

Corporate Debt Markets and Recovery Rates with Vulture Investors

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Abstract

Recovery rates are an important determinant of credit spreads, but debt pricing models typically struggle to match their pro-cyclical properties. I develop a parsimonious model of defaulted debt markets where a tragedy of the commons friction arising in reorganization induces a transfer of bond ownership away from traditional diversified holders toward risk-averse activist investors (vultures). Vulture funds improve emergence recovery values by consolidating bond ownership but demand a premium that increases with the concentration of their portfolio. The ratio of activist wealth to defaulted debt emerges as the key state variable that drives prices and turnover of defaulted bonds and expected recovery rates for pre-default bondholders. In empirical tests, this ratio is a significant determinant of both risk-adjusted bankruptcy period returns and post default trading activity. As the model predicts, the relationship between the activist wealth ratio and returns is strongest in firms with assets that are difficult to monetize and for fulcrum classes where the creditors are likely to emerge from bankruptcy holding the newly issued equity. When incorporated into a traditional bond pricing framework, my model of corporate debt markets captures the pro-cyclicality of recovery rates and significantly reduces pricing errors relative to various exogenously specified recovery rate formulations.

JEL Classifications: G12 and G23

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1 Introduction

As exhibited in Figure 1, companies that file for Chapter 11 reorganization see approximately 80% of their bonds turnover in the month following default as pre-default holders—typically mutual funds and insurance companies—liquidate their remaining holdings and sell to investors who specialize in defaulted securities. The role of these vulture funds can be justified by economic theory: when the costs of default born by creditors are increasing with the dispersion of debt ownership¹, consolidating the debt of defaulted firms can improve ex-post creditor recoveries. A simple tragedy of the commons friction induces concentrated ownership of defaulted bonds amongst a small group of holders generating endogenous intermediation in the market for distressed securities. Despite the potentially interesting asset pricing implications of this market and the apparent importance of recovery rates in the pricing of debt, the bond pricing literature has abstracted from the reorganization process by assuming that the costs of default are either fixed or follow an exogenously specified process of the underlying state space.

[Figure 1 about here.]

In this paper, I develop and test a model of distressed debt activism with two primary components. The first is a group of risk averse vulture investors, each of whom operate with the following objective: identify a defaulted firm and purchase a large ownership stake in the debt of that company. In doing so they overcome the dispersed ownership friction and deliver emergence payouts that increase with the proportion of debt they purchase. However, by consolidating large positions in defaulted companies, vulture funds gain exposure to the idiosyncratic risk of a target firm’s assets during the bankruptcy process. As is common in asset pricing with intermediaries², I model a world where fund managers care about the riskiness of their portfolio,³ therefore demanding additional returns as compensation for significant exposure to firm-specific risk. The amount of compensation activists require per dollar of risk decreases as they become wealthier so when the activist has little capital or is trying to consolidate ownership in a large firm, she demands a higher return and consolidates less of the outstanding debt thereby depressing payouts on emergence. A unique and stable equilibrium emerges in the market for defaulted bonds where larger vulture investors consolidate the debt of larger firms and relative size within a pair determines the optimal consolidation amount, returns, and emergence payouts.

In the spirit of Duffie (2010) I assume—and corroborate empirically—that capital flows to vulture funds do not anticipate high returns to defaulted bonds. Thus, instead of responding to potential investment opportunities, activist wealth follows the cyclicity of the overall market. This leads to the second element of my model: a consumption based asset pricing framework characterized by a

¹Bris and Welch (2005) provide a simple rational where a free rider problem amongst creditors decreases incentives to participate in reorganization resulting in lower recoveries when debtors are disperse.

²e.g. Xiong (2001); Basak et al. (2007); He and Krishnamurthy (2013); Kondor and Vayanos (2014)

³Activists have log preferences but any form with decreasing absolute risk aversion suffices.

representative agent where dynamics in the economy drive defaults and activist wealth. Putting the two components together, my model identifies the ratio of total activist wealth to the aggregate amount of defaulted debt outstanding as the key state variable whose time series properties interact with company specific characteristics to determine the prices, expected returns and eventual recovery rates on defaulted debt for ex-ante diversified holders.

The economic mechanism exploited in this paper can be summarized as follows: in recessions activist wealth falls at the same time the amount of distressed debt rises, leading vulture investors to demand high returns and lowering the expected recovery rates of ex-ante bondholders. On the other hand, in expansions, the ratio of activist wealth to defaulted debt increases, driving returns to a defaulted debt investment strategy toward zero and transferring all of the benefits from consolidation to pre default debtors. This simple dynamic endogenously replicates observed variation in post default trading prices and provides a suite of testable cross-sectional and time series predictions about returns and quantities in the market for defaulted securities.

To take the model to the data, I create an empirical measure of the activist wealth ratio, hereafter abbreviated AR , using Hedge Fund Research’s Distressed Restructuring assets under management as the numerator and the amount of defaulted debt outstanding according to Moody’s as the denominator. The first set of empirical tests examine the relationship between AR and reorganization period bond returns (defined as the returns to purchasing defaulted bonds during the month following the filing date and selling near or after plan approval.) The model extends a recent theme within the asset pricing literature—that the wealth of intermediaries should be relevant for pricing securities in segmented markets—by adding a supply element in the form of the amount of defaulted debt in the economy. A negative and significant relationship between AR at the time of default and risk adjusted reorganization period returns confirms primary prediction of my model. The results are economically meaningful: moving from the lowest tercile of the highest delivers a 60% decrease in bankruptcy period returns.

By endogenizing activist involvement, my model generates two additional returns-based empirical predictions that describe the interaction between the activist wealth ratio and firm characteristics. For firms with highly monetizable assets—defined as those with a high liquidation recovery—the model generates a weaker AR -returns relationship than for firms that cannot liquidate efficiently. Intuitively, when bondholders can sell assets on the open market at little deadweight cost, ownership concentration plays less of a role in determining post-bankruptcy recovery rates and the scope for activist involvement is limited. Since accounting information is not available for the vast majority of defaulted bonds, including the asset redeployability measure from Kim and Kung (2014) allows me to test the first cross-sectional hypothesis: that the sensitivity of defaulted bond returns to the activist wealth ratio should be dependent on the proportion of assets that are easily sold. Consistent with the model, I find that the impact of the activist wealth ratio on returns is most significant when redeployability is low and converges to zero when redeployability is high.

The framework in this paper focuses on the bondholders who are expected to obtain the preponderance of post-emergence equity value—referred to as fulcrum or loan-to-own creditors—but can be logically extended to consider other classes of debtor. Completely in-the-money classes should trade on a risk-adjusted yield basis over the expected duration of bankruptcy while completely out-of-the-money classes have very little influence in the process, making them behave like call options on an unexpected jump in firm asset value. This logic leads to the second cross-sectional prediction of the model—that the relationship between the activist wealth ratio and returns is stronger in fulcrum securities. In regression analysis I confirm this prediction by showing that the sensitivity of reorganization period returns to AR vanishes in the highly in-the-money or highly out-of-the-money bonds.

Unlike a traditional segmented market framework where one type of agent holds the entire supply of a particular asset, the endogenously founded intermediary framework I apply to defaulted debt predicts that the amount of bonds purchased by vulture funds is dependent on the activist wealth ratio. Activists face a tradeoff: by purchasing additional bonds they improve emergence recoveries but are forced to bear the additional risk associated with an increasingly concentrated portfolio and so when activists are undercapitalized and the amount of defaulted debt high, they can only purchase a small portion of outstanding claims. But as they become richer relative to their target companies, they take larger positions until they are wealthy enough to be effectively risk neutral toward a particular firm and choose to purchase all of the defaulted debt. Thus the model predicts a positive non-linear relationship between quantities traded after default and AR which I confirm empirically.

My model of activist vulture investors appears to capture the return and quantity dynamics in the market for defaulted bonds, but to be taken seriously in a model of credit spreads, it ought to explain expected recovery rates. The same mechanism that determines returns to individual defaulted claims is at work at the aggregate level. In recessions, when activist wealth relative to the amount of defaulted debt in the economy is high, the model predicts high loss given default and low post default trading prices and eventual recovery rates exactly as observed in the data. In normal times and booms, activist capital is sufficient to absorb the amount of defaults in the economy and recovery rates are high. This dynamic provides a model-implied trading price that exhibits an 82% correlation with Moody's post default trading prices—the most commonly used proxy for recovery rates. For comparison purposes, the total default rate—identified as the best single predictor of post default trading prices in Altman et al. (2005)—produces a time series correlation coefficient of approximately 60% in a univariate setting. By incorporating four additional explanatory variables to capture the state of the economy and market conditions, they show that the R^2 improves to 76%.⁴ The model presented here utilizes a single state variable and performs just as well making it a promising candidate for incorporation into a bond pricing model.

⁴The five variable specification achieves an R^2 of 81% in my sample as shown in Table 1

As Huang and Huang (2012) illustrate, the corporate bond yield curve exhibits a number of features that confound traditional asset pricing models. In order to replicate the observed spread between AAA and BBB securities, a model that is calibrated to match historical default and recovery rates must incorporate some combination of the following three mechanisms: negative covariance between the pricing kernel and asset prices, positive covariance between the pricing kernel and default boundary, and negative covariance between the pricing kernel and recovery rates. While structural models have improved in their ability to explain the AAA-BBB spread (e.g. Chen et al. 2008; Chen 2010; McQuade 2013), attempts to match spreads across the rating spectrum resemble a game of whack-a-mole where pinning down one particular moment results in losing discipline on others.⁵ This paper does not resolve the credit spread puzzle entirely, but provides another tool to improve the shape of model-implied spreads across all rating classes.

My model drives spreads through the relationship between the pricing kernel and expected recovery rates. Pre-default bondholders who anticipate selling to vultures in the event of bankruptcy will expect to recover a blended combination of the price activists pay for the consolidated portion of the debt plus the emergence recovery rate on the unconsolidated portion. My bargaining framework implies that the risk premium demanded by the activists is countercyclical and emergence recoveries are procyclical, driving expected recoveries down in bad states. Thus the ex-ante holders expect to receive low recoveries exactly when their marginal utility is highest.

Coval et al. (2009) show that, given the same amount of idiosyncratic risk across issues, safer securities will have a greater proportion of their defaults in recessions. My model delivers the same dynamic: AAA defaults are more likely to be systematic (i.e. in bad states of the world) than BBB defaults, while Speculative Grade bonds are most likely to default idiosyncratically (i.e. more randomly across both good and bad states of the world). Thus the highly pro-cyclical expected recovery rates implied by my renegotiation framework have a differential impact on spreads across rating classes. Specifically, adding the default-resolution process to a simple credit spread model increases the spreads on safe debt (AAA-BBB) while decreasing the spreads on speculative grade debt, thereby cutting overall pricing errors considerably for both 10 year and 4 year debt.

Finally, the model implies that the appropriate measure of recovery rates is a blended average of post default trading prices and eventual emergence recoveries. Existing models use one or the other, but the wedge between these quantities is also highly countercyclical making measurement error an important consideration in calibration. Specifically, when researchers target recovery rates to match emergence they are likely understating spreads on safe debt thus overstating the credit spread puzzle. The converse is true when pricing models calibrate to post default trading price. Because expected recoveries more closely follow post default prices, absent the ability to measure ex-ante expected recovery rates, my model suggests that post default trading prices are the preferred proxy.

⁵Agreement on the existence of this puzzle is not unanimous. Feldhütter and Schaefer (2014) argue that including the great depression in default rate estimates allows the Merton model to price spreads.

This paper links the activism and bankruptcy literature on the corporate side and the credit spreads literature from the asset pricing realm. The first papers to specifically investigate the role of activist investors in corporate restructures (Hotchkiss and Mooradian, 1997, 1998) show higher returns for bondholders, particularly when a vulture investor or outside acquirer takes control of the firm and management. Jiang et al. (2012) further shows that hedge fund involvement is associated with creditor friendly results across a range of metrics while Ivashina et al. (2015) show that vulture fund involvement and ex-post consolidation are associated with higher recoveries for the classes where the activists are involved. I utilize these results to substantiate model design choices in Section 2. Altman et al. (2005) provides evidence that supply dynamics of defaulted debt can affect aggregate recovery rates over time. They show that both the level and the change in the amount of defaulted debt are significant determiners of trading prices around filing date. Jankowitsch et al. (2012) instead focuses on the cross sectional determinants of recovery rates and shows that bond specific liquidity measures are strong predictors of trading prices post default. Both of these findings are complimentary to the results in this paper.

Almeida and Philippon (2007) establish the large spread component of expected asset losses in bankruptcy. Instead of addressing the importance of recovery rates generally, the study presented here establishes that the functional relationship between the economy and recovery rates have important implications for spreads. Culp et al. (2014) find that a significant portion of credit spreads in their pseudo bonds can arise from accounting for recovery rates and that the impact of recovery rate changes are proportionally largest for AAA bonds.

This paper is also related to the credit spread puzzle literature, namely the structural models of Chen et al. (2008); Chen (2010); Kuehn and Schmid (2014); McQuade (2013). Chen et al. (2008) is the closest to the results on spreads included in this paper. In their analysis, most of the ability to match AAA-BBB spread comes from habit preferences but they suggest that additional gains of a few basis points can be achieved using recovery rates that vary linearly with the consumption surplus ratio. In this paper the recovery rate is micro-founded by the activist consolidation process and is therefore determined endogenously and is a function of the state of the economy. As shown in later sections this delivers a much larger and targeted impact of recovery rate variation than in Chen et al. (2008).

Aside from structural models, a sizable amount of research has provided alternative explanations for the credit-spread puzzle. Specifically, but not exhaustively, Elton et al. (2001) explores the role of state level taxes in corporate spreads, Feldhütter and Lando (2008) shows that a convenience yield on treasuries can explain part of the high AAA spreads, and Adrian and Shin (2010); De Jong and Driessen (2012); Longstaff et al. (2005) all examine the role of liquidity in the pricing of defaulted bonds. Finally Feldhütter and Schaefer (2014) show that the credit spread puzzle seems to evaporate if models are calibrated to default rates starting in 1920.

This paper also leverages prior work on the theory of the firm regarding the optimal number of creditors which started with Bolton and Scharfstein (1996). In their paper limits to renegotiation increase the costs of liquidity default but decrease the incentives for strategic default. von Thadden et al. (2003); Bris and Welch (2005) expand this framework by incorporating coordination failure among creditors and costs of collecting on claims. LoPucki and Doherty (2007); Shleifer and Vishny (1997, 1992); Acharya et al. (2007) show that coordination failures can lead to inefficient liquidation or fire sales where creditors receive a lower than market value for their claims. The narrative bears some similarities to Shleifer and Vishny (1992), where lack of natural buyers low collateral resale value, and deep pocket investors can obtain return premiums and Hennessy and Zechner (2011), who provides a thorough treatment of post default trading behavior in a world with incomplete information using a risk neutral consolidator who provides debt relief to the stressed firm. Finally, this paper also leverages results from the growing literature on intermediary asset pricing by incorporating capital constraints and differences in the objective function of fund managers relative to that of the investors in the fund (e.g. Xiong 2001; Basak et al. 2007; He and Krishnamurthy 2013). Additionally this paper makes use of the mechanism presented in Coval et al. (2009) whereby AAA structured products are primarily exposed to systematic risk.

2 Model

The model consists of firms that issue risky debt and two types of agents: a continuum of diversified investors summarized by a price taking representative investor, and multiple activist investors.⁶ Firm assets follow an exogenous stochastic process that includes both systematic and idiosyncratic shocks. Default occurs when assets fall below an exogenous default boundary as in Chen et al. (2008). The diversified representative investor prices debt issues as the expected cash flow stream—coupon and interest payments while the firm operates and the recovery rate when the firm defaults—discounted by his SDF. After bankruptcy occurs the recovery for bondholders depends on the concentration of the ownership of the firm’s debt. When debt ownership is highly disparate the emergence recovery is expected to be lower than when it is held by a small group of investors leading to the first assumption of the model:

1. **Costs of default are decreasing in the concentration of ownership.** The theoretical foundation for this assumption is supplied by many corporate finance studies. The effort tradeoff here is most like Bris and Welch (2005) who describe a scenario where managers can extract value from the court driven restructuring when debt ownership is disperse. Alternatively, a coordination problem like von Thadden et al. (2003) might generate inefficient liquidation of complimentary assets thereby creating gains to consolidation of voting bonds. An immediate

⁶For consistency of exposition, I use the masculine pronouns for the representative investors and feminine pronouns for the activists.

result of this assumption is that ex-post debt consolidation will increase the expected value of a debtor's claims upon emergence.⁷

Vulture investors enter the market at this time looking for opportunities to consolidate firm debt by purchasing a large fraction of the bonds and eliminating the reorganization inefficiencies. The asset pricing implications of these natural intermediaries in the market for defaulted debt are derived from the preferences of the vulture funds, leading to the second assumption.

2. Consolidators care about the total volatility of their portfolios. In Basak et al. (2007) the relationship between portfolio performance and fund flows implies the manager's value function is defined over the performance of her entire portfolio, not just its co-movement with the SDF. In He and Krishnamurthy (2013) manager preferences and equity requirements force this relationship directly. For this paper I assume that activists care about the value of their portfolio and therefore demand a premium for bearing risk, and that capital flows to distressed investors do not anticipate—thereby eliminating—these excess returns.⁸ Empirically, Gabaix et al. (2007) and Adrian et al. (2014) provide evidence that the wealth of intermediaries is an important factor in pricing returns for various asset classes.

The above two assumptions deliver the main mechanism of my model. When companies file for default they face potentially high renegotiation costs. Some portion of this deadweight loss can be avoided if the outstanding claims to the company are consolidated. Doing so requires taking a concentrated position in the debt of the defaulted firm thereby exposing the activists to undiversifiable risk for which they require compensation.

The model makes predictions along three primary dimensions. First, upon default activists become the marginal pricers of the firm's debt. Their preferences and wealth relative to the amount of defaulted debt they are purchasing determine the price these investors are willing to pay for the defaulted bonds. As such, post default trading prices become a function of these time varying quantities. A second feature of the model is that these activists will demand a premium in exchange for consolidating debt ownership. Again, the model predicts that this premium varies based on the relative wealth of the activist investors. Finally, in describing a time varying process for recovery rates the model generates implications on the role of activists in determining credit spreads.⁹

⁷Previous versions of this paper utilized a reduced form framework where recoveries were an exogenous and increasing function of percentage bond ownership.

⁸I provide empirical evidence to support this assumption later in the paper.

⁹Appendix B provides a complete version of the model as well as the methodology for determining spreads.

2.1 Corporate Debt and the Bankruptcy Process

Following the setup from Chen et al. (2008), the assets of any individual firm evolve according to a stochastic process V given by dynamics

$$\Delta v_{k,t}(x_{t+1}) = \Delta p(x_{t+1}) + \sigma_k \epsilon_{k,t+1}$$

where $\Delta p(x_{t+1})$ is the change in value of a claim to the aggregate dividend, and $\epsilon_{i,t+1}$ is an idiosyncratic firm shock. The firm is assumed to be financed with both risky debt with face value D , and equity. The firm defaults at time τ when the value of assets crosses an exogenous default boundary B . In this simple model bondholders receive a counterfactual constant recovery rate $Rec = D - B$.¹⁰ In this paper I relax this relationship between B and Rec by modeling directly the market for defaulted securities. Dynamics in this market determine post default trading prices and eventual recovery rates.

When default occurs the activist can purchase a fraction $\alpha^{i,k}$ of the defaulted debt of firm k at a price $Z^{i,k}$ expressed as a fraction of face value of debt, D^k . As illustrated in Figure 2, two outcomes are possible at the end of bankruptcy. With a probability of $1-p$ bondholders do not successfully restructure the assets—it is fair to think of this as a liquidation—and all bondholders receive the low payout \underline{R} . With a probability p the firm enters reorganization where eventual recovery rates are a function of the maximum effort exerted by a single bondholder. As shown below, the eventual reorganization recovery $\tilde{R}(\alpha^{i,k})$ will be increasing in $\alpha^{i,k}$. Intuitively, as a single activist owns more of the outstanding debt of a firm, they have more stake in the outcome of reorganization and are willing to exert more effort to improve recovery rates.

[Figure 2 about here.]

In order to avoid holdouts who would complicate the model, the game is structured as an all or nothing tender offer by the activist. That is the activist bid of $Z^{i,k}$ is contingent on 100% of existing bondholders tendering $\alpha^{i,k}$ of their shares. Thus the tender is fully subscribed as long as the bid price is greater than the expected recovery without activist involvement:

$$Z^{i,k} \geq pf(0)(\bar{R}) + (1 - pf(0))(\underline{R}). \quad (2.1)$$

Activists will always bid at least enough to satisfy the representative agent's participation constraint in equation 2.1. In the model, bankruptcy resolution happens in the same period as default while in reality these processes take some time to resolve. This abstraction makes the model significantly more tractable without losing much in the way of real world applicability. Moreover it makes this

¹⁰McQuade (2013) combines stochastic volatility with an endogenous default boundary to generate a lower default boundary B in higher volatility states which delivers pro-cyclical default boundaries. A lower default boundary on the same amount of debt means lower recovery rates for bondholders when volatility is high meaning the model implicitly generates pro-cyclical recovery rates. However, this effect is either attenuated or entirely reversed when observed countercyclical financing costs are added.

model comparable to exogenously specified recovery rate regimes where recovery happens instantly upon default.

2.2 The Activist

I solve the activist manager optimization problem in two stages. First, once uncertainty about the state of the world is resolved, I calculate the optimal reorganization period effort exerted by the vulture fund given the previous $\alpha^{i,k}$ choice and the parameters of the firm.

Optimal effort comes from the solution to the maximization problem

$$\max_{e^{i,k}} u \left[W^i + \alpha^{i,k} D^k \left(e^{i,k} b \left(\alpha^{i,k} \right) \left(\bar{R} - \underline{R} \right) + \underline{R} - Z^{i,k} \right) - k \left(e^{i,k} \right) \right] \quad (2.2)$$

given a cost function

$$k \left(e^{i,k} \right) = \frac{\left(e^{i,k} \right)^u}{v} \quad (2.3)$$

and benefit function

$$b \left(\alpha^{i,k} \right) = \Theta \left(\alpha^{i,k} | \mu_{vt}, \sigma_{vt} \right). \quad (2.4)$$

The cost function is a polynomial cost function and the benefit function is the normal cumulative distribution function centered around a voting threshold μ_{vt} with variance σ_{vt} .¹¹ As long as utility is increasing in equivalent wealth, maximizing manager utility over effort choice is simply a matter of equating the marginal cost and benefits of effort. The optimal effort choice is given by

$$e^{i,k} = \left(\alpha^{i,k} D^k b \left(\alpha^{i,k} \right) \left(\bar{R} - \underline{R} \right) \frac{v}{u-1} \right)^{\frac{1}{u-1}}. \quad (2.5)$$

This gives up state equivalent wealth to the activist of

$$W_{reorg}^i = W^i + \alpha^{i,k} D^k \left(\tilde{R}(a^{i,k}) + \underline{R} - Z^{i,k} \right) \quad (2.6)$$

where

$$\tilde{R} \left(a^{i,k} \right) = \left(\frac{v^{\frac{u}{u-1}} - v^{\frac{1}{u-1}}}{(u-1)^{\frac{u}{u-1}}} \right) \left(\alpha^{i,k} \right)^{\frac{1}{u-1}} \left(D^k b \left(\alpha^{i,k} \right) \left(\bar{R} - \underline{R} \right) \right). \quad (2.7)$$

Given the expected value in the reorganization state, I solve for optimal $\alpha^{i,k}$ choices assuming that the activist has log utility over her emergence period wealth¹² and that the manager can either invest in the defaulted security or retain her initial wealth until emergence. The non-consolidation utility of

¹¹Approval of a plan of reorganization is the result of a voting process where both numerosity and total amount outstanding are both considered. Consistent with this process and as espoused in von Thadden et al. (2003), I model a scenario where the benefits to ownership are highest around these voting thresholds. $b \left(\alpha^{i,k} \right) = 1$ is an equally valid assumption and delivers different functional forms but the same intuitive result.

¹²Power utility is equally valid.

the manager, J_{nc} , represents her outside option.

$$J_{nc} = u(W^i) \quad (2.8)$$

$$\text{where } u(W) = \log(W^i) \quad (2.9)$$

Instead of holding her wealth, the vulture investor can choose to bid an amount $Z^{i,k}$ to purchase $\alpha^{i,k}$ portion of D^k , the total amount of defaulted debt for company k subject to some constraints that I describe later.

$$J_c(W^i, D^k | \alpha^{i,k}, Z^{i,k}) = \max_{\alpha^{i,k}, Z^{i,k}} \left[\begin{array}{l} pu \left(W^i + \alpha^{i,k} D^k \left(\tilde{R}(a^{i,k}) + \underline{R} - Z^{i,k} \right) \right) \\ + (1-p)u \left(W^i + \alpha^{i,k} D^k \left(\underline{R} - Z^{i,k} \right) \right) \end{array} \right] \text{ s.t. Constraints} \quad (2.10)$$

The participation constraint for the manager requires that the price paid in consolidation be such that the manager is at least as well off bidding so

$$J_c(W^i, D^k | \alpha^{i,k}, Z^{i,k}) \geq J_{nc}(W^i). \quad (2.11)$$

Though equilibrium bid prices will be determined by a bidding game amongst activists, it is useful to consider a situation where Bertrand like competition deprives activists of any surplus. Here the value an activist obtains from consolidating will not exceed the value they derive from non-consolidation, or

$$J_c(W^i, D^k | \alpha^{i,k}, Z^{i,k}) \leq J_{nc}(W^i) \quad (2.12)$$

In the Bertrand scenario, theoretical competition forces indifference amongst the activists and equations 2.11 and 2.12 combine to yield $J_c(W^i, D^k | \alpha^{i,k}, Z^{i,k}) = J_{nc}(W^i)$, making the activist transfer all surplus to ex-ante bondholders. The unique solution in the Bertrand competition case is given by the maximization function in equation 2.13.

$$\max_{\alpha^{i,k}, Z^{i,k}} E \left[Rec^{\text{ex-ante}} | \alpha^{i,k}, Z^{i,k} \right] \text{ s.t. } J_c(W^i, D^k | \alpha^{i,k}, Z^{i,k}) = J_{nc}(W^i) \quad (2.13)$$

where

$$E \left[Rec^{\text{ex-ante}} \right] = (1 - \alpha^{i,k}) \left(p\tilde{R}(a^{i,k}) + \underline{R} \right) + \alpha^{i,k} Z^{i,k}.$$

Since all surplus is transferred to the ex-ante holders, the unique Bertrand competitive share, bid tuple is the one that maximizes ex-ante bondholder eventual recovery. Below I show that, in many cases, explicitly modeling a matching game between firms and funds that determines the competitive equilibrium bid prices delivers a similar equilibrium. However in other cases when competition breaks down, bid prices and α choices can deviate substantially from this equilibrium.

2.3 Competition and Aggregation

I model a scenario where the number of activist (M) are fixed and the number of defaulted firms (N) fluctuates in any period. Competitive dynamics in a one-to-one matching game amongst activists will

determine actual bid prices and alpha choices for the set of consolidated firms. First I will explore a version of the model where when M is always strictly greater than N —hereafter perfect competition since virtually all fund surplus is eliminated—but also consider an extension where $N > M$ in some states in the world—hereafter the imperfect competition model because in these states each fund will retain a surplus that they do not pass on to ex-ante bondholders.

For the model to achieve a stable equilibrium, activist funds must be restricted in the number of firms they can attempt to consolidate in any given period. Consider a situation where a large fund can make multiple bids across defaulted firms. It might be just as well off outbidding a number of smaller funds to consolidate multiple small firms as it is bidding a larger discount on a bigger firm. Thus the multiplicity of potential bidding outcomes renders an equilibrium much harder to compute and less likely to be either unique or stable. To prevent this from happening I assume that each fund is endowed with one unit of time in each period and thus can choose to evaluate and bid on only one firm each period.¹³ In reality, the process of appraising and developing a plan of action for a defaulted company is time consuming, so this assumption is justifiable to the extent that the information processing capacity of vulture managers is limited.¹⁴ Finally I assume that each fund has full information about the size distribution and the number of competing funds as well as defaulted firms.

2.4 Bidding Game

The full game is characterized as follows: in each default period N firms reach their default boundary. The M activist firms are each able to make a “take it or leave it” bid on a company. The equilibrium bidding outcome is one such that each firm makes an optimal bid given the equilibrium bidding strategies of each other firm. Each activist firm combination is happiest with their chosen action and would not be better off deviating.

The activist-firm matching game maps to the “Marriage” game described in Becker (1973) where surplus can be shared arbitrarily amongst matches. In particular, the unique and stable equilibrium outcome of the activist-firm bidding game here is the special case where each group can be continuously characterized along one dimension. In this setup firms can be fully described by the amount of their defaulted debt D^i and activist funds can be described by their wealth W^k . In all simulations and results presented here, the bidding game satisfies the condition that guarantees a positive assortative

¹³Because cost of effort is increasing in total effort exerted, this condition often arises endogenously. Funds will always direct all their effort into a single reorganization, so the decision to purchase large stakes in two firms on file date relates the benefits of diversification against the price at which they can consolidate additional firms. In a competitive world this price appears to far exceed the potential benefits. I explore the conditions under which a stable 1-1 matching equilibrium emerges when 1-many matches are allowed in the forthcoming online appendix.

¹⁴Admittedly, one fund may have multiple managers each able to expend the time required to analyze a company. With preferences defined at the fund level, this would eliminate the equilibrium by allowing funds to pool idiosyncratic risk. The fund would have to have some employment contract with the managers, and assuming that the contract pays out based on that manager’s performance, then a fund with multiple managers can be thought of as a group of individual funds with capital split as per each manager’s mandate.

equilibrium.

Proposition 1. *When firms can be monotonically ranked across debt amount so $D^{k+1} > D^k \forall k \in \{1 \dots N\}$ and activist funds can be monotonically ranked in size so $W^{i+1} > W^i \forall i \in \{1 \dots M\}$ the matching game delivers a unique, positive assortative equilibrium where the largest activist, M , consolidates the firm with the largest amount of debt, N and so on until either all firms are consolidated or all funds have participated in a consolidation.*

Proof: See Appendix

In simple terms, Proposition 1 states that larger activists have a competitive advantage in consolidating the debt of larger defaulted companies. All else equal, increasing the size of the defaulted firm increases the potential reward to the activist but also increases the volatility of their final wealth in absolute terms. Because the vulture funds have decreasing absolute risk aversion, an increased dollar of risk induces a greater loss of utility for less wealthy activists. Thus larger funds are simply more capable of coping with the risk inherent in consolidating larger defaulted firms.

Positive assortative matching pins down the activist–firm pairs but does not explicitly determine equilibrium bid prices. There we need to understand how the potential surplus of consolidation is split between activists and ex-ante bondholders. Because ex-ante bondholders do not collaborate, they do not retain any bargaining power. Thus the surplus they enjoy will be entirely driven by the competitive nature of the activist space. Each individual activist will attempt to maximize their own utility but must bid enough to stave off less wealthy activists from trumping their bid. This leads to proposition 2.

Proposition 2. *Each activist fund i submits a quantity and bid combination $\{\alpha^{*i,k}, Z^{*i,k}\}$ such that $E[Rec_{ex-ante} | \alpha^{*i,k}, Z^{*i,k}] = E[Rec_{ex-ante} | \hat{\alpha}^{i-1,k}, \hat{Z}^{i-1,k}]$ where $\{\hat{\alpha}^{i-1,k}, \hat{Z}^{i-1,k}\}$ is given by*

$$\max_{\hat{\alpha}^{i-1,k}, \hat{Z}^{i-1,k}} E[Rec_{ex-ante} | \hat{\alpha}^{i-1,k}, \hat{Z}^{i-1,k}]$$

$$s.t. J_c(W^{i-1}, D^k | \hat{\alpha}^{i-1,k}, \hat{Z}^{i-1,k}) = J_c(W^i, D^k | \alpha^{*i,k}, Z^{*i,k}) .$$

Where

$$E[Rec^{ex-ante}] = (1 - \alpha^{i,k}) (p\tilde{R}(a^{i,k}) + \underline{R}) + \alpha^{i,k} Z^{i,k} .$$

Proof: See Appendix

Proposition 2 describes the unique bidding and alpha choices for all the activists and defaulted firms in my economy at any time. Here, each activist wants to maximize the surplus she is able to obtain. However she must be cautious of the fact that other activists might encroach on her firm if she does not bid enough. Because the equilibrium is positive assortative, the activist only needs to worry about how to outbid her closest rival for her target firm. Indeed activist k offers a package $\{\alpha^{*i,k}, Z^{*i,k}\}$ that provides exactly the expected recovery ex-ante bondholders would have received had they gone with

the maximum bid of the next smallest activist, $i - 1$. As long as activist i meets this threshold, she is able to choose the particular allocation that gives her the largest utility.

The bidding and allocation outcomes in this matching equilibrium are far richer than the Bertrand competition described in the previous section. As illustrated later in Section 3, this matching game approaches the Bertrand solution when M is much larger than N but can deliver drastically different bidding outcomes when competition breaks down. In scenarios where defaulted firms outnumber vulture funds, activists are able to appropriate the lions share of the consolidation benefits for themselves and leave ex-ante holders with very low recoveries.

3 Consolidation and Recovery Prices

3.1 Competitive Bargaining

When M is large compared to N and the fund and firm sizes are drawn from a lognormal distribution, the bidding model delivers results that are approximately equal to a Bertrand competition scenario. Under these conditions, nearly all surplus is eliminated and vultures are compensated exclusively for the idiosyncratic risk associated with consolidation. In addition the return premium of defaulted assets is purely a function of activist wealth relative to the size of the defaulted firm. This baseline model supplies a nice environment to analyze the intuitive relationship between activist decisions and arbitrage capital.

Assuming that the activist has log utility and applying parameters $p = 0.9$, $\underline{R} = 0.1$, and $\bar{R} = 0.7$,¹⁵ I solve numerically for a variety of interesting variables including optimal $\alpha^{i,k}$, emergence bond recoveries, the return to the activist and finally the combined recovery to ex-ante bond holders. Because the model uses power utility, the optimal alphas and bid prices case can be expressed using the ratio of activist wealth to the size of the defaulted firm, $AR^{i,k} = W^i/D^k$.¹⁶ In the full model, $\alpha^{*i,k}$ and $Z^{*i,k}$ are solved simultaneously in the matching equilibrium described above. However, for Figure 3 I assume a fixed bid price to illustrate the activist's participation criterion. When the activist has low wealth and anticipates paying a high bid price, she is better off simply holding on to her initial endowment. However, as depicted in panel (a), as the activist becomes wealthy her absolute risk aversion decreases, so the same dollar risk-reward gamble becomes more attractive. At a certain point the activist steps into the market for the firms assets and offers a high $\alpha^{i,k}$ at the fixed bid price. Figure 3(b) displays the

¹⁵Bris et al. (2006) estimate an average liquidation rate of 5% for liquidating firms. Since we do not observe the counterfactual liquidation value for reorganized firms, and to be conservative about the impact of this mechanism, I assume a slightly higher expected liquidation value for these firms. \bar{R} and ρ are set to bound the average recovery rates to what we see in the aggregate time series where ρ exists solely to add some uncertainty even in the case of full consolidation.

¹⁶Wealth and bid price can simply be scaled by the face value of defaulted debt since power utility is scale invariant. Any wealth/face value combination that delivers the same ratio will have the same optimal allocation. If firms vary in size, cross-sectional differences in post default trading prices and bankruptcy return occur depending on the bargaining outcome, but these differences are minuscule and do not alter the interpretations below.

relative utilities of consolidation versus non consolidation for the same activist. As the activist wealth ratio increases, a wedge develops between her consolidation and non consolidation utility as she begins to reap the gains from consolidation. In order to restore equation 2.13 to balance, the activist must shift some of her surplus to ex-ante bondholders.

[Figure 3 about here.]

Figure 4 displays the effects of a change in the activist wealth ratio at default, $AR^{i,k}$, on the competitive equilibrium outcomes of $\alpha^{i,k}$ choice, bid prices, returns, and emergence recoveries. When the activist’s wealth is low relative to the amount of defaulted debt, they are less able to bear the idiosyncratic risk associated with purchasing a large number of claims. As such their optimal $\alpha^{i,k}$ is an increasing function of $AR^{i,k}$.

A low $AR^{i,k}$ affects the price through two channels. Low $\alpha^{i,k}$ means the expected recovery on claims post emergence governed by $f(\alpha)$ will also be low: the rewards to consolidation are lower in these states. Secondly, low $AR^{i,k}$ means the activist will require more return per unit of idiosyncratic risk. So the price must adjust accordingly. Panel (c) exhibits this increase in return demanded by the relatively poor investors. Activists’ risk aversion is fairly low in this framework so as wealth increases, alpha and price paid quickly approach a “risk neutral” level highlighting the importance of restricted capital flows in delivering these results.

[Figure 4 about here.]

3.2 Capital Flows and Limits to Arbitrage

The model predicts that relatively low activist wealth generates low recovery prices and high bankruptcy process returns. In a world with no barriers to capital flow, agents would direct capital to the arbitragers when their returns were expected to be high thereby reducing the impact of the mechanism presented in this paper. Such opportunistic capital movements predict increased funds to vultures in periods of high default—a phenomenon contradicted by flows to HFR Distressed Restructuring firms which appear to be correlated with market returns.. The hedge fund flow data is more in line with a slow moving capital framework (Duffie, 2010) where capital migrates to markets with higher risk premia over long horizons, but does not adjust contemporaneously when expected returns to a particular asset class spike.

The relationship between flows and future period distressed returns is formalized in Table 1 where capital flows to the distressed investment strategy are regressed against a variety of variables including the contemporaneous default rate, future returns to purchasing distressed bonds as described in more detail later in Section 4.3¹⁷, as well as the future returns on the HFR distressed restructuring index.

¹⁷Weighted by class value to convert to a time series.

Distressed asset flows do not anticipate future returns and, by some measures, even recede in anticipation of high default or high return periods. The result is intuitive: the volume of opportunities available to distressed investors is countercyclical, while the capital investors are able to allocate is pro-cyclical. Thus returns are at their highest when investors are the least able to direct fund flows to this sector.

[Table 1 about here.]

3.3 Recovery Rates

Figure 5 (a) displays the relationship between $AR^{i,k}$ and the return to ex-ante bondholders, which, as before can be calculated by

$$E[Rec^{ex-ante} | \alpha^{i,k}, Z^{i,k} | \alpha^{i,k}, Z^{i,k}] = E[\alpha Z^{i,k} + (1 - \alpha^{i,k}) Rec_{observed}]$$

where

$$Rec_{observed} = pf(\alpha^{i,k})(\bar{R}) + (1 - pf(\alpha^{i,k}))(\underline{R}).$$

Bondholders can expect to receive a combination of $Z^{i,k}$ and the eventual recovery value $Rec_{observed}$ when a firm files for default. Figure 5(b) depicts these various measures of recovery rate. Since $\alpha^{i,k}$ approaches 1 as AR increases, all three converge upon the bid price as activist wealth increases. But when activist wealth is low bid prices are low thus dragging down expected returns for prior holders. This drop in $E[Rec^{ex-ante}]$ is attenuated by the fact that returns to the activist are high in bad states leading to high post emergence recoveries even when bid prices are low. The share retained by ex-ante bondholders— $1 - \alpha^{i,k}$ —is high in these states so they get to participate in these returns.

[Figure 5 about here.]

3.4 Imperfect Competition

Relaxing the assumptions of competition from Section 3.1 adds an additional dynamic to recovery rates: when the number of defaulted firms, N , is high, competition to consolidate those firms amongst M possible bidders is low and the returns for defaulted bonds spike. Figure 6 (a) exhibits the value weighted recovery rates to existing bondholders as the number of defaulted firms in the economy increases. To illustrate the competition channel, I first plot the solid blue line which represents the perfect competition scenario with a large number of very wealthy activists. An increase in the number of defaulted firms has a negligible effect on expected recovery rates in the economy as these wealthy vulture funds are able to soak up defaulted assets.

The red dotted line illustrates the imperfect competition regime where activists are individually wealthy but less numerous. As we can see the two models deliver comparable results when $N < M$.

However, the imperfect competition regime delivers a clear discontinuity at $N = M$ when activists are no longer forced to bid competitively for defaulted companies. Positive assortative matching between activists and defaulted firms still holds, but in this scenario the smallest activist fund is only obliged to pay the ex-ante holder’s outside option: \underline{R} . A low bid in the initial pair cascades through each successive pair delivering a substantially reduced surplus to ex-ante holders at all wealth levels as exhibited in panel (b). Finally, as the competitive environment worsens, this transfer of value to activists increases.

[Figure 6 about here.]

3.5 Cross Section of Recovery Rates

For a given level of debt consolidation the outcome of the reorganization process will depend on firm-specific characteristics. In particular, differences in the ease by which firms can sell their assets affect the risks and rewards faced by vulture funds leading to variation in their optimal decisions. The potential improvement attributable to activist involvement will be larger (smaller) when liquidating the firm’s assets are more (less) costly. Therefore a firm with mostly highly monetizable assets such as trucks, real estate, or, at the very extreme cash, will, in the parlance of my framework, have a higher \underline{R} than a firm whose assets are largely intangible, for example human capital.

[Figure 7 about here.]

Figure 7 displays how various liquidation values affect the model. First notice that the assets will never trade below their low recovery value. Thus the returns throughout bankruptcy are capped at $\frac{\bar{R}}{\underline{R}} - 1$. As the liquidation value of assets increases the maximum return decreases mechanically. At the extreme, when a firm’s assets can be sold without facing any reorganization costs— $\underline{R} = \bar{R}$ —returns during bankruptcy are zero. In addition to this mechanical effect, a larger portion of easily liquidated assets effectively reduces the amount of risk taken by the activists. In the case where $\underline{R} = 0.3$ and $\bar{R} = 0.6$, the activist is only exposed to a potential loss of $Z^* - 0.3$ which is significantly more palatable to a risk averse agent than $Z^* - 0.1$. Through both a reduction in the amount of risk born for a given face value of defaulted debt, and the mechanical reduction in maximum returns, a higher liquidation value of assets pushes down distressed debt returns and drives up post default trading prices.

4 Implications and Testing of the Renegotiation Model

4.1 Testable Hypotheses

The results in Section 2 link the ratio of arbitrage capital to defaulted debt in the economy with recovery rates and returns. The supply side dynamics of the model—that the amount of defaulted

debt outstanding should negatively explain post default trading prices—are consistent with current empirical literature as in Altman et al. (2005). The model also suggests that the demand for these assets is important as well and thus offers the following predictions about the relationship between landscape in the market for defaulted bonds and the activist wealth ratio. Moreover, my activist consolidation framework differentiates itself from other models that explain cyclical recovery rates by predicting that the ratio of arbitrage capital to total defaulted assets should forecast an extra risk premium provided to those activists willing to consolidate when times are tough. As shown in Figure 4(c), the expected return on bonds throughout the bankruptcy process spike when activist AR is low. Formally stated, the second empirical contribution is to test the following.

H1: The debt of defaulted companies carries a return premium which decreases when the relationship between arbitrage capital and total defaulted debt increases.

This hypothesis is tested by running the following regression

$$r_{c,t} = \alpha + \beta_1 AR_t^{agg} + \mathbf{B}\vec{X}_{c,t} + \epsilon_{c,t} \quad (4.1)$$

where $r_{c,t}$ is the log return to holding the defaulted debt of security class c (defined below) when the company defaults at time t . AR_t^{agg} is the aggregate arbitrage capital ratio derived below and $X_{c,t}$ is a vector of controls and risk factors. $H1$ predicts that the coefficient β_1 is negative: a higher ratio implies lower returns for a distressed strategy.

These tests are performed in the return space as opposed to the price level space because post default prices are exceptionally noisy and dependent on multiple company specific characteristics like seniority level, percentage securitized, firm-specific default boundary, etc, many of which I do not observe for the firms in my sample. But returns are largely removed from these cross sectional differences in post default trading prices. The activists in my model are going to demand a certain return for a certain amount of risk, it doesn't matter whether the bonds start trading at 10 with ultimate expected recovery of 15 or start trading at 50 with ultimate expected recovery of 75, the expected return AR relationship should remain the same.

As discussed in Section 3.5, a firm with a larger portion of intangible assets or assets which are non-transferable is more likely to suffer in a default than a firm whose primary asset base includes easily resellable assets. The former will rely more on a well executed reorganization process than the latter. I capture the difference between the two firms by altering their in the low recovery outcomes, with firms who have easily monetizable assets having a relatively large recovery in the low state. The easily sellable assets provide a floor on recovery rates that allows funds to accept a lower risk premium per dollar of wealth. This cross sectional dynamic implies hypothesis $H2$

H2: The negative relationship between returns to defaulted bonds and activist wealth should attenuate when assets are easily liquidated.

In light of the fact that many of the firms examined in this paper are not publicly traded either

before or after default, I do not observe their asset composition directly. Here I use the results from Kim and Kung (2014) which provides a measure of “Asset Redeployability” at the 4 digit NAIC code level eliminating the need to gather individual firm data. Their redeployability measure utilizes the BEA input output tables to capture the alternative uses of assets within a particular industry. For example heavy trucks are used in a variety of industries for a variety of purposes while oil and gas machinery is used in only one industry, oil and gas. So it stands to reason that a company whose assets constituted mainly of heavy trucks would have an easier time disposing of their assets in a liquidation scenario than a oil extraction company.

Using the asset redeployability measure, I test $H2$ using the following specification:

$$r_{c,t} = \alpha + \beta_1 AR_t^{agg} + \beta_2 REDEP_c + \beta_3 AR_t^{agg} * REDEP_c + \mathbf{B}\vec{X}_{c,t} + \epsilon_{c,t} \quad (4.2)$$

The model suggests that when activist wealth is high, post default trading prices will be high and defaulted firms will carry no risk premium regardless of the redeployability of their assets. Only when activist wealth is low does redeployability become important. Here high redeployability will reduce the risk premium demanded by activists. Similarly, when redeployability is high (low), the sensitivity of returns to activist wealth should be low(high). Partial derivatives of return with respect to AR_t and RDP_c are

$$\frac{\partial E[r_{c,t}]}{\partial AR_t} = \beta_1 + \beta_3 REDEP_c \quad (4.3)$$

$$\frac{\partial E[r_{c,t}]}{\partial REDEP_c} = \beta_1 + \beta_3 AR_t \quad (4.4)$$

Using the above logic, the model implies a negative β_1 , negative β_2 , and critically, a positive β_3 .

The model in this paper is designed to capture the dynamics of the so called “fulcrum” class of creditors. Figure 8 displays the capital structure of a fictitious company. The shaded region represents the asset value while the greater box is divided into the various creditor classes. Because the asset value more than covers the senior secured creditors, they are unlikely to be concerned with the outcome of renegotiation. Their claims will trade on a yield basis with some minor chance of impairment should the asset value decrease precipitously. The subordinated notes face the opposite issue: these securities are very far out-of-the-money and, according to the waterfall rules in bankruptcy, they would need a dramatic increase in asset value to receive any distribution at all. For both of these classes one should not expect the activist wealth ratio to be a primary determinant of process returns.

[Figure 8 about here.]

In Figure 8 the subordinated notes are trading at two cents on the dollar, the secured bonds are trading near par and the Senior bonds sandwiched in the middle are the fulcrum creditors trading at 45. The seniors are the most interested in the eventual recovery values as they are the portion of

capital structure likely to become the post emergence equity. In addition, due to their position in the waterfall they are also most able to influence their eventual recovery rates as the judge would have to “cramdown” any plan these creditors did not vote for.

H3 : AR is a significant determinant of returns for fulcrum classes but not for highly in-the-money or out-of-the-money securities.

The test of this hypothesis is similar to that of *H3*.

$$r_{c,t} = \alpha + \beta_1 AR_t^{agg} + \beta_2 FULCRUM_c + \beta_3 AR_t^{agg} * FULCRUM_c + \mathbf{B}X_{c,t}^{\vec{}} + \epsilon_{c,t} \quad (4.5)$$

$FULCRUM$ here is a dummy variable that captures the classes of debtors that are likely to emerge as primary equity holders. Again the partial derivative of returns with respect to the activist wealth ratio becomes

$$\frac{\partial E[r_{c,t}]}{\partial AR_t} = \beta_1 + \beta_3 FULCRUM_c.$$

In this case though, the model predicts a positive and significant β_3 and an insignificant β_1 .

Panel (a) of Figure 4 exhibits the tradeoff activists make between increasing the portion of debt consolidated and the riskiness of a concentrated portfolio. As they become wealthier relative to the size of their target firm, vulture funds purchase more debt until they own nearly all outstanding bonds and have achieved the largest possible emergence value. This tradeoff motivates hypothesis 4,

H4 : The amount of turnover post default should be increasing non-linearly in the activist wealth ratio.

which I test using regression equation 4.6.

$$TURNOVER_{c,t} = \alpha + \beta_1 AR_t^{agg} + \beta_2 AR_t^{agg^2} + \mathbf{B}X_{c,t}^{\vec{}} + \epsilon_{c,t} \quad (4.6)$$

Here the model predicts a positive and significant β_1 which indicates that turnover as a percentage of principal amount outstanding in the month following default is positively related to AR but a negative β_2 which indicates that the slope of this relationship declines as AR increases.

While returns and turnover tests are limited to observations post 2002 because they rely on TRACE transaction data as described below, the proxy used for the activist wealth ratio begins in 1990. To establish that the model is relevant prior to 2002, I examine the model’s ability to explain the time series of aggregate post default trading prices thus yielding *H5*.

H5 : Aggregate post default trading prices are non-linearly related to the activist wealth ratio.

4.2 Data

The variable of interest for the empirical section of this paper is the ratio of arbitrage capital to defaulted assets in the economy. The numerator is constructed using capital flows information from Hedge Fund Research (HFR.) The HFR media reference guide 2013 contains annual data on the estimated amount

of capital allocated to the distressed/restructuring strategy through the end of 2012. I call the stock of this capital W_t^{data} and, where necessary for returns based tests, interpolate within years to identify the stock at a particular time t .¹⁸ The various hedge fund research providers are all subject to their own biases. As long as HFR is accurate with respect to the change in distressed capital from year to year, the relative magnitude of this series is not important to the empirical tests as the coefficients will scale as necessary.

The denominator is constructed using Moody’s monthly default rate data.. D_t^{data} is equal to the total defaulted debt interpolated within month to the filing date t . Thus the arbitrage capital ratio for a class of claims c that files at time t is constructed as

$$AR_t^{agg} = \frac{W_t^{data}}{D_t^{data}}.$$

[Figure 9 about here.]

The primary data set used to construct returns is the registered bond transaction database from Trade Reporting and Compliance Engine (TRACE.) TRACE began collecting data on trade size up to 1mm for high yield issues and 5mm for investment grade, yield at the time of trade, the price of transaction, and other relevant data for all transactions of registered securities starting in 2002. The raw TRACE enhanced dataset contains errors so I follow the procedure advocated by Bessembinder et al., 2009 to drop any canceled, duplicate, subsequently corrected, or commission trades and add additional screens to capture potential CDS settlement trades.¹⁹

For security specific information, I use the Fixed Income Security Database (FISD) which provides comprehensive issuance information about each bond. For the purposes of this study I focus on the bankruptcy filing information, particularly the filing date, type of proceeding, plan approval date and emergence date as well as the total offering amount of the bond and the unique parent issuer.

Combining these data sets provides trade information for securities prior to and through the bankruptcy process for companies that file after TRACE begins recording transaction data (2002) through 2012. I find 1280 issues that have defaulted for which trading information around the time of default is available. Securities are excluded from this study if no price is available at the time of bankruptcy filing. Because these results are primarily focused on establishing the return for securities throughout the bankruptcy process, dropping securities that do not meet the post filing trading isn’t likely to induce bias in the results.

Upon file date, all securities with a given level of seniority are put into a class together. These

¹⁸Results are robust to the particular interpolation regime used, either linear, end of period, or mapped to changes in AUM across all hedge fund strategies where a monthly series is available.

¹⁹Because trades examined focus around bankruptcy filing dates, there is some risk that CDS settlements occurring at par instead of real trades are captured. To prevent this from occurring, I determine trade context as the average trading price of trades which are not executed at exactly par. I then discard any trades which occur exactly at par and are more than 10% outside of this context.

securities are almost always treated as equivalent in the eyes of the bankruptcy court and thus must receive equal treatment during the reorganization process.²⁰ The class designations used in this paper follow largely those dictated by the bankruptcy court documents. In a few cases, for example those where inter creditor agreements result in two securities classed together that receive different treatments, the court designations are not appropriate for this paper. Thus I also group bonds within a designated class based on their accrued-adjusted post default filing prices. If the difference in average trading price falls below a given threshold—I use 5%—I note that these two securities are likely in the same class together. Finally I hand check the cases where a particular seniority level has multiple classes to determine whether the classification is appropriate with the bankruptcy code and court documents. Using this technique I group the 1280 defaulted securities for which I have bankruptcy trading data upon default into 288 issuer class combinations. A yearly summary of issuer-class level data is displayed in Table 2.

Risk adjustment data is gathered from the usual sources. Fama French portfolios for the market, SMB, HML, and UMD are taken from WRDS. Similarly, Pastor-Stambaugh (PS) liquidity index data and returns to their liquidity portfolio are also downloaded from WRDS. Finally the bond risk factors TERM and DEF are calculated using the difference between the risk free return and the Barclays US government long bond index daily total return and the Barclays BAA corporate bond index respectively.

[Table 2 about here.]

4.3 Calculating Returns

For the purposes of my study, three major events typically occur throughout bankruptcy: 1) the company files for Chapter 11 protection and enters a restructuring phase, 2) the court approves a suitable plan of reorganization, and 3) the company emerges from bankruptcy or liquidates if no agreed upon plan is reached. The bonds of the defaulted company continue to trade between plan approval and eventual emergence which provides me with a window during which all uncertainty is resolved but the pre-default bonds have not been canceled and reissued as new securities. I exploit this window to assess the expected emergence recovery values for any particular class of debtor that has bonds which trade during this window (where classes were defined in Section 4.2 as a group of creditors to a defaulted firm who are entitled to the exact same distribution upon emergence).

In particular, to calculate reorganization period returns, I first calculate the entry price PF using a similar methodology to Jankowitsch et al., 2012: for each class c where i security is a member of that

²⁰The case of Spansion provides a rare example: the subordinated bond with the same official seniority level as the convertible bond traded at a large premium because of an x-clause on the convertible that, in the case of bankruptcy, pledged any recovery to the subordinated security until it had been paid in full. These securities were officially in the same class during bankruptcy, but their outcomes were very different.

class, I average trades indexed by k with amount vol and price p over the first 30 days of bankruptcy.

$$PF_c = \frac{1}{T+1} \sum_{s=t_{file}}^{t_{file}+T} \left(\frac{\sum_k (p_{k,i,s} vol_{k,i,s})}{\sum_k vol_{k,i,s}} \right)$$

The exit price is calculated in a similar way using the window of trading after the plan approve date prior to actual emergence date.

$$PE_c = \frac{1}{T+1} \sum_{s=t_{approve}}^{t_{approve}+T_{emerge}} \left(\frac{\sum_k (p_{k,i,s} vol_{k,i,s})}{\sum_k vol_{k,i,s}} \right)$$

This methodology for determining PE_c is not straightforwardly applied in two special cases: 1) the firm has not yet approved a plan of reorganization (this happens if the firm undergoes a liquidation or was still involved in the process of reorganization at the end of the trading period) and 2) the firm has confirmed a plan but the security in question did not trade after the plan was confirmed.

To address the first scenario I either use the last available trade, or drop observations where that trade does not occur within 120 days of the last trade in my database. All results are robust to both treatments. To address the second scenario I, where readily available, obtain the plan of reorganization and use the plan expected distribution as the emergence recovery. In the few cases where I am unable to accurately infer an emergence value, I either drop the observation or use the last available trade prior to plan approval. Again all results are robust to various treatments.

Because I must make a number of assumptions about the treatment of emergence prices, these data are a potentially biased indicator of unconditional return moments to a distressed strategy. In particular, if the cases where I do not find emergence prices are generally bad outcomes, the unconditional returns to this strategy are likely overstated in my sample. However, all tests I perform in this analysis are on the relationship between returns and the activist wealth ratio. Thus any systematic measurement error would have to be correlated (negatively if the story above were true) with my variable of interest to bias the estimated coefficients toward finding a result. I find that this is not the case. A linear probability model reveals a slightly positive, statistically meaningless relationship between the probability of obtaining a price during the post-approval window and AR .

The final obstacle to using this data is that returns to defaulted classes are positively skewed. Charter Communications, Pilgrim's Pride Group, Mirant, and some Lehman Brothers issues, to name a few, return more than 2000% over the course of the bankruptcy (or in some cases until the latest trade date.) Indeed my model predicts this skewness in Figure 4(c). However these extreme returns can pose problems for standard linear regression analysis when using raw returns. In order to both reduce the impact of extreme values and be more consistent with the implications of the model, I use the log of the return as the primary dependent variable: $r_c^{log} = \log(\frac{PE_c}{PF_c})$.²¹

²¹Using log returns is likely necessary to avoid a bias in these results. Prior to taking logs, the returns over bankruptcy are positively skewed meaning that, in a small sample, the fewer the observations, the more likely we are to underestimate

I adjust these returns for traditional risk factors in two ways. In the first set of tests I avoid any issues caused by lack of trading data by including the returns of a relevant risk factor over the reorganization period in the regression specification as a control, a common practice in the bankruptcy literature. To the extent that reorganizations are universally exposed to a particular risk factor say, liquidity, the coefficient on the returns of the PS index should be negative and significant. However, this does allow for different exposures to risk, so if higher risk firms are likely to default in states when AR is high, the specification will misattribute returns associated with traditional risk factors to the arbitrage wealth ratio.

Firm level risk exposures can be calculated by adjusting return windows to account for infrequent trading data. Specifically, I designate all of the N trading days with daily average price p within a class c between t_{file} and $t_{approve}$ as the set $\{p_{c,1}, p_{c,2}, \dots, p_{c,N}\}$ and let t_n be the date on which trade n occurs. The return between any two consecutive trading days is simply $r_{c,n}^{risk} = p_{c,n}/p_{c,n-1} - 1$. The n period return on a relevant risk factor f specific to class c , $r_{c,n}^f$, is calculated as the cumulative return on the factor between two trade dates or $r_{c,n}^f = \left(\prod_{s=t_{n-1}}^{t_n} R_s^f\right) - 1$, where R_s^f is the daily return on f . Class betas are calculated over the default window using the following regression form:

$$r_{c,n}^{risk} = \alpha + \mathbf{Br}_{c,n}^f + \epsilon_{c,n}$$

where $\mathbf{r}_{c,n}^f$ is a vector of factor returns. Requiring a minimum of 20 trade observations reduces the number of classes to 165.²²

De Jong and Driessen, 2012 note that, as hybrid instruments between treasuries and equities, corporate bonds are exposed to factors that affect both types of securities. As such I include the Fama French 4 factors as well as the bond factors $TERM$ and DEF in all risk adjustments. As noted in Section 1 recent research has identified that liquidity is an important determinant of bond returns so the PS liquidity factor is also included in these risk adjustments.

4.4 Arbitrage Capital and Excess Returns

$H2$ predicts that the activist wealth ratio drives post default bond trading prices. When distressed funds are capital constrained and the volume of defaults is high, post-bankruptcy trading prices should

the mean. AR decreases when there are more bankruptcies generating more observations at low values of AR . Thus we have a larger sample for low AR meaning the small sample properties of skewed random variables might mechanically deliver a negative relationship. Taking logs eliminates this skewness and the potential for a mechanical relationship. One caveat is that I cannot have any observations where $PE = 0$. However in a handful of cases where I examine court documents I find claims that have been completely wiped out. In these cases I set the observed return to the lowest in the sample.

In the interest of robustness I check these results in the raw return space. After diminishing the impact of hugely extreme observations where bond classes experienced 10,000% (Mirant is an example) by either weighing by market value of class size at file date, windsorizing at the 1%, or simply dropping classes that trade for less than 2 cents on the dollar at filing to eliminate the purely option-like securities, the results in sections 4.4 and 4.6 are effectively unchanged while the results in Section 4.5 remain unchanged in economic magnitude and direction but, in some specifications dip below 10%.

²²Subsequent tests are robust to extending the risk adjustment window to include pre-filing trades.

be lower because the competitive dynamics that would ordinarily bid up prices are attenuated. I test this hypothesis using the regression specification in equation 4.1.

[Table 3 about here.]

Under $H2$ the coefficient on the activist wealth ratio, β_1 , should be negative and significant. As exhibited in Table 3, this prediction is upheld in the data.. In periods of low arbitrage capital, returns to defaulted securities over the reorganization process are high. The coefficient on $RATIO$ hovers in the -0.2 range, thus a one standard deviation in AR_t (1.9) equates to a reduction of 0.4 in r_c^{log} . Thus the arbitrage ratio is both significant and economically meaningful.

As evidenced by the coefficient on $MKTRF$ and HML , the bonds of bankrupt firms are on average high beta value securities. These securities show insignificant exposure to the remaining Fama French factors except for the bond factor $TERM$, where the coefficient is negative. The coefficients on returns during the bankruptcy process do not significantly load on the liquidity factor. However, the coefficient on the level of the PS liquidity index at filing date is significant. It seems as though market wide illiquidity at the time of default drives subsequent returns to bankruptcy, but there does not appear to be a significant loading on the liquidity factor for defaulted bonds, a finding that is consistent with the results in (Jankowitsch et al., 2012) to the extent that market wide illiquidity partially predicts individual bond illiquidity.

Finally, the number of days in bankruptcy and file price enter significantly as well. Here, the hypothesized coefficient for each is unclear. A longer process should mean higher returns simply because the holding period is longer. At the same time, longer bankruptcies are also likely to incur larger costs throughout the process. Thus ex-post one might suspect a long reorganization to be one that returns less to bondholders. In this Table 3, it appears as though the higher costs effect dominates. The effect of $FILEPRICE$ on returns is likely non-linear due to the embedded option in the bonds, a phenomenon I discuss in more detail in section 4.6. Here it enters as a control in much the same way as liquidity. If default period returns are driven by the liquidity event around default, then the post filing price should be a negative predictor of returns. I do not find evidence consistent with that hypothesis.

One potential concern with these results is that the measure of arbitrage capital is capturing omitted risk factors. The arbitrage capital ratio is low in states of the world where expected returns are high and defaulted securities are likely to carry high systematic and idiosyncratic risk. If the coefficient vector \mathbf{B} does not capture this risk exposure properly then we may still have an omitted variable problem. Table 4 performs the same regressions using the risk adjusted return for each class over the bankruptcy process. The regression period for determining risk adjustment coefficients overlaps the bankruptcy process.

[Table 4 about here.]

Again the coefficient on the arbitrage wealth ratio is negative and significant. In fact the economic magnitude of this coefficient is, if anything, larger when considering the traditional risk adjustment. Hence, Table 4 omitted risk factors are not driving the observed results. In fact, the magnitudes and significance levels increase as additional risk factors are introduced, suggesting that the risk factor captured here—the activist wealth ratio—is orthogonal to those commonly used to price assets.

4.5 Asset Redeployability and Returns

Hypothesis 3 makes a cross-sectional prediction about the nature of the risk premium associated with defaulted bonds. In particular, it submits that this return sensitivity to the activist wealth ratio should be much stronger for firms whose assets are not easily sold off. Any competing explanation for the significant coefficient on the activist wealth ratio must also interact with the asset redeployability measure in the exact way the model specifies. This hypothesis is tested by running the regression specified in equation 4.2 and predicts that the coefficients β_1 and β_2 are negative and, most importantly that the coefficient on the activist wealth ratio interacted with the redeployability measure, β_3 , is positive.

[Table 5 about here.]

Table 5 illustrates the results of including the asset redeployability in Specification 4.2 and upholds the predictions in hypothesis *H3*. There is sufficient evidence to reject the null hypothesis of the coefficient on $\text{RATIO*REDEP} = 0$ at the 95% or 90% level depending on the specification. In fact for firms with the highest asset redeployability measure—around 0.4—the return sensitivity to activist wealth expressed in equation 4.3 is just slightly below zero. On the other hand, the return sensitivity for firms with the lowest asset redeployability—near 0.1—is about three times higher in magnitude than the unconditional results from Table 3.

Redeployability itself, while not significant in all specifications, does always carry the predicted sign when the interaction term is included. In Table 3 defaulted bond returns did not load significantly on the liquidity factor, however, when redeployability is included in the regressions, the liquidity factor returns becomes significant. Thus when accounting for differences in redeployability, there is evidence that liquidity returns are associated with defaulted bond returns. This relationship begs further investigation, but remains outside the scope of this paper.

4.6 Fulcrum Securities and Returns

Hypothesis 4 represents the final cross-sectional return prediction of the model: the activist wealth ratio should be a determinant of bankruptcy returns for fulcrum securities but not for classes that

are clearly in-the-money or out-of-the-money. This leads to regression 4.5 where a negative β_3 and an insignificant β_1 are consistent with a return-activist wealth sensitivity specific to the fulcrum securities. Since the fulcrum class is not defined ex-ante, I display results for two different sets of boundaries. For the option-like securities I test a cutoff of 2.5 cents and 5 cents and for the in-the-money bonds I test cutoffs of 85 and 90 cents.

[Table 6 about here.]

Table 6 displays results in support of *H4*. Columns (3) and (4) illustrate the cases where the moneyness cutoffs are strictest {2.5,90}. Here the results clearly indicate that returns to classes outside the “fulcrum creditor” have no relationship with *AR*. Consistent with the theoretical motivation behind this section, as the definition of the fulcrum class narrows in columns (1) and (2), the β_3 coefficient increases while β_1 decreases. When the boundary tightens, more securities that are sensitive to *AR* are falling outside the “fulcrum” basket.

4.7 Post-Default Trade Quantities

The activist driven renegotiation framework in this paper makes a clear prediction (*H4*) that the turnover around default should be an increasing and concave function of the activist wealth ratio. Table 7 provides the coefficient estimates from regression equation 4.6. The table includes a tercile rank and log transformation of *AR* as regressors to augment the identification of this non-linear relationship.

[Table 7 about here.]

As exhibited in column (1), the coefficient on β_1 is positive but insignificant. However, when adding the squared term in column (2), the coefficient β_1 becomes positive and significant while the coefficient on β_2 is negative and significant. This is indicative of an increasing but concave relationship between post default turnover and *AR*. In fact, for the highest *AR* observation in the sample of defaulted bonds, 12.37, the partial derivative of Turnover with respect to $AR - \beta_1 + \beta_2 * AR$ —is nearly zero, indicating that for high values of activist wealth, turnover is at its most but almost completely insensitive to local changes in *AR*.

Columns (3) and (4) solidify the evidence of a nonlinear relationship. In (3) the regressor for activist wealth is replaced by tercile dummies, where *RATIORANK* 1 takes a value of 1 if *AR* is in the lowest tercile and so on. Since the regression is run with an intercept, the coefficient on *RATIORANK* 1 can be interpreted as the change in turnover when moving from the highest to lowest tercile of the activist wealth ratio. The coefficient is negative and significant while the coefficient on *RATIORANK* 2 is negative but insignificant. Finally column (4) replaces AR_t^{agg} with $\log(AR_t^{agg})$ thus forcing a non-linear relationship. The coefficient on $\log(AR_t^{agg})$ is positive and significant just as the model predicts.

4.8 Time Series of Recovery Rates

Altman et al. (2005) point out that default rates and recovery rates covary in the time series. They suggest that supply and demand dynamics within the market for defaulted assets might be driving the observed covariance. Indeed their linear model regresses trading prices against both the levels and changes of the economy wide default rate, GDP, and the S&P index and is able to account for up to 76% of the observed fluctuations in filing trading prices.²³

As stated by *H1*, the activist framework described in Section 2 suggests a non-linear relationship between the post default trading prices and the arbitrage wealth ratio. Figure 4 illustrates the expected bid price for any arbitrage capital ratio. In good states of the world market returns are high and defaults are low, hence the expected trade price of claims post default obtains a maximum and remains inelastic to changes in the AR ratio. Conversely, when AR is low, the elasticity of trade price to arbitrage wealth increases, and trading prices become highly sensitive to the economic state.

To test the models ability to match observed post default trading prices from Ou et al. (2011), I normalize the activist wealth ratio derived in Section 4.2 such that the model matches the post default trading price observed in 2001 .²⁴ I then compare the model-implied post default trading prices for all other years to those observed in the data. As shown in Figure 10 the model does a great job of capturing the time series of post default trading prices, boasting a correlation between two series of 82%.

[Figure 10 about here.]

Table 8 breaks down sources of improvement in R^2 over the linear model employed by Altman et al. (2005). The table reports two sets of R^2 coefficients of a linear regression of post default trading prices on a number of variables in a univariate setting as well as the best performing multivariate model from their work. The variables include the AR ratio defined above, a ratio calculated using the level of the S&P instead of the HFR AUM, the percentage default rate in the economy, the return on the S&P500 index. Finally I benchmark my results against the DSG model which contains the default rate, the change in the default rate, S&P returns, change in S&P returns, and GDP growth. Here the results are similar to that of prior research: default rate is the best linear predictor of post default trading prices. Both wealth ratio variables do similarly well while S&P returns are a poor linear predictor of post default trading prices. Finally, the regression here achieves a slightly higher R^2 for the DSG model relative to Altman et al. (2005).

The second line of R^2 coefficients are between actual post default trading prices and the model-

²³I replicate their specification and get an R^2 of 81% over my sample period.

²⁴First I find the activist wealth ratio that delivers the observed post default trading price in 2001 and label this AR_{2001}^{model} . I scale the data such that $AR_{2001}^{model} = AR_{2001}^{scaled}$. Formulaically, I define the scaled data series as $AR_t^{scaled} = \frac{W_t^{data}}{D_t^{data}} \frac{D_{2001}^{data}}{W_{2001}^{data}} AR_{2001}^{model}$. Any equivalent normalization would be equally valid.

implied post default trading prices using the same four measures from above as the state variables calibrated in the same way to capture the post default trading price in 2001. This line makes apparent the massive improvement of the AR ratio over the other variables considered. The R^2 jumps to 82%, beating even the multivariate DSG model. Other variables do not show nearly the same improvement in explanatory power with default rate being only marginally better when run through the model. Thus the improved fit along the time series delivered in this paper is a complimentary combination of the new measure suggested by the bargaining framework as well as the functional form implied by the model.

[Table 8 about here.]

5 Spreads

Section 3.1 describes the consolidation mechanism’s impact on post default trading prices and returns on defaulted assets. Both of these have an impact on expected recovery rates for ex-ante bondholders and therefore impacts spreads.

In bad states of the world the governing ratio AR is low for two reasons. First, barriers preventing capital flows cause activist wealth to follow the process of returns for the overall economy so in bad states the numerator of AR is low.²⁵ Second, after a string of bad systematic shocks, default rates are high so the denominator of AR is high. Thus the model delivers high activist returns and low activist bid prices when investors most care about their recoveries. Since AAA debt is more likely to default due to systematic shocks while Speculative Grade has a high proportion of defaults from idiosyncratic shocks, the activist determination of post default trading prices generates a large increase in AAA spreads while having little effect on Speculative Grade.

Partial consolidation means that the returns on defaulted assets have an opposite affect on spreads. The activist’s α choice is low when AR is low so pre-default stakeholders are forced to retain a significant portion of their claims. As seen in Figure 4(c), at the same time α is low, returns over the bankruptcy period are high, so retaining claims is actually beneficial for the diversified agents. Thus the bankruptcy return process actually mitigates some of the impact of low trading prices in bad states.

These countervailing processes drive a wedge between post default trading prices, observed recovery rates, and bondholder expected losses given default. As shown below in Section 5.3, models calibrated to match recovery rates after the completion of the bankruptcy process will over-estimate the expected cash flow to bondholders and consequently undershoot credit spreads. Alternatively, models calibrated to match post default trading prices will tend to underestimate true recoveries and overestimate spreads. This wedge is largest when the SDF of the representative agent is highest, implying that that some portion of the credit pricing puzzles may be a matter of measurement error.

²⁵This dynamic is consistent with capital flow observations from HFR as shown in Table 1.

5.1 Pricing Kernel and Firm Cash Flow Process

The focus of this paper is on enriching the bankruptcy process. As such the model uses a flexible reduced form asset pricing kernel (similar to Zhang 2005) to calculate bond prices. The stochastic discount factor M_t is a function of the mean reverting state variable x_t as follows.

$$\log M_{t+1} = \log \beta + \eta_t(x_t - x_{t+1}) \quad (5.1)$$

The risk aversion parameter η_t is given by

$$\eta_t = \eta_0 + \eta_1(x_t - \bar{x}) \quad (5.2)$$

with $\eta_1 < 0, \eta_0 > 1$ and where \bar{x} is the average level of the state variable x_t . Notably, I assume that the ex-ante investors approach log utility preferences in the best states of the world. Dynamics for x_t are as follows:

$$x_{t+1} = (1 - \rho)\bar{x} + \rho x_t + \sigma_x \epsilon_{x,t+1} \quad (5.3)$$

where $\epsilon_{x,t+1} \sim \mathcal{N}(0, 1)$.

Aggregate dividend growth is modeled directly as a function of x_t .

$$\frac{d_{t+1}}{d_t} = e^{(\mu_d + x_{t+1} - \bar{x} + \sigma_d \epsilon_{d,t+1})} \quad (5.4)$$

Moving from the aggregate claim to an individual firm, we follow Chen et al. (2008) and assume that each firm's value process, Δv has both an aggregate and idiosyncratic component as follows:

$$\Delta v_{k,t}(x_{t+1}) = \Delta p(x_{t+1}) + \sigma_k \epsilon_{k,t+1} \quad (5.5)$$

where $\epsilon_{i,t+1} \sim \mathcal{N}(0, 1)$ and $\Delta p(x_{t+1})$ are the dynamics of the aggregate claim.

I use an iterative process to solve for the price of an aggregate claim to dividends. Straightforward manipulation of the standard pricing equation $1 = E[MR]$ yields the following definition of the price dividend ratio $I(x_t)$ for any state.

$$I(x_t) = \frac{P_t}{d_t}(x_t) = E_t \left[M_{t+1} \frac{d_{t+1}}{d_t} \left(1 + \frac{P_{t+1}}{d_{t+1}}(x_{t+1}) \right) \right]$$

$I(x_t)$ can be solved recursively using numerical methods.²⁶

$$P_t(d_t, x_t) = d_t I(x_t) \quad (5.6)$$

Plugging the dynamics of the aggregate dividend price process from equation 5.6 into equation 5.5 yields a solution for the firm asset value process.

²⁶As in Zhang (2005) I employ a Rouwenhorst discretization of the AR(1) state space. Then the price of an aggregate dividend claim in a state x_t is the level of the dividend multiplied by $I(x_t)$.

5.2 Bond Prices

The price of a zero coupon bond of maturity is given by

$$B_{k,t} = E_t \left[\left(\prod_{s=1}^{\tau} M_{t+s} \right) \mathbf{1}_{\tau < T} Rec_{\tau} \right] + E_t \left[\left(\prod_{s=1}^T M_{t+s} \right) \mathbf{1}_{T < \tau} \right] \quad (5.7)$$

where the first term captures the discounted payoff if the firm defaults at some future date τ and the second term is the discounted payoff when no default occurs.

In a fixed recovery rate environment computing spreads is straightforward given a process for M_t and equation 5.7. In my model recovery rates are themselves a stochastic and in particular they are a function of the activist wealth ratio. So to compute bond prices it is first necessary to solve for AR in all potential periods and states. Calculating $AR(x_t)$ requires determining the wealth in the activist sector, $W^{agg}(x_t)$, and the economy wide amount of defaulted debt, $D^{agg}(x_t)$.

As shown in Table 1, capital flows to the activist sector are pro-cyclical so in the model I assume that these flows are positively correlated with returns. More precisely, AR is governed by two components, the claim to aggregate dividends and an idiosyncratic shock that hits each period.

$$\frac{\Delta W_{x_{t+1}}^{agg}}{W_{x_t}^{agg}} = \rho_{w,p} \frac{\Delta P_{t+1}(d_{t+1}, x_{t+1})}{P_t(d_t, x_t)} + \sigma_w \epsilon_{w,t+1} \quad (5.8)$$

The volume of defaulted debt, $D^{agg}(x_t)$, in any given state x_t is equal to the probability of default for all debt outstanding in x_t times the total amount of debt outstanding. Because x is a persistent process, the probability of default in any given state is a function of the state in which that debt was issued. So solving for $E_{x_0}[D^{agg}(x_t)]$, the expected amount of defaulted debt in some future state x_t given that a bond is being issued today in state x_0 , requires solving for $\rho_{x_t}^{s,v}$, the probability that a bond with issued in state s at time v defaults in state x at time t and $\mu^{s,v}|x_t$, the amount of debt with issued in state s at time t given the current state x and time v . Putting these two together, and summing over each rating class r , the aggregate defaulted debt in the economy when a bond defaults in state x_t is equal to

$$D^{agg}(x_t) = \sum_r \sum_s \sum_{v=\tau}^{-\infty} \rho_{x_t}^{r,s,v} \mu^{r,s,v} |x_t.$$

I compute ρ by performing Monte Carlo simulation of the firm value processes from each discretized issuance state over the average bond lifespan and calculating the default rate in each future state. $\mu^{r,s,v}|x_t$ is calculated by multiplying $q^{s,v}|x_t$ —the probability the world was in state s at time t —by the amount of debt of rating class r issued in state s at time v that has not already defaulted between v and t . The latter requires making both a distributional assumption on the amount of debt in each rating category and the average length of the issuance cycle; these are described below.

5.3 Calibration

The model is largely calibrated to match the usual asset pricing moments. The counter-cyclicality of risk aversion component, η_1 is increased to help match the spectrum of credit spreads. To assuage concerns that the increase in risk aversion drives the main results in this paper, I run all tests under the exact calibration from Zhang (2005). In an absolute sense all models decrease in accuracy, but the differential improvement in terms of pricing errors of adding the bargaining framework over fixed or linear recovery specifications is actually larger—likely because there is more room for improvement—than in the calibration presented here.²⁷

[Table 9 about here.]

Default probabilities depend on the default boundary for various rating classes. In this application the boundary is calibrated in each issuance state to match historical default rates by particular rating class as provided in Ou et al. (2011).²⁸ I set the unconditional starting value of AR_0 such that the model delivers an average recovery rate across all rating classes equal to the 0.45.²⁹ For simplicity I assume that the starting value of AR_0 is state independent though this assumption can be relaxed by mapping the discretized state process to the observed ratios.

The correlation between the aggregate claim and the wealth process, $\rho_{w,p}$, is calculated by regressing changes in the HFR distressed restructuring index on S&P 500 returns. The coefficient on S&P returns is 0.5 while the standard deviation of the error term, which maps to σ_w , is 0.18. Table 10 illustrates the cyclicity of corporate debt within the model. Expansion periods are characterized by the top 80% of dividend growth states while recessions are the bottom 20%. Recovery rates and default rates are averaged across all issuance classes and are calculated using the perfect competition model. The model succeeds in capturing the cyclicity of both post default trading prices and default rates.

[Table 10 about here.]

To complete the activist problem for the imperfect competition model, M and N must be mapped to real world values. Data on the number of vulture funds is limited and would likely confound funds

²⁷ Additionally the model assumes no dividend growth. While unrealistic in practice, the point of this exercise is to relate the cross-section of credit spreads to a microstructure model of recovery rates. Thus the time series of debt to equity ratios is assumed to be constant. Then the simplest way to capture a constant debt to equity ratio is to set dividend growth to zero and keep a fixed default boundary.

²⁸The model delivers issuance state invariant unconditional default probabilities. In practice the probability of default for debt issued in bad states might be higher than debt issued in good states. Extending this model to allow for such variation would likely increase the magnitude of the effect generated by this mechanism as a larger percentage of overall defaults would occur in highly priced states.

²⁹In order to compare this model with a fixed recovery rate model and one that expresses recovery rates as a linear function of the underlying state space, I impose that the average recover rate is the same across all models so that any observed variation in spreads results from the shape of the recovery rate function, not that the model delivers a higher or lower recovery rate. Interestingly, while calibration process for AR is different than in Section 4.2, they yield an average value for AR within 10% of each-other.

that take a true activist role and funds that do not. However the number of defaulted firms for any year is available in Ou et al. (2011). I adjust these for the number of firms accessing the debt markets then choose a constant $M = 50$ such that the major periods of default in 1990, 2001, 2005, and 2008 induce non-competitive bidding states. The distribution of outstanding debt by rating class used to derive μ was kindly provided by Moody's. I use a 10 year issuance cycle to calculate the state contingent μ as described in Section 5.2. Naturally, to match the same 0.45 average recovery rate, the imperfect competition model has a higher unconditional wealth value than the perfect competition model.

5.4 Spread Results

Many “credit spread puzzle” papers begin with a set of target spreads over a number of horizons as previously calculated in Altman et al. (1998). At that time the market for spec grade debt was far from transparent, and with the advent of TRACE and highly liquid CDS markets, my first step in this paper was to verify that I was targeting the correct spreads. I do so using MARKIT prices where calculating the spread by rating class is a simple matter of linking with mergent to cross-check underlying ratings and get issuer size weightings to aggregate across securities. The resulting spreads (5 year B spreads of 461 and 10 year B spreads of 475) are actually nearly identical to the targets originally provided in Altman et al. (1998). Unable to improve on these past measurements I use these as my targets.

With the benchmarks established, Table 11 shows the impact of the consolidation mechanism on 10 year spreads. For comparison it also includes the model-implied spreads for a fixed recovery rate regime of $E[Rec^{ex-ante}] = 0.45$ as well as a mode where recovery rates are calibrated as a linear process of the underlying state space where on average $Rec^{ex-ante}$ equals 0.45.

The fixed recovery model displays the issues many asset pricing models encounter in replicating the data. Spreads on AAA and BBB are too low across all maturities while speculative grade debt is slightly too cheap given its default and recovery rate. A few asset pricing studies allow recovery rates to vary with the underlying state variables in an attempt to match spreads. In these models, time varying recovery rates are combined with various other mechanisms to improve the model's bond pricing. Chen et al. (2008) explicitly mention a linearly calibrated recovery rate model and suggest that it is able to improve fits by “a few basis points.” In Table 11, adding a linear recovery rate function does improve fit for AAA, BBB and increases the spread between the two by about 10bps, allowing the model to match the AAA-BBB spread. However, including linear recovery rates blows out spreads on riskier debt. Where the model was somewhat close on B rated securities in a fixed recovery regime, the linear recovery regime overshoots by 60bps. This dynamic is even more apparent in panel B where spreads are provided relative to AAA. Matching the AAA-BBB spread using linear recovery rates hugely skews the spread between AAA-B.

[Table 11 about here.]

Adding variable recovery rates as delivered by the consolidation process from Section 2 aids in matching spreads across the entire spectrum. The idiosyncratic nature of B rated defaults means that they generally recover a large amount of principal when they default meaning the mechanism actually decreases spreads for this rating class. However, AAA and BBB securities tend to default in recessions when recovery rates are lower and these low recoveries are highly priced. Spreads increase for both AAA and BBB debt, but as a percentage of the baseline model the effect on AAA is highest. The competitive bargaining model has total squared pricing errors of 60.5% compared to 70.5% for the linear recovery rate model and 92.8% for the fixed recovery model.

The advantage of the bargaining driven reorganization models is most apparent in Panel B which displays various spreads as a distance to AAA instead of Treasuries. Here the perfect and imperfect competition models are able to match both the spreads between AAA and BBB and get very close to matching the spreads to speculative grade bonds. The squared pricing errors on the linear model is 23.1%, worse in fact than the fixed recovery rate model, but only 17.1% for the competitive bargaining model. As with most models, the largest mismatch is at the safer end of the spectrum.

The improvement over the linear recovery rate model comes from the functional form relating marginal utility and recovery rates with significantly higher curvature. It generates very low recoveries in the highest marginal utility states but in normal periods and booms, activist wealth has little impact on recovery rates. Keeping average recovery rates the same, the absolute impact on spreads is much larger in this framework. Thus the non-linearity implicit in this model generates both the differential effects across rating classes and also higher magnitudes than some other research.

This dynamic is exacerbated when moving to the imperfect competition model, which achieves the smallest pricing errors on both the spreads to treasury, 53.8%, and the spreads to AAA, 15.6%. The improved performance comes from two sources. First, as detailed in Section 3.4, when in the non-competitive state, activists retain a larger share of the consolidated firm for themselves. Thus they participate entirely in the increased returns in these states leaving ex-ante bondholders with lower combined recoveries. Second, the two regime nature of the imperfect competition model effectively increases the curvature of the relationship between activist wealth and expected recoveries. The decline in recoveries as defaults increase is not nearly as gradual as in the baseline model. This increased curvature is clearly exhibited in Figure 6. Speculative debt is much more likely to default in the $N < M$ world while AAA is most likely to default in $N > M$ states. Together these mechanisms flatten the yield-rating relationship beyond that already achieved in the baseline formulations and improve the ability to match observed spreads.

[Table 12 about here.]

Table 12 displays the same results for 4 year spreads. Here models generally have more difficulty matching the various spread targets, but the relative improvement in moving from a fixed recovery

regime to the model presented in this paper is significant. Pricing errors on spreads to treasury improve by about 20% moving from fixed recoveries to the imperfect competition model. Since a huge portion of the 4 year model's pricing error is between AAA and Treasury, the spread to AAA pricing errors are nearly cut in half when recovery rates are determined using imperfect competition bargaining.

5.5 Recovery Rate Measurement

As noted in Section 2, the model makes an important distinction between various measurements of recovery rates. Risk premia fluctuate in response to the arbitrage capital ratio because the activist requires higher returns to consolidate when her wealth is relatively low. The gap between trade price post default and observed recoveries is highest for defaults that occur in low AR states. While the eventual recovery rate for firms that default in low vs high arbitrage capital ratio states may be similar, an ex-ante bondholder will receive a low recovery on α portion of their claims when AR is low because the activist demands higher returns in those states. As emphasized previously, this gap is widest when the marginal utility of the representative investor is highest making the correct recovery rate choice important when assessing the existence and magnitude of credit spread puzzles.

[Table 13 about here.]

Table 13 illustrates the choice of recovery rate metric on spreads. A model that uses observed recovery rates instead of $E[Rec^{ex-ante}]$ is likely to underestimate spreads on AAA and overestimate on B thereby exacerbating the credit spread puzzle. As shown in Figure 4, emergence recovery rates in the model are much less volatile and bounded in a tighter band than $E[Rec^{ex-ante}]$. Thus the recovery rate in the worst states is similar to that in the best states minimizing the differential impact of the mechanism across rating classes. Conversely, a model that uses post default trading prices will produce an opposite phenomenon. There, ex-ante bondholders receive only the low price at default and do not benefit from the positive effects of consolidation. Again, to compare apples to apples, the calibrated must deliver the an average post default trading price of 0.45. Since the post default trading prices are lower than $E[Rec^{ex-ante}]$ in bad states, the average wealth of the activist has to increase to compensate. In net the low prices in bad states increases spreads on AAA while increasing average AR decreases the spreads speculative grade. As such, a model calibrated to match post default trading prices will actually understate the credit spread puzzle.

6 Conclusion

Adding to a growing literature which examines the asset pricing implications of corporate finance frictions, this paper models the relationship between creditor dispersion and the market for defaulted debt.

The fundamental economics force—a tragedy of the commons type problem where individual creditors’ choices are not optimal for the class of debtors—endogenously motivates concentrated ownership by activist investors in defaulted securities. When these activists are risk averse and barriers inhibit immediate capital flow to the vulture funds, the model delivers a rich set of asset pricing implications.

The ratio of activist wealth to the amount of defaulted debt in the economy emerges as a key state variable in determining the prices, returns and eventual recovery rates on defaulted debt. When activist wealth is low relative to the amount of bankrupt assets, activists demand a higher return and consolidate a smaller fraction of defaulted firms. This in turn drives both post default trading prices and eventual recovery rates lower. Based on this single state variable the model captures 82% of the aggregate time series variation in post default trading prices. The model is unique in its prediction of an additional defaulted debt risk premium that increases when activist wealth is low except in cases when the scope for activist involvement is minimal. In empirical tests I confirm that this return sensitivity appears in the data but diminishes when asset redeployability is high or when the securities are deeply in or deeply out-of-the-money. This paper is the first in the asset pricing literature to micro-found the market for distressed debt. The implied non-linear relationship between post default trading prices and the activist wealth ratio influences spreads in a more subtle way than moving from a fixed recovery rate regime to those where recovery rates are a linear function of the state space. Safer debt is less subject to idiosyncratic shocks and defaults proportionally more in bad states. So pro-cyclical recovery rates lead to a differential impact of the model’s mechanism on various security ratings: it drives the prices of safe debt lower while leaving spreads on speculative grade debt largely unchanged. Thus, this model generally reduces pricing errors on corporate debt and succeeds in matching both the 10 year AAA-BBB and AAA-B spreads simultaneously.

In general, the optimal ownership structures implied by the fundamental economic frictions studied in corporate finance seem at odds with the common assumption of “diversified representative investors.” This paper takes a simple free rider framework and backs out rich dynamics in the market for defaulted bonds, but the logic can be applied—with potentially unique implications depending on the underlying friction being studied—whenever the ownership structure of an asset effects the expected payout of that asset. This line of questioning seems especially promising as asset pricing research increasingly focuses on emerging economies where agency issues are likely to play a stronger role in firm and investor decisions.

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A Equilibrium in Bidding Game

The activist-firm matching game presented here maps to the Becker (1973) marriage game where transfers are allowed between matches (funds can share surplus with firms.) This is a special case of the matching game that includes potential transfer across non-matched pairs. There a strictly positive cross-partial derivative of the household function guarantees a positive assortative equilibrium.

In the bidding game between firms and activists, the surplus function is characterized by the activist's utility over the potential bankruptcy outcomes. If an activist is able to bare more risk, they can purchase more bonds and deliver a higher ex-post reorganization value to be shared amongst the relevant parties. Thus showing a stable and unique equilibrium positive assortative matching requires showing that $U_{WD}(W, D)$ is strictly positive for the considered set of parameters where

$$U(W, D) = pu(W - \alpha ZD + \alpha (\tilde{R}(a) + \underline{R}) D) + (1 - p)u(W - \alpha ZD + \alpha \underline{R}D). \quad (\text{A.1})$$

Equation A.1 captures the utility gained by an activist of size W from purchasing α shares of its existing debt D for a price of Z . To consider the case where α is fixed and equal to 1 so $f(\alpha) = 1$ and participants have log preferences. The activist can always optimize further by altering α until $\frac{\partial U}{\partial \alpha} = 0$, so this case subsumes the case where the activist reoptimize given a change in either D or W . For notational simplicity I normalize $D = \bar{R} = 1$ which, given full effort exertion, implies $\tilde{R}(a) + \underline{R} = 1$ and $\underline{R} = 0$.

A.1 Proof of Proposition 1

As noted, the unique and stable equilibrium from the matching game without intra-firm or intra-activist transfers is assortative positive in the character traits when $U_{WD}(W, D) > 0$.

$$U_{DW} = -\frac{p(1 - Z)}{(W + 1 - Z)^2} + \frac{(1 - p)(Z)}{(W - Z)^2} > 0$$

Combining the first and second terms over a common denominator and solving for the inequality, U_{WD} is always positive as long as the equation below holds:

$$W < \frac{Z - Z^2}{p - Z} + \sqrt{\frac{pZ - p^2Z - pZ^2 + p^2Z^2}{(p - Z)^2}}$$

As noted in the body of this paper, bid prices cannot be derived analytically. In any equilibrium presented in this paper I verify that the second cross partial derivative of the activist utility function is negative for all firms, funds, optimal bid prices and α choices. As an example, Figure 11 displays the relationship between the maximum wealth given for a particular bid price to achieve a positive assortative equilibrium and the competitive equilibrium wealth-bid price relationship derived in Section 2. For every possible bid price, the activist wealth is below the required threshold.

[Figure 11 about here.]

A.2 Proof of Proposition 2

The proof here is simple. Take a new possible set of bids $\{\alpha'^{i,k}, Z'^{i,k}\} \neq \{\alpha^{*i,k}, Z^{*i,k}\}$. If

$$E \left[Rec^{ex-ante} | \alpha'^{i,k}, Z'^{i,k} \right] > E \left[Rec^{ex-ante} | \hat{\alpha}^{i-1,k}, \hat{Z}^{i-1,k} \right]$$

then the activist k is transferring more wealth than she needs to in order to stave off a competitive bid from activist $k - 1$. Thus she is strictly better off decreasing Z until

$$E \left[Rec^{ex-ante} | \alpha'^{i,k}, Z'^{i,k} \right] = E \left[Rec^{ex-ante} | \hat{\alpha}^{i-1,k}, \hat{Z}^{i-1,k} \right].$$

Otherwise if

$$E \left[Rec^{ex-ante} | \alpha'^{i,k}, Z'^{i,k} \right] < E \left[Rec^{ex-ante} | \hat{\alpha}^{i-1,k}, \hat{Z}^{i-1,k} \right]$$

then activist $i - 1$ can increase her utility by consolidating firm k instead of firm $k - 1$ which violates Proposition 1 above. In this case activist i would be better off improving her bid to beat out activist $i - 1$.

A.3 Simple Equilibria

Consider the case where $M = 3$, indexed with $i \in \{0, 1, 2\}$ and $N = 2$ indexed with $k \in \{1, 2\}$ and that, for simplicity of exposition, $\alpha^{*i,k} = 1$ for all i and k . From Proposition 1 we know that the smallest activist fund, $k = 0$, will not participate in consolidation of any sort. The bid $\hat{Z}^{0,1}$ that makes activist 0 indifferent between consolidating firm 1 and holding on to her wealth is given by solving the equivalence below.

$$J_c \left(W^0, D^1 | \hat{Z}^{0,1} \right) = J_{nc} \left(W^0 \right).$$

For activist 1 to outbid 0, she must bid at least $Z^{*1,1} \geq \hat{Z}^{0,1}$. Bidding any more will only provide additional surplus to the firm's ex-ante bondholders, so she will bid exactly $Z^{*1,1} = \hat{Z}^{0,1}$. The maximum bid activist 1 would make for firm 2 is given by

$$J_c \left(W^1, D^2 | \hat{Z}^{1,2} \right) = J_c \left(W^1, D^1 | Z^{*1,1} \right).$$

$Z^{*2,2} = \hat{Z}^{1,2}$ completes the set of equilibrium bids. Since Proposition 1 holds we know that this arrangement is unique and stable. In this equilibrium almost all of the surplus due to consolidation is transferred to the pre default bond holders. In fact as the difference in size between firms and funds approaches 0, this outcome approaches the competitive bidding outcome described in equation 2.13 where, all expected returns to defaulted bonds is in compensation for the risk taken by the activist.

Now consider the case where $i \in \{1, 2\}$ and $k \in \{0, 1, 2\}$. The smallest activist fund now faces no

competition, and will choose to bid on the second largest defaulted firm but only has to provide ex-ante bondholders with what they would receive in liquidation. So $Z^{*1,1} = \underline{R}$. The maximum bid fund 1 will make on firm 2 is given by

$$J_c(W^1, D^2 | \hat{Z}^{1,2}) = J_c(W^1, D^1 | \underline{R}).$$

Exactly as before, fund 2 will bid $Z^{*2,2} = \hat{Z}^{1,2}$ to consolidate firm 2 thus completing the equilibrium. Notice that here, the lack of competition for the smallest consolidated firm transfers a significant amount of the surplus to activists. Again, as the difference in size between funds and firms approaches zero, firms are consolidated at the expected liquidation value and all surplus is transferred to the activist.

The equilibrium outcome to this game is characterized by two insights that parallel the marriage matching game literature. First, firms and funds are matched where the pairwise surplus is maximized. Because the activists have decreasing absolute risk aversion, a less wealthy activist faces a larger cost to consolidate the same firm than a richer activist. As such surplus is maximized when larger activists consolidate larger firms. Second, in the marriage game, gains from union are attributed disproportionately to the group with the better competitive position. If there are more (less) men than women, the men receive less (more) of the surplus. The same is true here for firms and funds. When there are more funds than firms the surplus goes almost entirely to the ex-ante bondholders.

B Full Baseline Model

The model consists of firms that issue risky debt and two types of agents, a diversified representative investor and activist investors. The firm value process has systematic and idiosyncratic components and defaults occur at an exogenous boundary imposed to match historical default rates. The diversified agent prices debt issued by a single firm as the expected cash flow streams discounted by his SDF, M_t , where the cash flows are determined by the coupon and principal repayments when firms do not default and the expected recovery rate, $E[Rec^{ex-ante}]$, when the firm defaults. Vulture activists descend on defaulted firms and purchase large stakes in the outstanding bonds thereby eliminating the free-rider inefficiencies that occur as a result of default.

B.1 Representative Investor and Firm

The stochastic discount factor M_t is a function of the mean reverting state variable x_t as follows.

$$\log M_{t+1} = \log \beta + \eta_t(x_t - x_{t+1}) \tag{B.1}$$

The risk aversion parameter η_t is given by

$$\eta_t = \eta_0 + \eta_1(x_t - \bar{x}) \tag{B.2}$$

with $\eta_1 < 0, \eta_0 > 1$ and where \bar{x} is the average level of the state variable x_t . Dynamics for x_t are as follows:

$$x_{t+1} = (1 - \rho)\bar{x} + \rho x_t + \sigma_x \epsilon_{x,t+1} \quad (\text{B.3})$$

where $\epsilon_{x,t+1} \sim \mathcal{N}(0, 1)$.

Aggregate dividend growth is modeled directly as a function of x_t .

$$\frac{d_{t+1}}{d_t} = e^{(\mu_d + x_{t+1} - \bar{x} + \sigma_d \epsilon_{d,t+1})} \quad (\text{B.4})$$

An individual firm follows a value process Δv which has both an aggregate and idiosyncratic component as follows:

$$\Delta v(x_{k+1}) = \Delta p(x_{t+1}) + \sigma_k \epsilon_{k,t+1} \quad (\text{B.5})$$

where $\epsilon_{i,t+1} \sim \mathcal{N}(0, 1)$ and $\Delta p(x_{t+1})$ are the dynamics of the aggregate claim.

Straightforward manipulation of the standard pricing equation $1 = E[MR]$ yields the following definition of the price dividend ratio $I(x_t)$ for any state.

$$I(x_t) = \frac{P_t}{d_t}(x_t) = E_t \left[M_{t+1} \frac{d_{t+1}}{d_t} \left(1 + \frac{P_{t+1}}{d_{t+1}}(x_{t+1}) \right) \right]$$

$I(x_t)$ can be solved recursively using numerical methods. Then the price of an aggregate dividend claim in a state x_t is the level of the dividend multiplied by $I(x_t)$.

$$P_t(d_t, x_t) = d_t I(x_t) \quad (\text{B.6})$$

Plugging the dynamics of the aggregate dividend price process from equation B.6 into equation B.5 yields a solution for the firm asset value process.

$$B_{k,t} = E_t \left[\left(\prod_{s=1}^{\tau} M_{t+s} \right) \mathbf{1}_{\tau < T} Rec_{\tau} \right] + E_t \left[\left(\prod_{s=1}^T M_{t+s} \right) \mathbf{1}_{T < \tau} \right] \quad (\text{B.7})$$

Equation B.7 shows that the price of a zero coupon bond is equal to the discounted expected payout of the bond. When the value of the firm slips below a default boundary prior to maturity, the equity holders optimally default and the bondholders receive an amount Rec_{τ} .

B.2 Activists

In the baseline model, Rec_{τ} is determined by a competitive bidding process where activists competitively bid on the debt of the firm. When an asset defaults at time τ the manager can offer to purchase α of the claims in the company from the diversified representative holders for a price $Z^{i,k}$ yielding utility

$$J_c(W^i, D^k | \alpha^{i,k}, Z^{i,k}) = \max_{\alpha^{i,k}, Z^{i,k}} \left[\begin{array}{l} pu \left(W^i + \alpha^{i,k} D^k \left(\tilde{R}(a^{i,k}) + \underline{R} - Z^{i,k} \right) \right) \\ +(1-p)u \left(W^i + \alpha^{i,k} D^k \left(\underline{R} - Z^{i,k} \right) \right) \end{array} \right] \text{ s.t. Constraints} \quad (\text{B.8})$$

With probability p the bonds emerge in a high value state recovering $D^k \tilde{R}(\alpha^{i,k})$ while with probability $(1 - p)$ the bonds emerge in the low value state and only return $D^k \underline{R}$. The activist maximizes her expected utility over these two states by choosing $\alpha^{i,k}$ given a bid price $Z^{i,k}$.

The participation constraint for the manager requires that the price paid in consolidation be such that the manager is at least as well off bidding as receiving the reservation utility of simply holding her wealth, so

$$u(W^i) \geq J_c(W^i, D^k | \alpha^{i,k}, Z^{i,k}) \quad (\text{B.9})$$

In the case when the competitive bidding model always holds, $M > N$ in all periods, a positive assortative 1-1 matching equilibrium results that is approximated by a Bertrand competition equilibrium where all surplus is passed to ex-ante investors and each vulture fund is close to their indifference curve between participating and not participating. Equation B.10 holds approximately.

$$u(W^i) \approx J_c(W^i, D^k | \alpha^{i,k}, Z^{i,k}) \quad (\text{B.10})$$

Solving Equation B.10 numerically yields a bid price for any activist wealth ratio $AR^{i,k}$. Dynamics for the numerator of this ratio are given by

$$\frac{\Delta W_{x_{t+1}}^{agg}}{W_{x_t}^{agg}} = \rho_{w,p} \frac{\Delta P_{t+1}(D_{t+1}, x_{t+1})}{P_t(D_t, x_t)} + \sigma_w \epsilon_{w,t+1} \quad (\text{B.11})$$

where $\rho_{w,p}$ is the correlation between activist wealth and the returns on the aggregate claim and σ_w is the standard deviation of the idiosyncratic component of activist wealth. The denominator is given by

$$D^{agg}(x_t) = \sum_r \sum_s \sum_{v=\tau}^{-\infty} \rho_{x_t}^{r,s,v} \mu^{r,s,v} | x_t.$$

the sum of all outstanding debt conditional on default occurring x_t . The bond price is solved numerically on a grid where the extra state variable $AR^{i,k}$ determines the recovery rate of any defaulted claims.

Figure 1: Post-Default Turnover

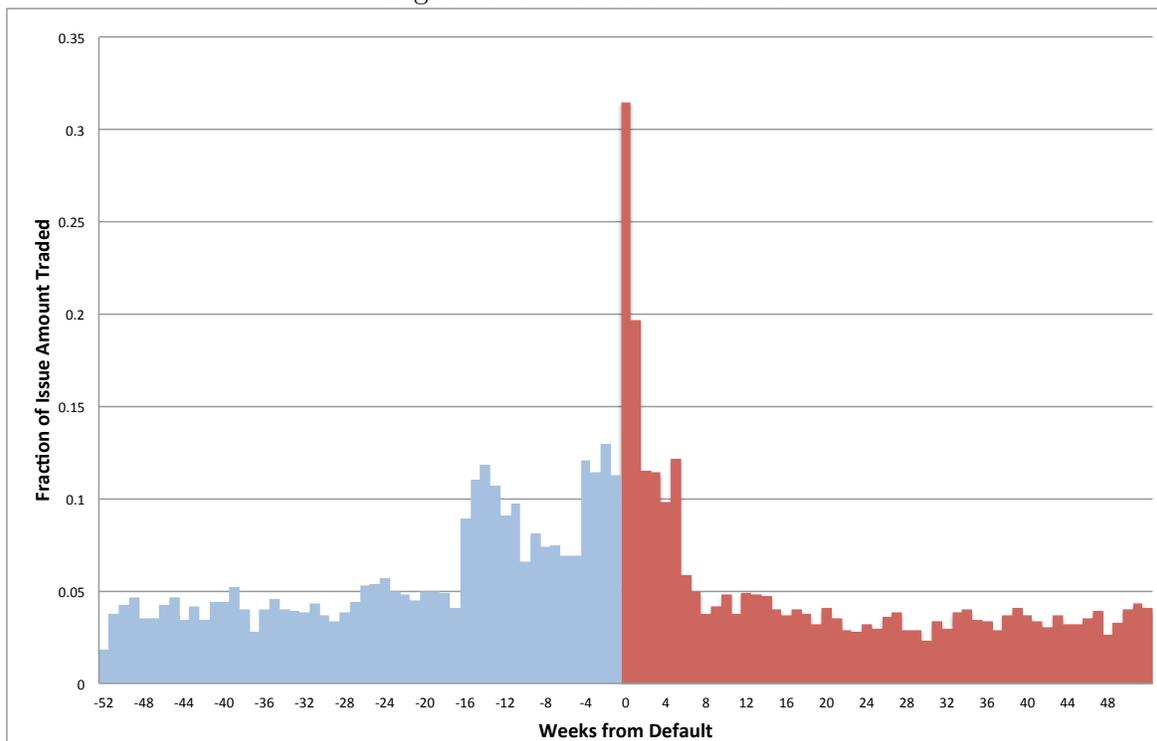


Figure 1 displays the median weekly turnover as a percentage of principal amount outstanding for defaulted bonds in my sample starting 52 weeks prior to default and continuing 52 weeks after default. The median turnover in the month of default is approximately 70% of the bond's principal amount.

Figure 2: Bankruptcy Resolution

$$\begin{array}{l}
 \text{Upon} \\
 \text{Default} \\
 \text{Activist} \\
 \text{Chooses} \\
 \alpha \text{ and } Z
 \end{array}
 \begin{array}{l}
 \nearrow p \\
 \searrow 1-p
 \end{array}
 \begin{cases}
 Rec_{reorg}^{bonds} = e^{i,k} b(\alpha^{i,k})(\bar{R} - \underline{R}) + \underline{R} \\
 W_{reorg}^i = W^i + \alpha^{i,k} D^k (b(\alpha^{i,k})(\bar{R} - \underline{R}) + \underline{R} - Z) - k(e^{i,k}) \\
 \\
 Rec_{liq}^{bonds} = \underline{R} \\
 W_{liq}^i = W^i + \alpha^{i,k} D^k (\underline{R} - Z)
 \end{cases}$$

Figure 2 displays the bankruptcy resolution game. An activist can purchase a large share $\alpha^{i,k}$ of the defaulted debt for a price $Z^{i,k}$. With probability $1 - p$ the company liquidates and bondholders receive \underline{R} and with probability p the company reorganizes with recovery to bondholders that increases in the effort $e^{i,k}$ exerted by activist i on firm k according to the benefits of effort function $b(\alpha^{i,k})$. Activist wealth in each state is given by W_{liq}^i and W_{reorg}^i respectively. An ex-ante bondholder receives a combination of $\alpha^{i,k} * Z$ and Rec_{reorg}^{bonds} in the up state or Rec_{liq}^{bonds} in the down state.

Figure 3: Consolidation Outcomes

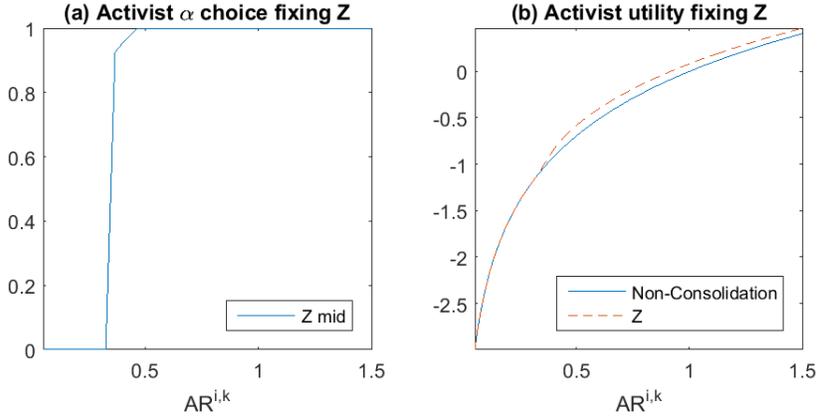


Figure 3 displays the first stage optimization for a particular activist. The x-axis in both panels is the ratio of activist wealth to the face value of defaulted debt for a particular target firm. Panel (a) shows the optimal α choice for a given bid price. When the activist is too poor she is unwilling to purchase any shares, and once she obtains a certain relative wealth she is willing to purchase a significant portion of the debt. Panel (b) illustrates the utility comparison between purchasing α shares at a price Z and non-consolidation.

Figure 4: Consolidation Outcomes

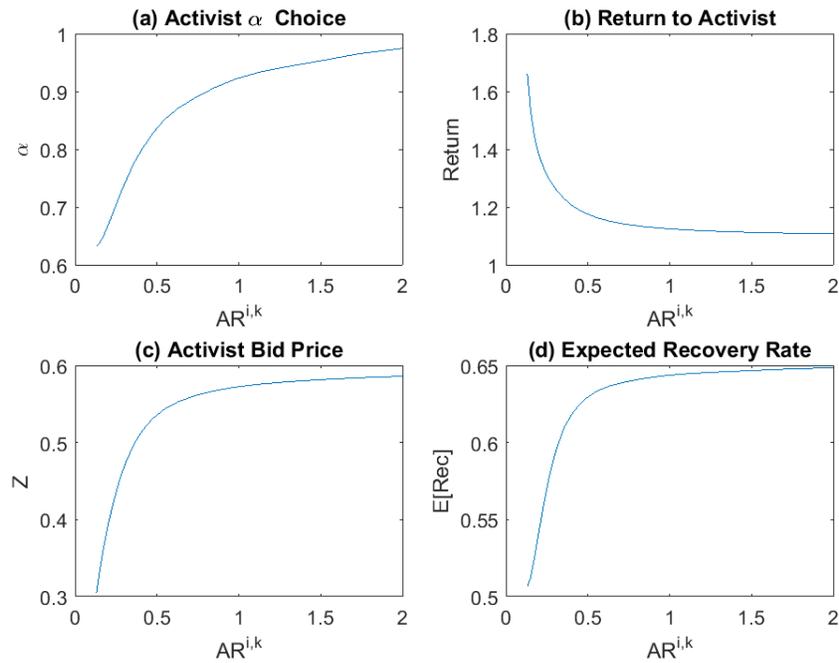


Figure 4 illustrates the primary outcomes of the perfect competition activist bargaining framework. The x-axis in all graphs is the activist wealth ratio between an activist and successful target. Panel (a) illustrates the increase in share purchased in response to increasing relative wealth, (b) the eventual recovery rate post emergence, (c) the return demanded by the activist, and (d) the bid price as a percent of face value.

Figure 5: Combined Recovery to Ex-Ante Bondholders

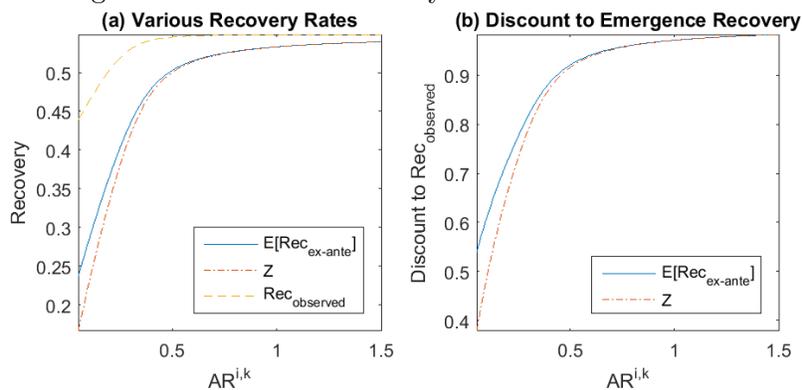


Figure 5 compares different measures of the recovery rate in the perfect competition model. In panel (a), $E[Rec_{ex-ante}]$ is the model's expected recovery rate for ex-ante investors which increases with activist wealth. $E[Rec_{ex-ante}]$ is a combination of α , the percent of debt sold to activists, multiplied by the post default trading price Z and $(1 - \alpha)$ multiplied by the ex-post observed recovery rate. Panel (b) shows discounts to the ex-post recovery rate.

Figure 6: Augmented Model Recoveries

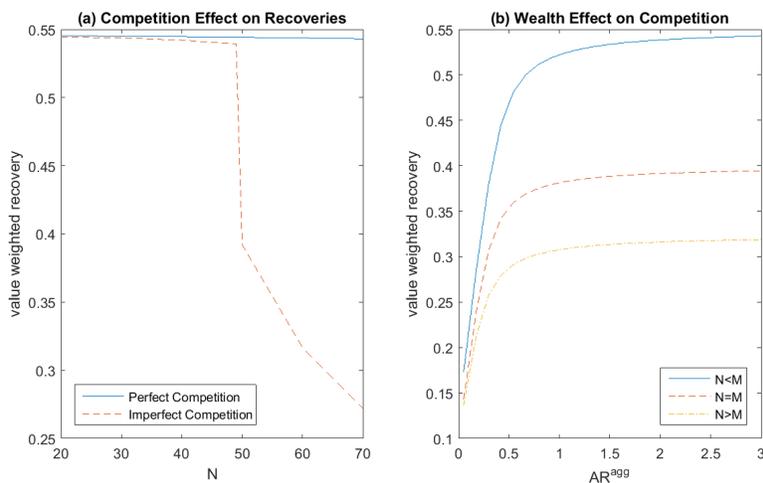


Figure 6 compares the expected recovery rates for the perfect competition and imperfect competition models. In (a) the aggregate wealth ratio is held constant while the number of defaulted firms increases. In the competitive model this dynamic has very little impact on expected recovery rates, but once the number of firms increases past the number of activists, competition breaks down and expected recoveries decrease precipitously. Panel (b) shows how the overall expected recovery rate changes as a function of the activist wealth ratio for various levels of competition.

Figure 7: Augmented Model Recoveries

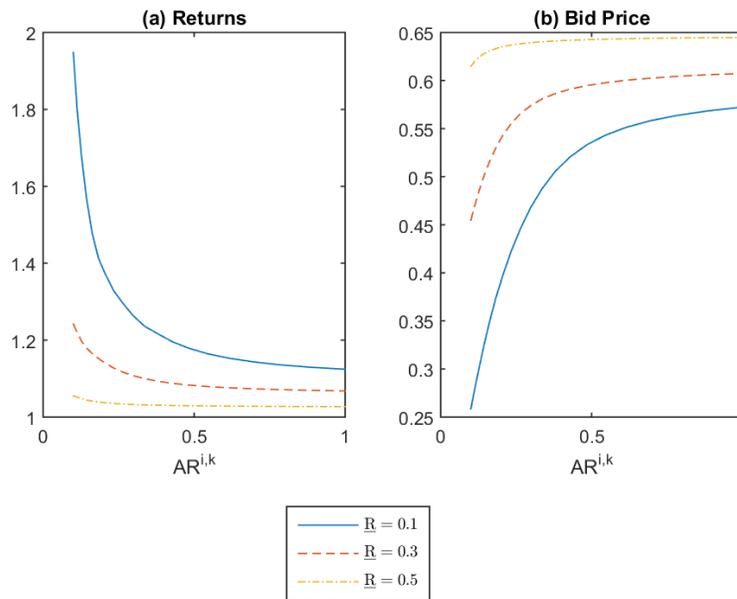


Figure 7 graphs the returns demanded (a) and resulting post default trading prices (b) for three different levels of R . The horizontal axis displays the activist wealth relative to the size of the firm they are consolidating. As R increases the sensitivity of returns and post default prices to the activist wealth ratio decreases.

Figure 8: The Fulcrum Creditors

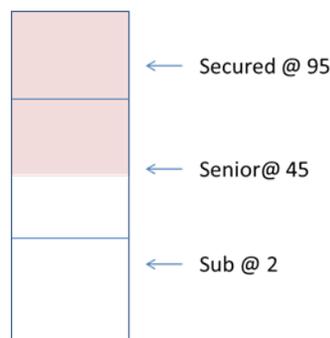
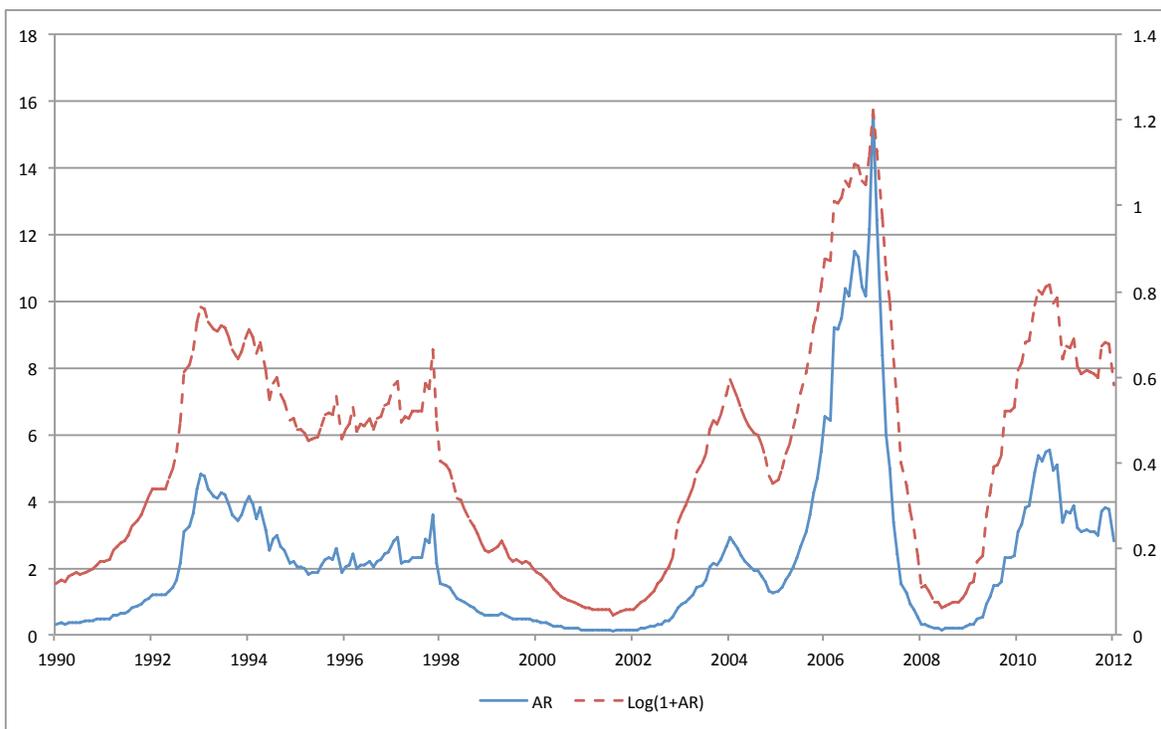


Figure 8 displays the capital structure of a simplified firm. The red shaded region is the estimated asset value. The numbers indicate the hypothetical trading prices where Secured @ 95 means the secured bonds are trading at 95 cents on the dollar. In this case the senior secured creditors will be paid out in full and the sub notes are expected to receive no value. In this case the senior notes are the "Fulcrum" class and represent the claims that are likely to receive the post reorganization equity.

Figure 9: Activist Wealth Ratio Over Time



$$AR = \frac{W^{HFR}}{D^{Moody's}}$$

Figure 9 depicts the activist wealth ratio (AR) and the log of 1+AR over time. The numerator is the AUM for the distressed hedge fund strategy from Hedge Fund Research and the denominator is the amount of defaulted debt from Moodys. The maximum raw value is just over 16 in 2007 when defaults were negligible while the minimum is 0.11 in 2002.

Figure 10: Historical Trading Price Post-Default

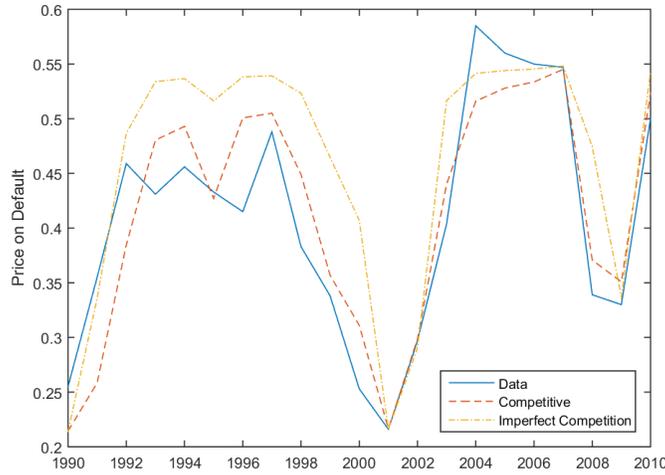
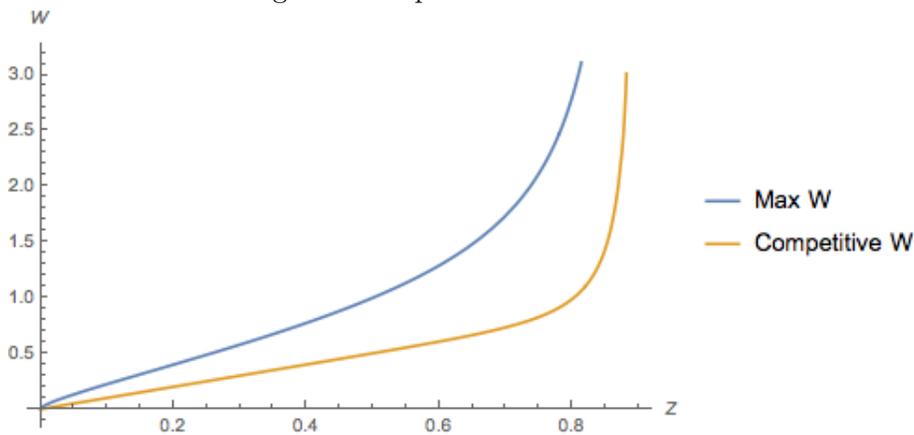


Figure 10 graphs the aggregate post default trading price implied by both the competitive and non-competitive model against Moody’s data for 1990-2011. model-implied prices are driven by the activist wealth ratio as measured by the HFR Distressed/Restructuring AUM divided by total defaulted debt from Moody’s. The wealth ratio is arbitrarily calibrated to match the lowest observation of post default trading prices in 2005. The resulting R^2 between the competitive model and the data is 0.82.

Figure 11: Equilibrium Conditions



The blue line in Figure 11 describes the maximum wealth given a bid price for the positive assortitive equilibrium to hold for an arbitrary $pf(\alpha) = 0.9$. For any bid price above the blue line, $U_{FW} < 0$ and the assortative equilibrium breaks down. The yellow line plots the equilibrium bid price assuming in the competitive model. Notably this line is always below the blue line meaning that the competitive model delivers a unique and stable positive assortative equilibrium.

Table 1: Determinants of Capital Flows

$$HFR_{t-1,t}^{flow} = \alpha + \beta_1 DRATE_t + \beta_2 Ret_{t,t+1} + \epsilon_t$$

This table illustrates the primary determinants of capital flows to the distressed investment strategy as detailed by Hedge Fund Research. The dependent variable in all regressions is the year over year change in distressed AUM between $t - 1$ and t . DRATE is the default rate in the economy at time t , DISTRESSEDRET is the returns between t and $t+1$ to a distressed investment strategy of purchasing bonds on default and selling on emergence, and HFRRET is the returns between t and $t + 1$ to the HFR distressed investment index.

Dependent Variable	(1)	(2)	(3)	(4)
INTERCEPT	0.098* (1.92)	0.073** (2.11)	0.108** (2.22)	0.098** (2.37)
DRATE	-0.223 (-0.10)			0.655 (0.45)
DISTRESSEDRET		0.038 (0.47)		0.052 (0.67)
HFRRET			-0.109 (-0.29)	-0.366 (-0.84)
R^2	0.000334	0.01830	0.006922	0.09680
Cluster	Firm	Firm	Firm	Firm
N	22	20	22	20

Table 2: Summary Statistics for Registered Bond Defaults

This table compiles summary statistics for companies that filed for bankruptcy within the period for which TRACE captured trade information. Emerge represents the number of firms that filed in a particular year that eventually emerge from bankruptcy within the data set. RA indicates the number of firms with enough trading activity to perform traditional risk adjustment. Duration, File Price and Emerge Price are equally weighted across observations within the year.

Year	Classes	Emerged	Priced	RA	Duration	File Price	Emerge Price
2002	40	37	34	17	213	30	34
2003	55	50	41	26	279	37	46
2004	21	20	19	7	235	52	46
2005	24	22	21	15	511	46	66
2006	15	15	13	4	250	64	44
2007	9	7	8	5	81	59	41
2008	36	31	33	23	305	27	28
2009	68	63	65	38	282	23	47
2010	13	12	12	7	275	29	24
2011	22	13	20	12	316	44	38
2012	25	14	22	11	117	39	35
	328	284	288	165	272	36	42

Table 3: Return Regressions with Average Risk Adjustment

$$r_{c,t}^{log} = \alpha + \beta_1(RA_t) + \mathbf{B}X_{c,t}^{\vec{}} + \epsilon_{c,t}$$

This table reports estimated coefficients from a regression with log returns as the dependent variable and the arbitrage capital ratio as the primary variable of interest. $X_{c,t}^{\vec{}}$ is a vector of risk adjustment and control variables whose coefficients appear in the table. Risk adjustment parameters, MKTRF, SMB, UMD, HML, TERM, DEF, and LIQRET are calculated as the returns to the factor portfolio over the period corresponding to the calculation of $r_{c,t}^{log}$. LIQ is the level of the Pastor-Stambaugh liquidity index at filing date, FILEPRICE is the price in cents on the dollar around filing date, LDAYS is the log number of days in default, SECURED and SENIOR are a dummy variables that takes a value of one if the class was a secured or senior creditor respectively. . T-statistics are presented in parentheses and significant levels are indicated by *, **, and *** for 0.1, 0.05 and 0.01 respectively.

	(1)	(2)	(3)	(4)
INTERCEPT	2.970*** (2.74)	2.903*** (2.79)	2.300** (2.27)	1.459 (1.55)
ACTIVIST RATIO	-0.267*** (-3.26)	-0.247*** (-2.87)	-0.252*** (-2.97)	-0.217*** (-2.72)
MKTRF	2.738*** (2.76)	2.785** (1.99)	2.815** (2.15)	3.471** (2.50)
SMB		-3.704 (-1.37)	-3.569 (-1.34)	-3.012 (-1.21)
HML		3.393* (1.77)	3.732* (1.92)	2.085 (0.93)
UMD		-0.648 (-0.70)	0.245 (0.27)	-0.080 (-0.06)
TERM				-2.319 (-1.15)
DEF				-1.154 (-0.53)
LIQRET			-1.486 (-1.25)	-1.346 (-1.07)
LIQ			-5.195** (-2.28)	-4.817** (-2.07)
FILEPRICE	0.013*** (2.80)	0.010** (2.41)	0.011** (2.53)	0.011** (2.37)
LDAYS	-0.613*** (-3.07)	-0.592*** (-3.29)	-0.502*** (-2.91)	-0.310* (-1.90)
SECURED	-0.431 (-0.96)	-0.425 (-1.02)	-0.419 (-1.08)	-0.422 (-1.14)
SENIOR	-0.350 (-0.68)	-0.352 (-0.75)	-0.403 (-0.89)	-0.398 (-0.96)
Firm Ctrls	Yes	Yes	Yes	Yes
Cluster	Month	Month	Month	Month
R^2	0.1993	0.2218	0.2489	0.2683
N	288	288	288	288

Table 4: Return Regressions with Traditional Risk Adjustment

$$r_{c,t}^{log} = \alpha + \beta_1(RA_t) + \mathbf{B}X_{c,t}^{\vec{}} + \epsilon_{c,t}$$

This table reports estimated coefficients from a regression with returns as the dependent variable and the arbitrage capital ratio as the primary variable of interest. $X_{c,t}^{\vec{}}$ is a vector control variables. LIQ is the level of the Pastor-Stambaugh liquidity index at filing date, FILEPRICE is the price in cents on the dollar around filing date, LDAYS is the log number of days in default, SECURED and SENIOR are a dummy variables that takes a value of one if the class was a secured or senior creditor respectively. Risk adjustment is performed by taking regressing the returns data over the bankruptcy period on the relevant risk factors. $r_{c,t}^{log}$ is then calculated as the log of one plus excess returns over the bankruptcy period. (1) uses a CAPM model, (2) a Fama French 4 factor model, (3) uses FF4 and Pastor Stambaugh Liquidity for risk adjustment and finally (4) adds the Fama French bond pricing risk factors TERM and DEF. T-statistics are presented in parentheses and significance levels are indicated by *, **, and *** for 0.1, 0.05 and 0.01 respectively.

	(1)	(2)	(3)	(4)
INTERCEPT	0.301 (0.56)	-0.358 (-0.41)	-0.385 (-0.43)	0.132 (0.17)
ACTIVIST RATIO	-0.328*** (-3.97)	-0.233*** (-3.46)	-0.209*** (-3.24)	-0.230** (-2.52)
LIQ	-5.109* (-1.80)	-3.910 (-1.33)	-4.494 (-1.54)	-2.569 (-0.99)
FILEPRICE	0.008 (1.06)	0.006 (0.83)	0.006 (0.76)	0.003 (0.37)
SECURED	-0.225 (-0.35)	-0.168 (-0.26)	-0.263 (-0.36)	-0.195 (-0.28)
SENIOR	-1.955*** (-3.96)	-1.367* (-1.75)	-1.486* (-1.84)	-1.791*** (-2.68)
Firm Ctrls	Yes	Yes	Yes	Yes
Cluster	Year	Year	Year	Year
R^2	0.1091	0.05347	0.05280	0.05517
N	169	169	169	169

Table 5: Redeployability and Returns

$$r_{c,t}^{log} = \alpha + \beta_1 AR_t^{agg} + \beta_2 REDEP_c + \beta_3 AR_t^{agg} * REDEP_c + \mathbf{B}X_{c,t} + \epsilon_{c,t}$$

Table reports estimated coefficients from a regression with log returns as the dependent variable and the arbitrage capital ratio, asset redeployability, and their interaction term as the primary variables of interest. $X_{c,t}$ is a vector of risk adjustment and control variables whose coefficients appear in the table. Risk adjustment parameters, MKTRF, SMB, UMD, HML, TERM, DEF, and LIQRET are calculated as the returns to the factor portfolio over the period corresponding to the calculation of $r_{c,t}^{log}$. LIQ is the level of the Pastor-Stambaugh liquidity index at filing date. FILEPRICE, LDAYS, SENIOR, and SECURED are not displayed for brevity. T-statistics are presented in parentheses and significant levels are indicated by *, **, and *** for 0.1, 0.05 and 0.01 respectively.

	(1)	(2)	(3)	(4)
INTERCEPT	3.315** (2.03)	4.378** (2.62)	4.411** (2.62)	4.558** (2.49)
ACTIVIST RATIO	-0.530*** (-2.84)	-1.567*** (-3.71)	-1.526*** (-3.44)	-1.563*** (-3.10)
REDEP	-1.463 (-0.55)	-4.736 (-1.49)	-4.715 (-1.46)	-5.008 (-1.48)
AR*REDEP		3.410** (2.48)	3.281** (2.29)	3.379** (2.21)
MKTRF	0.870 (0.69)	0.402 (0.33)	0.555 (0.39)	-0.334 (-0.18)
SMB	-1.142 (-0.34)	0.956 (0.30)	0.838 (0.26)	1.465 (0.44)
HML	1.926 (0.79)	2.347 (0.96)	2.586 (1.16)	2.789 (1.25)
UMD	-1.569 (-1.26)	-2.254* (-1.97)	-1.973 (-1.40)	-0.967 (-0.66)
TERM				-2.005 (-0.76)
DEF				2.736 (0.90)
LIQRET	0.300 (0.14)	0.682 (0.30)	0.480 (0.20)	0.005 (0.00)
LIQ			-1.044 (-0.35)	-0.768 (-0.25)
Firm Ctrls	Yes	Yes	Yes	Yes
Cluster	Year	Year	Year	Year
R^2	0.4572	0.5082	0.5089	0.5131
N	105	105	105	105

Table 6: Fulcrum Classes and Returns

$$r_{c,t}^{log} = \alpha + \beta_1 AR_t^{agg} + \beta_2 FULCRUM_c + \beta_3 AR_t^{agg} * FULCRUM_c + \mathbf{B}\vec{X}_{c,t} + \epsilon_{c,t}$$

This table reports estimated coefficients from a regression with log returns as the dependent variable and the arbitrage capital ratio. Risk adjustment parameters, MKTRF, SMB, UMD, HML, TERM, DEF, and LIQRET are calculated as the returns to the factor portfolio over the period corresponding to the calculation of $r_{c,t}^{log}$. LIQ is the level of the Pastor-Stambaugh liquidity index at filing date. FILEPRICE, LDAYS, SENIOR, and SECURED are not displayed for brevity. T-statistics are presented in parentheses and significant levels are indicated by *, **, and *** for 0.1, 0.05 and 0.01 respectively.

	(1)	(2)	(3)	(4)
INTERCEPT	2.172** (2.05)	2.340** (2.20)	1.900 (1.60)	1.562 (1.31)
ACTIVIST RATIO	-0.089 (-0.79)	-0.050 (-0.42)	-0.002 (-0.03)	-0.004 (-0.06)
<i>FULCRUM</i> _{5,85}	1.258*** (3.50)	1.252*** (3.55)		
AR * FULCRUM _{5,85}	-0.218* (-1.82)	-0.235** (-2.05)		
<i>FULCRUM</i> _{2.5,90}			1.093** (2.37)	0.996** (2.30)
AR * FULCRUM _{2.5,90}			-0.316** (-2.61)	-0.305** (-2.62)
MKTRF	2.869*** (2.84)	3.096** (2.12)	2.552** (2.53)	2.565* (1.75)
SMB		-4.235 (-1.52)		-2.983 (-1.10)
HML		3.190* (1.80)		3.301* (1.75)
UMD		-0.405 (-0.47)		-0.523 (-0.59)
LIQRET		-0.543 (-0.48)		-1.020 (-0.89)
Firm Ctrls	Yes	Yes	Yes	Yes
Cluster	Month	Month	Month	Month
R^2	0.2305	0.2385	0.2163	0.2392
N	288	288	288	288

Table 7: Turnover and the Activist Ratio

$$TURNOVER_{c,t} = \alpha + \beta_1 AR_t^{agg} + \beta_2 AR_t^{agg^2} + \mathbf{B}X_{c,t} + \epsilon_{c,t}$$

This table reports estimated coefficients from a regression with turnover as a percentage of total amount outstanding in the month after default as the dependent variable and the arbitrage capital ratio, Pastor–Stambaugh liquidity level LIQ, bond market abnormal volume, and firm controls FILEPRICE, LDAYS, SENIOR, and SECURED are not displayed for brevity. T-statistics are presented in parentheses and significant levels are indicated by *, **, and *** for 0.1, 0.05 and 0.01 respectively.

	(1)	(2)	(3)	(4)
INTERCEPT	1.182** (2.07)	0.960 (1.55)	1.283** (2.47)	1.201** (2.11)
ACTIVIST RATIO	0.019 (0.67)	0.204* (1.68)		
RATIO ²		-0.021* (-1.67)		
RATORANK 1			-0.623*** (-2.93)	
RATORANK 2			-0.044 (-0.19)	
LOG(RATIO)				0.141** (2.12)
Firm Ctrls	Yes	Yes	Yes	Yes
Cluster	Month	Month	Month	Month
R ²	0.01707	0.02612	0.04506	0.02940
N	324	324	324	324

Table 8: Explaining Post Default Bond Prices

$$Z_t = \alpha + \beta X_t + \epsilon_t$$

This table reports R^2 statistics from linear regressions taking the above form and implied spreads from the competitive bidding model for post default trading prices using four variables: the activist wealth ratio (RATIO), the ratio between the S&P index and the amount of defaulted debt (S&P RATIO), the aggregate default rate DRATE (or -DRATE for model implied spreads), and the returns to the S&P index. For comparison purposes I include the linear regression results from the DSG model which includes 5 regressors: $DRATE$, $\Delta DRATE$, $S\&P\ RET$, $\Delta S\&P\ RET$, GDP growth.

	AR	S&P RATIO	DRATE	S&P RET	DSG
Beta	4.3	14.0	-5.8	0.2	-
T-Stat	(3.6)	(3.9)	(-5.5)	(1.6)	-
$R^2 Linear$	40.3	44.9	61.3	11.8	81.4
$R^2 Model$	82.7	54.4	61.0	12.2	-

Table 9: Parameters

The calibration parameters for this paper are taken largely from Zhang (2005) with the primary exception that the cyclicity of risk aversion, η_1 , is 2000 vs 1000 in his paper. This does not have a large effect on the typical asset pricing moments, but gets the model in the ballpark of matching the typical AAA-BBB credit spread puzzle target. Importantly the magnitude impact of the mechanism is similar using the calibration from Zhang (2005).

Parameter	Value	Parameter	Value	Moment	Value
\bar{x}	-5	η_0	50	\bar{R}_f	1.5%
σ_x	.007	η_1	-2000	σ_{R_f}	2.3%
ρ	.95	β	0.96	R_m	6.2%
μ_d	0	$\rho_{w,p}$	0.59	$\frac{R_m - R_f}{\sigma_m}$	0.42
σ_d	0	σ_w	0.18		
σ_k	0.17				

Table 10: model-implied Cyclicalty

This table displays the model-implied and data cyclicalty's for recovery rates and default rates. The model is calibrated to match the individual default rates for each asset rating class while the initial activist wealth ratio is calibrated to match an average expected recovery rate of 0.45.

	Competitive Model	Data
Default Rate Recession	3.2%	2.9%
Default Rate Expansion	0.9%	0.7%
Trading Price Recession	30.6%	29.3%
Trading Price Expansion	50.2%	46.0%

Table 11: model-implied 10 Year Spreads

This table shows results of running both the fixed recovery ($Rec = 0.45$), linear recovery, competitive bargaining and augmented models on 10 year bonds. Panel A displays the model implied spreads to treasuries while panel B displays the implied spreads relative to AAA. Cumulative default probabilities are taken from 1982-2013 as reported by Moody's. Historical spreads data are taken from Altman, Caouette, and Narayanan (1998) and are cross checked with spreads calculated from CDS prices starting in 2005.

Panel A: Spreads to Treasury

Rating	Data	Fixed Rec		Linear		Perfect Comp		Imperfect Comp	
	Spread	Spread	%Dev	Spread	%Dev	Spread	%Dev	Spread	%Dev
AAA	47.0	16.6	-64.7	20.1	-57.2	20.2	-56.9	21.4	-54.4
AA	69.0	30.0	-56.5	36.2	-47.5	36.4	-47.3	38.3	-44.6
A	96.0	67.7	-29.4	81.2	-15.5	81.0	-15.6	84.0	-12.5
BBB	150.0	103.0	-31.4	122.8	-18.1	121.9	-18.8	125.0	-16.7
BB	310.0	295.1	-4.8	346.3	11.7	326.8	5.4	321.0	3.5
B	470.0	491.2	4.5	564.8	20.2	491.1	4.5	472.6	0.6
%Dev ²			92.8		66.4		61.2		53.9

Panel B: Spreads to AAA

Rating	Data	Fixed Rec		Linear		Perfect Comp		Imperfect Comp	
	Spread	Spread	%Dev	Spread	%Dev	Spread	%Dev	Spread	%Dev
AA	22.0	13.4	-39.0	16.1	-26.8	16.1	-26.6	16.8	-23.6
A	49.0	51.2	4.4	61.0	24.6	60.8	24.1	62.5	27.6
BBB	103.0	86.4	-16.1	102.7	-0.3	101.6	-1.3	103.5	0.5
BB	263.0	278.5	5.9	326.2	24.0	306.6	16.6	299.5	13.9
B	423.0	474.6	12.2	544.7	28.8	470.8	11.3	451.2	6.7
%Dev ²			19.9		27.3		16.9		15.6

Table 12: model-implied 4 Year Spreads

This table shows results of running both the fixed recovery ($Rec = 0.45$), linear recovery, competitive bargaining and imperfect competition models on 4 year bonds. Panel A displays the model implied spreads to treasuries while panel B displays the implied spreads to AAA. Cumulative default probabilities are taken from 1982-2013 as reported by Moody's. Historical spreads data are taken from Altman, Caouette, and Narayanan (1998) and are cross checked with spreads calculated from CDS prices starting in 2005.

Panel A: Spreads to Treasury

Rating	Data	Fixed Rec		Linear		Perfect Comp		Imperfect Comp	
	Spread	Spread	%Dev	Spread	%Dev	Spread	%Dev	Spread	%Dev
AAA	47.0	6.5	-86.2	7.9	-83.1	8.0	-82.9	8.5	-82.0
AA	69.0	18.9	-72.7	22.8	-66.9	23.0	-66.6	23.9	-65.3
A	96.0	46.1	-52.0	55.3	-42.4	55.3	-42.4	56.3	-41.3
BBB	150.0	94.5	-37.0	112.2	-25.2	110.8	-26.1	110.5	-26.3
BB	310.0	339.3	9.5	393.8	27.0	368.2	18.8	349.0	12.6
B	470.0	676.4	43.9	770.5	63.9	671.8	42.9	626.5	33.3
%Dev ²			187.9		186.4		159.9		146.5

Panel B: Spreads to AAA

Rating	Data	Fixed Rec		Linear		Perfect Comp		Imperfect Comp	
	Spread	Spread	%Dev	Spread	%Dev	Spread	%Dev	Spread	%Dev
AA	22.0	12.4	-43.7	14.9	-32.3	15.0	-31.8	15.4	-29.8
A	49.0	39.6	-19.1	47.4	-3.4	47.3	-3.6	47.8	-2.4
BBB	103.0	88.0	-14.5	104.3	1.2	102.8	-0.2	102.0	-0.9
BB	263.0	332.8	26.5	385.9	46.7	360.1	36.9	340.6	29.5
B	423.0	669.9	58.4	762.6	80.3	663.8	56.9	618.0	46.1
%Dev ²			66.0		96.8		56.3		38.9

Table 13: Recovery Rates and Spreads

This table shows results of three competitive bargaining models on 4 and 10 year bonds. It highlights the difference in model-implied spreads from using various data points as the expected recovery for bondholders. Using the post default price increases the implied curvature beyond that of the expected recovery rate model while using while post emergence rates result in a more stable relationship between the state of the economy and recovery rates. Cumulative default probabilities are taken from 1982-2013 as reported by Moody's. Historical spreads data are taken from Altman, Caouette, and Narayanan (1998) and are crosschecked with spreads calculated from CDS prices starting in 2005.

Panel A: 10 Year Spreads

Rating	Data	Blended Rec		Post Default Price		Emergence Rec	
	Spread	Spread	%Dev	Spread	%Dev	Spread	%Dev
AAA	47.0	20.2	-56.9	21.1	-55.2	18.1	-61.5
AA	69.0	36.4	-47.3	37.7	-45.4	32.7	-52.5
A	96.0	81.0	-15.6	83.2	-13.3	73.8	-23.2
BBB	150.0	121.9	-18.8	124.4	-17.1	111.9	-25.4
BB	310.0	326.8	5.4	325.0	4.8	314.0	1.3
B	470.0	491.1	4.5	479.0	1.9	500.0	6.4
%Dev ²			61.2		56.0		77.6

Panel B: 4 Year Spreads

Rating	Data	Blended Rec		Post Default Price		Emergence Rec	
	Spread	Spread	%Dev	Spread	%Dev	Spread	%Dev
AAA	47.0	8.0	-82.9	8.3	-82.3	7.2	-84.8
AA	69.0	23.0	-66.6	23.7	-65.7	20.7	-69.9
A	96.0	55.3	-42.4	56.2	-41.5	50.5	-47.4
BBB	150.0	110.8	-26.1	111.4	-25.7	103.0	-31.4
BB	310.0	368.2	18.8	359.9	16.1	360.3	16.2
B	470.0	671.8	42.9	646.7	37.6	691.1	47.0
%Dev ²			159.9		151.5		177.9