How and Why Do U.S. Public Firms Participate in Swap Markets?

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Abstract

We study publicly traded U.S. firm participation in swap markets, relying on the open swap positions reported to Swap Data Repository for the five major swap markets, including IRS, FX, CDS/CDX, Commodity, and Equity, between 2018 and 2021. Our regression discontinuity design approach around discrete financial and credit risk thresholds show larger, more levered, older firms, with fewer intangible assets, and large foreign profits are more likely to use swaps. Furthermore, firms that experience an increase in access to financing are less likely to hedge, *ceteris paribus*, except those firms with limited access to external public debt markets. Similarly, firms which transition from negative to positive profits are less likely to hedge, *ceteris paribus*. Some of the most novel observations are that young firms are as interested in using IRS as old firms, and that besides healthcare, most industries actively participate in the swap markets, with 50% or greater participation by firms in chemicals, energy, manufacturing, and consumer durables and non-durables. This is the first study establishing these stylized facts across multiple hedging instruments on the most complete sample of publicly traded U.S. firms in a panel data setting.

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How do corporations make their risk management decisions? Survey evidence (e.g., Biambona et al. 2018 among others) suggest that, indeed, risk management is considered one of the most important objectives of financial executives.[1] Despite the significance of risk management in firms' financial policy, straightforward questions such as the determinants of swap usage, which firms use swaps, why they use them, and how much usage is optimal (if any) received seemingly ambiguous answers in the extant literature. The most common response to such criticism has been that the data on risk management is very difficult to collect and systemically quantify. [2]

Notwithstanding the pernicious effects that result from *vis major* public disclosure limitations, the sample selection criteria used in extant studies introduces additional challenges. Prior literature has limited analysis to mostly large firms (i.e. the S&P 500), single years, firms within a particular industry, and only for a given swap product type. At best, this makes conclusions based on such specifications, such as firm motivations or determinants of swap usage, limited in scope and lacking in out-of-sample applicability. For example, some studies focus on one particular industry, thereby obscuring the role of highly heterogeneous business and financial risks across industries with respect to hedging decisions. Similarly, single fiscal-year subsamples and measurements based on a single hedging instrument introduce time-dependent effects and are limited in broader applicability to predictions of theoretical models (e.g. Smith and Stulz (1985)).

In this study we examine the use of swap markets by the publicly traded firms (end-users) in the U.S. Our study focuses on the five major swap markets, including IRS, FX, CDS/CDX, Commodity, and Equity, during fifteen quarters between 2018 and 2021. While our study follows on prior literature that has explored similar questions, it is the first comprehensive study to establish some of the stylized facts identified by prior literature regarding the primary motivations for using swaps, and introduces novel findings across

[1] Swap usage by end-users has been categorized as belonging to one of three core purposes: (1) hedging, (2) speculation, or (3) market frictions (including market timing). Allayannis and Ofek (2001) argue that firms utilize swap markets for hedging purposes, Guay and Kothari (2003) suggest that firms rely on swaps to speculate, and Faulkender (2005) concludes that firms use these markets to engage in market timing.

[2] Until the policy change starting in 2010 incentivizing central clearing, most swaps have been traded in over-the-counter (OTC) markets which have contributed to a lack of understanding how and why firms use these instruments. Publicly available data on swaps usage is limited. FASB issued SFAS 119 in 1994, which required firms to report the notional values of derivatives contracts. FASB updated this requirement with SFAS 133, which required firms to report the "fair market value" of derivatives contracts which limited the required disclosure of certain detailed information, such as the notional values, intended purpose, and terms of various derivatives exposures. See notation in Campello et al. (2011) for more information

several swap instruments on the most comprehensive sample of U.S. publicly traded firms in a panel data setting.

Our first set of analysis focuses on swap market participation across various S&P index constituents. Somewhat in contrast to prior studies, we find that, swap market participation is common both among the largest firms (S&P 500 index constituents), as well as the smallest firms (firms that are not part of an S&P index), around 85% and 26% respectively, which stays about the same across the fifteen quarters. The participation to the swap market slightly increases for the small-cap firms (S&P 600), from 47% to 52%, and slightly decreases for mid-cap firms (S&P 400) from 69% to 65%. Second, we observe that FX and IRS are the two most widely held swaps among U.S. public firms, across all index and non-index constituents. While FX seems to be more dominated by large firms (around 72% for S&P500 constituents and 10% for non-index firms), IRS seems to be preferred across all index categories (around 60% for S&P 500 constituents and 20% for non-index firms). For the remaining three swap types, CDS/CDX, Commodity swaps, and Equity swaps, the participation is mostly driven by large-cap firms (S&P 500 constituents) with limited or no participation by small-cap firms and non-index firms, depending on the swap product. Even among the large-cap firms, the participation to these three swap markets (CDS/CDX, Commodity, and Equity) decline considerable over time, with the sharpest decline in equity swap market participation.

Our second set of analysis focuses on the swap market participation across different industries. Our results are particularly novel, because unlike most prior studies, we have a comprehensive coverage of publicly traded firms in U.S. For example, we observe that firms in the healthcare industry are the least represented industry as a swap user, where about 6% of the firms use IRS, and about 9% of firms use FX, with almost no participation to the remaining three swap markets. On the other hand, firms in utilities have the highest participation to the IRS, CDS/CDX, and Commodity swaps. Second, five non-financial industries: chemicals, manufacturing, energy, consumer durables, and consumer non-durables, have more than 50% of the firms participating to one of the five swap markets we examine. Firms in business equipment, wholesale, and telecom are also relatively common swap users, with close to 40% participation in one of the five swap markets. In IRS, participation among telecom, chemicals, consumer durables, consumer non-durables, wholesale, and manufacturing ranges from 25% to 40%. While participation to IRS in the quarters of our sample declines among these industries, firms in the energy almost double in number in terms of their IRS use. In FX, firms in chemicals industry have a growing percentage of participation across time, reaching over 60% of the firms in the industry by the end of our sample period. Manufacturing, consumer durables, chemicals also have a substantial showing, with close to 50% of the firms in these industries using FX. Participation of CDS/CDX is most common among utilities, with growing participation in the last five quarters of the sample, while the percentage of firms in telecommunication participating to the CDS/CDX market declines over time by half. Commodity swaps are most popular among firms in energy, where close to 50% of the firms in the industry participate to the swap market. Firms in the chemical industry also show strong interest in Commodity swaps, with the participation increasing from 20% to 30% of the firms in the industry over the time period we examine.

Finally, we estimate predictive regressions to determine the likelihood of a firm becoming a swap market participant as a function of its characteristics, which capture the costs and benefits of risk management. Our regression results establish that firm size is the most important predictor of a firm's decision to become a swap user. Firm size is particularly important for the likelihood of firms using FX and CDS/CDX, suggesting that larger firms are more likely to benefit from a risk management program. Firm age is almost as important as size in determining the likelihood of a firm using a swap, with the exception of IRS, where participation does not seem to be affected by firm age. This is a novel finding as prior studies generally suggest that swaps are used by mature firms. Firms' book leverage is also an important determinant of swap market participation across all swap categories, consistent with the high cost of a risk management program being more likely to be mitigated for firms with high financial leverage. We also find that firms with high capital investment are more likely to participate to a swap market, as they benefit from a risk management program that allows them to maintain their investment decisions. On the other hand, firms with high tangible assets are less likely to participate to a swap market, which is consistent with the notion that benefits from a risk management program are marginal for these firms, as they can use collateral to more easily access external public capital debt markets. Another novel finding is that firms with higher foreign sales are more likely to use a swap, and this effect is present across all swap categories, suggesting that these firms are most likely to benefit from a risk management program.

Given that there are several sources of potential biases in our results, due to the simultaneity of hedging and financing decisions, measurement error arising from the opacity of disclosures with respect to hedging polices, as well as biases resulting from omitted characteristics that might perform a role in firms' risk management decisions, we conduct a regression discontinuity estimation. A Regression Discontinuity Design (RDD), which is a quasi-experimental evaluation, measures the impact of an intervention (treatment), by applying a treatment assignment mechanism based on an eligibility index[3]. We use firms' issuer level S&P credit ratings and their level of indebtedness proportional their profits (Debt/EBITDA) as the treatment assignment, and conduct our regression analysis around two different cut-off points: one where firms are considered to be at the cusp of the highest-to-high credit risk, and the second where firms are considered to be at the cusp of being considered low and medium credit risk. The results from these analyses support the conclusion that firm size and leverage have a first order impact on firms' decision to use swaps. We also confirm that firms with large foreign profits are more likely to use swaps, especially if they are at the cusp of the highest-to-high credit risk threshold, whereas older firms with high capital expenditures and intangible assets are more likely to use swaps, especially if they are at the cusp of the moderate-to-low credit risk threshold. A similar RD design using the Debt/EBITDA measure highlights the significance of negative profits in firm hedging decisions. Specifically, at the negative-to-positive Debt/EBITDA threshold, we find that firms with intangible assets are less likely to use swaps, contrary to our findings that isolate firms at the cusp of moderate-to-low credit risk. The second Debt/EBITDA cutoff point we consider to isolate the hedging decisions of firms facing high default risk, further supports the conclusion that firms with high growth opportunities are less likely to use swaps.

The remaining discussion of the paper is as follows: In Section I, we discuss the related research on corporate hedging. In Section II, we discuss methodology of the paper and our approach. In Section III, we describe our data. In Section IV, we present our empirical results. Section V concludes.

I. Related Research

Prior literature has examined the various aspects of hedging considerations of firms, however, examination of swaps across a broad panel of public firms has heretofore been absent. Stylized facts related to firms' use of swaps have largely centered on interest rate swaps (IRS) and foreign-exchange swaps (FX), with much more limited attention given to credit default swaps (CDS/CDX) and commodity swaps. Publicly available data has also materially limited the scope of prior studies; for the few empirical studies that have examined determinants of swap usage, they are either limited to a single cross-section of large firms, or to a particular industry. The small-sample subsets, or industry-specific attention in prior

[3] See, e.g., Chang et al. (2015), Falato and Liang (2016), Dittmar et al. (2020), and Garcia and Steele (2022) for a discussion on the use of regression discontinuity design as a source of exogenous variation to address concerns of endogeneity.

literature, have often led to conflicting results for determinants of swaps usage, and a lack of consensus on the important considerations related to optimal firm hedging policies.

A. Optimal Hedging Decision

Smith and Stulz (1985) provide a theoretical basis for optimal firm hedging policy that maximizes firm value. They identify three corresponding incentives for value-maximizing firms to use swaps, including, (1) convexities in the corporate tax schedule, (2) expected costs of financial distress that are increasing in the volatility of firm value, and (3) managerial risk aversion that reduces the value of ill-diversified fixed compensation claims. [4] Their argument is that since the tax code has zero tax on negative income and a moderately progressive structure for positive income, firms will benefit from hedging if their function of after-tax income becomes more concave. Similarly, since bankruptcy costs are estimated, on average, at approximately 15% of firm value, value-maximizing firms may find such bankruptcy costs as sufficient incentive to hedge, so long as the costs of hedging are less than the expected bankruptcy costs.[5] Smith and Stulz (1985) also provide a channel through which managerial compensation and motivations may create positive incentives for value-maximizing firms to hedge, such as in the case of variance-increasing positive NPV projects with hedging. While managerial risk aversion may lead some managers to hedge, they may not, especially if their compensation is more option-based.

Since Smith and Stulz (1985), there have been a wealth of studies debating firms' hedging motivations, which generally fall into one of three categories: (1) value-maximizing firm hedging, (2) speculation, and (3) market-timing considerations. Some prior literature has attempted to test the theoretical implications, with often conflicting and differing results, which in part may be due to sample limitations.

B. Do firms use hedging to maximize firm value, speculate, or time the market?

Allayannis and Ofek (2001) use a sample of non-financial S&P 500 firms for the year-ending 1993 and find that currency derivatives hedging reduces the exchange-rate exposure firms experience. Their results are consistent with the expected determinants of optimal hedging, including exposure to factors related to foreign sales and foreign trade, as well as size and R&D expenditures. They also find that the decision on

[4] Smith, Smithson, and Wakeman (1988) provide supporting empirical evidence for such model conclusions in the context of interest rate swaps

[5] This particular incentive has been investigated somewhat more thoroughly in prior literature, especially in so far as a firm can reduce costs of financial distress and firm financing costs through mitigating negative payoffs in adverse states, or reducing overall cash flow volatility.

how much to hedge is exclusively driven by the degree of exposure through foreign sales and trade. Campello et al. (2011) examine firm hedging and show that it has a first order effect on firm financing and investment. In particular, firm hedging can lower the odds of negative realizations to reduce the cost of financial distress. They also show that firms experience improved access to capital though a lower price of bank loans, and improve their ability to invest by minimizing contractual restrictions on investment spending.

Guay and Kothari (2003) test firm hedging with derivatives and find that derivatives contribute only a small portion to firm cash flows, based on their fair-value estimations. They examine 234 large non-financial corporations using derivatives and report estimates of the magnitude of the risk exposure hedged by financial derivatives. The authors find that the derivative hedging programs of firms are not large enough to have a noticeable effect on stock return volatility and that increases in firm value may be driven by other risk management activities that are correlated with derivatives use. They find that, by their estimations, firm derivatives programs are only able to hedge approximately 3% to 6% of aggregate interest rate and currency rate exposures. The authors argue that their results are consistent with firms attempting to fine-tune exposures, use derivatives for purposes of speculation, or for internal budgeting and performance evaluation.

Faulkender (2005) examines the question of whether firms are hedging or market timing with respect to interest rate swaps. In a small sample of 133 chemical firms, with 275 debt issuances over six years, he finds evidence that final interest rate exposure is determined largely by the slope of the yield curve at the time of debt issuance. Importantly, he shows that the shape of the yield curve is a key determinant of whether a firm's newly issued debt instruments are fixed or floating. He further postulates that some of the usage of derivatives may be related to short-term earnings management and speculation. Chernenko and Faulkender (2011) provide additional arguments that firms engage in speculative derivatives behaviour, following Faulkender (2005). They find results consistent with Campello et al. (2011) in that firms use hedging to improve their ability to fund investment opportunities, but contrary to the same, Chernenko and Faulkender (2011) argue that their results are not consistent with firms hedging to mitigate the costs of financial distress (or tax rate convexity).

While there is sufficient evidence, even with caveats, to suggest that firms use derivatives and more specifically swaps, to hedge, the determinants of firm swap usage have been incomplete to date. Of course, this is partially due to the existing data limitations on firm usage, but also due to the complexity of the problem, in so far as firms in different industries and possessing different characteristics will have diverse hedging needs. Necessarily, this also affects the mode of hedging and product choice (e.g. IRS vs. FX). This gap in the literature certainly calls for a comprehensive investigation across a broad range of firms and industries to sufficiently detail determinants of usage; such an examination empowers further investigation of the ambitious questions detailed by Smith and Stulz (1985), and may yield a conclusive answer to such hedging considerations.

C. Empirical Evidence on the Determinants of Swap Usage

Bodnar et al. (1995) provide one of the earlier attempts at a comprehensive survey of derivatives usage by non-financial firms, relying on a survey of 530 firms. Firms reported that the primary reason for derivatives usage is to hedge firm commitment transactions (80%), while the second most reported use is to hedge anticipated transactions (less than or equal to 12 months) for 75% of such firms. Firms further reported that the most important objective for firms to hedge (among appearance of the balance sheet, accounting earnings fluctuations, and cash flow fluctuations), is to minimize fluctuations in cash flow. Howton and Perfect (1998) conducted a survey of IRS and FX derivatives use for 451 Fortune and S&P 500 firms and 461 randomly selected firms from Compustat for those not already in the first sample. Their results for a Fortune and S&P 500 combined sample suggest derivatives use that is consistent with minimizing the costs of financial distress and external financing, as well as to decrease their expected tax liabilities.

Geczy, Minton, and Schrand (1997) provide an overview of the determinants of currency derivatives use among 372 of the Fortune 500 non-financial firms as of 1990. Importantly, the authors find that firms with greater growth opportunities (proxied by R&D, PPE, and B/M) and tighter financial constraints (interest coverage ratio and long-term debt ratio) are more likely to use currency derivatives. The authors suggest that firms may use currency derivatives to reduce cash flow variation that would prevent them from investing in valuable growth opportunities. Similar to Howton and Perfect (1998), the authors show that firms with foreign-exchange rate exposure (proxied by foreign pre-tax income or foreign sales), is a significant determinant of currency derivative use. Brown (2001) finds in a single-firm case study that there is limited evidence for classic explanations in the literature, such as minimizing expected taxes, avoiding costs of financial distress, managerial risk aversion, and coordination of cash flows and investment. He concludes from discussions with firm management and statistical tests that more likely explanations are the smoothing of earnings, facilitating internal contracting, and obtaining competitive pricing advantages in the product market. Zhou and Wang (2013) examine how derivatives usage among 500 U.K. non-financial firms affects their foreign exchange risk management activity. The authors find that firms are somewhat successful in hedging against the risk of unfavorable exchange rate movements, which may reduce firm cost of capital and increase firm value. A summary of predictions for firms' use of hedging depending on their firm characteristics in summarized in Appendix A.

II. Methodology

A. Endogeneity: Regression Discontinuity Design

Predicting the likelihood of swap usage as a function of the costs and benefits of such a decision is inherently subject to endogeneity. For example, the coefficient estimates in our models might be biased either up or down, because of omitted characteristics, such as the amount of private debt and off-balance sheet financing, or characteristics that are relevant for firms' decision to use swaps, but are not directly observable. In addition, the coefficient estimates could be biased upward, due simultaneity, as not only firms with high leverage might be more likely to hedge to minimize the expected costs of financial distress, but also firms that hedge their financial risk with swaps might choose to have higher leverage ratios as swap use increases firms' debt capacity.[6]

In this section, we attempt to address these endogeneity concerns with a quasi-experimental regression discontinuity design (RDD), by focusing on the hedging decision for firms at discontinuous jumps in the continuum of both firm financial and credit risk.[7] We consider two potential candidates to identify the discontinuous jumps in the likelihood of being a swap user, which we discuss next.

1. S&P Issuer-Level Credit Rating: Sharp Regression Discontinuity

We consider the firm issuer-level credit rating, which is integral to hedging and financing considerations, but also a characteristic that is quite suitable for an RDD identification strategy, since firms in the same

[6] See, e.g., Gilje and Taillard (2017) utilize a Difference-in-Differences approach in the context of an exogenous change in basis risk to analyze channels through which hedging has an impact on firm value; the authors find evidence, consistent with Smith and Stulz (1985), that reducing default risk and underinvestment are channels through which hedging affects firm value.

[7] There are several aspects of RD estimation that requires careful attention: (1) the presence of a treatment effect (i.e., existence of a threshold) (2) the appropriate regression discontinuity model specification (sharp or fuzzy), (3) the potential for manipulation of observations above and below a threshold, either through self-selection or other non-random assorting assignment, which biases the treatment effect, (4) the correct specification for polynomial order of the estimation, (5) the bandwidth selection criteria and sensitivity of the estimation results to the same through the inclusion of more or less observations around the threshold, and (6) sensitivity to various model parameters, such the underlying kernel probability distribution. We conduct a thorough examination of these concerns using a battery of tests.

credit rating group are assessed by the credit rating agency to have similar credit risk, the assignment to treatment occurs as a known and measured deterministic rule, and firms cannot precisely manipulate the outcome. We identify two discontinuities: a high-yield to speculative high-yield cutoff (B+), as well as an investment grade cutoff (BBB).[8] For firms whose credit ratings fall above the investment grade cutoff, such firms tend to exhibit positive earnings and lower financing costs; this enables them to lower the marginal cost of substitution between financing and hedging. Similarly, for firms which fall above the speculative high-yield cutoff, they are better able to access traditional forms of high-yield financing, without onerous incurrence covenant restrictions on firm operations and investment activities[9]; this is further improved with decreased counterparty risk for the financial intermediaries of the firm. To the extent that firms can lower financing costs through higher ratings, particularly above sensitive thresholds, such as high-yield and investment grade, which affect upstream portfolio inclusion, firms may experience discontinuous jumps in lowering financing costs. Moreover, similar effects can be seen with respect to hedging, as firms with higher credit ratings can reduce the need for interest rate hedges, as they are able to secure long-term financing at lower rates, with particular benefit for those firms just above the threshold at the investment grade and speculative high-yield cutoffs.

We also consider three different specification designs to examine robustness with respect to model selection for the S&P RDD (linear probability sharp RD, multi-cutoff linear sharp RD, and panel Probit sharp RD). The first specification we use is a linear sharp RD:

$$SU_i = \beta_0 + \beta_1 T_i + \beta_2 DTC_i + \varepsilon_i \tag{1}$$

The outcome variable, *SU*, is a binary variable that is equal to one if a firm is using a swap (IRS, FX, CDS/CDX, Commodity, or Equity swap), and zero otherwise. The treatment variable, *T*, is an indicator variable, which is assigned a value of 1 if the credit rating is greater than or equal to the respective cutoff, and zero otherwise. *DTC* is the distance between the observed value of the credit rating and the cutoff. Since the running variable and the proximity and sign relative to the cutoff may confound the analysis, we include the same in our estimations[10]. We address the usual considerations with respect to predicted

[8] To visually identify the presence of these thresholds we plot the histogram of swap usage across group based on firms' credit ratings, following the binning procedure was originally suggested by Lee and Lemieux (2008).

[9] The NBER working paper of Bräuning, Ivanshina, and Ozdagli (2022) demonstrates how incurrence covenants restrict viable firm investment opportunities and firm operation decisions as a binding constraint, which are most prevalent among high-yield leveraged loans.

[10] The inclusion of the distance to the cutoff in the regression specification follows the approach of Chava and Roberts (2008) in attempting to address similar concerns of manipulation of the accounting variable by the firm. We

probabilities in a linear framework, and specify a Probit sharp RD as follows, where *Ind* represents the indicator function[11]:

$$\text{Ind}\ [SU_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 DTC_{it} + \beta_3 X_{it} + \ldots + \beta_k X_{it} + \varepsilon_{it}] \geq 0 \tag{2}$$

While the underlying assumption of a regression discontinuity design is local continuity, one can also include additional covariates, *X*, to control for variables of interest or concern as it pertains to the treatment effect or the dependent variable. It is also possible, such as in our situation, that a cumulative multi-cutoff regime exists. This requires a similar analysis of each individual cutoff, but it also provides an opportunity for weighted/pooled estimation of the regression discontinuities. This is similar in nature to a more general weighted estimation procedure of distinct sample estimations, but in this case with a weighted estimation of individual regression discontinuity estimations for each cutoff.

2. Debt-to-EBITDA: Fuzzy Regression Discontinuity[12]

The second measure we consider is Debt-to-EBITDA.[13] As discussed by Graham (2022), debt/EBITDA is the most popular measure of debt usage among firms; specifically, Graham notes that approximately 60% of small firms and more than 70% of large firms rely on this measure as one of their three most frequently used debt ratios. The Debt/EBITDA measure serves as a proxy for default risk by lenders and rating agencies in assessment of firm credit quality, and is used extensively for debt covenants. We examine two cutoff points: the first one is for the positive/negative Debt-to-EBITDA threshold, and the second one is the high-yield to speculative high-yield threshold for firms which exhibit significant financial and default risk.[14] Firms with negative earnings are highly sensitive to economic shocks, as they risk the ability to service and rollover existing debt or to generate sufficient cash flow to reduce leverage. Similarly, as firms shift from high-yield to speculative high-yield in terms of financial risk, they face a very significant jump in

take a similarly conservative approach to ensure that the marginal estimates for the treatment effect address the potential for the same.

[11] In our context, since we are predicting the likelihood of swap usage with firm characteristics, we do have concerns with respect to the typical considerations of predicted probabilities falling outside of the bounded interval, I = [0,1]. The linear probability model is instructive nonetheless as a potential baseline estimation, especially for RD models with a linear polynomial functional form, and we address such concerns with the subsequent panel Probit estimation.

[12] Our implementation of fuzzy regression discontinuity design is similar to Keys et al. (2010).

[13] Dichev and Skinner (2002), as well as others, have documented the importance of Debt/EBITDA in relation to access to finance and default probability. Debt-to-EBITDA measure does not restrict us to the subsample of rated firms, and it is the most common financial covenant included in firm debt (see Dichev and Skinner (2002)).

[14] To visually identify the presence of these thresholds we first sort the sample using Debt/EBITDA and created 20 groups. Next, we plot the histogram of swap usage across these ventiles.

their expected cost of financial distress. While hedging may be desirable for such firms, as shown by Giambona and Wang (2020), access to finance is limited[15]. This also introduces a potential distinction with respect to rated firms: while credit-rated firms with high credit risk can still access external public capital debt markets, albeit at a higher premium, firms without a credit rating and increased financial risk are dually constrained in both access to external public capital debt markets as well as financial intermediaries, including derivative markets.

We also implement a fuzzy RD approach using Debt/EBITDA, where the assignment to treatment is probabilistic in nature due to the continuous nature of the variable[16]. While the general procedure is analogous to the sharp regression discontinuity design, the model estimation is slightly different. The inherent miss-assignment between treatment and control groups makes the average treatment effects of pre and post-cutoff for a sharp RD suspect, since firms may self-select around the threshold and exhibit differences with respect to unobservable covariates. Thus, in the fuzzy RD design, the treatment effect common to the population is the ratio in differences of the expected outcome divided by the change in the propensity score for assignment. The interpretation of resulting coefficient estimates changes such that the average treatment effect is the switch from assignment to treatment non-recipient to treatment recipient crossing the threshold value.

We similarly examine four specifications for the Debt/EBITDA RDD (linear probability sharp RD, multi-cutoff linear sharp RD, linear probability fuzzy RD, and IV Probit fuzzy RD). We execute the following model as a linear fuzzy regression discontinuity:

$$D_i = \gamma_0 + \gamma_1 T_i + \gamma_2 DTC_i + \pi_1(Debt/EBITDA) + \eta_i \qquad (3)$$

$$SU_i = \beta_0 + \beta_1 D_{it} + \beta_2 DTC_i + \pi_2(Debt/EBITDA) + \varepsilon_i \qquad (4)$$

[15] Giambona and Wang (2020) rely on a Difference-in-Difference approach with the Safe Harbor or 2005 and find that fuel hedging by airlines increased for those closest to financial distress.

[16] Since Debt/EBITDA is continuous, the forcing variable divided into 30 bins to the left and right of the positive-negative threshold. Of course, the use of a fuzzy RD necessarily implies that there is not a discrete assignment to treatment or control and that there is the inherent potential for manipulation around the cutoffs in the form of self-selection. That said, since we are concerned with the probability of assignment, the failure to reject the null hypothesis may still lend robustness to other forms of non-random assignment, or limit the concerns applicable to self-selection. As is the same in the case of the sharp RD, ideally one would utilize thresholds where one fails to reject the null hypothesis of no discontinuity in the forcing variable, i.e. no non-random assignment or manipulation at any meaningful level of significance. Similar to the sharp RD, one ought to examine both the quantitative and qualitative elements of the McCrary (2008) test for the fuzzy RD thresholds; we examine each individual threshold for potential manipulation via the McCrary test in the form of self-selection or non-random assorting assignment, similar to the sharp RD specification.

D = 1 if firm i receives treatment, and 0 otherwise, T = 1 if firm i is assigned to treatment based on cutoff rule, and 0 otherwise, and π_n (Debt/EBITDA) = the probability f(x) (uniform) between Debt/EBITDA and the treatment receipt for firm i. To limit the potential for bias, we construct bandwidths that are relatively narrow around the threshold (or utilize the mean-squared optimal bandwidth), which results in less efficient estimates of the fuzzy RD treatment effect. However, to the extent that estimates are broadly similar between low-bandwidth and large-bandwidth specifications, and robust to the inclusion of fixed effects and clustering, or additional firm characteristics, we may be able to rely on estimates more externally valid.

We execute the fuzzy regression discontinuity model specification, with the same variables as in equations (3) and (4), as an instrumental variables Probit, with the following procedure:

$$D_i = \text{Ind}\ [\gamma_0 + \gamma_1 T_i + \gamma_2 DTC_i + \gamma_3 X_i + \ldots + \gamma_k X_i + \pi_1(Debt/EBITDA) + \eta_i] \geq 0 \tag{5}$$

$$SU_i = \text{Ind}\ [\beta_0 + \beta_1 D_i + \beta_2 DTC_i + \beta_3 X_i + \ldots + \beta_k X_i + \pi_2(Debt/EBITDA) + \varepsilon_i] \geq 0 \tag{6}$$

Where, X, represents the additional baseline covariates to control for variables of interest or concern as it pertains to the treatment effect or dependent variable, and *Ind* represents the indicator function. One drawback of the fuzzy IV Probit RD, inherent to the instrumental variable approach, is the more limited external validity. To the extent possible, we attempt to address this through robustness estimations with wider bandwidths. The lack of a high degree of sensitivity to bandwidth selection is promising in so far as it further suggests that the results of the fuzzy RD estimation are more externally valid.

3. *Regression Discontinuity Threshold Validation*

To examine potential manipulation for the chosen thresholds, we implement various tests.[17] Specifically we implement the McCrary (2008) test, where the null hypothesis is lack of discontinuity in the forcing variable. In addition, we utilize the local polynomial density estimation plot[18] for a visual assessment as to the distribution of observations around the cutoff, relative to the remainder of the distribution density. To the extent that a particular threshold is insensitive to small changes in polynomial order, narrower or

[17] This is useful in validating concerns regarding the self-selection or non-random assorting assignment (see implementation in Cattaneo, Jansson, and Ma (2018)).
[18] The plots are constructed using the *rddensity* package (see Cattaneo et al. (2020, 2021a, 2021b) for STATA package documentation)

wider bandwidths, and changes to an appropriate kernel selection, such elements tend to be indicative of a robust cutoff designation.

III. Data

In this section, we first describe the swap data repository dataset on swap contracts. We then describe the construction of the firm-level identification of swap users that we utilize in our empirical analysis.

A. Swap Data Repository (SDR) Data

In response to the 2008 global financial crisis, in September 2009, G-20 countries agreed on a broad reform agenda to improve the level of transparency in the over the counter derivatives (OTC) market by establishing a reporting requirement to grant policymakers and regulators access to high-quality, high-frequency data. This reform was turned into law by the Dodd-Frank Act of 2010, which established SDRs as the data warehouse, where trades and open positions of all swaps, encompassing anything denominated in any currency (that a financial economist would call a non-exchange-traded derivative) by U.S.-reporting entities are housed.[19] The SDRs collect, verify, and assemble the data, and share it with the CFTC. This paper is focused on the operating firms that are publicly traded. The data on the swap transactions and positions of individual entities (e.g. subsidiaries of a parent company) are identified by their LEIs. We aggregate the information of these individual entities up the level of the parent company. Initial reporting of the SDR data began in 2013, after the CFTC promulgated the regulations in accordance with Dodd-Frank [20] .

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[19] Dodd-Frank divides the relevant universe into security-based swaps (e.g., credit default swaps on individual corporations, total return swaps on individual stocks) which are regulated by the SEC, and swaps (e.g., interest rate swaps, foreign exchange, credit default swap indexes, commodity swaps, and equity swaps) which are regulated by the CFTC. In this paper, we focus on the swaps covered under CFTC regulatory framework. U.S. reporting entities include U.S. entities, U.S. subsidiaries of foreign entities, and swap dealers registered with the CFTC, who may be foreign entities

[20] In the EU, this policy was implemented under the guidance of the European Market Infrastructure Regulation (EMIR) which requires that EU reporting entities report the details of derivative transactions to a trade repository authorized by the European Securities and Markets Authority (ESMA). This reporting obligation covers all asset classes and applies to clearinghouses, financial counterparties, and nonfinancial counterparties that are legal entities under the EU jurisdiction. This reporting obligation was first introduced in February 2014, and expanded to include a formal data validation process in November 2014.

B. Financial Data

Our sample considers all publicly traded U.S. firms with financial data available between 2018 and 2021. We use the CIK identifier in CRSP/Compustat Merged Database to search for these firms in the S&P LEI hierarchy database, which allows us to link the parent companies (the publicly traded U.S. companies) to their subsidiaries. Unlike other financial instruments, the unique identifier for swaps and swap users is their Legal Entity Identifiers (LEI), which is used across markets and jurisdictions to uniquely identify a legally distinct entity that engages in a financial transaction.[21] We must conduct this intermediate step to link parent companies to their subsidiaries, because the open swap positions data reported to the CFTC with the procedures described under Part 45 of the Commodity Exchange Act is at the subsidiary level.[22]

We have slightly over ten thousand firm-year observations of U.S. public firms for financial data available in CRSP/Compustat. While we use this universe for most of the analysis presented in figures, for our statistical analysis, we remove utilities and financial firms from the sample. This restriction leaves us close to seven thousand firm-year observations, where close to 40% are identified as swap users. The financial characteristics we consider include: firm size (proxied for by natural logarithm of total assets), capital expenditures (scaled by total assets), asset tangibility (proxied for by property, plant and equipment and scaled by total assets), profitability (EBITDA scaled by sales), foreign profits (foreign EBITDA scaled by sales), book leverage (proxied for by the sum of short and long term debt scaled by the sum of short and long term debt and book equity), intangible assets (proxied for by R&D expense scaled by sales and selling

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[21] LEI is a 20-digit alphanumeric code and associated set of six reference data items to uniquely identify a legally distinct entity that engages in financial market activities. This global standard meets the 2012 specifications of the International Organization for Standardization (ISO 17442:2012). The LEI system first proposed in November 2010 by the OFR and in 2013 Financial Stability Board facilitated the oversight of the global adoption of LEI by Regulatory Oversight Committee. A large financial intermediary, for example, will have an LEI identifying the parent entity and a LEI for each of its legal entities that buy or sell stocks, bonds, swaps, or engage in other financial market transactions

[22] The 2010 Dodd Frank Act (DFA) mandates reporting of these data for OTC derivatives through Swap Data Repositories (SDRs) to the relevant regulatory agencies to improve the transparency of the swaps market. The data is structured as two complementary data sets containing information on trades and open positions for all swap transactions involving a CFTC regulated entity. The data on trades are collected daily and represents a flow of transactions between counterparties with information describing the size and pricing of trades. The data on open positions are reported weekly as a stock of open exposures between counterparties containing information detailing the current valuation of open traders. Even though the data on open positions is constructed as an aggregate of past trading activity, these two data sets are not directly comparable as a trade may undergo several transformations during its lifetime including novations, compressions, or allocation to a central counterparty, which may be overlooked by grossing up past trading. Consequently, while the trades data accurately describes the original terms of transaction, the open positions data is a faithful representation of the point in time economic exposure between counterparties.

expense scaled by sales), firm age (proxied for by the natural logarithm of the number of years the firm has been public), HHI which proxies for industry-level competition, dividend payer (indicator variable that takes the value 1 if the firm has paid out dividends in the fiscal year and zero otherwise), Altman Z-Score (proxies for firms' two-year default probability), operating cash flow volatility (firm's quarterly cash flow volatility over three prior years), short-term debt scaled by sum of short and long term debt, and cash (cash and cash equivalents scaled by total assets). HHI is constructed as the natural logarithm of the Herfindahl-Hirschman Industry Index, using sales within Fama-French 48 Industry Classification (FF48). Its value range between 0 and 10,000, where an increase in the HHI Index corresponds with a decrease in industry concentration. Altman Z-Score is constructed as used in Campello et al. (2011), following Altman (1968, 2002). The S&P credit ratings are obtained from Bloomberg. A more detailed description of these variables is provided in Appendix B.

We identify a firm as a swap user by screening the Part 45 data for the open swap positions as of the second to last Friday of every quarter between 2018 and 2021, totaling fifteen quarters for each of the five swap markets (IRS, FX, CDS/CDX, Commodity, and Equity). Our screen includes both the parent firm's LEI as well as all its subsidiaries, as they are identified by the S&P LEI database. The mapping between the financial data and the swap data is done via CIK.[23] Part 45 data is only used to generate indicator variables for whether a firm is a swap user or not, which in essence is disclosed in their annual 10-K filings with the SEC. Our analysis at this point does not consider any other information about the firms' swap position (such as the position size or their counterparties).

IV. Empirical Analysis

A. Univariate Analysis

Our first step in investigating the participation of the public corporations in the swaps markets is to revisit some of stylized facts documented in prior studies. We conduct a simple univariate analysis comparing swap users and non-users over a number of firm characteristics that are either predicted to be important for firms' risk management decisions in theoretical studies, or shown by the empirical literature as

[23] This matching process leaves a small percentage of S&P 1500 firms unmatched (<1%), but presumably a larger fraction of the smallest firms in the swaps data unmatched to the CRSP/Compustat data. For these firms we need to conduct additional searches, which is not yet part of the analysis presented in this paper.

important factors influencing firms' decisions to use instruments to manage risk. This analysis is presented in Table I, Panels A and B.

[Insert Table 1 Here]

Table I, Panel A, presents the number of observations, mean, standard deviation, t-stat and p-value of the mean difference of firm characteristics between the two categories of firms (swap users and non-users). Largely consistent with prior studies, we find that swap users tend to be larger, older, more levered, with more long-term debt than short-term debt, and more profitable. Swap users also have more tangible assets, fewer intangible assets, fewer growth opportunities, and have a larger fraction of their sales and profits originating from foreign operations. Swap users also tend to be less financially constrained (a larger fraction of them are dividend payers), but hold less cash on their balance sheet for immediate access. Table I, Panel B, presents the univariate correlation statistics for each of the firm characteristics examined in the comparison of swap users and non-users in Panel A.

We consider the relationships identified in Panel A, i.e. older, larger, more levered, and more profitable firms, with a higher percentage of long-term debt, specifically with respect to financing access through credit rating and index participation channels in the correlation statistics of Panel B. In so far as financing may have complementary or substitution effects with respect to firm hedging decisions, the correlation statistics can provide some insight into the underlying firm characteristics. We find a higher degree of correlation among rated firms with respect to measures of size (assets/sales), profitability, age, leverage, foreign profitability, OCF volatility, and index participation. It is worth noting that while being S&P-rated is positively correlated with leverage and negatively correlated with R&D, the S&P rating conditional on being rated is negatively correlated with leverage and positively correlated with R&D. Similarly, we find a higher degree of correlation among index participation categorization with size (assets/sales), profitability, age, foreign profits, OCF volatility, and dividend payers. While the univariate analysis thus far divides the sample between swap users and non-users, we know from the prior literature that credit access is important to the risk management decisions of firms.

Thus, our second step is to conduct a similar investigation of swap users/non-users for S&P-credit rated/non-rated firms. Our univariate analysis comparing the S&P credit-rated and non-S&P credit rated firms for the selected firm characteristics is consistent with prior literature regarding the impact of firm credit ratings.

[Insert Table II Here]

Table II, Panel A, presents the S&P credit rating group, numeric rating equivalent for purposes of subsequent analysis, frequency of observations, and percent of total S&P credit-rated observations. Since our particular interest is initially with respect to the S&P-rated subset of U.S., non-financial firms, the rating table is limited to the same. The S&P issuer credit ratings are centered around B- to A+, with BB exhibiting the highest number of S&P-rated firms. Similar to the comparison of swap users and non-users in Table I, we examine S&P-rated versus non-rated firms in Table II, Panel B.

Table II, Panel B, presents the univariate statistics, including observation count, mean, standard deviation, t-stat of the difference, and associated p-value difference for S&P-rated and non-rated firms. Similar to our consideration of swap users and non-users in Table I, Panel A, S&P-rated firms tend to be larger, more profitable, more levered, older, have lower R&D expenditures, a higher percentage of long-term debt, lower cash holdings, and increased index participation. Having identified important characteristics at the univariate level, we further investigate swap usage by S&P index participation (size), S&P credit rating (external debt market access), swap product (hedging use case), and industry (hedging intensity) in Figures 1 through 5.

B. Swap Market Participation Among the S&P Index Constituents and Non-Constituents

As our next step, we examine the use of swaps among firms by categorizing them based on their status as an S&P index constituent. More specifically, for each of the fifteen quarters examined between 2018 and 2021, we calculate the percentage of firms using a particular swap in a given index category. The graphs plotting the percentage of swap users across time is presented in Figure 1.

[Insert Figure 1 here]

We draw a number of novel observations from Figures 1a through 1f mapping swap use by index participation across time. First, swap market participation is common, both among the largest firms (S&P 500 index constituents), as well as smallest firms (firms that are not part of an S&P index), around 85% and 35% respectively, which stays about the same across the fifteen quarters. The participation to the swap market slightly increases for the small-cap firms (S&P 600), from 50% to 54% and slightly decreases for mid-cap firms (S&P 400) from 72% to 65%.

Second, we observe that FX and IRS are the two most widely held swaps among public firms across all index and non-index constituents; while FX seems to be more dominated by large firms (around 72% for

S&P 500 constituents and 25% for non-index firms), IRS seems to be preferred across all index categories (around 60% for S&P 500 constituents and 30% for non-index firms). For the remaining three swap types, CDS/CDX, Commodity swaps, and Equity swaps, the participation is mostly by large-cap firms (S&P 500 constituents), with little or modest participation by small-cap firms and non-index firms. Even among the large-cap firms, the participation to these three swap markets (CDS/CDX, Commodity, and Equity) declines considerably over time, with the sharpest decline in equity swap market participation the last quarters.

It is further worth noting the impact of the pandemic period, with a sharp decline in commodity swap usage, as well as a modest decline in IRS usage, followed by an increase from 2020 Q3 to 2020 Q4. FX, CDS/CDX, and Equity swaps appear to largely unaffected by the pandemic period as it pertains to usage.
To analyze the preference for participating to one of the five swaps we examine, we next look at percentage of participation in a given index group. The graphs plotting the percentage firms in a given index group participation to various swap markets across time is presented in Figure 2.

[Insert Figure 2 here]

The results in Figures 2a through 2d suggest that for firms in mid-cap (S&P 400) and small-cap (S&P 600), participation to the FX and IRS markets are about the same across the fifteen quarters examined, except that for small-cap firms, IRS becomes gradually more utilized, and FX becomes gradually less utilized, starting with the second quarter in 2019. The contrast between the large-cap (S&P 500) and the smallest firms in our sample (non-index firms) is quite stark: while both IRS and FX are the two most commonly used swaps, the use of IRS is more than 50% as common as the use of FX for the smallest firms, whereas the use of FX is 25% more common compared to IRS for the largest firms.

C. Swap Market Participation Across Industries

One of the most novel aspects of our study is its comprehensive coverage of publicly traded firms in the U.S., as most prior studies examining corporate firm risk management decisions are conducted on select industries. To examine the use of swaps across firms operating in different industries, we group firms into 12 categories, using the Fama-French 12-industry classification (FF12). More specifically, for each of the fifteen quarters between 2018 and 2021, we calculate the percentage of firms using a particular swap in a given industry. The graphs plotting the percentage of swap users across time is presented in Figure 3.

[Insert Figure 3 here]

From industry-swap usage Figures 3a through 3f, we make a number of novel observations. First, firms in the healthcare industry are the least represented industry as swap users, where about 9% of the firms use IRS and about 13% of the firms use FX, and there is almost no participation to the remaining three swap markets. On the other hand, firms in utilities have the highest participation to the IRS, CDS/CDX, Commodity, and Equity swaps, aside from financials.

Second, five non-financial industries: chemicals, manufacturing, energy, consumer durables, consumer non-durables have more than 50% of the firms participating to one of the five swap markets we examine. Firms in business equipment, wholesale, and telecom are also relatively common swap users, with close to 40% participation in one of the five swap markets. In IRS, participation among telecom, chemicals, consumer durables, consumer non-durables, wholesale, and manufacturing ranges from 25% to 40%. Firms in the energy industry increase by 50% in number in terms of their IRS use. In FX, firms in the chemicals industry have a significant percentage of participation across time, reaching over 60% of the firms in the industry by the end of our sample period. Manufacturing, consumer durables, and chemicals also have high usage, with close to 50% of the firms in these industries using FX. The participation of CDS/CDX is most common among utilities, with growing participation in the last nine quarters of the sample, while the percentage of firms in telecommunication participating in the CDS/CDX markets declines over time. Commodity swaps are most popular among firms in energy, where close to 50% of the firms in the industry participate in the swap markets, with utility usage roughly similar. Firms in the chemical industry also show strong interest in commodity swaps, with the participation increasing from 20% to 30% of the firms in the industry, over the time period we examine. These results emphasize the substantial heterogeneity in swap usage across industries, which has important implications for the broader applicability or external validity of results in single-industry studies.

We further examine swap market participation by partitioning based on firm S&P credit rating classification. The graphs plotting the percentage of swap users across time by S&P rating status is presented in Figure 4.

[Insert Figure 4 Here]

From Figures 4a through 4f, we find that across all swap usage, the percentage of usage among S&P rated firms is higher, as well as for FX and Commodity swaps. Surprisingly, however, for IRS, CDS/CDX, and Equity swaps, swap usage as a percentage of firms is higher among unrated firms. For non-S&P rated firms, it is universally the case across all swap product categories that the percentage of use is lower among non-S&P rated firms, and is roughly consistent across time.

We provide similar further context to the Figure 2 index participation results by splitting swap product market usage by index and S&P credit rating in Figure 5.

[Insert Figure 5 Here]

Consistent with the percentage usage among rated and non-S&P rated firms in Figure 4, in Figures 5a through 5d, we find a higher usage in each product market by index participation for S&P rated firms. For the largest firms, this difference is slightly starker, with S&P 400 and S&P 600 firms exhibiting relatively similar percentages of swap usage by product category among both rated and non-S&P rated firms. The difference between the percentage of usage among rated and non-S&P rated firms is most visible among non-S&P index firms, consistent with increased access to financial intermediaries for index firms.

D. Predicting Swap Market Participation

Next, we conduct a multivariate analysis by estimating a Probit model to assess which firm characteristics are important in determining the likelihood that a firm participates in the swap markets. In our estimation we control for industry fixed effects and year fixed effects, with robust-clustered t-statistics. The results are presented in Table III, Panels A and B. Panel A presents the results for the baseline Probit estimation with some of the most important firm characteristics identified in the prior literature as it pertains proxies for various aspects of firm hedging decisions. Panel B includes additional relevant firm characteristics to hedging decisions.

[Insert Table III Here]

The regression results in Table III, Panels A and B, establish that firm size is the most consistent contributor to firms' decision to become a swap user. Firm size is particularly important for the likelihood of firms using IRS, FX, CDS/CDX, and Commodity swaps, suggesting that larger firms are more likely to benefit from a risk management program. Firm age is similarly important in determining the likelihood of a firm using a swap, with the exception of IRS, where participation does not seem to be affected by firm age. This is a novel finding as prior studies generally suggest that swaps are used by mature firms. Firms' book leverage is also a particularly important determinant of swap market participation across all swap categories, except equity swaps, consistent with the cost of a risk management program lessened for firms with high financial leverage. We also find that firms with high capital investment are more likely to participate in a swap market, and specifically FX, as they benefit from a risk management program that allows them to maintain their long-term capital investment decisions. On the other hand, firms with high tangible assets are less likely to participate to an FX swap market, which is consistent with the notion that benefits from a risk management program are marginal for these firms, as they can use their collateral to more easily access external public capital debt markets. Interestingly, the high tangible assets have a positive and opposite effect as FX for commodity swaps, with firms being more likely to use swaps. Another novel finding is that firms with higher foreign sales are more likely to use a swap, and this effect is present across all swap categories, suggesting that these firms are most likely to benefit from a risk management program. Profitability, R&D, and SG&A coefficients are both negative and significant for IRS and FX, meaning that firms with higher Profitability, R&D, and SG&A expenses are less likely to use such swaps, consistent with expectations regarding growth opportunities and future investment.

Some of our findings are thought provoking. In Table III, Panel A, we find that firms with increased intangible assets, proxied by selling expense, are less likely to use IRS and commodity swaps, while we do not find statically significant results in other specifications. On the other hand, Table III, Panel B, shows that being a dividend payer and industry competition are not significant across any of the specifications. Operating cash flow volatility is significant for Commodity swaps, meaning firms with higher operating cash flow volatility have a greater need for hedging activity, though it is insignificant for other swap markets. Finally, S&P index participation is highly significant for FX swap usage and positive, meaning index firms are much more likely to use FX swap markets. While S&P index participation is positive and significant for general swap market participation and FX swap usage, it is negative and highly significant for IRS usage. We postulate that this might be due to the high degree of fixed-float swaps with respect to index firms and their access to long-term capital debt markets.

E. Swap Market Participation by Rated and Unrated Firms

Following the examination of swap market participation determinants for the full sample of U.S. public non-financial firms, we split the sample according to the S&P issuer rating status of the firm. We conduct a similar analysis to assess on which firm characteristics are important in determining the likelihood that a firm participates in the swap markets, with the S&P credit rating serving as a proxy for the default probability of a firm and the access of the firm to external public capital debt markets. In our estimations, we control for industry fixed effects and year fixed effects, with robust-clustered t-statistics. The results are presented in Table IV, Panels A and B. Panel A provides the Probit estimations for S&P credit-rated firms, and Panel B provides the Probit estimations for non-S&P rated firms.

[Insert Table IV Here]

The regression results in Table IV, Panels A and B, demonstrate that firm size is important for both S&P credit-rated and non-S&P rated firms, with relatively similar magnitude to the full sample baseline specifications in Table III. This is consistent with larger firms being more likely to benefit from a risk management program. Unlike the full sample estimation, Panels A and B show that firm age is particularly important for non-S&P rated firms, but not as important for S&P rated firms (except for FX swap market participation). Older firms are more likely to use swaps, and for non-rated firms, more mature firms are more likely to use FX and CDS/CDX.

We also find interesting results with respect to book leverage as compared with the baseline Probit estimation. As shown in Table IV, Panel A, for S&P credit-rated firms, higher financial leverage is not predictive of increased IRS swap usage, whereas for the non-S&P rated firms in Panel B, it is highly predictive. This highlights the impact of the existence of a credit rating for a firm on determinants of swap usage. For capital investment and tangible asset intensity, we find similar results for rated and unrated firms to the baseline Probit estimation. We also find novel findings with respect to R&D for rated vs. unrated firms; while increased R&D expenditures are only predictive of reduced IRS usage for rated firms, increased R&D expenditures are predictive of reduced swap market participation, IRS, and FX usage for unrated firms. This is consistent with firm investment in future growth opportunities and real options as a substitute effect. Heretofore, we provided important univariate and multivariate Probit results which resolve prior disputes in the literature by utilizing the full universe of public firms and splitting the sample on important firm characteristics as it relates to hedging and access to external public capital debt markets. Yet, we cannot draw causal conclusions from the same, however compelling the evidence, and hence the subsequent specifications utilizing a regression discontinuity approach.

F. Regression Discontinuity

As noted, we give special attention to the potential for endogeneity in the Probit estimations. We implement two distinct regression discontinuity designs to partially address such concerns, as well as to examine the impact on significance and magnitude of the estimates of the firm characteristics. We conduct a multivariate analysis by estimating a sharp regression discontinuity for swap market participation for the subsample of credit rated firms, by exploiting a source of reasonably exogenous variation to the firm; this approach relies on two cutoffs identified by binning plots (Figure 7a), B+ and BBB[24]. We also implement a fuzzy regression discontinuity approach for swap market participation for the full sample of firms using Debt/EBITDA. This similarly relies on two cutoffs identified in a ventile binning procedure (Figure 6b), i.e. a positive/negative threshold and a high-yield threshold, with a Debt/EBITDA cutoff of 0 and 5.7, respectively. Importantly, both estimation procedures produce broadly consistent results as it pertains the baseline Probit estimations in Tables III and IV, for the full sample and subsample of S&P credit-rated firms, respectively. We start our RD analysis in Figure 6a with the subsample of S&P credit-rated firms, mapping swap usage by credit grade.

1. Regression Discontinuity: S&P Credit Rating

To examine the existence and validity of the designated S&P credit cutoffs, we first produce a plots of the cutoffs (Figure 7a) and McCrary (2008) test statistics for the same (Figure 8a and Figure 8b). We first group S&P ratings by letter grade, with the associated count, mean, median, standard deviation, min, max, and 25th/75th percentiles included in Table V, Panel B.

[Insert Table V Here]

For the two respective cutoffs of the sharp RD S&P credit rating estimation, the average credit rating groups are 13 (BBB, second cutoff for sharp RD with S&P), and 8 (B+, first cutoff for sharp RD with S&P). We similarly provide the histogram of the S&P credit rating distribution for visual inspection in Figure 6a.

[Insert Figure 6a Here]

Consistent with the analysis of prior literature, the S&P credit rating for U.S. non-financial public firms is bi-modal. In Figure 7a, we plot the respective cutoffs by S&P rating group to examine the existence of discontinuities in swap usage by bin average.

[Insert Figure 7a Here]

Indeed, we observe a sharp discontinuity in the S&P credit rating plot at B+ (S&P rating group 8) and a similar drop at BBB (S&P rating group 13). Due to the discrete nature of the S&P rating and partially exogenous determination of the issuer credit rating by S&P, we utilize a sharp RD for the estimation of the S&P credit-rated subsample. As is typical in RD estimations, we also conduct McCrary (2008) manipulation testing. This test examines manipulation around the respective cutoff thresholds to examine the potential for non-random assignment. The McCrary (2008) robust test statistics for the first

[24] This follows the procedure of Lee and Lemieux (2008) for regression discontinuity threshold identification, as well as the approach utilized in Chava and Roberts (2008).

and second cutoff of each RD estimation are provided in Figure 8a and Figure 8c, as well as the plot of the distributions around the cutoffs.

[Insert Figure 8a and 8c Here]

As show in the S&P credit-rated subsample McCrary (2008) tests of Figure 8a and 8c, for the first cutoff (B+), we fail to reject the null hypothesis of no manipulation in the threshold. However, for the second cutoff (BBB), we reject the null hypothesis of no manipulation in the cutoff threshold at the alpha 1% level, implying that there is a potential for non-random assignment. While not necessarily prohibitive, this may indicate that the investment grade threshold cutoff is subject to some non-random assignment above and below the cutoff, making the inclusion of *DTC* quite appropriate to control for the same[25].

Using two cutoffs, B+ and BBB, we estimate sharp RD results within designated bandwidths (using mean-square error (MSE) optimal bandwidths where applicable) in Table VI, Panels A and B, and include various controls for industry fixed effects, year fixed effects, and firm characteristics of the particular interest in the baseline Probit estimation of Table III (the same covariates as Table IV for the S&P-rated subsample). We include robust-clustered t-statistics in each estimation. The results are presented in Table VI, with the results for the first cutoff (B+) included in Table VI, Panel A, and the results for the second cutoff (BBB) included in Table VI, Panel B.

[Insert Table VI Here]

In each specification (1)-(7) of Table VI, Panel A, for the first threshold (B+), except the wider RD bandwidth of 5 (without fixed effects), we find a highly significant and negative treatment effect for firms crossing the threshold. This is a novel finding for the literature, namely that firms that experience a sharp increase in their access to capital markets decrease usage of swap markets. This is consistent with a substitution effect between access to external public capital debt markets and firm hedging decisions, and indeed shows that financially more constrained firms are more likely to hedge using swaps[26].

Noting the potential limitation with respect to the investment grade threshold for S&P ratings, we provide a weighted and pooled estimation of the regression discontinuity design in the format of a cumulative multi-cutoff scenario[27]. Observations with a numeric rating less than or equal 10 (BB) are classified as

[25] Following the approach of Chava and Roberts (2008) for the treatment of the accounting variable thresholds.
[26] This is consistent with the findings of Giambona and Wang (2020) for their study examining the airline industry and the 2005 Safe Harbor Reform.
[27] For the linear RD pooled and weighted estimation procedure, we utilize the *rdmc* package in STATA, following Cattaneo et al. (2015a, 2015b, 2017). For the panel Probit estimations, we report each threshold treatment effect

belonging to the first high-yield (HY, B+) estimation, and observations with a numeric rating greater than 10 are classified as belonging to the second investment grade (IG, BBB) estimation.[28] The numeric results of this multi-cutoff weighted regression are presented in Table VI; the first cutoff (B+) is shown in Panel A, column (1), the second cutoff (BBB) is shown in Panel B, column (1), and the weighted results are shown in Panel C, column (1)). Figures 9a through 9c detail the visual plot of the multi-cutoff sharp regression discontinuity.

[Insert Figure 9a, Figure 9b, and Figure 9c Here]

As shown from the results in Table VI, Panels A through C, both cutoffs are significant in the linear sharp RD estimation and the weighted estimation procedure, but not significant in the pooled regression (unreported). The treatment effect at the HY (B+) threshold is such that a change from non-treated to treated results in a decrease in the probability of swap usage by 5.05%. Similarly, the treatment effect at the IG (BBB) threshold is such that a change from non-treated to treated results in a decrease in probability of swap usage by 15.23%. While the coefficient estimate for the IG threshold is approximately three times greater than the estimate for the HY threshold, we fail to reject the null hypothesis that the average effect differs between the two estimates.[29] It is worth noting that the distance to the cutoff variable is itself is insignificant at the alpha 10% level, but the p-value for the conventional estimate is 0.104, meaning its inclusion in the panel Probit estimation for the regression discontinuity is likely appropriate. The pooled estimation results in a coefficient estimate that is negative, but is insignificant, whereas the weighted approach results in a coefficient estimate that is similarly negative and of comparable magnitude to the individual estimations, and significant at the alpha 1% level. To the extent that firms with higher credit ratings differ materially from firms with lower credit ratings, these results are expected, and a weighted approach is appropriate for our situation. The weighted treatment effect is such that a change from non-treated to treated results in a 10.07% decrease in the probability of swap usage, *ceteris paribus*. For comparable results with the baseline Probit estimations of Table III and IV as to the determinants of swap usage, we conduct an analogous panel Probit regression discontinuity design in Table VI.

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separately, given the concerns regarding the potential for manipulation at the IG threshold as evidenced by the McCrary test.

[28] This is done to avoid oversampling of the interior, and thus biased estimates in the pooled and weighted linear estimations.

[29] Test of the linear difference between the coefficient estimate of the two thresholds results in a p-value not significant at any meaningful level of significance.

We estimate the same sharp RD using a panel Probit approach, columns (2) through (7) of Table VI, akin to our baseline regression model. We conduct several estimations with varying bandwidths (mean-square error (MSE) optimal where appropriate) and the inclusion of fixed effects and firm characteristics. In Table VI, Panel A, for the HY (B+) threshold and a narrower bandwidth (two S&P rating grades above and below the cutoff) without fixed effects or baseline controls in column (2), the treatment and distance to cutoff variables are both significant at the alpha 5% and 1% levels, respectively. The treatment effect is negative with a magnitude of -1.06, i.e. a change from non-treated to treated results in a 1.06% decrease in the probability of swap usage, *ceteris paribus*. The distance to cutoff (*DTC*) is positive, with a smaller magnitude of 0.84. Including industry and time fixed effects in column (3) yields similar results, with the treatment effect negative and significant at the alpha 1% level, and *DTC* positive and significant at the alpha 1% level.

When including the baseline Probit controls in column (4), the treatment effect is still negative and significant at the alpha 10% level, where a change from non-treated to treated results in a 0.95% decrease in the probability of swap usage. When the firm characteristics are included as regressors, *DTC* is no longer significant at any meaningful level of significance, while *Size*, *Book Leverage*, and *Foreign Profits* are all significant with similar magnitudes as the baseline Probit estimation.

In Table VI, Panel A, estimating the panel Probit sharp RD model with a larger bandwidth (five S&P rating grades above the cutoff) for the HY (B+) threshold yields consistent results; for the panel Probit RDD estimated with this larger bandwidth in column (5), the treatment effect is still negative with a magnitude of -0.55, but no longer significant. *DTC* is positive and significant with a magnitude of 0.56. The inclusion of industry and time fixed effects in column (6) yields a treatment effect that is negative and significant, where a change from non-treated to treated resulting in a 0.78% decrease in the probability of swap usage. *DTC* is positive and significant with a marginal effect of 0.54. Inclusion of the firm characteristics as regressions as well as industry and time fixed effects result in the treatment effect that is negative and statistically insignificant, and *DTC* slightly positive and insignificant. *Size*, *Book Leverage*, and *Foreign Profits* are all positive and significant, with similar magnitudes as in the S&P-rated baseline regression in Table IV, Panel A. The decline in the significance of the HY (B+) threshold with the larger bandwidth is suggestive of reduced external validity for the HY RDD.

The results for the panel Probit sharp RD estimation with a narrower bandwidth for the IG (BBB) threshold (columns (2)-(4) of Table VI, Panel B) are quite similar to that of the HY threshold.[30] The treatment effect for the IG threshold is negative and significant, with and without the inclusion of industry and time fixed effects in columns (2) and (3) of Table VI, Panel B. Similarly, *DTC* is positive and significant. With the inclusion of fixed effects, a change from non-treated to treated results in a 1.10% decrease in the probability of swap usage. Similarly, *DTC* is positive and significant with a magnitude of 0.55.

Including firm characteristics as regressors (column (4) of Table VI, Panel B) results in *DTC* as being no longer significant. The treatment effect is negative and significant at the alpha 10% level, with a magnitude of -0.95, i.e. a change from non-treated to treated resulting in a -0.95% decrease in the probability of swap usage, *ceteris paribus*. Comparing this with the baseline panel Probit estimation in Table IV, *Size, CapEx*, *Prop. Plant & Equipment.*, *Book Leverage*, and *Firm Age* are all significant with similar magnitudes as that of the original specification in Table IV, Panel A, except *Book Leverage*, which increases by 69.94%.

Estimating the model with a larger bandwidth (six S&P rating grades above and below the cutoff) for the IG (BBB) threshold yields consistent results (Table VI, Panel B, columns (5)-(7)). Without fixed effects in column (5), the treatment effect is negative and significant, and *DTC* is positive and significant. With industry and time fixed effects in column (6), a change from non-treated to treated results in a 1.25% decrease in the probability of swap usage. *DTC* is positive and significant with a magnitude of 0.63.

The inclusion of the baseline controls in column (7) lends to the significance of *DTC* attenuating, similar to the prior specifications and suggestive of it serving as a proxy for the baseline controls. With fixed effects and baseline controls, the treatment effect is positive and significant, with a change from non-treated to treated resulting in a 1.26% decrease in the probability of swap usage. Consistent with the narrower bandwidth, *Size*, *CapEx*, *Book Leverage*, and *Firm Age* are all positive and significant with similar magnitudes. *Prop. Plant & Equipment* loses its significance with the wider bandwidth, while *R&D* becomes significant.

[30] As to the McCrary (2008) test and to address concerns as to differences among firms above and below the IG threshold, we conduct a series of univariate t-tests to examine sample differences of those firms just above and below the IG cutoff for all the covariates included in the baseline panel Probit estimation of the determinants of swap usage. The univariate t-tests result in p-values insignificant at the alpha 5% threshold, with the exception of Altman Z-Score, book leverage, and index participation; Altman Z-Score is expected given its relation to predicted two-year default probability.

Across the S&P rating specifications, there are several conclusions we draw. First, the treatment effect is negative and significant regardless of the HY/IG (B+/BBB) threshold, inclusion of industry and time fixed effects, or inclusion of the firm characteristics as regressors (except the wider bandwidth of HY). The magnitude of the treatment coefficient across these specifications suggests that a change from non-treated to treated results in an approximate 1% decrease in the probability of swap usage. This emphasizes the significance of credit risk and access to finance as it relates to hedging decisions of the firm. A second takeaway is that the magnitude of swap use determinants in the baseline Probit specification for the subset of rated firms (Table IV, Panel A) has relatively consistent estimates with the regression discontinuity design for the subset of S&P-rated firms (Table VI, Panels A and B) intended for addressing endogeneity concerns. While there are some slight changes, they are mostly consistent in magnitude except for *Book Leverage* in the IG (BBB) specifications of Table VI, Panel B, which increases in magnitude by 69.94% (column 7). This serves to further highlight the importance of S&P investment grade standing as it relates to firm access to financing and maximizing firm value. The last important conclusion is that the *DTC* variable loses significance with the inclusion of firm characteristics as additional regressors, i.e., there is no addition information included in the distance to the cutoff, once baseline covariates and industry and time fixed effects are included.

The results from the S&P credit-rated regression discontinuity design indicate the causal relationship as a substitution effect between access to external debt markets and hedging, with an increased marginal effect for constrained firms around the threshold. However, these results are only sufficiently justified for S&P credit-rated firms, i.e. firms with substantial access to external debt markets, even those that are more credit risky and financially constrained. As discussed by Graham (2022), Debt/EBITDA is the most important measure of financial risk more broadly for firms, and we rely on this measure in developing our approach for a regression discontinuity design with estimation results applicable to the broader universe of public firms.

2. Regression Discontinuity: Debt/EBITDA

In a similar fashion as we examine the thresholds for the RD estimation procedure of the S&P-rated subsample, we generate a plot of swap usage by ventile using the Lee and Lemieux (2008) binning procedure (Figure 7b), as well as McCrary (2008) threshold statistics to examine the existence and validity of the designated cutoff (Figures 8b and 8d). We group Debt/EBITDA by ventile bin; the associated count, mean, median, standard deviation, min, max, and $25^{th}/75^{th}$ percentiles are included in Table V.

[Insert Table V Here]

For the two respective cutoffs of the fuzzy RD Debt/EBITDA estimation, the cutoffs are centered at the positive to negative threshold (0) and the approximate speculative high-yield threshold (5.7), designated based on the data (see Figure 7b) and economic explanation previously discussed for financial and default risk of investment grade and highly leveraged firms. We similarly provide the histogram Debt/EBITDA distribution for visual inspection in Figure 6b.

[Insert Figure 6b Here]

Debt/EBITDA exhibits significant distribution outliers, which are winsorized at the alpha 1% level. In Figure 7b, we plot the respective cutoffs by Debt/EBITDA ventile to examine the existence of discontinuities in swap usage by bin average.

[Insert Figure 7b Here]

The Debt/EBITDA ventile plot shows a jump at the positive/negative threshold (ventile 6), as well as high-yield (ventile 18)[31]. For Debt/EBITDA, we utilize a fuzzy RD design, since the classification of firms above and below the two thresholds is probabilistic in nature, and the variable Debt/EBITDA is continuous. It is also worth noting that Debt/EBITDA covenants for high-yield debt contain firm-specific modifying provisions that make the fuzzy discontinuity approach more appropriate.

As is typical in RD estimations and consistent with our approach up to this point, we conduct McCrary (2008) manipulation testing for the designated thresholds (Figures 8a and 8d). This test examines manipulation around the respective cutoff thresholds to examine the potential for non-random assignment. The McCrary (2008) robust-test statistics for the first and second cutoff of each RD estimation are provided in Figures 8b and 8d, as well as the plots of the distributions around the cutoff.

[Insert Figure 8b and Figure 8d Here]

For Debt/EBITDA in Figures 8b and 8d, neither cutoff is significant at the alpha 10% level, meaning that one fails to reject the null hypothesis of no manipulation at the cutoff threshold. Indeed, in Figure 8b and Figure 8d, there is no significant observable increase in the density of observations indicative of cutoff manipulation. This lends some degree of confidence that there is no self-selection by firms or other form of non-random assignment around the designated cutoffs where we observe a discontinuity in the probability of swap usage.

[31] Based on the ventiles of Table V, we designate the cutoffs at the interior of the midpoint.

We estimate a fuzzy RDD model using of Debt-to-EBITDA as detailed by equations (5) and (6) in Section III detailing the methodology of our approach. The cutoffs for the fuzzy RD closely correspond with the cutoffs used in the S&P-rated subsample, as evidenced by Table V, Panels A and B (i.e. the investment grade cutoff of 13 (BBB) corresponds to the positive/negative Debt/EBITDA (0), and the high-yield grade cutoff of 8 (B+) corresponds with the Debt/EBITDA cutoff at approximately 5.7).

In each specification (columns (1)-(6), Panels A and B of Table VII), we find a highly significant and negative treatment effect for firms crossing both the positive-negative and speculative high-yield thresholds. This is consistent with the results from S&P credit-rated subsample, namely that for non-highly leveraged firms that experience a sharp decline in their credit risk, and an increase in their access to capital markets, decrease usage of swap markets, consistent with a substitution effect between access to external public capital debt markets and firm hedging decisions. Correspondingly, firms which are more financially constrained increase their hedging activities. Our first pass is to examine a simpler sharp RD estimation in the multi-cutoff context (column (1), Panels A, B, and C of Table VII). The results of the individual estimations for positive-negative and speculative high-yield cutoffs, respectively, are reported below, with robust bias-corrected inference, as well as the pooled and weighted estimations (column (1), Panel C, of Table VII). Observations with debt-to-EBITDA less than 2 are classified as belonging to the positive-negative estimation, and observations with a debt-to-EBITDA greater than or equal to 2 are classified as belonging to the speculative high-yield estimation, thus removing oversampling bias of the interior in the pooled and weighted linear estimations[32]. The numeric results of this multi-cutoff weighted regression are presented in Table VI; the first cutoff (0) is shown in Panel A, column (1), the second cutoff (5.7) is shown in Panel B, column (1), and the weighted results are shown in Panel C, column (1)). Figures 10a through 10c detail the visual plot of the multi-cutoff sharp regression discontinuity.

[Insert Figure 10a, Figure 10b, and Figure 10c Here]

The positive/negative and speculative high-yield treatment effects (cutoff of a debt/EBITDA of 0 and 5.7, respectively) are both significant and negative in the sharp RD estimation of polynomial order one, with the positive/negative cutoff treatment effect significant at the alpha 5% level, and the speculative high-yield cutoff treatment effect is statistically significant at the alpha 1% level. The treatment effect at the positive/negative threshold results in a change from non-treated to treated results in a decrease in the

[32] For more explanation, please see the description included in Table VII.

probability of swap usage by 0.14%. Similarly, the treatment effect at the speculative high-yield threshold results in a change from non-treated to treated results in a decrease in probability of swap usage by 0.12%. We fail to reject the null hypothesis that the average effect differs between the two estimates at any meaningful level of significance, akin to the analysis in the S&P-rated subsample.[33] The running variable for debt-to-EBITDA is statistically significant, implying that the fuzzy RD estimation ought to include the same for correct model specification. Both the pooled and weighted estimation of the treatment effect are negative and significant at the alpha 1% threshold, with similar treatment effect magnitudes as the individual RD regressions. The weighted treatment effect is such that a change from non-treated to treated results in a 0.12% decrease in the probability of swap usage, and the pooled treatment effect (unreported) is such that a change from the non-treated to treated results in a 0.85% decrease in the probability of swap usage, As noted, in generating the pooled and weighted estimations for both cutoffs simultaneously, we execute the estimation to partition the interior, so as to not oversample the same and bias the estimates.

This specification highlights a potential difference between S&P credit-rated firms and the broader universe of firms. As noted before, while credit-rated firms with high credit risk can still access external public capital debt markets, albeit at a higher premium, firms without a credit rating and increased financial risk are dually constrained in both access to external public capital debt markets as well as financial intermediaries, including derivative markets. The resulting implication is that there exists an asymmetry for extremely leveraged firms, depending on whether they have access to external public debt markets with an associated S&P credit rating. For the S&P credit-rated subsample, firms are more likely to hedge if they are financially constrained around both the high-yield (B+) and investment grade (BBB) thresholds (i.e. substitution between hedging and access to external public capital debt markets). While we observe similar results with the Debt/EBITDA regression discontinuity for the broader use of firms that are not highly leveraged, or moderately leveraged, we observe *reduced* hedging activity for firms that are extremely leveraged (i.e. Debt/EBITDA greater than 5.7). We investigate this further with additional specifications.

For the first threshold in Table VII, Panels and B, for both the positive/negative and speculative high-yield thresholds, we examine the appropriate fuzzy RD in a linear probability context for both narrow and large

[33] A test of the linear difference between the coefficient estimate of the two thresholds results in a p-value of 0.63.

bandwidths (MSE-optimal, 0.5, and 2). For the positive/negative threshold (Table VII, Panel A, column 2), the treatment effect is negative and significant the bandwidth of (0.25 above and below the threshold), with a change in assignment from treated to non-treated corresponding with a 0.15% decrease in the probability of swap usage. For the bandwidth of 1.36 (Table VII, Panel A, column 3), the assignment to treatment effect is similarly negative and significant, with a 0.06% decrease in the probability of swap usage.

Our fuzzy RD model estimation using a Probit (columns (4)-(6) of Panel A, Table VII), in accordance with the baseline Probit estimations of the determinants of swap usage in Table III. In Table VII, Panel A, column (4), the assignment to treatment effect is negative and significant, and *DTC* positive but not statistically significant and robust to the inclusion of industry and time fixed effects. With fixed effects (Table VII, Panel A, column 5), the treatment effect is negative and significant, with a change in assignment from non-treated to treated resulting in a 0.96% decrease in the probability of swap usage. *DTC* is positive and significant, with a magnitude of 0.59. It is worth noting that the assignment to treatment magnitudes for the debt-to-EBITDA fuzzy RD estimation are quite similar to the mirrored results of the S&P credit rating sharp RD estimation in Table VI.

Following Stock and Yogo (2005), we produce the Cragg-Donald Wald F-Statistic for the IV weak identification test for a linear 2SLS estimation. The F-statistic has a value of approximately 13, which suggests that the chosen IV is indeed not a weak instrument.[34]

For Table VII, Panel A, even after the inclusion of firm characteristics as regressors, the treatment effect remains positive and significant (column 6), with a change in assignment to treatment from non-treated to treated resulting in a 1.34% decrease in the probability of swap usage, which is similar in magnitude to the prior S&P credit rating sharp RD. *DTC* is still positive and significant, with a magnitude of 0.69. Similar to the baseline Probit estimation, *Size*, *Book Leverage*, *Firm Age*, *R&D*, and *Foreign Profits* are all significant with the same signs, albeit with materially reduced magnitudes. *CapEx* and *Profitability*, although significant in the overall baseline Probit estimation, they are not significant in the debt-to-EBITDA fuzzy RD estimation. The Probit fuzzy RD estimation results are quite similar in magnitude to the estimates of the sharp RD for the S&P-rated subsample (Table VI), but greater than the linear RD estimates for debt-

[34] While not a strict rule, and depending on the covariates, Stock and Yogo (2005) suggest that an F-statistic less than 10 is indicative of a weak instrument.

to-EBITDA (Table VII, column (1)); that is to say that the linear probability under sharp RD was biased downward toward zero, and the effect of crossing the positive/negative threshold on hedging activity (i.e positive EBITDA) is much greater with the unbiased parameter estimate using the fuzzy RD approach. Furthermore, the estimation includes fixed effects and robust standard errors, with no material change in the coefficient estimate of the assignment to treatment effect, or the significance thereof. However, it is worth noting that the positive-negative cutoff is more sensitive to the bandwidth selection on the left side of the cutoff in so far as significance is concerned, meaning that while the results are likely robust for estimation around the positive-negative threshold, external validity may be more suspect the further to the left of the cutoff the debt-to-EBITDA of a firm rests.[35]

Given the greater uncertainty as to the exact high-yield cutoff around 5.7, we slightly expand the bandwidth of the estimation for the speculative high-yield fuzzy RD (column (4) of Panel B, Table VII). The linear fuzzy RD treatment effects for the speculative high-yield threshold, both with and without fixed effects are quite similar (column (2) and column (3) of Panel B, Table VII). The assignment to treatment effect is negative and significant in both estimations, with a magnitude of -0.23 and -0.11, respectively. Addressing the same concerns regarding the linear probability framework, we examine the Probit fuzzy RD results, including industry and year fixed effects, and controls with robust standard errors.[36] Without fixed effects (column (4), Panel B, Table VII), the assignment to treatment effect is negative and significant, and *DTC* itself is close to zero and not significant. The magnitude of the treatment effect is such that a change from assignment from treated to non-treated results in a 0.95% decrease in the probability of swap usage. With the inclusion of industry and time fixed effects (column (5), Panel B, Table VII), the treatment effect remains significant, with a magnitude of -0.47. *DTC* similarly remains insignificant. The F-statistic has a value of approximately 208, which suggests that the chosen IV is indeed not a weak instrument.[37]

The treatment effect remains significant, even with the inclusion of firm characteristics as regressors, in addition to industry and time fixed effects (column 6). The marginal effect for the treatment effect in the

[35] This may be due, in part, to the change in variance for pre and post-threshold in so far as binary dependent variable models are affected by changes in variance.
[36] Note that we utilize a uniform propensity of assignment at the threshold for the stochastic control/treatment assignment procedure, with attention to the interior $p<0.6$ for purposes of estimation.
[37] While not a strict rule, and depending on the covariates, Stock and Yogo (2005) suggest that an F-statistic less than 10 is indicative of a weak instrument.

fuzzy Probit RD is a discrete change from non-treated to treated assignment classification, and is a decrease in the probability of swap usage by 1.38%. *DTC* is insignificant and close to zero. *Size*, *Book Leverage*, and *Foreign Profits* are all significant for the speculative high-yield threshold in the fuzzy Probit RD, with materially reduced magnitude relative to the baseline estimation model (Table III), but consistent with the positive-negative threshold estimation. *CapEx*, *Age*, *Profitability*, and *R&D* are all insignificant in the speculative high-yield RD estimation addressing the endogeneity concerns. The F-statistic has a value of approximately 19, which suggests that the chosen IV is indeed not a weak instrument.

Examining the debt-to-EBITDA regression discontinuity specifications as a whole, there are some conclusions that we can draw. Similar to the S&P sharp RD estimation procedures, the treatment effect is persistently negative and significant, regardless of the threshold (speculative high-yield or positive/negative), inclusion of industry and time fixed effects, or the inclusion of firm characteristics as regressors. The magnitude of the coefficients for the fuzzy Probit RD estimations are similar to that of the sharp RD estimations of the S&P credit rating for the IG/positive-to-negative threshold, suggesting that a change from assignment to non-treated to treated corresponds with an approximate 1% decrease in the probability of swap usage. Since the debt-to-EBITDA RD regression is not limited to the narrower subset of S&P credit rated firms, and addresses some of the endogeneity concerns of the baseline Probit estimation, the results also suggests broader applicability as to the universe of U.S. public firms. Firms with low to moderate financial risk consistently substitute expanded access to finance with hedging activities, as evidenced by the negative coefficient on the assignment to treatment effect.

Comparing the two RD designs, we show that for firms with broad access to external public debt markets, increased credit risk (S&P-Rated) results in an increased likelihood to hedge using derivatives, regardless of the threshold, but for high firms with limited access and extremely high financial risk (Debt-EBITDA), they are less likely to hedge using derivatives following deterioration. This is the first study establishing these stylized facts across multiple hedging instruments on the most complete sample of publicly traded firms in US in a panel data setting. Second, there are some changes between the baseline Probit and the debt-to-EBITDA RD estimations, namely, only *Size*, *Book Leverage*, *Firm Age*, *R&D*, and *Foreign Profits* are significant for either of the cutoffs (speculative high-yield or positive/negative), and they have significantly reduced magnitudes. *Size* and *Book Leverage* are the only consistently significant determinants of swap usage across all of the two regression discontinuity approaches (S&P credit rating and debt-to-EBITDA).

V. Conclusion

In this study we examine the use of swap markets by the publicly traded firms (end-users) in the U.S. Our study focuses on the five major swap markets including IRS, FX, CDS/CDX, Commodity, and Equity, during fifteen quarters between 2018 and 2021. While our study follows on prior literature that have asked similar questions, it is the first study establishing some of the stylized facts identified by prior literature, and introduces novel findings across several hedging instruments on the most complete sample of publicly traded firms in US in a panel data setting.

Our findings highlight that swap users tend to be larger, older, more levered, and more profitable. Swap users also tend to have more tangible assets, fewer intangible assets, fewer growth opportunities, and have a larger fraction of their sales and profits originating from foreign operations. Among the two most common swaps; the use of FX stays about the same during the pandemic, while the use of IRS becomes marginally more common, especially among larger firms. For CDS/CDX, Commodity Swaps, and Equity swaps, which are predominantly used by the largest public firms, their use declines over the time period we examine. Some of the most novel findings are that younger firms use IRS, while they refrain from the use of other swaps. Additionally, besides healthcare industry, most industries actively participate in the swap markets, with 50% or greater participation in chemicals, energy, manufacturing, consumer durables, and consumer non-durables.

Results from our regression discontinuity design (RDD) allow us to conclude that that firm size and leverage have a first order impact on firms' decision to use swaps. We also confirm that firms with large foreign profits are more likely to use swaps, especially if they are at the cusp of highest-to-high credit risk threshold with access to external public debt markets, whereas older firms with high capital expenditures and intangible assets are more likely to use swaps, especially if they are at the cusp of the moderate-to-low credit risk threshold. The same RDD design using the Debt/EBITDA measure highlights the significance of negative profits in firm hedging decisions. Specifically, we find that at the negative-to-positive Debt/EBITDA threshold, firms with intangible assets are less likely to use swaps, contrary to our findings that isolate firms at the cusp of moderate-to-low credit risk. The second cutoff point we consider, using Debt/EBITDA to isolate the hedging decisions of firms facing moderate default risk, further supports that firms with high growth opportunities are less likely to use swaps. We also show that for firms with broad access to external public debt markets, increased credit risk results in an increased likelihood to hedge using derivatives, but for high firms with limited access and high financial risk, they are less likely to hedge using derivatives following deterioration. Relying on our regression discontinuity design, we are able to draw causal conclusions with respect to why and how firms use swaps as it pertains to firm access to finance and risk management.

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Appendix A. Summary of predictions based on prior literature

Variable	Sign	Associated Papers
Size	+	IRS: BHMS (1995), CF (2011); FX: BHMS (1995), GMS (1997), AO (2001), HZ (2019); COM: NF(2002)
Sales	+	IRS: BHMS (1995), CF (2011); FX: BHMS (1995), GMS (1997), AO (2001), HZ (2019)
Market-to-Book	+	IRS: GMS(1997) FX: GMS (1997)
CapEx	+	IRS: CF(2011); FX: HHZ(2019)
R&D	+	IRS: CF(2011); FX: GMS(1997), AO(2001), HHZ(2019)
R&D Indicator	+	IRS: CF(2011); FX: GMS(1997), AO(2007), HHZ(2019)
Selling Expense	+	FX: AO(2001)
Prop., Plant, & Equip.	+	IRS: CF(2011); FX: GMS(1997)
Profitability	-	IRS: CF(2011); FX: AO(2001)
St Debt / Total Debt	-/+	IRS: T(1992); CF (2011); FX: GMS (1997), B (2001); COM: NF(2002)
Book Leverage	-/+	IRS: CF(2011)
Dividend Payer	-/+	IRS: CF(2011); FX: GMS(1997), AO(2007)
Cash	-/+	IRS: CF(2011); FX: GMS(1997), AO(2007), HHZ(2019)
Firm Age	+	IRS: CF(2011); FX: GMS(1997), AO(2007)
Foreign Sales	+	IRS: CF(2011); FX: GMS(1997), AO(2007)
Foreign Profits	+	IRS: CF(2011); FX: GMS(1997), AO(2007)
HHI	+	IRS: CF(2011); FX: GMS(1997), AO(2007), HHZ(2019)
Dividend Payer	-/+	FX: GMS(1997), AO(2001), HHZ(2019), ACS(2007)
Altman Z-Score	+	IRS: F(2005), CF(2011), SSW(1993)
Operating Cash Flow Volatility	+/.	IRS: AO(2001), GK(2003); FX: AO(2001), GK(2003); COM: AO(2001), GK(2002)

Appendix B: Variable definitions

Variable	Description
Size	natural logarithm of total assets.
Sales	natural logarithm of total sales.
Market-to-Book**	market capitalization divided by book value, measured following Baker, Stein, and Wurgler (2003).
CapEx**	firm capital expenditures scaled by total assets.
R&D***	R&D expenditures scaled by total sales, following Geczy, Minton, and Schrand (1997). For firms which do not report any R&D expenditures, the null value is replaced with zero.
R&D Indicator	equal to one if a firm has R&D expenses and zero otherwise.
Selling Expense*	SG&A scaled by total sales.
Prop., Plant, & Equip.	PPE expenditures scaled by total assets.
Profitability*	EBITDA scaled by total sales.
St Debt / Total Debt	short-term debt divided by the sum of short-term and long-term debt.
Book Leverage	firm leverage, following Baker and Wurgler (2002).
Dividend Payer	dummy variable equal to one if a firm pays dividends, and zero otherwise.
Cash	cash equivalents scaled by total assets.
Firm Age	natural logarithm of the age of the firm since becoming public.
Foreign Sales***	foreign earnings before taxes scaled by total sales. For firms which do not report any foreign sales, the null value is replaced with zero.
Foreign Profits***	foreign earnings before taxes scaled by total earnings before taxes. For firms which do not report any foreign sales, the null value is replaced with zero.
HHI	natural logarithm of the Herfindahl-Hirschman Industry Index using sales within Fama-French 48 (between 0 and 10,000). An increase in the HHI Index corresponds with a decrease in concentration
Altman Z-Score	two-year default probability, as used in Campello et al. (2011), and following Altman (1968) and Altman (2002).
S&P Rating	historical S&P Long-Term Local Currency Issuer Credit Rating (RTG_SP_LT_LC_ISSUER_CREDIT). The S&P long-term issuer credit rating is provided from Bloomberg,
Index Indicator	dummy variable equal to one if a firm is part of the S&P 1500 index and zero otherwise.
Operating Cash Flow Volatility	firm quarterly cash flow volatility over three prior years, following Minton and Schrand (1999). Null values of components for quarterly inputs are replaced with zero.

* winsorized on the right tail at 99^{th} percentile, ** winsorized at the 1^{st} and 99^{th} percentiles, *** winsorized at the 5^{th} and 95^{th} percentiles.

Table I. Summary Statistics

This table presents the summary statistics of firm characteristic variables and the tests of means between swap user and non-users for publicly traded, U.S. firms excluding utilities and financials, encompassing the sample period 2018-2021. *Size* is the natural logarithm of total assets, *Market-to-Book* is the firm market capitalization divided by book value, *CapEx* includes firm capital expenditures scaled by total assets, *Prop. Plant & Equip.* is the firm PPE expenditures scaled by total assets, *Profitability* is EBITDA scaled by total sales, *Book Leverage* is the firm leverage following Baker and Wurgler (2002), *Firm Age* is the natural logarithm of the number of years a firm has been public, *R&D* includes R&D expenditures scaled by total sales, *R&D Indicator* is a dummy variable equal to one if a firm has a null value for R&D expenses and zero otherwise, *Selling Expense* is firm SG&A scaled by total sales, *Foreign Profits* includes the earnings before taxes scaled by total earnings before taxes, *HHI* is the Herfindahl-Hirschman industry competition measure using the Fama-French 48 Industry Classification (FF48), *Dividend Payer* is a dummy variable equal to one if a firm pays dividends and zero otherwise, *Altman Z-Score* is a measure of firms' two-year default probability, *OCF Volatility* is the firm quarterly cash flow volatility over the prior three years, following Minton and Schrand (1999), *St Debt / Total Debt* is portion of total debt that is short-term, *Sales* is the natural logarithm of total sales, *Cash* is the firm cash equivalents scaled by total assets, *Foreign Sales* includes the foreign earnings before taxes scaled by total sales, *S&P Index Category* is a categorical variable from zero (Non-S&P) to three (S&P 500) indicating the S&P 1500 participation of a firm, *S&P Rating Indicator* is a dummy variable equal to one if a firm has a long-term issuer credit rating by S&P and zero otherwise, and *S&P Rating* is S&P long-term issuer credit rating . See Appendix A for variable definitions.

Panel A. Comparison of Swap Users and Non-Users

	User			Non-User			Difference	
Variables	N	Mean	SD	N	Mean	SD	T-Stat	P-Value
Size	2841	8.25	1.65	4666	5.48	1.85	77.04	0.00
Market-to-Book	2836	3.83	8.00	4662	4.38	8.79	-5.84	0.00
CapEx	2840	0.04	0.04	4656	0.03	0.04	9.32	0.00
Prop. Plant & Equip.	2840	0.29	0.25	4662	0.19	0.22	12.11	0.00
Profitability	2833	0.14	0.41	4161	-0.99	2.41	30.53	0.00
Book Leverage	2833	0.61	0.25	4643	0.47	0.34	25.37	0.00
Firm Age	2839	3.03	0.97	4630	2.30	1.09	32.03	0.00
R&D	2833	0.04	0.11	4162	0.41	0.77	-30.66	0.00
R&D Indicator	2841	0.39	0.49	4666	0.27	0.45	16.67	0.00
Selling Expense	2833	0.22	0.24	4162	0.67	1.45	-20.13	0.00
Foreign Profits	2841	0.31	0.38	4662	0.09	0.24	23.90	0.00
HHI	2841	6.86	0.57	4666	6.78	0.48	-3.89	0.00
Dividend Payer	2841	0.56	0.50	4666	0.19	0.39	39.85	0.00
Altman Z-Score	2836	3.02	3.46	4655	4.14	8.96	-12.37	0.00
OCF Volatility	2623	216.59	298.10	3807	34.49	91.47	38.72	0.00
St Debt / Total Debt	2785	0.11	0.17	3996	0.25	0.29	-11.45	0.00
Sales	2833	7.92	1.65	4162	4.91	2.47	62.39	0.00
Cash	2841	0.11	0.12	4666	0.36	0.32	-49.38	0.00
Foreign Sales	2833	0.03	0.04	4162	0.00	0.02	26.72	0.00
S&P Index Category	2820	1.41	1.23	4520	0.34	0.72	26.72	0.00
S&P Rating Indicator	2841	0.60	0.49	4666	0.12	0.33	26.72	0.00
S&P Rating	1703	11.16	3.19	561	9.07	2.75	26.72	0.00

Panel B. Correlation Statistics

Variables	Size	Market-to-Book	CapEx	Prop. Plant & Equip.	Profitability	Book Leverage	Firm Age	R&D	R&D Indicator	Selling Expense	Foreign Profits	HHI	Dividend Payer	Altman Z-Score	OCF Volatility	ST Debt / Total Debt	Sales	Cash	Foreign Sales	S&P Index Category	S&P Rating Indicator	S&P Rating*
Size	1.00																					
Market-to-Book	0.03	1.00																				
CapEx	0.11	-0.05	1.00																			
Prop. Plant & Equip.	0.15	-0.12	0.65	1.00																		
Profitability	0.38	-0.02	0.14	0.17	1.00																	
Book Leverage	0.10	-0.06	0.03	0.13	0.05	1.00																
Firm Age	0.29	-0.04	0.00	0.06	0.26	-0.01	1.00															
R&D	-0.33	0.07	-0.18	-0.24	-0.89	-0.09	-0.27	1.00														
R&D Indicator	0.10	-0.12	0.23	0.32	0.18	0.07	0.03	-0.27	1.00													
Selling Expense	-0.27	0.03	-0.11	-0.16	-0.48	-0.08	-0.18	0.40	-0.15	1.00												
Foreign Profits	0.30	0.02	-0.05	-0.11	0.14	0.00	0.19	-0.11	-0.12	-0.06	1.00											
HHI	0.04	-0.06	0.04	0.10	0.00	-0.01	0.15	-0.03	0.00	-0.01	0.05	1.00										
Dividend Payer	0.45	-0.02	0.05	0.13	0.25	0.06	0.41	-0.26	0.12	-0.18	0.18	0.08	1.00									
Altman Z-Score	0.15	0.20	-0.02	-0.13	0.18	-0.45	0.09	-0.12	-0.09	-0.06	0.07	0.00	0.10	1.00								
OCF Volatility	0.66	0.03	0.07	0.08	0.15	0.14	0.27	-0.14	0.03	-0.11	0.18	0.06	0.31	0.00	1.00							
St Debt / Total Debt	-0.40	-0.03	-0.09	-0.13	-0.16	-0.07	-0.04	0.12	-0.07	0.11	-0.08	0.02	-0.17	-0.03	-0.12	1.00						
Sales	0.90	0.01	0.12	0.14	0.64	0.17	0.36	-0.59	0.13	-0.38	0.28	0.03	0.47	0.16	0.58	-0.34	1.00					
Cash	-0.38	0.17	-0.26	-0.39	-0.57	-0.23	-0.28	0.68	-0.31	0.31	-0.10	-0.07	-0.31	0.14	-0.17	0.17	-0.53	1.00				
Foreign Sales	0.34	0.07	-0.02	-0.11	0.18	-0.01	0.24	-0.14	-0.13	-0.12	0.56	0.04	0.24	0.15	0.23	-0.08	0.32	-0.10	1.00			
S&P Index Category	0.70	0.07	0.03	0.01	0.25	0.04	0.42	-0.22	-0.03	-0.15	0.30	0.05	0.44	0.17	0.55	-0.19	0.64	-0.23	0.41	1.00		
S&P Rating Indicator	0.65	-0.03	0.08	0.14	0.24	0.25	0.25	-0.25	0.12	-0.18	0.22	0.06	0.36	-0.06	0.48	-0.29	0.59	-0.34	0.24	0.50	1.00	
S&P Rating*	0.69	0.20	-0.08	-0.18	0.22	-0.25	0.42	0.23	-0.21	0.08	0.24	0.01	0.47	0.51	0.51	0.15	0.70	0.16	0.42	0.70	.	1.00

Table II. S&P Credit Ratings

This table presents the distribution of the issuer level S&P Credit Ratings and the firm characteristics of the rated and the unrated sample. Panel A presents the mapping between the S&P long-term issuer credit rating letter grade of a firm, and the numeric ordinal equivalent from D(0) to AAA(21). Panel B presents the summary statistics of firm characteristics for rated and unrated firms and the tests of means between the two subsamples. The sample is drawn from publicly traded U.S. firms, excluding utilities and financials, encompassing the sample period 2018-2021. See Table 1 and Appendix A for variable definitions.

Panel A.

S&P Long-Term Credit Rating	S&P Numeric Rating Equivalent	Frequency	Percent
AAA	21	6	0.24
AA+	20	8	0.32
AA	19	16	0.63
AA-	18	22	0.87
A+	17	47	1.86
A	16	72	2.86
A-	15	89	3.53
BBB+	14	168	6.66
BBB	13	321	12.73
BBB-	12	195	7.74
BB+	11	264	10.47
BB	10	340	13.49
BB-	9	285	11.31
B+	8	243	9.64
B	7	220	8.73
B-	6	135	5.36
CCC+	5	60	2.38
CCC	4	14	0.56
CCC-	3	7	0.28
CC	2	5	0.20
C	1	0	0.00
D	0	4	0.16
Total		2,521	100

Panel B. Comparison of Rated Firms and Unrated Firms

	S&P Rated			Non-S&P Rated			Difference	
Variables	N	Mean	SD	N	Mean	SD	T-Stat	P-Value
Size	2521	8.75	1.38	6170	5.55	1.77	90.06	0.00
Market-to-Book	2515	3.66	9.04	6163	4.33	8.36	-3.20	0.00
CapEx	2521	0.04	0.04	6105	0.03	0.04	10.75	0.00
Prop. Plant & Equip.	2521	0.31	0.26	6159	0.19	0.22	19.48	0.00
Profitability	2520	0.18	0.21	5386	-0.89	2.32	33.70	0.00
Book Leverage	2512	0.67	0.24	6142	0.45	0.33	33.86	0.00
Firm Age	2507	3.05	0.98	6116	2.25	1.16	32.50	0.00
R&D	2520	0.03	0.06	5389	0.38	0.74	-34.70	0.00
R&D Indicator	2521	0.44	0.50	6170	0.29	0.46	13.20	0.00
Selling Expense	2520	0.19	0.15	5389	0.65	1.42	-23.27	0.00
Foreign Profits	2521	0.28	0.37	6110	0.12	0.27	20.50	0.00
HHI	2521	6.86	0.55	6170	6.83	0.55	1.75	0.08
Dividend Payer	2521	0.61	0.49	6170	0.20	0.40	36.54	0.00
Altman Z-Score	2515	2.38	2.26	6100	4.60	9.04	-17.87	0.00
OCF Volatility	2284	267.48	318.73	4895	32.96	75.94	34.71	0.00
St Debt / Total Debt	2519	0.08	0.12	5155	0.25	0.29	-35.41	0.00
Sales	2520	8.35	1.43	5389	5.01	2.40	77.02	0.00
Cash	2521	0.10	0.10	6170	0.34	0.32	-53.33	0.00
Foreign Sales	2520	0.02	0.04	5389	0.01	0.03	20.27	0.00
S&P Index Category	2501	1.56	1.25	5785	0.35	0.72	45.21	0.00
S&P Rating Indicator	2521	1	0	6170	0	0	N/A	N/A

Table III. Predicting the Likelihood Swap Market Participation

This table presents the relation between the propensity to use swaps and selected covariates using panel Probit specifications for publicly traded U.S. firms, excluding utilities and financials, encompassing the sample period 2018-2021. The dependent variables, *Swap User*, *IRS User*, *FX User*, *CDS User*, *COM User*, and *EQ User*, are binary dependent variables for firm swap usage, equal to one if a firm exhibits usage, and zero otherwise. *Swap User* denotes usage of any swap type (IRS, FX, CDS/CDX, Commodity, or Equity). All regressions use industry-fixed effects and year-fixed effects, with robust-clustered standard errors. Industries are classified according to the Fama-French 48 industry classification (FF48) using two-digit SIC industry codes. Robust-clustered t-statistics are shown in parentheses. Column titles represent the left-hand side variable in each regression. McFadden's pseudo r-squared value is provided for each Probit specification. Significance is indicated at the alpha 1%, 5%, and 10% levels by ***, **, and *, respectively. See Table 1 and Appendix A for variable definitions.

Panel A. Baseline

Variables	**(1)** **Swap User**	(2) IRS User	(3) FX User	(4) CDS User	(5) COM User	(6) EQ User
Size	1.70***	1.14***	1.91***	2.15***	1.79***	2.27
	(14.04)	(12.76)	(12.71)	(3.88)	(8.19)	(1.63)
Market-to-Book	-0.01	0.00	-0.01	0.01	-0.01	0.00
	(-0.89)	(0.56)	(-0.71)	(0.40)	(-0.82)	(0.04)
CapEx	5.34**	-0.15	8.14***	11.68	4.78	8.51
	(2.52)	(-0.07)	(2.81)	(1.50)	(1.37)	(0.64)
Prop. Plant & Equip.	0.022	-0.17	-3.57***	-3.10	4.54***	-3.03
	(0.04)	(-0.31)	(-4.89)	(-1.24)	(4.38)	(-1.01)
Profitability	-0.26*	-0.33**	-0.53***	0.56	-0.61*	1.55
	(-1.65)	(-2.21)	(-3.39)	(0.35)	(-1.90)	(0.47)
Book Leverage	1.75***	1.87***	1.72***	3.44**	2.50***	2.72
	(5.27)	(5.54)	(4.89)	(2.26)	(4.35)	(1.11)
Firm Age	0.50***	-0.00	0.91***	1.61**	0.64***	0.48
	(4.91)	(-0.04)	(6.81)	(2.26)	(3.55)	(1.03)
R&D	-2.54***	-3.71***	-2.93***	-1.88	-2.97	3.24
	(-3.37)	(-2.75)	(-3.60)	(-0.39)	(-1.38)	(0.47)
R&D Indicator	-0.18	-0.16	-1.43***	0.081	0.41	-0.98
	(-0.75)	(-0.65)	(-4.49)	(0.09)	(1.07)	(-1.16)
Selling Expense	-0.47	-2.39***	-0.95**	-3.32	-0.09	-1.17
	(-1.41)	(-3.41)	(-2.36)	(-0.83)	(-0.17)	(-0.26)
Foreign Profits	0.83***	0.44**	0.98***	-0.47	-0.34	-0.26
	(4.16)	(2.38)	(4.61)	(-0.87)	(-0.98)	(-0.31)
Observations	6,907	6,916	6,916	6,916	6,744	6,539
Number of Firms	2,574	2,577	2,577	2,577	2,513	2,436
Industry FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pseudo R-Squared	0.33	0.23	0.30	0.33	0.40	0.43

Panel B. Additional controls

Variables	(1) Swap User	(2) IRS User	(3) FX User	(4) CDS User	(5) COM User	(6) EQ User
Size	1.60***	1.29***	1.69***	2.27***	1.71***	1.76
	(12.34)	(11.19)	(10.37)	(2.89)	(6.05)	(0.56)
Market-to-Book	-0.00	0.01	-0.01	-0.00	-0.00	-0.02
	(-0.57)	(1.48)	(-0.63)	(-0.05)	(-0.23)	(-0.68)
CapEx	5.81**	-0.09	9.49***	11.21	7.01	-7.45
	(2.43)	(-0.04)	(2.80)	(0.25)	(1.63)	(-0.31)
Prop. Plant & Equip.	-0.05	-0.48	-3.80***	-3.43	4.46***	-2.93
	(-0.08)	(-0.81)	(-4.58)	(-0.54)	(3.34)	(-0.61)
Profitability	-0.18	-0.26	-0.56***	-0.23	-0.27	4.01
	(-1.05)	(-1.45)	(-2.90)	(-0.05)	(-0.82)	(0.47)
Book Leverage	1.91***	2.07***	1.70***	5.71	1.93**	0.37
	(5.52)	(5.86)	(4.36)	(0.90)	(2.55)	(0.10)
Firm Age	0.33***	0.10	0.66***	2.31	0.50**	1.22
	(2.62)	(0.77)	(4.05)	(0.15)	(2.11)	(0.45)
R&D	-2.52***	-3.75***	-3.35***	-5.43	-3.52	5.56
	(-2.88)	(-2.58)	(-3.65)	(-0.10)	(-1.11)	(0.33)
R&D Indicator	-0.26	-0.20	-1.47***	0.30	0.37	-1.80
	(-1.01)	(-0.77)	(-4.26)	(0.08)	(0.86)	(-0.99)
Selling Expense	-0.51	-3.15***	-1.18**	-2.46	0.16	0.98
	(-1.08)	(-5.39)	(-2.56)	(-0.13)	(0.35)	(0.22)
Foreign Profits	0.86***	0.48**	0.97***	-0.17	-0.34	-0.69
	(4.13)	(2.46)	(4.24)	(-0.05)	(-0.94)	(-0.36)
S&P Index Indicator	0.37*	-0.59***	0.97***	-0.87	-0.20	-1.24
	(1.83)	(-2.68)	(3.86)	(-0.21)	(-0.45)	(-0.41)
HHI	-0.28	0.72	-0.81	-0.14	-1.45	-0.82
	(-0.58)	(1.58)	(-1.35)	(-0.03)	(-1.35)	(-0.48)
Dividend Payer	0.17	-0.04	0.23	2.65	0.40	3.20
	(0.80)	(-0.17)	(0.91)	(0.14)	(1.05)	(0.49)
Altman Z-Score	-0.03	-0.05*	-0.03	0.22	-0.19**	-0.29
	(-1.58)	(-1.79)	(-1.07)	(0.65)	(-2.42)	(-0.91)
OCF Volatility	0.00	-0.00	0.00	-0.00	0.00*	0.00
	(0.47)	(-1.10)	(1.57)	(-0.05)	(1.77)	(1.07)
Observations	5,975	5,984	5,969	5,984	5,786	5,467
Number of Firms	2,283	2,286	2,280	2,286	2,214	2,088
Industry FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pseudo R-Squared	0.33	0.23	0.34	0.37	0.39	0.45

Table IV. Does the swap market participation vary among Rated and Unrated Firms?

This table presents the relation between the propensity to use swaps and selected covariates using panel Probit specifications for the S&P rated subsample of publicly traded U.S firm, excluding utilities and financials, encompassing the sample period 2018-2021. The dependent variables, *Swap User*, *IRS User*, *FX User*, *CDS User*, *COM User*, and *EQ User*, are binary dependent variables for firm swap usage, equal to one if a firm exhibits usage, and zero otherwise. *Swap User* denotes usage of any swap type (IRS, FX, CDS/CDX, Commodity, or Equity). For each firm, swaps usage at the subsidiary level is mapped to the ultimate parent of the firm. All regressions use industry-fixed effects and year-fixed effects, with robust-clustered standard errors. Industries are classified according to the Fama-French 48 industry classification (FF48) using two-digit SIC industry codes. Robust-clustered t-statistics are shown in parentheses. Column titles represent the left-hand side variable in each regression. McFadden's pseudo r-squared value is provided for each Probit specification. Significance is indicated at the alpha 1%, 5%, and 10% levels by ***, **, and *, respectively. See Table 1 and Appendix A for variable definitions.

Panel A. Rated firms

Variables	**(1)** **Swap User**	(2) IRS User	(3) FX User	(4) CDS User	(5) COM User	(6) EQ User
Size	1.58***	1.19***	1.69***	2.17**	2.09**	2.55***
	(7.59)	(7.22)	(7.87)	(2.51)	(2.12)	(4.78)
Market-to-Book	-0.02	0.01	-0.02*	0.00	-0.01	0.00
	(-1.50)	(1.16)	(-1.96)	(0.04)	(-0.62)	(0.11)
CapEx	8.17*	-1.40	8.56**	16.11	7.29	15.52
	(1.85)	(-0.37)	(2.30)	(0.77)	(0.80)	(0.27)
Prop. Plant & Equip.	-0.07	-0.50	-3.89***	-2.55	7.66**	-2.01
	(-0.07)	(-0.60)	(-4.59)	(-0.44)	(2.57)	(-0.35)
Profitability	-0.44	-1.24***	-0.55	-0.26	-1.93***	-1.40
	(-1.19)	(-2.92)	(-0.96)	(-0.11)	(-3.03)	(-0.37)
Book Leverage	1.63**	0.89	2.45***	4.27	2.40	3.64
	(2.46)	(1.62)	(3.78)	(0.55)	(0.78)	(0.94)
Firm Age	0.22	-0.01	0.86***	1.86	0.64	1.23
	(1.20)	(-0.06)	(4.45)	(0.95)	(0.89)	(0.55)
R&D	1.65	-7.54**	1.63	1.54	2.96	15.11
	(0.56)	(-2.23)	(0.53)	(0.048)	(0.30)	(1.12)
R&D Indicator	-0.05	0.11	-1.29***	-0.15	0.19	-0.52
	(-0.12)	(0.27)	(-2.88)	(-0.07)	(0.26)	(-0.22)
Selling Expense	-0.51	-1.66	0.09	-4.45	-1.13	-8.54
	(-0.56)	(-1.58)	(0.10)	(-0.15)	(-0.17)	(-1.17)
Foreign Profits	0.84**	0.35	0.88***	-0.53	-0.85	0.03
	(2.50)	(1.33)	(2.91)	(-0.54)	(-1.29)	(0.02)
Observations	2,189	2,229	2,223	2,247	2,181	1,931
Number of Firms	809	823	821	830	805	713
Industry FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pseudo R-Squared	0.20	0.15	0.32	0.24	0.33	0.39

Panel B. Unrated firms

Variables	(1) Swap User	(2) IRS User	(3) FX User	(4) CDS User	(5) COM User	(6) EQ User
Size	1.66***	1.01***	1.84***	3.73***	1.86**	1.21
	(10.66)	(9.93)	(7.45)	(3.17)	(2.49)	(1.32)
Market-to-Book	-0.01	-0.01	0.01	0.28**	0.01	-0.03
	(-0.55)	(-1.23)	(0.90)	(2.48)	(0.11)	(-0.16)
CapEx	3.76	-0.78	8.46	16.63	3.38	-28.59
	(1.52)	(-0.30)	(1.61)	(0.58)	(0.56)	(-0.39)
Prop. Plant & Equip.	0.25	0.41	-3.16*	-12.15	3.10	-6.34
	(0.36)	(0.60)	(-1.86)	(-1.62)	(0.84)	(-0.52)
Profitability	-0.26	0.02	-0.55**	7.71	-0.58	4.70
	(-1.54)	(0.09)	(-2.43)	(0.95)	(-0.65)	(1.04)
Book Leverage	1.50***	1.84***	1.01*	2.56	2.40	-1.73
	(3.77)	(4.48)	(1.77)	(0.71)	(1.02)	(-0.49)
Firm Age	0.55***	-0.05	0.78***	2.19*	0.65	-0.58
	(4.04)	(-0.43)	(3.09)	(1.72)	(1.03)	(-0.94)
R&D	-2.56***	-2.43**	-3.22**	-297.40	-3.53	-33.34
	(-3.18)	(-2.02)	(-2.38)	(-1.24)	(-0.44)	(-0.68)
R&D Indicator	-0.16	-0.29	-1.24**	-3.39	0.95	-2.48
	(-0.53)	(-0.95)	(-2.32)	(-0.98)	(1.04)	(-0.93)
Selling Expense	-0.47	-2.48***	-1.44**	-0.79	-0.10	5.59
	(-1.42)	(-2.68)	(-2.22)	(-0.09)	(-0.04)	(1.31)
Foreign Profits	0.71***	0.28	0.78**	-1.06	0.29	0.84
	(2.82)	(1.04)	(2.21)	(-0.39)	(0.22)	(0.49)
Observations	4,657	4,640	4,417	3,154	2,842	841
Number of Firms	1,809	1,803	1,717	1,213	1,094	441
Industry FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pseudo R-Squared	0.26	0.18	0.26	0.43	0.37	0.58

Table V. Regression Discontinuity Categories

This table presents the distribution of the treatment variable across the subsamples. Panel A presents the mean, SD, min, p25, p50, p75, and max value of Debt/EBITDA as well as the p50, mean, min, and max value of the credit rating of each ventile. The Debt/EBITDA ventiles are constructed by as 20 equal groups corresponding to the distribution of Debt/EBITDA, ordered from highest to lowest. Panel B presents the mean, SD, min, p25, p50, p75, and Max value of the associated numeric S&P credit grade mapping, as well as the p50, mean, min, and max of the Debt/EBITDA for each credit grade group. The S&P long-term issuer credit rating is a numeric ordinal equivalent from D(0) to AAA(21). *Note that Debt/EBITDA is winsorized at the 1st and 99th percentiles. Please see Appendix A for variable definitions

Panel A = Debt/EBITDA

Ventile	N	Mean	SD	Min	p25	p50	p75	Max	p50	Mean	Min	Max
				Debt/EBITDA					Credit Rating			
1	564	-15.91	8.90	-30.09	-24.34	-12.25	-8.11	-6.07	10	10.11	0	19
2	563	-4.06	0.95	-6.06	-4.77	-3.86	-3.23	-2.74	12	11.23	5	17
3	563	-2.02	0.36	-2.73	-2.31	-2.00	-1.71	-1.44	13.5	12.23	0	20
4	563	-1.06	0.22	-1.44	-1.24	-1.06	-0.85	-0.71	13	12.31	2	21
5	563	-0.44	0.15	-0.71	-0.57	-0.42	-0.31	-0.19	13	13.33	6	19
6	563	0.00	0.10	-0.19	-0.09	0.00	0.09	0.17	13	13.24	0	20
7	563	0.33	0.09	0.17	0.25	0.33	0.40	0.48	13	12.80	6	21
8	563	0.65	0.10	0.48	0.56	0.65	0.73	0.81	13	12.67	5	20
9	563	0.97	0.10	0.81	0.88	0.98	1.06	1.15	13	12.60	6	20
10	563	1.34	0.11	1.15	1.24	1.35	1.43	1.52	13	12.42	6	19
11	564	1.70	0.11	1.52	1.61	1.71	1.80	1.88	12.5	12.22	6	20
12	563	2.08	0.11	1.88	1.98	2.07	2.18	2.28	12	11.73	5	19
13	563	2.50	0.13	2.28	2.38	2.49	2.61	2.73	11	11.57	6	18
14	563	2.97	0.15	2.74	2.84	2.97	3.11	3.22	11	10.85	6	19
15	563	3.53	0.18	3.22	3.38	3.52	3.69	3.84	11	10.77	6	17
16	563	4.19	0.21	3.84	4.01	4.19	4.37	4.57	10	10.19	0	17
17	563	5.06	0.28	4.57	4.82	5.05	5.29	5.57	10	10.40	2	17
18	563	6.28	0.47	5.58	5.87	6.24	6.68	7.16	9	9.72	0	17
19	563	8.82	1.18	7.16	7.83	8.58	9.76	11.41	8	8.60	3	16
20	563	23.36	10.26	11.42	14.42	19.65	34.10	39.50	8	8.44	3	15

Panel B. Credit Rating

	N	Mean	SD	Min	p25	p50	p75	Max	p50	Mean	Min	Max
	S&P Credit Rating								Debt/EBITDA*			
0	4	0	0	0	0	0	0	0	1.33	-1.06	-13.73	6.81
2	5	2	0	2	2	2	2	2	-0.73	-0.78	-9.97	4.76
3	7	3	0	3	3	3	3	3	17.13	13.20	-0.74	24.20
4	14	4	0	4	4	4	4	4	9.98	8.19	-13.73	24.20
5	60	5	0	5	5	5	5	5	6.96	5.97	-13.73	24.20
6	135	6	0	6	6	6	6	6	5.24	5.65	-13.73	24.20
7	220	7	0	7	7	7	7	7	4.71	5.44	-9.75	24.20
8	243	8	0	8	8	8	8	8	3.91	3.86	-13.73	24.20
9	285	9	0	9	9	9	9	9	3.39	3.51	-13.73	24.20
10	340	10	0	10	10	10	10	10	2.77	2.98	-13.73	24.20
11	264	11	0	11	11	11	11	11	2.53	2.49	-13.73	23.44
12	195	12	0	12	12	12	12	12	2.17	2.27	-13.73	14.73
13	321	13	0	13	13	13	13	13	2.07	2.40	-13.73	24.20
14	168	14	0	14	14	14	14	14	1.76	1.58	-13.73	21.41
15	89	15	0	15	15	15	15	15	1.32	1.27	-2.55	5.56
16	72	16	0	16	16	16	16	16	1.56	1.49	-2.40	5.90
17	47	17	0	17	17	17	17	17	1.40	1.25	-0.35	3.76
18	22	18	0	18	18	18	18	18	1.09	0.84	-1.42	2.43
19	16	19	0	19	19	19	19	19	0.77	0.22	-7.71	2.93
20	8	20	0	20	20	20	20	20	0.25	-0.41	-2.60	1.56
21	6	21	0	21	21	21	21	21	-0.25	-0.27	-1.03	0.38

Table VI. Regression Discontinuity Design: S&P Credit Rating

This table reports the results of a sharp RD design implemented using firms' S&P credit rating. The following equations are estimated:

Column 1: Sharp RDD (OLS): $SU_i = \beta_0 + \beta_1 T_i + \beta_2 DTC_i + \varepsilon_i$

Columns 2-7: Sharp RD (Probit): Ind $[SU_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 DTC_{it} + \beta_3 X_{it} + \ldots + \beta_k X_{it} + \varepsilon_{it}] \geq 0$

The outcome variable, *SU*, is a binary variable that is equal to one if a firm is using a swap (IRS, FX, CDS/CDX, Commodity, or Equity swap), and zero otherwise. The treatment variable, *T,* is an indicator variable, which is assigned a value of 1 if the credit rating is greater than or equal to the respective cutoff, and zero otherwise. The two cutoff points considered are: B+ (Panel A) and BBB (Panel B). These cutoff points are chosen based on data fit (see Figure 6). *DTC* is the distance between the observed value of the credit rating and the cutoff. The vector *X* represents *Size, Market-to-Book, CapEx, Prop. Plant and Equip., Profitability, Book Leverage, Firm Age, R&D Expense, R&D Indicator, Selling Expense, Foreign Profits*. Column 1 reports local linear sharp RD coefficient estimates using the mean-square error (MSE) optimal bandwidth (Panel A: 2, Panel B: 4). Columns 2 through 7 report the panel Probit sharp RD coefficients with the mean-square error (MSE) optimal bandwidth as well as a wider bandwidth selection. Columns 2 through 7 also adjust by specification to include fixed effects and baseline Probit estimation control variables. Panel C, reports the same model as in Column 1 estimated using a weighted treatment, as the average of the local linear sharp RD coefficient estimates for the first and second cutoffs, using the mean-square error (MSE) optimal bandwidth; note that to prevent oversampling of the interior, the bandwidths for C_2 are 2 and 4 for below and above the cutoff, respectively. Each column title indicates the stata function used to estimate the model. The unconstrained regression sample includes 2,189 observations of rated firms. Regressions using industry and year-fixed effects are noted as such. Baseline controls include. All estimations are reported using robust-clustered standard errors. McFadden's pseudo r-squared value is provided for each Probit specification. Significance is indicated at the alpha 1%, 5%, and 10% levels by ***, **, and *, respectively. See Appendix A for variable definitions.

Panel A: C_1 >=B+

	(1) Sharp rdmc	(2) Sharp xtprobit	(3) Sharp xtprobit	(4) Sharp xtprobit	(5) Sharp xtprobit	(6) Sharp xtprobit	(7) Sharp xtprobit
Treatment	-5.05**	-1.06**	-1.22***	-1.01**	-0.55	-0.78*	-0.30
DTC	-2.63	0.84***	0.76***	0.53***	0.56***	0.54***	0.16
Constant	-	2.51***	2.91	-8.73***	2.44***	3.81*	-10.99***
Size				1.28***			1.61***
Market-to-Book				-0.01			-0.02
CapEx				7.67			5.42
Prop. Plant & Equip.				0.21			-0.06
Profitability				-0.21			-0.63
Book Leverage				1.90**			1.79**
Firm Age				0.06			0.16
R&D				-2.38			0.45
R&D indicator				-0.17			-0.25
Selling Expense				-0.21			-1.28
Foreign profits				0.78*			0.89**
Observations	1,083	1,083	1,034	1,018	1,855	1,806	1,790
Number of Firms	450	450	430	424	704	686	680
Bandwidth	2	2	2	2	5	5	5
Industry FE	N	N	Y	Y	N	Y	Y
Time FE	N	N	Y	Y	N	Y	Y
Pseudo R2		0.02	0.14	0.19	0.04	0.13	0.19

Panel B: C_2 >= BBB

	(1) Sharp rdmc	(2) Sharp xtprobit	(3) Sharp xtprobit	(4) Sharp xtprobit	(5) Sharp xtprobit	(6) Sharp xtprobit	(7) Sharp xtprobit
Treatment	-15.23**	-0.51*	-1.10**	-0.95*	-0.94**	-1.25***	-1.26***
DTC	-2.63	0.45***	0.55***	-0.01	0.64***	0.63***	0.08
Constant	-	5.02***	6.39***	-11.35***	4.83	6.50***	-11.22***
Size				1.60***			1.55***
Market-to-Book				-0.02			-0.02
CapEx				8.81*			11.65**
Prop. Plant & Equip.				-2.10*			-1.55
Profitability				-1.25			-0.56
Book Leverage				2.77***			2.35***
Firm Age				0.49**			0.44**
R&D				4.51			6.25*
R&D indicator				-0.23			-0.04
Selling Expense				-1.74			-0.54
Foreign profits				0.37			0.53
Observations	1,051	1,610	1,501	1,496	1,854	1,763	1,752
Number of Firms	398	617	576	574	707	674	669
Bandwidth	4	4	4	4	6	6	6
Baseline Controls	N	N	N	Y	N	N	Y
Industry FE	N	N	Y	Y	N	Y	Y
Time FE	N	N	Y	Y	N	Y	Y
Pseudo R2		0.02	0.12	0.18	0.04	0.14	0.21

Panel C: $Cutoff_1$ & $Cutoff_2$	(1) Sharp rdmc
Weighted Treatment	-10.07***
DTC	-2.63
Constant	-
Observations	2,134
Number of firms	848
Bandwidth	2; 4
Baseline Controls	N
Industry FE	N
Time FE	N

Table VII. Regression Discontinuity Design: Debt-to-EBITDA

This table reports the results of a sharp (column 1) and fuzzy RD design (columns 2-6) implemented using Debt-to-EBITDA. The following equations are estimated:

Column 1: Sharp RD (OLS): $SU_i = \beta_0 + \beta_1 T_i + \beta_2 DTC_i + \varepsilon_i$

Columns 2 & 3: Fuzzy RD (OLS)

Stage 1 (unreported): $D_i = \gamma_0 + \gamma_1 T_i + \gamma_2 DTC_i + \pi_1(Debt/EBITDA) + \eta_i$

Stage 2: $SU_i = \beta_0 + \beta_1 D_{it} + \beta_2 DTC_i + \pi_2(Debt/EBITDA) + \varepsilon_i$

D = 1 if firm *i* receives treatment, and 0 otherwise

T= 1 if firm *i* is assigned to treatment based on cutoff rule, and 0 otherwise

π_n (*Debt/EBITDA*) = the probability f(x) (uniform) between debt/EBITDA and the treatment receipt for firm *i*

Columns 4-6: Fuzzy RD (Probit)

Stage 1: $D_i = \text{Ind}\ [\gamma_0 + \gamma_1 T_i\ \ \gamma_2 DTC_i + \pi_1(Debt/EBITDA_i) + \eta_i] \geq 0$

Stage 2: $SU_i = \text{Ind}\ [\beta_0 + \beta_1 D_i + \beta_2 DTC_i + \pi_2(Debt/EBITDA_i) + \varepsilon_i] \geq 0$

The outcome variable, *SU*, is a binary variable that is equal to one if a firm is using a swap (IRS, FX, CDS/CDX, Commodity, or Equity swap), and zero otherwise. The treatment variable, *T,* is an indicator variable, which is assigned a value of 1 if the Debt/EBITDA is greater than or equal to the respective cutoff, and zero otherwise. The two cutoff points considered are: 0 (Panel A) and 5.7 (Panel B). These cutoff points are chosen based on data fit (see Figure 6). *DTC* is the distance between the observed value of Debt/EBITDA and the cutoff. Column 1 reports the local linear sharp RD coefficient estimates using the mean-square error (MSE) optimal bandwidth (Panel A: 0.28, Panel B: 2.24). Columns 2 and 3 report the linear probability fuzzy RD coefficients using mean-square error (MSE) optimal bandwidth (Panel A: 0.25 and 1.36; Panel B: 0.47 and 2.58). Columns 4 through 6 report the fuzzy RD coefficients estimated using an instrumental variables Probit model and a bandwidth selected manually (Panel A: 0.5, Panel B: 2). In Panel C, reports the same model same model as in Column 1 estimated using a weighted treatment, as the average of the local linear sharp RD coefficient estimates for the first and second cutoffs, using the mean-square error (MSE) optimal bandwidth. Cragg-Donald Wald F-Statistic is the weak identification IV test for Columns 4 through 6. The unconstrained regression sample includes 8,861 observations. Regressions using industry and year-fixed effects are noted as such. Baseline controls include *Size, Market-to-Book, CapEx, Prop. Plant and Equip., Profitability, Book Leverage, Firm Age, R&D Expense, R&D Indicator, Selling Expense, Foreign Profits*. All estimations are reported using robust-clustered standard errors. McFadden's pseudo r-squared value is provided for each Probit specification. Significance is indicated at the alpha 1%, 5%, and 10% levels by ***, **, and *, respectively. See Appendix A for variable definitions.

Panel A: C_1 >=0

	(1) Sharp rdmc	(2) Fuzzy rdrobust	(3) Fuzzy rdrobust	(4) Fuzzy IV ivprobit	(5) Fuzzy IV ivprobit	(6) Fuzzy IV ivprobit
Treatment	-0.14**	-0.15**	-0.06*	-0.96*	-0.97*	-1.34*
DTC	-0.08***	-	-	0.28	0.59**	0.69**
Constant	-	-	-	0.03	0.24	-2.50
Size						0.33**
Market-to-Book						0.01
CapEx						0.79
Prop. Plant & Equip.						-0.03
Profitability						-0.06
Book Leverage						0.63***
Firm Age						0.15*
R&D						-0.79*
R&D indicator						0.20
Selling Expense						0.02
Foreign profits						0.68*
Observations	738	655	3,158	1301	1,301	1,164
Number of firms	577	528	1,705	903	903	810
Bandwidth	0.28	0.25	1.36	0.5	0.5	0.5
Industry FE	N	N	N	N	Y	Y
Time FE	N	N	N	N	Y	Y
Pseudo R-Squared				0.01	0.06	0.21
1^{st} Stage *Treatment*				0.19***	0.20***	0.13**
Cragg-D F-Statistic				12.8	12.9	12.0

Panel B: C_2 >=5.7	(1) Sharp rdmc	(2) Fuzzy rdrobust	(3) Fuzzy rdrobust	(4) Fuzzy IV ivprobit	(5) Fuzzy IV ivprobit	(6) Fuzzy IV ivprobit
Treatment	-0.12***	-0.23**	-0.11**	-0.95**	-0.47**	-1.38*
DTC	-0.08***	-	-	-0.02	0.12	0.05
Constant	-	-	-	0.48**	0.77	-1.24
Size						0.36**
Market-to-Book						-0.01*
CapEx						0.80
Prop. Plant & Equip.						0.18
Profitability						0.01
Book Leverage						0.47*
Firm Age						0.03
R&D						-0.56
R&D indicator						-0.09
Selling Expense						-0.15
Foreign profits						0.43*
Observations	1,859	362	2,230	1,460	1,436	1,334
Number of firms	1,050	258	1,246	962	947	871
Bandwidth	2.24	0.47	2.58	2	2	2
Baseline Controls	N	N	N	N	N	Y
Industry FE	N	N	N	N	Y	Y
Time FE	N	N	N	N	Y	Y
Pseudo R-Squared				0.00	0.10	0.19
1^{st} Stage *Treatment*				0.25***	0.64***	0.11**
Cragg-D F-Statistic				21.9	208.3	19.0

Panel C: $Cutoff_1$ & $Cutoff_2$	(1) Sharp rdmc
Weighted Treatment	-0.12***
DTC	-0.08***
Constant	-
Observations	2,597
Number of firms	1,627
Bandwidth	0.28; 2.24
Baseline Controls	N
Industry FE	N
Time FE	N

Figure 1. Participation to Swap Markets as a Percent (%) of Firms in a Given Index Category

The graphs below plot the percent (%) of firms using swaps in a given index category across time. Index participation is classified according to S&P 500 Large-Cap (SPX), S&P 400 Mid-Cap (MID), S&P 600 Small-Cap (SML), and non-index, according to the last trading day of the fiscal year-quarter. *Swap User* denotes usage of any swap type (IRS, FX, CDS/CDX, Commodity, or Equity). The variables, *Swap User*, *IRS User*, *FX User*, *CDS User*, *COM User*, and *EQ User*, are binary variables for firm swap usage, equal to one if a firm exhibits usage, and zero otherwise. For each firm, swaps usage at the subsidiary level is mapped to the ultimate parent of the firm. Note that for CDS/CDX and EQ swap usage, single-name CDS and single-name equity swaps are excluded (these do not fall under CFTC jurisdiction). The sample spans 15 quarters between 2018 and 2021. Please see Appendix A for variable definitions.

Figure 1a Any Swap Use by Index Category

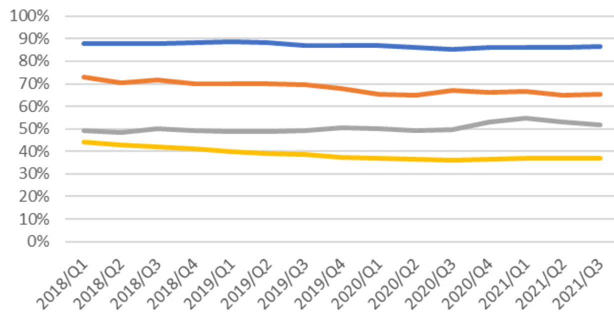


Figure 1b IRS Use by Index Category

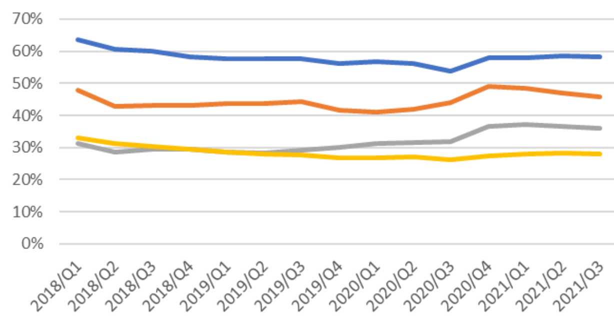


Figure 1c FX Use by Index Category

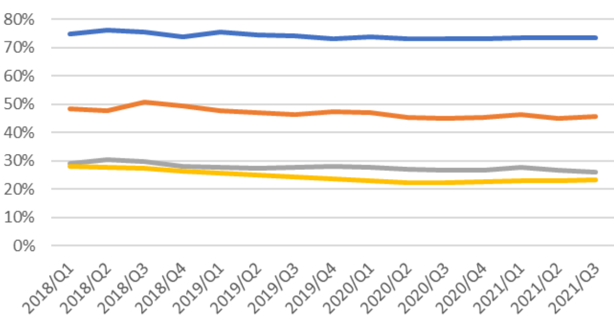


Figure 1d CDS/CDX Use by Index Category

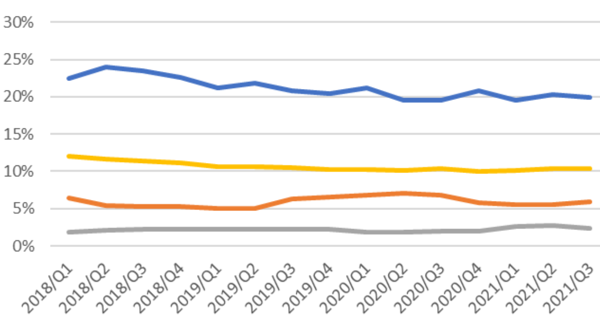


Figure 1e COM Use by Index Category

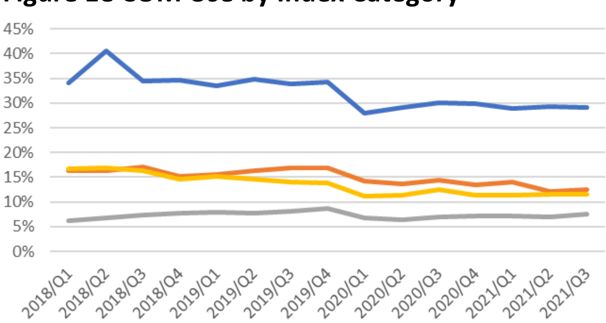


Figure 1f EQ Use by Index Category

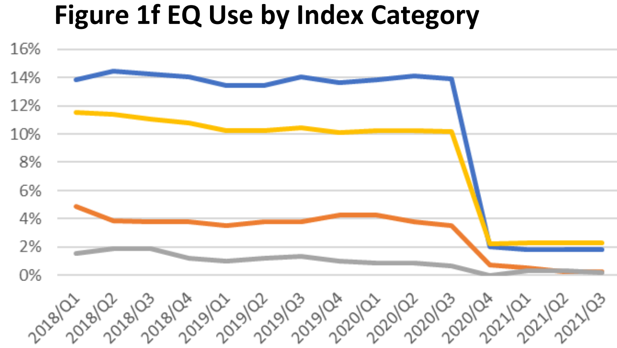


Figure 2. Participation to Swap Markets Across Products in a Given Set of Index Participations

The graphs below plot the percent (%) of firms using a particular swap category across for a given S&P index category. Index participation is classified according to S&P 500 Large-Cap (SPX), S&P 400 Mid-Cap (MID), S&P 600 Small-Cap (SML), and non-index, according to the last trading day of the fiscal year-quarter. *Swap User* denotes usage of any swap type (IRS, FX, CDS/CDX, Commodity, or Equity). The variables, *Swap User*, *IRS User*, *FX User*, *CDS User*, *COM User*, and *EQ User*, are binary variables for firm swap usage, equal to one if a firm exhibits usage, and zero otherwise. For each firm, swaps usage at the subsidiary level is mapped to the ultimate parent of the firm. Note that for CDS/CDX and EQ swap usage, single-name CDS and single-name equity swaps are excluded (these do not fall under CFTC jurisdiction). The sample spans 15 quarters between 2018 and 2020. Please see Appendix A for variable definitions.

Figure 2a S&P 500 Swap Use by Product

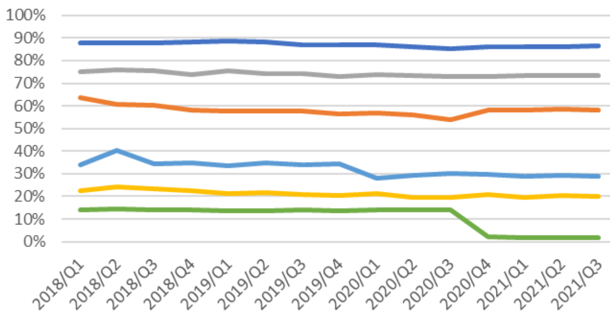


Figure 2b S&P 400 Swap Use by Product

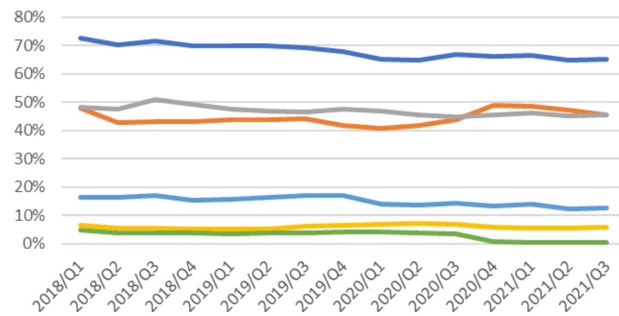


Figure 2c S&P 600 Swap Use by Product

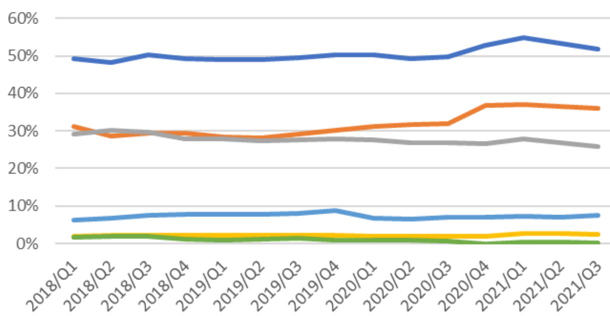


Figure 2d Non-SP Index Swap Use by Product

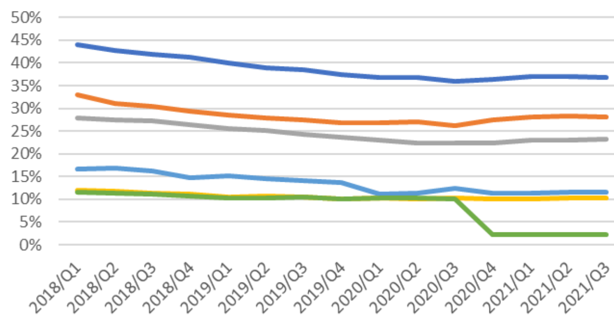


Figure 3. Participation to Swap Markets Across Products in a Given Set of Index Participations

The graphs below plot the percent (%) of firms using swaps in a given industry classification across time. Industries are classified according to the Fama-French 12 industry classification (FF12), using two-digit SIC industry codes. *Swap User* denotes usage of any swap type (IRS, FX, CDS/CDX, Commodity, or Equity). The variables, *Swap User*, *IRS User*, *FX User*, *CDS User*, *COM User*, and *EQ User*, are binary variables for firm swap usage, equal to one if a firm exhibits usage, and zero otherwise. For each firm, swaps usage at the subsidiary level is mapped to the ultimate parent of the firm. Note that for CDS/CDX and EQ swap usage, single-name CDS and single-name equity swaps are excluded (these are not subject to the reporting requirement under CFTC jurisdiction). The sample includes all US public firms and spans 15 quarters between 2018 and 2021. Please see Appendix A for variable definitions.

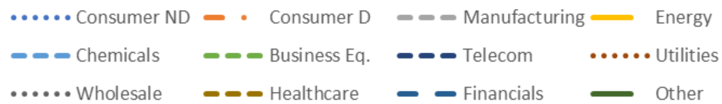


Figure 3a Any Swap Use by Industry

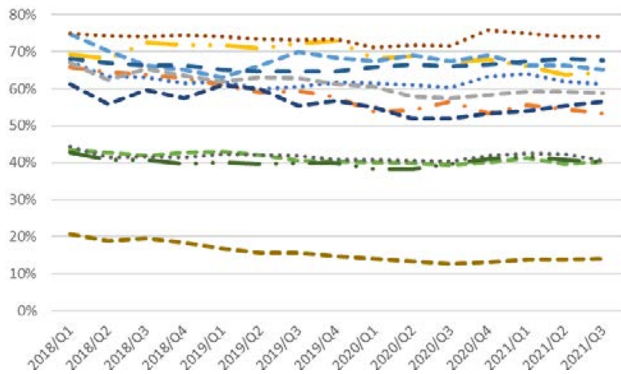


Figure 3b IRS Use by Industry

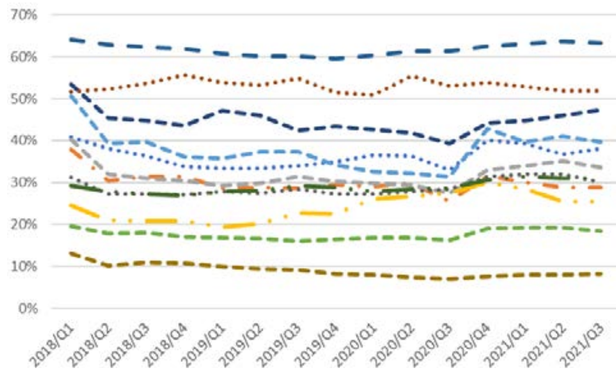


Figure 3c FX Use by Industry

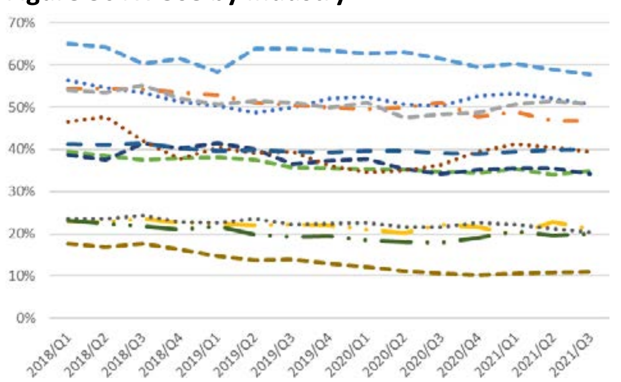


Figure 3d CDS/CDX Use by Industry

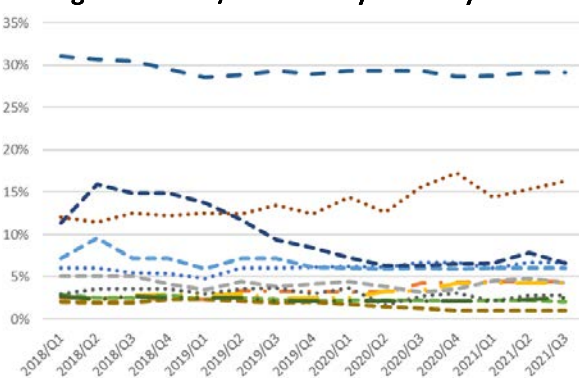


Figure 3e COM Use by Industry

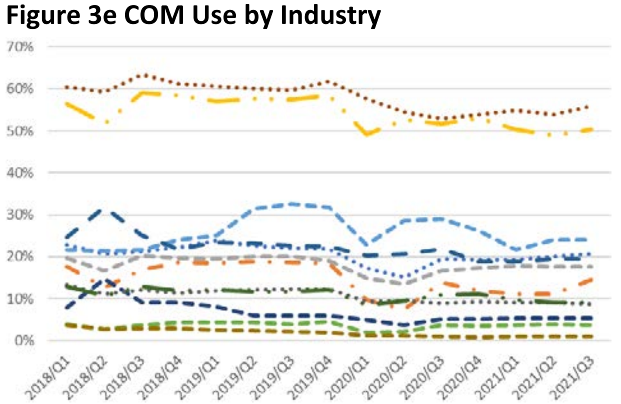


Figure 3f EQ Use by Industry

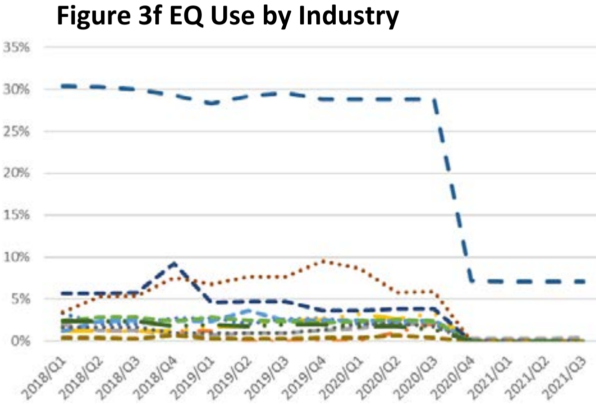


Figure 4. Participation to Swap Markets Across Products by S&P Credit Rating Classification

The graphs below plot the percent (%) of firms using swaps by swap product category and S&P credit rating classification across time. *R* denotes that a firm is credit rated by S&P, *NR* denotes that a firm is not credit rated by S&P, *User* denotes usage of any swap type (IRS, FX, CDS/CDX, Commodity, or Equity). The variables, *Swap User*, *IRS User*, *FX User*, *CDS User*, *COM User*, and *EQ User*, are binary variables for firm swap usage, equal to one if a firm exhibits usage, and zero otherwise. For each firm, swaps usage at the subsidiary level is mapped to the ultimate parent of the firm. Note that for CDS/CDX and EQ swap usage, single-name CDS and single-name equity swaps are excluded (these do not fall under CFTC jurisdiction). The sample spans 15 quarters between 2018 and 2021. Please see Appendix A for variable definitions.

User/R User/NR Non-User/R Non-User/NR

Figure 4a Any Swap Use by Rating

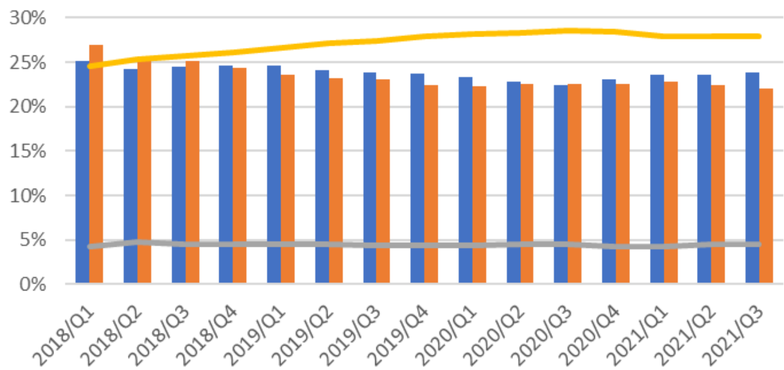


Figure 4b IRS Use by Rating

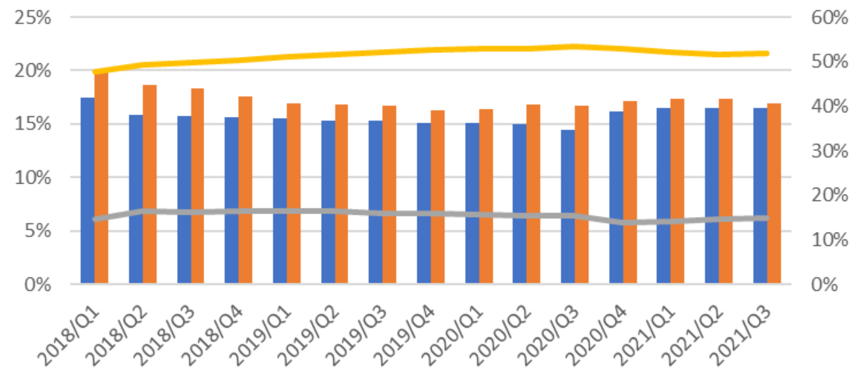


Figure 4c FX Use by Rating

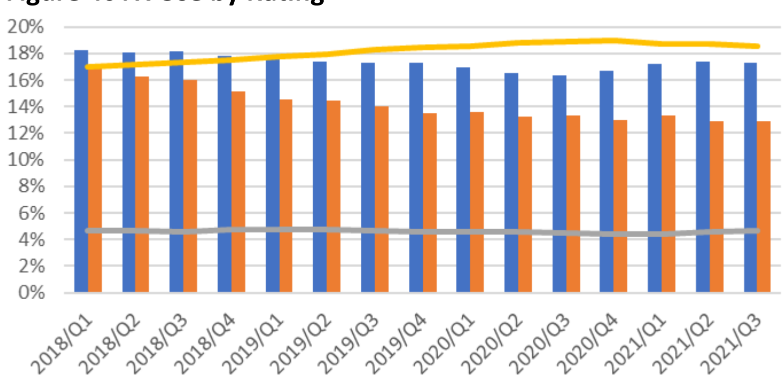


Figure 4d CDS/CDX Use by Rating

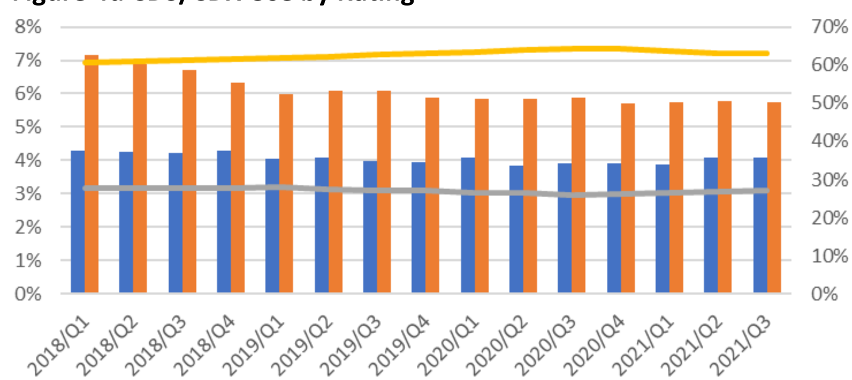


Figure 4e COM by Rating

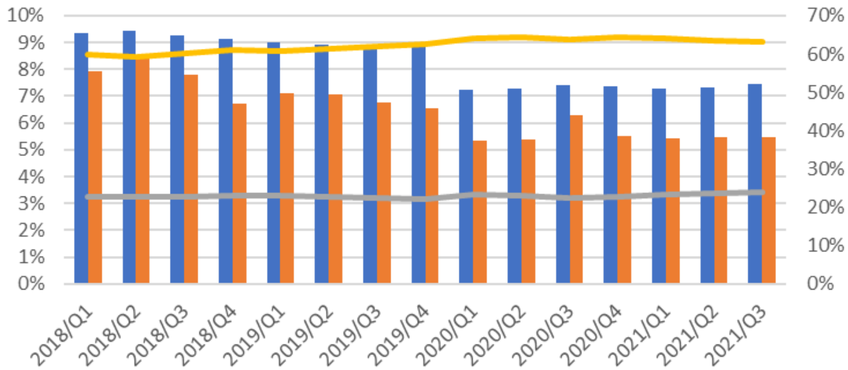


Figure 4f EQ Use by Rating

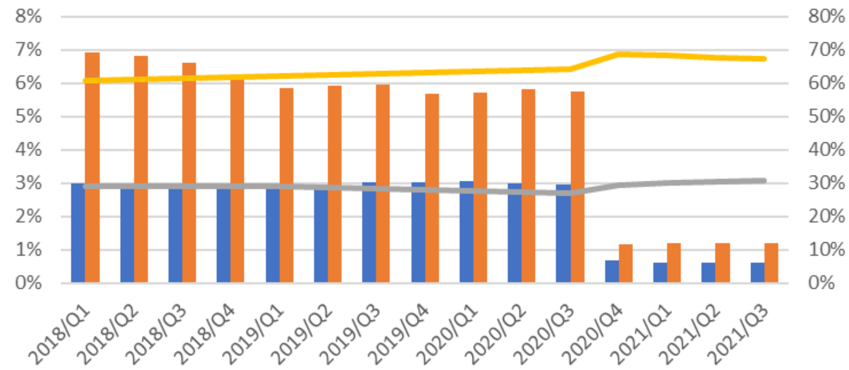


Figure 5. Swap Participation Across Products for a Given Index Participation: Rated vs. Non-Rated

The graphs below plot the percent (%) of firms using a particular swap category for a given S&P index category. Index participation is classified according to S&P 500 Large-Cap (SPX), S&P 400 Mid-Cap (MID), S&P 600 Small-Cap (SML), and non-index, according to the last trading day of the fiscal year-quarter. *R* denotes that a firm is credit rated by S&P, *NR* denotes that a firm is not credit rated by S&P, *Swap User* denotes usage of any swap type (IRS, FX, CDS/CDX, Commodity, or Equity). The variables, *Swap User*, *IRS User*, *FX User*, *CDS User*, *COM User*, and *EQ User*, are binary variables for firm swap usage, equal to one if a firm exhibits usage, and zero otherwise. For each firm, swaps usage at the subsidiary level is mapped to the ultimate parent of the firm. Note that for CDS/CDX and EQ swap usage, single-name CDS and single-name equity swaps are excluded (these do not fall under CFTC jurisdiction). The sample spans 15 quarters between 2018 and 2020. Please see Appendix A for variable definitions.

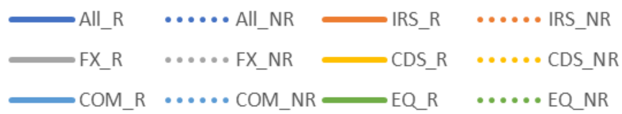


Figure 5a S&P 500 Swap Use by Product/Rating

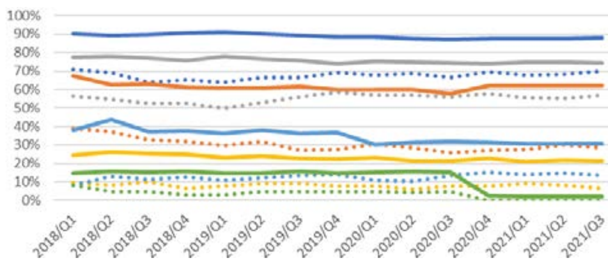


Figure 5b S&P 400 Swap Use by Product/Rating

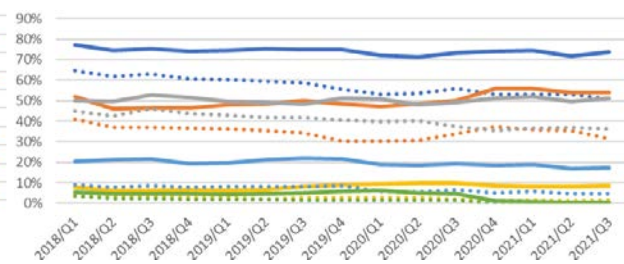


Figure 5c S&P 600 Swap Use by Product/Rating

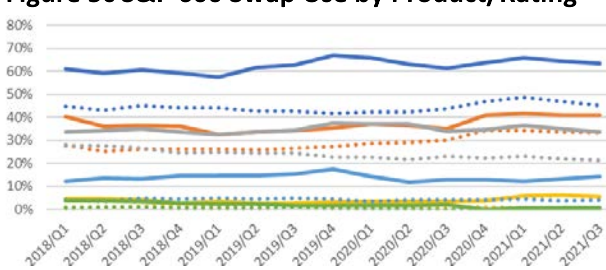


Figure 5d Non-SP Index Swap Use by Product/Rating

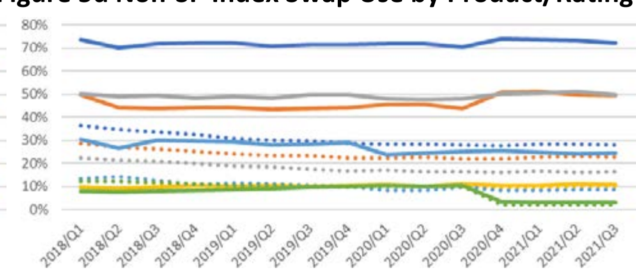


Figure 6. S&P Credit Rating and Debt/EBITDA Distributions

This figures below present the histograms for the S&P long-term issuer credit rating letter grade (Figure 7a) and winsorized Debt/EBITDA (Figure 7b) for the 2018-2021 sample, excluding financials and utilities. S&P ratings are defined as an ordinal number, from D (0) to AAA (21). Please see Appendix A for variable definitions.

Figure 6a: S&P Credit Rating Histogram

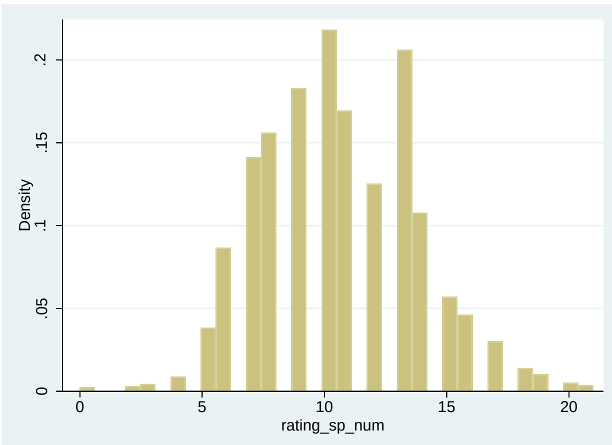


Figure 6b: Debt/EBITDA Histogram

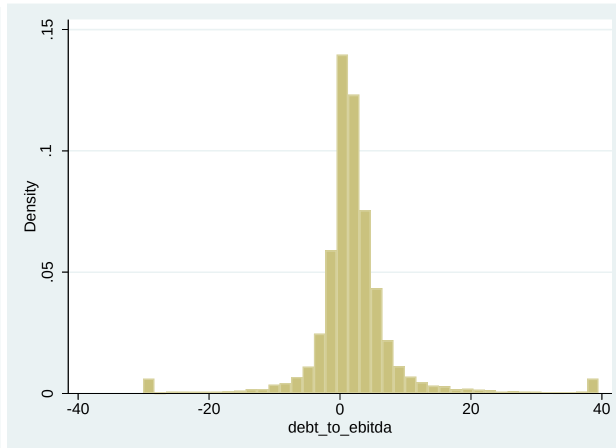


Figure 7. Proportion of Swap Usage by S&P Credit Rating and Debt/EBITDA

This figure presents the average proportion of swap usage by the S&P long-term issuer credit rating letter grade (Figure 6a) and Debt/EBITDA ventile (Figure 6b) for the 2018-2021 sample, excluding financials and utilities. S&P ratings are defined as an ordinal number, from D (0) to AAA (21). Credit ratings below CCC- are excluded from the plot. The vertical red lines for each plot represent the RD cutoff thresholds corresponding to the RD estimations (Panel A: B/B+, BBB-/BBB; Panel B: 0, 5.7). Please see Appendix A for variable definitions.

Figure 7a: S&P Credit Rating Grade

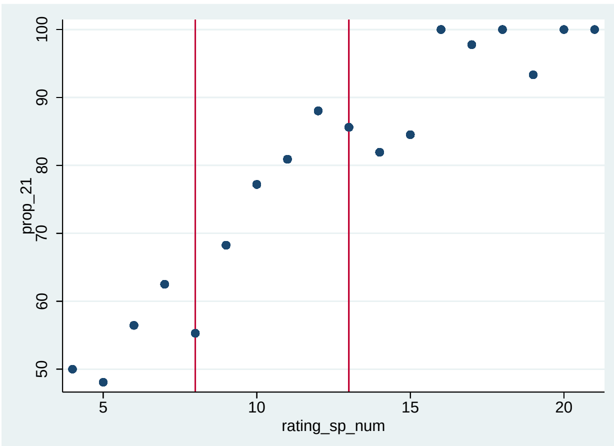


Figure 7b: Debt/EBITDA Ventile

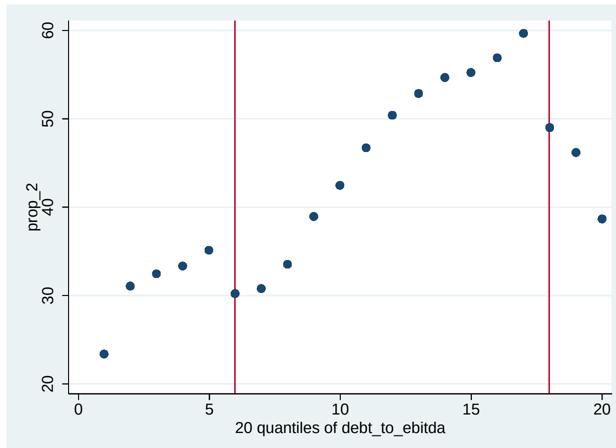


Figure 8. McCrary (2008) Cutoff Manipulation Testing

Figures 8a though 8d present the histograms for the cutoff manipulation test around the respective thresholds for S&P credit ratings and Debt/EBITDA. The table includes the test statistics for the McCrary (2008) cutoff manipulation testing around the respective thresholds for S&P credit ratings and Debt/EBITDA. The test is based on the notion that the density of pre-cutoff and post-cutoff distributions are relatively continuous in absence of a non-random assignment. The robust t-statistics provide the bias-corrected density estimates around the designated cutoff. The null hypothesis, H_0, is no discontinuity in a forcing variable, i.e. no non-random assignment or manipulation at the designated level of significance. The package used for the construction if the plot is *rddensity* (see Cattaneo et al. (2020, 2021a, 2021b) for STATA package documentation). The unrestricted model estimates the density without any restrictions, i.e. two-sample unrestricted inference. The bandwidth method of MSE indicates the median of three mean-square error (MSE) optimal bandwidth estimations (MSE of each density estimator separately with two different bandwidths, MSE of two density estimators with common bandwidth, MSE of sum of two density estimators with common bandwidth). The kernel specifies the local polynomial estimator, i.e. K(u) = (1 - |u|) * (|u|<=1). Significance is indicated at the alpha 1%, 5%, and 10% levels by ***, **, and *, respectively. Please see Appendix A for variable definitions.

Figure 8a: S&P Credit Rating Cutoff 1 (C_1 >=B+)

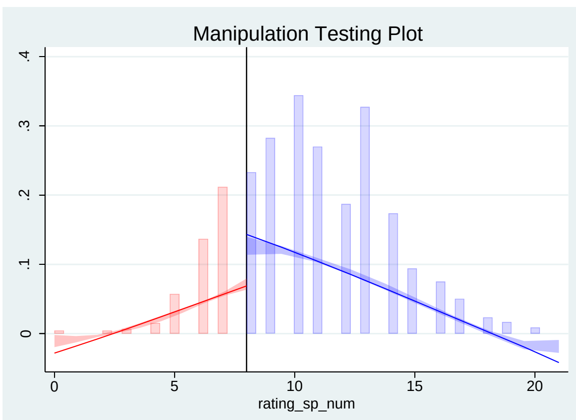


Figure 8b: Debt/EBITDA Cutoff 1 (C_1 >=0)

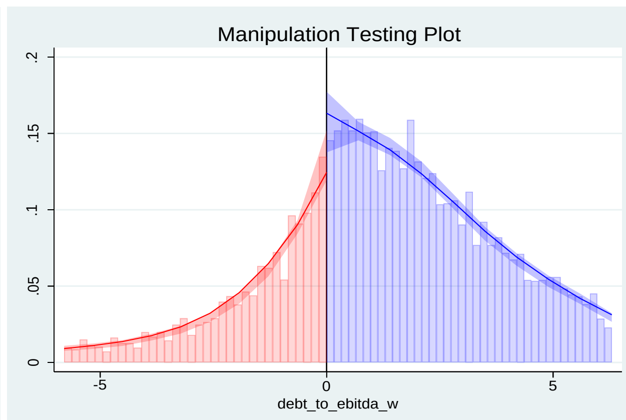


Figure 8c: S&P Credit Rating Cutoff 2 (C_2 >=BBB)

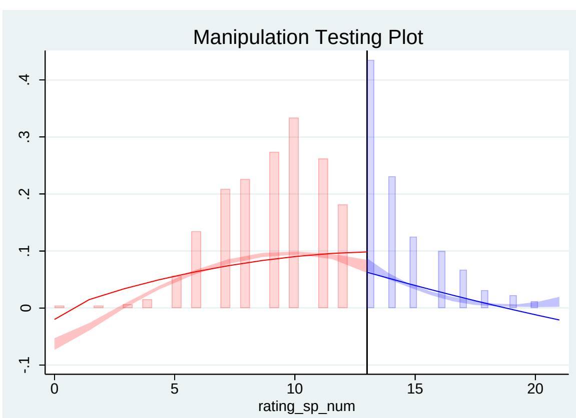
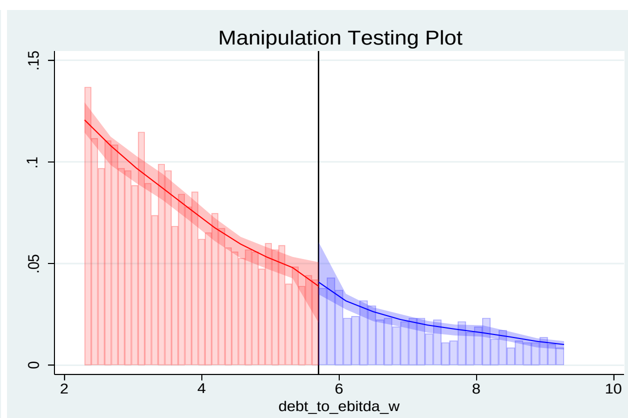


Figure 8d: Debt/EBITDA Cutoff 2 (C_2 >=5.7)



	S&P Rating C_1 >= B+	S&P Rating C_2 >= BBB	Debt/EBITDA C_1 >= 0	Debt/EBITDA C2 >= 5.7
Robust T-Statistic	-1.49	2.94	1.60	1.18
P-Value	0.14	0.00***	0.11	0.24
Model	Unrestricted	Unrestricted	Unrestricted	Unrestricted
Bandwidth Method	MSE	MSE	MSE	MSE
Kernel	Triangular	Triangular	Triangular	Triangular
VCE Method	Jackknife	Jackknife	Jackknife	Jackknife

Figure 9. S&P Credit Rating RD Plots

The figures below present the linear regression function fit for S&P long-term issuer credit rating. Figures 9a and Figure 9b present cutoffs 1 and 2, respectively. Figure 9c presents the multi-cutoff in a single linear regression function fit. Each dot represents the sample average for the proportion of swap usage for a given S&P long-term issuer credit rating letter grade bin. A regression function fit of polynomial order one is constructed for above and below each respective cutoff. The STATA package used for the construction is *rdplot* for the plots in Figures 9a and 9b and *rdmc* for the plot in Figure 9c (see Cattaneo et al. (2015a, 2015b, 2017)) and *rdmc* for the plot in Figure 9c (see Cattaneo et al. (2016, 2020)). Please see Appendix A for variable definitions.

Figure 9a: S&P Credit Rating RD Plot for Cutoff 1 (C_1 >=B+)

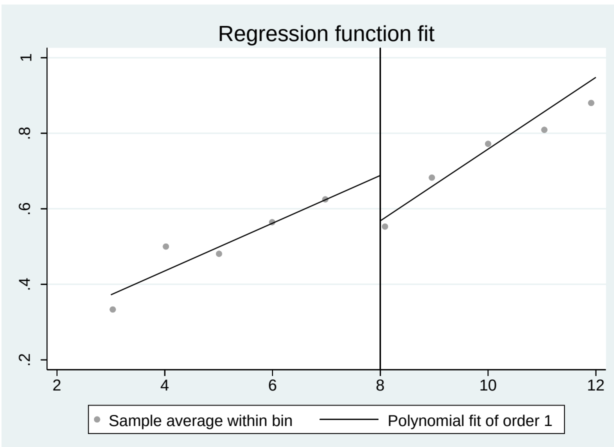


Figure 9b: S&P Credit Rating RD Plot for Cutoff 2 (C_2 >=BBB)

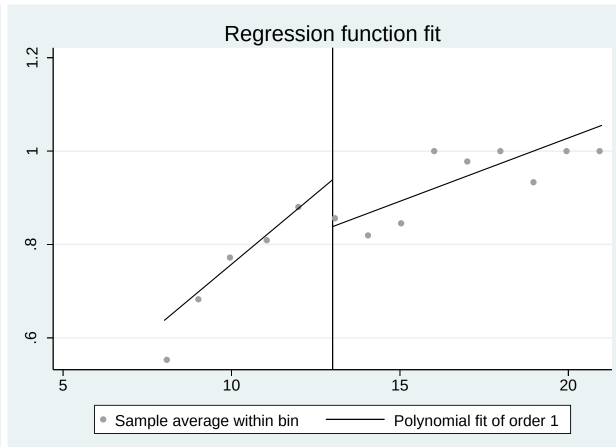


Figure 9c: S&P Credit Rating Multi-Cutoff RD Plot (C_1 >=B+ and C_2 >=BBB)

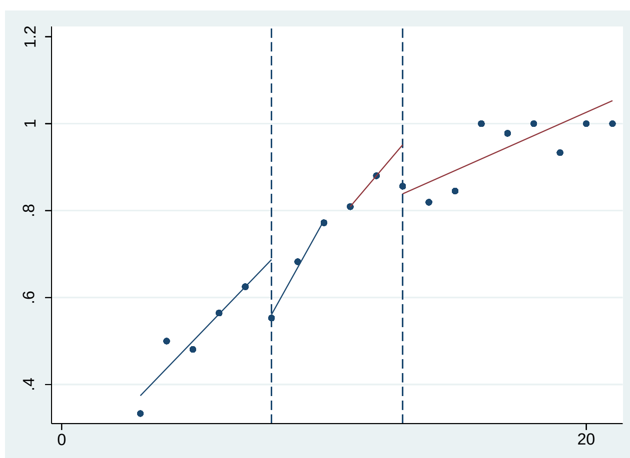


Figure 10. Debt/EBITDA RD Scatter Plot

The figures below present the binned scatter plot and linear regression function fit for Debt/EBITDA cutoffs 1 (Figure 10a) and 2 (Figure 10b). Figure 10c presents the multi-cutoff binned scatter plot and linear regression function fit for Debt/EBITDA cutoffs 1 and 2. Following Lee and Lemieux (2008), each dot represents the sample average for the proportion of swap usage for a given bin. Inclusion of additional bins or varying bin widths produces similar results to the figures above. A regression function fit of polynomial order one is constructed for above and below each respective cutoff. The package used for the construction of the plots is cmogram for Figures 10a and 10b (see Robert (2010)) and rdmc for Figure 10c (see Cattaneo et al. (2016, 2020). Please see Appendix A for variable definitions.

Figure 10a: Debt/EBITDA RD Scatter Plot for Cutoff 1 (C_1 >=0)

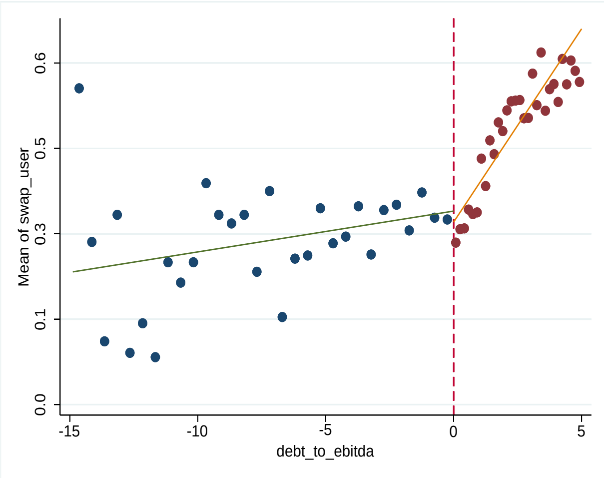


Figure 10b: Debt/EBITDA RD Scatter Plot for Cutoff 2 (C_2 >=5.7)

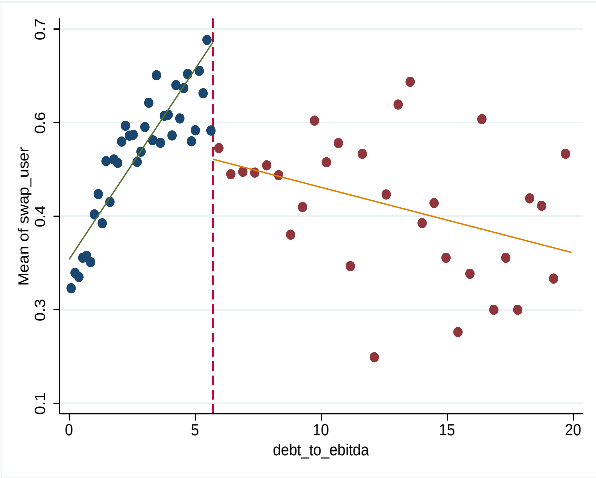


Figure 10c: Debt/EBITDA Multi-Cutoff RD Plot (C_1 >=0 and C_2 >=5.7)