket Flow	-0.055***	-0.043***	-0.038***	-0.037***	-0.032***
	(-4.67)	(-3.97)	(-3.67)	(-3.62)	(-3.34)
Exclude Recession	N	Y	N	N	N
Issue X AAA-BBB Beta	N	N	Y	N	N
Monthly Rating Polynomial	None	None	None	1	2
Issue FE	Y	Y	Y	Y	Y
Rating FE	Y	Y	Y	Y	Y
Time X Yr to Mat FE	Y	Y	Y	Y	Y
Rating X AAA-BBB Beta	Y	Y	Y	Y	Y
R^2	0.853	0.860	0.886	0.858	0.859
Observations	1,727,596	1,625,977	1,727,596	1,727,596	1,727,596

Note: This table shows OLS regressions similar to those estimated in Table 2. Each specification includes all variables from Column 3 of Table 2. *No Recession* removes observations for all months classified as a recession by the NBER. *Issue* × *BBB Spread* is an interaction of an issue fixed effect with the BBB-AAA yield spread, collected from FRED. In Columns 4 - 5 we include as additional controls the interaction of monthly fixed effects with an N-degree polynomial of ordinal credit ratings, where N is denoted in the column footer. All other variables are defined in Table 2. Reported *t*-statistics in parentheses are heteroscedasticity-robust and double clustered by issue and month. ***p<0.01, **p<0.05, *p<0.1.

Table 6. Rating Bucket Inflows: Pseudo Bonds

	Yield		
	(1)	(2)	(3)
Rating Bucket Flow (Implied Rating)	0.191	0.175	-0.209
	(0.96)	(0.93)	(-1.44)
Issue FE	Y	Y	Y
Time FE	Y	N	N
Rating FE	Y	Y	Y
Time X Yr to Mat FE	N	Y	Y
Rating X AAA-BBB Betas	N	N	Y
R^2	0.528	0.584	0.591
Observations	582,928	582,928	582,928

Note: This table shows OLS regressions for different variants of Equation (15). The dependent variable is the end-of-month traded yield for pseudo bonds created synthetically through a long equity, sold in-the-money call position. The main variable of interest is *Rating Bucket Flow*, the relative change in par outstanding in a credit rating bucket for the associated rating for each pseudo bond, measured at a monthly frequency. *Rating Bucket Flow* is first winsorized at the 1% level, and then standardized. When constructing fixed effects, *Time* refers to the monthly level and *Rating* refers to granular credit ratings. *Yr to Mat* equals the remaining years to maturity, rounded to the nearest yearly value. *BBB-AAA* is the monthly difference in BBB yields relative to AAA corporate yields, collected from FRED. Reported t-statistics in parentheses are heteroscedasticity-robust and double clustered by issue and month. ***p<0.01, **p<0.05, *p<0.1.