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Collateral Constraints, Financial Constraints, and Risk Management: Evidence From Anti-Recharacterization Laws

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Abstract

We use the staggered enactment of anti-recharacterization laws as a plausibly exogenous shock to the value of securitizing collateral through special purpose vehicles (SPVs) and test how collateral values impact corporate risk management. Following the laws' enactment, we find increases in commodity, foreign exchange, and interest rate hedging, especially for firms with exposure to these risks and that rely on SPVs. Supporting the collateral constraints literature, the effect is weaker for firms that likely need the collateral for external financing, such as financially constrained firms. Our findings highlight fluctuations in collateral values as an important consideration in risk management decisions.

I. Introduction

Risk management plays an important role in the financial strategy of many firms. Still, the theoretical motivation for managing risk through hedging has shifted. Traditional models such as those in Froot, Scharfstein, and Stein (1993) suggest that it is optimal for firms to hedge cash flow risk when the wedge between the cost of internal and external funds is relatively wide as hedging may preserve internal funds needed to capture investment opportunities. However, this theoretical prediction does not square with the empirical observation that firms facing relatively low costs of accessing capital are more likely to use derivative securities to hedge cash flow risk.[1]

Recent theoretical work provides a rationale for this potentially puzzling observation. Specifically, several financial policies of firms are partially determined by collateral constraints, or limitations on the availability of assets to be used to back financing and risk management activities. As both external financing and risk management utilize assets as collateral to mitigate default risk, these two activities

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[1]See Nance, Smith, and Smithson (1993), Stulz (1996), Géczy, Minton, and Schrand (1997), Guay and Kothari (2003), Purnanandam (2008), and Rampini, Sufi, and Viswanathan (2014).

compete for collateral (Rampini and Viswanathan (2010)). Firms with limited internal funds will utilize collateral for financing to capture valuable investment opportunities, while other firms are more likely to pledge assets to preserve net worth through risk management (Rampini and Viswanathan (2013)).

Several recent studies support these theoretical arguments. For example, Rampini et al. (2014) document that the practice of hedging of fuel costs within the airline industry is found within firms that are financially unconstrained and far from default. Further, Li, Whited, and Wu (2016) provide structural and empirical evidence that collateral values impact leverage. In this article, we directly consider the mechanism underlying the theoretical work. Specifically, does an increase in the value of a firm's collateral increase the propensity for that firm to hedge cash flows using derivative securities? If so, is this observed effect less pronounced in firms that place a relatively high value on utilizing collateral to finance investment using external sources? To test these questions, we use a plausibly exogenous shock to the value of a particular type of collateral: the securitization of assets through special purpose vehicles (SPVs). Specifically, we implement a difference-in-differences approach to test for variation in risk management activities following the staggered adoption of anti-recharacterization laws (ARLs or "the laws").

ARLs shift the value of these securitized assets held by firms as collateral. Firms commonly use SPVs to hold assets that will act as collateral. The assets in SPVs are intended to remain remote from the parent firm in the event of bankruptcy. Ayotte and Gaon (2011) discuss why lenders value collateral in an SPV vis-à-vis collateral in a securitized loan. Specifically, lenders can typically access assets of the SPV in the event of bankruptcy by the sponsor firm because the SPV is bankruptcy remote. Alternatively, lenders are limited in accessing assets collateralizing secured loans by the bankruptcy's automatic stay. Importantly, the use of SPV is common, and the practice of holding these SPVs increases over our sample period. By 2004, most firms are estimated to have an SPV (Feng, Gramlich, and Gupta (2009)).

However, prior to the enactment of ARLs, courts used discretion to recharacterize the transfer of assets into an SPV as a loan instead of a sale. This recharacterization results in making the asset more difficult to reclaim as part of the bankruptcy process as the assets are no longer considered remote from the sponsor firm. The increased cost of repossession lowers the value of the asset as collateral to the lending firm. Several states enacted ARLs, which limit the ability of courts to recharacterize the assets in SPVs. In the presence of these laws, lenders can still reclaim collateral in the SPV in the event of bankruptcy by the parent firm. We follow the literature in using these laws as an exogenous shift in the value of the collateral (Li et al. (2016), Chu (2020)) to test whether plausibly exogenous increases in the value of collateral affect the propensity to hedge.

Our sample consists of Compustat industrial firms with necessary variables for analysis. Risk management variables come from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database of the U.S. Securities and Exchange Commission (SEC), so we begin our sample period in 1996 when this database is populated for all public firms. The sample period ends in 2003 as federal legislation

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this year raised doubt as to whether a change in federal law would supersede state-level ARLs going forward.[2]

We test for shifts in the use of derivative securities to hedge before and after the enactment of these laws. The treatment firms are those incorporated in states that have enacted ARLs and control firms are incorporated in states that have not yet enacted the laws.

Our measures of firms' risk management behavior are based on discussions of hedging activity in firms' 10-K filings. We use a scripting language and classify a firm-year as hedging risk if the corresponding 10-K has language indicating the use of derivatives for exposures to commodities, foreign exchange (FX), or interest rate risk.[3] This approach has both disadvantages and advantages. Some papers hand-collect the proportion of a firm's exposure to a particular risk that is hedged. For instance, Rampini et al. (2014) utilize data on the proportion of fuel expenses hedged by firms in the airline industry. Given the nonstandardized way in which these data are reported, a limitation of using text from firms' 10-K filings is the inability to collect a continuous measure of hedging activity that captures the amount of exposure that is hedged. As such, by using an indicator variable, we largely identify the extensive margin in hedging activity. However, the advantages to using text-based data are that we can collect data across a broad cross-section of firms, for various types of risk management, and over a relatively long sample period.

Our primary specification is a linear probability model. The dependent variable is a hedging indicator variable that takes the value of 1 if a firm is classified as hedging commodity, FX, or interest rate risk. We estimate a difference-in-differences specification with state of headquarter-by-year, industry-by-year, and firm fixed effects to control for time varying state-level, time varying industry-level, and time invariant firm-level fixed effects that may be correlated with the adoption of the laws and the propensity to hedge cash flow risk using derivative securities.

We find a significant increase in hedging with derivative securities following the adoption of the ARLs. Firms increase their propensity to hedge by 2.7% relative to control firms following the law's enactment. This represents an increase of about 7.8% relative to the unconditional sample mean of 34.5%, suggesting an economically meaningful impact. These results suggest that an exogenous increase in the value of a firm's collateral results in an increase in hedging activity, consistent with the theoretical predictions in Rampini and Viswanathan (2010), (2013).

A causal interpretation of the relation between the adoption of ARLs and hedging behavior must satisfy the parallel trends assumption that the average change in hedging behavior would have been the same for both treatment and control firms absent the treatment. A number of observations are consistent with this assumption. First, we find that changes in hedging propensities appear 1 year

[2]The effect of the established federal precedent on state-level anti-recharacterization laws is unclear. As such, we consider the robustness of our results to ending our sample period in 2006 in Section IV.D.

[3]A firm is classified as hedging if it uses positive hedging language such as "manage fuel price risk." This classification is then removed if the language includes negative phrases such as "does not manage fuel price risk." The classification of a firm-year as hedging is discussed further in Section III.A, and the exact search phrases are included in Table A1 of the Supplementary Material.

after and not before the enactment of ARLs. This alleviates concerns of reverse causality.

Another concern is that the treatment and control firms differ in dimensions that impact hedging activity, which might suggest that firms' hedging policies differ from one another for reasons other than shifts in the value of collateral assets. We address this issue in several ways. First, we match treatment firms to control firms based on observable firm-level characteristics that differ significantly prior to the match using propensity score matching. Second, we use an inverse propensity weighting model. This model conditions on the likelihood of being a treatment firm by weighting observations by the inverse of the propensity score. Last, we match firms to nearest neighbors using the Mahalanobis distance as the matching metric. Our findings are robust to each of these approaches, suggesting that the findings are not attributable to differences between treatment and control firms.

Last, we note that we include state-by-year fixed effects based on the state of headquarter and industry-by-year fixed effects based on the Fama–French 49-industry classification codes in all models. These fixed effects control for any state-level or industry-level, time varying factors that may be correlated with both the enactment of the laws and variation in hedging activity. Collectively, these findings suggest that our results are robust to addressing concerns with the parallel trends assumption.

An advantage of using the text from annual statements to collect hedging data is that we are able to consider the impact of the enactment of the ARLs across various types of hedging. We next show that the increased propensity to hedge following the enactment of these laws is significant across all three types of hedging: commodity hedging, FX hedging, and interest rate hedging. Further, the effect varies for proxies of the underlying exposure faced by the firm. Specifically, commodity hedging increases more significantly for airline firms, an industry commonly found to hedge oil exposures (e.g., Rampini et al. (2014)), following the enactment of the laws. Further, the increased propensity to use FX hedges is more pronounced for firms with foreign operations, and the increased propensity to hedge interest rate risk is significantly lower for firms with relatively low or zero debt financing.

The theory in Rampini and Viswanathan (2010), (2013) predicts that increases in collateral value will lead to greater hedging activity. The use of ARLs allows us to test this theory, but it only applies to collateral securitized through SPVs. This type of collateral is important to lenders as it allows them to avoid the automatic stay of bankruptcy (Ayotte and Gaon (2011)). However, not all firms utilize SPVs. To validate the paper's results, we test whether the effects of ARLs on hedging is most prevalent for firms that use SPVs. Consistent with this argument, we find that firms likely using SPVs are most impacted by the laws.

An important implication of the theory on collateral constraints is cross-sectional variation in how firms respond to changes in collateral value. Firms with a significant wedge between the cost of internal and external funds or firms in financial distress place a high value of raising external funds for investment. For these firms, the increased value of collateral is likely used to increase borrowing. In contrast, firms with relatively easy access to external capital are more likely to

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value collateral for hedging purposes, suggesting the positive relation between hedging and ARLs should stem from these firms.

We test this prediction using several proxies to test for this cross-sectional variation. First, we use six proxies to capture firms with a high wedge between internal and external funds, or high financial constraints.[4] We also consider firms near default (Bharath and Shumway (2008)) and firms with low net worth (Rampini et al. (2014)) as having high external financing needs. Consistent with theoretical predictions, we find the positive relation between hedging and ARLs is weaker for financially constrained firms, firms near default, and firms with low net worth.

The results presented are also robust to a number of considerations. First, we follow past literature (e.g., Hoberg and Moon (2017), Qiu (2019)) and use 1 plus the natural logarithm of the count of mentions of hedging activity as an alternative dependent variable. By doing this and including firm fixed effects, we capture higher values for firms that discuss hedging activity more or less in a particular year. Using this approach, we continue to find a robust increase in hedging (in aggregate and across all three types of hedging) following the enactment of the anti-recharacterization laws.

We also consider adjustments to the construction of our sample. First, federal legislation in 2003 raised questions regarding the efficacy of state-level ARLs. As such, we end our sample period in this year. However, it is unclear whether the scope of this federal legislation is large enough to materially impact all state-level ARLs. We extend the sample to 2006, which adds three additional treated states, to ensure that our results are not attributable to ending the sample period in 2003. We continue to find a significant increase in hedging with the use of derivative securities after the enactment of the laws.

We ensure that the findings are not impacted by noise in the assignment of firms' states of incorporation, which is the relevant state for the law. To do so, we remove firm-years that have a backfilled state of incorporation from Compustat and, separately, any firm that changes its state of incorporation during the sample period. This latter adjustment also ensures that the findings are not impacted by firms selecting into states with advantageous business environments. The increase in hedging after the enactment of the laws is robust to these changes.

Our paper contributes to two related strands of literature. First, the recent theoretical literature in Rampini and Viswanathan (2010), (2013) suggests that collateral value impacts the decision to hedge, rationalizing the observation that unconstrained firms hedge more. Rampini et al. (2014) empirically support this literature by providing evidence that high net worth airline firms hedge fuel exposures more than other airline firms. We complement their work by showing that hedging is more pronounced for unconstrained firms. Rampini et al. ((2014), p. 289) also note that it is "an empirical challenge to isolate the precise reason for the strong positive relation between net worth and hedging." We provide empirical evidence that a plausibly exogenous increase in collateral value, the exact

[4]Constrained firms are firms without an investment grade credit rating, firms with no credit line (Sufi (2009)), firms that do not pay dividends, and firms with a high HP (Hadlock and Pierce (2010)), WW (Whited and Wu (2006)), or HM (Hoberg and Maksimovic (2015)) financial constraints index value.

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mechanism underlying this theoretical literature, results in greater hedging, especially for firms with high net worth.

The paper also contributes to papers that show a shift in firm-level policies resulting from fluctuations in collateral value (e.g., Ersahin (2020)). Our paper is closely related to two papers on the effect of anti-recharacterization laws on borrowing. First, Li et al. (2016) show that firms increase leverage following the adoption of these laws. Second, firms decrease the use of leases following the enactment of laws, especially firms with financial constraints (Chu (2020)). We provide complimentary evidence by showing that financially unconstrained firms utilize the expanded collateral value to increase risk management practices.

II. Hypothesis Development and Institutional Detail

A. Hypothesis Development

Traditional theories of risk management suggest that firms nearer to default or that are financially constrained are more likely to manage risk through hedging (Smith and Stulz (1985), Froot et al. (1993), and Purnanandam (2008)). The intuition behind these models is that hedging cash flow risk can mitigate the deadweight costs of financial distress or insolvency and allow for firms to take advantage of valuable growth opportunities by preserving less-costly internal funds. However, these theoretical predictions do not square with the empirical observations documented consistently across a number of papers that firms hedging with derivative securities tend to be large, financially unconstrained, and far from default.

More recent theoretical models square this puzzling observation by including in their models the potential role that collateral constraints play on the propensity for a firm to hedge. Specifically, both financing and risk management activities utilize assets as collateral to back promises to pay (Rampini and Viswanathan (2010)). Firms with limited internal funds, such as financially constrained firms, will utilize collateral for financing to capture investment opportunities (Rampini and Viswanathan (2013)). An implication of these models is that firms with a significant difference between the cost of internal and external financing will value the collateral to raise external funds and take advantage of valuable investment opportunities. Alternatively, a firm with easier access to external financing will take advantage of the collateral to hedge cash flow risk and preserve the firm's net worth.

Several papers have documented that firms that are financially unconstrained or with high net worth are more likely to hedge using derivative securities, while constrained firms value external financing. For example, Rampini et al. (2014) document that the practice of hedging of fuel costs within the airline industry is found within firms that are financially unconstrained and far from default. Further, Li et al. (2016) provide structural and empirical evidence that collateral values impact leverage. These findings are consistent with models of collateral constraints. Yet, there is little direct evidence that changes in the value of collateral affect the propensity to hedge cash flow risk using derivatives.

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One limitation on testing this direct prediction stems from the inability to observe collateral values. However, the staggered adoption of anti-recharacterization laws significantly shifts the value of one particular type of collateral: assets securitized in SPVs. Firms commonly transfer ownership of assets to a separate legal entity called an SPV to isolate the value of collateral from default by the SPV's sponsor firm, and this securitization makes it more feasible for a lender to reclaim the value of the collateral in the event of bankruptcy at the sponsor firm (Feng et al. (2009), Ayotte and Gaon (2011)). This feature of SPVs makes assets within SPVs valuable collateral by protecting lenders in the event of bankruptcy by the sponsor firm.

However, courts often use discretion and may classify this securitization of assets as a loan instead of a sale. In the event of bankruptcy, this recharacterization adds protection to the assets held in the SPV. As a result, this bankruptcy protection makes the assets more difficult to reclaim as part of the bankruptcy process. Bankruptcy protection reduces the value of the asset as collateral. Several states have eliminated courts' discretion by enacting anti-recharacterization laws.

These laws limit the ability of courts to recharacterize the assets in SPVs as a loan, keeping the assets remote from the sponsor firm. In the presence of these laws, lenders can still reclaim collateral in the SPV in the event of bankruptcy by the sponsor firm as the assets stay remote from bankruptcy protection. As such, anti-recharacterization laws serve as a positive shock to the value of collateral securitized in SPVs. Rampini and Viswanathan (2013) predict that an increase in collateralizability increases risk management (see Panel B of Figure 5 in Rampini and Viswanathan (2013)). This leads to the empirical prediction that corporate risk management increases following the adoption of anti-recharacterization laws as these laws increase the value of the collateral assets held in SPVs.

B. Institutional Background of Anti-Recharacterization Laws

1. The Effect of Anti-Recharacterization Laws on Collateral Value

The use of SPVs by sponsor firms is common, and these vehicles impact the value of a firm's collateral. Feng et al. (2009) report that by 2004, 58.3% of firms are estimated to have an SPV. These SPVs isolate the value of collateral from default by the SPVs' sponsor firms, making it more feasible for a lender to reclaim the value of the collateral. Anti-recharacterization laws limit the ability of courts to recharacterize these assets as loans, which risks their bankruptcy remote status, increasing the value of assets in SPVs as collateral. We use the staggered enactment of these laws as a quasi-exogenous shock to the value of collateral held in SPVs.

Yet, some question the practical application of these laws. First, some suggest bankruptcy is governed by federal law, not state law. Second, even if states govern bankruptcy law, questions remain whether state bankruptcy courts will enforce the laws as written (Kettering (2008)). However, precedent has been set that states govern property rights in the event of bankruptcy, and bankruptcy courts' decisions during bankruptcy have been shown to be influenced by anti-recharacterization laws (Chu (2020)). As such, we follow the literature in using these laws as an exogenous shift in the value of the collateral assets (see Li et al. (2016), Chu (2020)).

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2. Is the Enactment of These Laws Exogenous?

As with the enactment of any law, it is important that we consider whether the enactment of anti-recharacterization laws is exogenous with respect to firms' risk management decisions as the enacting states are not randomly assigned. Importantly, lobbying was a large factor in the enactment of these laws across states. However, the lobbying activities were largely driven by financial institutions that wanted to preserve the value of assets in securitized lending (Janger (2003), Li et al. (2016), and Chu (2020)). In this article, we consider the risk management practices of industrial firms by excluding utility and financial firms. It is unlikely that the enactment of these laws was influenced by firms' preferences to manage risk using derivative securities, implying that reverse causality does not play a significant role in any of the paper's findings.

A separate, but related concern is that the economic environment for or characteristics of firms incorporated in states that enact anti-recharacterization laws differ from the economic environment for and characteristics of firms incorporated in other states. To the extent that this is the case, these differences may threaten the parallel trends assumption that, absent the enactment of the law, there would be no shift in the risk management practices of treatment and control firms. We address concerns stemming from this consideration using a variety of empirical approaches (e.g., the inclusion of various control variables and fixed effects and methods to match treatment and control firms on observable dimensions) throughout the paper. In the presence of these tests, we consider anti-recharacterization laws exogenous with respect to risk management practices.

III. Research Design and Sample Selection

A. Empirical Methodology

To assess the relation between the enactment of anti-recharacterization laws and corporate risk management, we implement a difference-in-differences research design and estimate the following panel regression model:

$$
\begin{aligned}
(1)\quad \mathrm{HEDGE}_{i,s,t} = {} & \alpha_1 \mathrm{ARLs}_{s,t} + \beta_1 \mathrm{FIRM\_SIZE}_{i,s,t-1} + \beta_2 \mathrm{FIRM\_AGE}_{i,s,t-1} \\
& + \beta_3 \mathrm{LEVERAGE}_{i,s,t-1} + \beta_4 \mathrm{MTB}_{i,s,t-1} + \beta_5 \mathrm{CAPEX}_{i,s,t-1} \\
& + \beta_6 \mathrm{ROA}_{i,s,t-1} + \beta_7 \mathrm{RD}_{i,s,t-1} + \beta_8 \mathrm{RD\_MISS}_{i,s,t-1} \\
& + \beta_9 \mathrm{TANGIBILITY}_{i,s,t-1} + \beta_{10} \mathrm{DIVIDEND\_PAYER}_{i,s,t-1} \\
& + \beta_{11} \mathrm{CASH\_HOLDING}_{i,s,t-1} + \delta_h{}' \omega_t + \eta_k{}' \omega_t + \upsilon_i + \varepsilon_{i,s,t},
\end{aligned}
$$

where $\mathrm{HEDGE}_{i,s,t}$ is an indicator set to 1 if firm i, incorporated in state s, is classified as hedging either commodity, FX, or interest rate according to its annual 10-K filings in year t, and 0 otherwise. We first classify firms as hedging if they use any of a variety of phrases that indicate hedging activity (e.g., "hedges its exchange rate risk"). We then remove this classification if the firm uses

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language to negate the suggestion that the firm hedges (e.g., "not hedge its exchange rate risk").[5]

The variable $\text{ARLs}_{s,t}$ is an indicator set to 1 if state s has adopted the anti-recharacterization laws by year t, and 0 otherwise. We account for potential omitted, correlated variables using a number of control variables. We select control variables used in recent work on risk management (Hoberg and Moon (2017), Qiu (2019)). To ensure that control variables are not creating a bias in our variable of interest, we show all of our results both without and with controls and, when controls are included, they are lagged by 1 year to mitigate simultaneity concerns.

Control variables include the natural logarithm of the beginning of year book assets ($\text{FIRM\_SIZE}_{i,s,t-1}$), firm age ($\text{FIRM\_AGE}_{i,s,t-1}$), leverage ($\text{LEVERAGE}_{i,s,t-1}$), market to book ratio ($\text{MTB}_{i,s,t-1}$), the ratio of capital expenditures to book assets ($\text{CAPEX}_{i,s,t-1}$), the ratio of net income to book assets ($\text{ROA}_{i,s,t-1}$), the ratio of research and development expense (R&D) to sales ($\text{RD}_{i,s,t-1}$), an indicator set to 1 if R&D is missing, and 0 otherwise ($\text{RD\_MISS}_{i,s,t-1}$), tangibility ($\text{TANGIBILITY}_{i,s,t-1}$), an indicator set to 1 if common dividends are positive, and 0 otherwise ($\text{DIVIDEND\_PAYER}_{i,s,t-1}$), and cash holdings ($\text{CASH\_HOLDING}_{i,s,t-1}$).

All of our models also include state of headquarters (HQ)-by-year fixed effects ($\delta_h{}'\omega_t$), industry-by-year fixed effects based on the Fama–French 49-industry classification codes ($\eta_k{}'\omega_t$), and firm fixed effects (υ_i). The HQ state-by-year fixed effects account for omitted state-level, time varying factors (such as GDP growth, etc.). The industry-by-year fixed effects control for omitted industry-level, time varying factors (such as shifts in industry production technology, etc.) that could simultaneously affect corporate risk management as well as the likelihood that a state adopts the anti-recharacterization laws. The firm fixed effects account for time-invariant omitted firm characteristics and ensure that, rather than simple cross-sectional correlations, estimates of α_1 represent average, within-firm changes in corporate risk management over time. One concern with using hedging indicator variables based on the text in firms' 10-K filings is that there is little year-over-year variation in the extensive margin of a firm's hedging policy. The inclusion of firm fixed effects mitigates this concern.

We correct estimated standard errors in all regressions for clustering by the state of incorporation. In robustness tests, we consider clustering at the firm level as well as double clustering at the firm and year level and also double clustering at the state of incorporation and year level. As the adoption of the anti-recharacterization laws varies at the state level, these clustering procedures account for the concerns that residuals are serially correlated within a firm and correlated across firms within the same state (Bertrand, Duflo, and Mullainathan (2004)). An advantage of our setting is that as different states adopt the laws at different times, a firm incorporated in a given state could be in both the control group in early years and the treatment group in later years after the firm's incorporation state has adopted the law. Therefore, the staggered adoption of the laws suggests that the control group is not limited to those firms incorporated in states that never adopt the laws.

[5]The complete list of positive and negative hedging phrases is included in Table A1 of the Supplementary Material.

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Compustat only reports the latest incorporation information (i.e., this information is backfilled). We utilize historical states of incorporation and supplement this information with the state of incorporation from Compustat. First, we retrieve historical state of incorporation data of a firm from "The Notre Dame Software Repository for Accounting and Finance" database, which is populated across all firms beginning in 1996. The state of incorporation is retrieved from the 10-K filings in the EDGAR database of the U.S. SEC. We use the data between 1996 and 2003. If the previous step produces missing information, we utilize the Compustat header information, which is the most recent state of incorporation of the firm since it was first covered by Compustat. Compustat information is used for 2,237 firm-years, or 5.6% of the sample. We consider robustness to the exclusion of these firms in Section IV.D.

Several tables in the paper test for cross-sectional variation in our main effect from testing equation (1). For these tables, we estimate triple interactions based on a cohort approach (see, e.g., Gormley and Matsa (2011)). Specifically, we treat each law passage as an event, and we select control firms for that event. Control firms are firms in states that do not enact the law in the 3 year window around the treatment state's enactment of the law. The treatment firms and the control firms for each event constitute a cohort. We then pool cohorts to estimate the average treatment effect across cohorts. This model in equation (2) is estimated as follows:

$$\text{HEDGE}_{i,k,c,s,t} = \alpha_1 \text{ARLs}_{s,t} \times X_{i,c} + \omega_t{}'\mu_c + \upsilon_i{}'\mu_c + \zeta_s{}'\omega_t + \eta_k{}'\omega_t + \varepsilon_{i,k,c,s,t}. \quad (2)$$

$X_{i,c}$ captures firm-level variables that we use to test for cross-sectional variation in the main effect (e.g., underlying risk exposure and financial constraints). These characteristics are measured in the year before the cohort's enactment of the law and held constant throughout the cohort window to ensure the values are not impacted by the law. An important feature of this approach is that it allows us to capture cross-sectional variation in firm characteristics in the year prior to the adoption and to control for cross terms of the triple interaction (through the use of fixed effects). The coefficient of interest in these models, α_1, captures the interaction between i) being a treatment firm, ii) the year being after the enactment of the law, and iii) the cross-sectional variable of interest. To properly specify this model, we need to control for the single interaction of each pair of these three variables and the variables individually. These terms are controlled for by the year-by-cohort fixed effects ($\omega_t{}'\mu_c$), the firm-by-cohort fixed effects ($\upsilon_i{}'\mu_c$), the state of incorporation-by-year fixed effects ($\zeta_s{}'\omega_t$), and the industry-by-year fixed effects ($\eta_k{}'\omega_t$).[6]

B. Compustat Sample Selection

We utilize the CRSP/Compustat merged data for firms incorporated in the U.S. with nonmissing information for our main analyses between 1996 and 2003. As corporate risk management information is available from 1996, the sample

[6]As discussed, this cohort approach allows for a robust consideration of cross-sectional variation in our main finding. Importantly, we note that the paper's main findings, which are reported in Table 4, are robust to this cohort approach (see Table A4 of the Supplementary Material).

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period begins 1 year prior to the earliest adoption of the anti-recharacterization laws by Louisiana and Texas in 1997 and ends 1 year after the last event when Delaware adopted the anti-recharacterization laws in 2002. Although three states (i.e., South Dakota, Virginia, and Nevada) adopted the laws after 2003, the main analyses concentrate on states adopting the laws before 2003 to mitigate the effect of federal preemption, as in Li et al. (2016) and Chu (2020).[7] Table 1 reports that Louisiana and Texas, Alabama, and Delaware adopted the laws in 1997, 2001, and 2002, respectively. For our tests, we focus on industrial firms by excluding utility firms (SIC codes 4900–4999) and financial firms (SIC codes 6000–6999) following practice common in the literature.

These sample selection procedures produce a sample size of 40,066 firm-years for the main analyses. We winsorize continuous variables at their 1st and 99th percentiles and express dollar values in constant 2009 dollars. The Appendix provides detailed variable definitions. Table 2 shows summary statistics for the variables in our tests. According to our text search, over one-third (34.5%) of the firm-years in the sample are classified as hedging cash flow risk using derivative securities. Firms most commonly hedge interest rate risk (22.4% of firm-years). The second most common type of hedging is FX hedging (20.1% of firm-years). Last, 5.3% of firm-years hedge commodity risk. Just under 10% of firm-years come from firms in the treatment group, or firms that are incorporated in a state that has enacted anti-recharacterization laws. The average values of firm-level control variables are similar to those in the past literature (e.g., Qiu (2019)).

C. Corporate Risk Management and Financial Constraints

As previously mentioned, several empirical papers document that firms with relatively easy access to external financing, or financially unconstrained firms, are more likely to hedge using derivative securities. We next verify this empirical observation in our sample of firms based on the hedging data collected from EDGAR filings. We report the results in Table 3. We utilize six measures of financial constraints. First, firms without an investment grade credit rating are likely to have constrained access to finance (Campello, Graham, and Harvey (2010)). Also, firms without a credit line (Sufi (2009)) and that do not pay dividends are likely to be financially constrained. Last, we use three indexes that are meant to capture financial constraints: the HP index (Hadlock and Pierce (2010)), the WW index (Whited and Wu (2006)), and the HM index (Hoberg and Maksimovic (2015)). Following common practice in the financial constraints literature, we classify the bottom (top) tercile of each index as financially unconstrained (constrained).

We tabulate mean hedging activity across both constrained and unconstrained firms and then test for a univariate difference in these means. We first consider differences in the aggregate measure of hedging with derivative securities. This indicator variable takes the value of 1 if the firm uses derivative

[7]The main result is robust to removing effect of federal preemption (i.e., expanding the sample and redefining ARLs so that the variable includes the late adopting state information) as discussed in Section IV.D.

TABLE 1

Sample Distribution and Law Adoption Across States

Table 1 documents the number and percentage of sample firm-years across the state of incorporation. States with adoption year information are those that adopted the anti-recharacterization laws. The main analyses focus on states adopting the laws before 2003, which are highlighted, to mitigate the effect of federal preemption, as in Li et al. (2016) and Chu (2020).

State	Adoption Year	No. of Firm-Years	% of Firm-Years
Alabama	2001	30	0.075
Alaska		16	0.040
Arizona		107	0.267
Arkansas		17	0.042
California		1,864	4.652
Colorado		775	1.934
Connecticut		128	0.319
D.C.		8	0.020
Delaware	2002	22,730	56.731
Florida		1,067	2.663
Georgia		471	1.176
Hawaii		29	0.072
Idaho		27	0.067
Illinois		175	0.437
Indiana		328	0.819
Iowa		96	0.240
Kansas		79	0.197
Kentucky		45	0.112
Louisiana	1997	122	0.304
Maine		19	0.047
Maryland		336	0.839
Massachusetts		798	1.992
Michigan		369	0.921
Minnesota		1,184	2.955
Mississippi		32	0.080
Missouri		195	0.487
Montana		30	0.075
Nebraska		49	0.122
Nevada	2005	1,416	3.534
New Hampshire		9	0.022
New Jersey		665	1.660
New Mexico		23	0.057
New York		1,511	3.771
North Carolina		284	0.709
North Dakota		3	0.007
Ohio		774	1.932
Oklahoma		155	0.387
Oregon		345	0.861
Pennsylvania		778	1.942
Rhode Island		37	0.092
South Carolina		78	0.195
South Dakota	2003	28	0.070
Tennessee		240	0.599
Texas	1997	832	2.077
Utah		383	0.956
Vermont		15	0.037
Virginia	2004	470	1.173
Washington		462	1.153
West Virginia		17	0.042
Wisconsin		339	0.846
Wyoming		76	0.190
Total		40,066	100.000

securities to hedge commodity risk, FX risk, or interest rate risk, and 0 otherwise. We find across all six measures that financially unconstrained firms are significantly more likely to hedge. The economic magnitude of the difference is stark. For example, firms with an investment grade credit rating or with a credit line are more than twice as likely to hedge as firms without an investment grade credit rating or without a line of credit, respectively. These findings are in line with the documented difference in the extant literature that the propensity to hedge is much higher for financially unconstrained firms.

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TABLE 2

Summary Statistics

Table 2 documents summary statistics for the main variables utilized in the regression models. The sample includes Compustat industrial firms between 1996 and 2003 and consists of 40,066 firm-year observations. All variables are defined in the Appendix.

	Mean	Std. Dev.	P25	Median	P75
HEDGE	0.345	0.475	0.000	0.000	1.000
COMMODITY_HEDGE	0.053	0.223	0.000	0.000	0.000
FX_HEDGE	0.201	0.401	0.000	0.000	0.000
INTEREST_RATE_HEDGE	0.224	0.417	0.000	0.000	0.000
ln(1 + HEDGE_COUNT)	0.561	0.900	0.000	0.000	1.099
ln(1 + COMMODITY_COUNT)	0.050	0.236	0.000	0.000	0.000
ln(1 + FX_COUNT)	0.267	0.601	0.000	0.000	0.000
ln(1 + INTEREST_RATE_COUNT)	0.355	0.749	0.000	0.000	0.000
ARLs$_t$	0.091	0.288	0.000	0.000	0.000
FIRM_SIZE$_{t-1}$	4.763	2.272	3.251	4.746	6.263
FIRM_AGE$_{t-1}$	1.769	1.203	0.693	1.792	2.708
LEVERAGE$_{t-1}$	0.275	0.396	0.023	0.191	0.382
MTB$_{t-1}$	2.957	5.830	1.088	1.549	2.654
CAPEX$_{t-1}$	0.066	0.076	0.020	0.042	0.081
ROA$_{t-1}$	−0.206	0.834	−0.148	0.015	0.067
RD$_{t-1}$	0.284	1.180	0.000	0.000	0.085
RD_MISS$_{t-1}$	0.388	0.487	0.000	0.000	1.000
TANGIBILITY$_{t-1}$	0.268	0.227	0.089	0.199	0.384
DIVIDEND_PAYER$_{t-1}$	0.208	0.406	0.000	0.000	0.000
CASH_HOLDING$_{t-1}$	0.191	0.233	0.021	0.085	0.286

TABLE 3

Mean Risk Management Activity and Financial Constraints

Table 3 documents univariate results comparing the mean risk management activity for firms that are considered constrained in year $t-1$ to firms that are considered unconstrained in year $t-1$. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, for a t-test of whether the two samples have equal means. The sample includes Compustat industrial firms. The variable HEDGE in columns 1–2 is an indicator set to 1 if a firm discusses either commodity, foreign exchange, or interest rate hedging contracts in its annual 10-K filings at least once in a year, and 0 otherwise. COMMODITY_HEDGE in columns 3–4, FX_HEDGE in columns 5–6, and INTEREST_RATE_HEDGE in columns 7–8 are defined similarly. INVESTMENT GRADE is an indicator set to 1 if S&P domestic long-term issuer credit rating falls between AAA and BBB−, and 0 otherwise. CREDIT LINE is an indicator set to 1 if a firm has credit line information, and 0 otherwise, as in Cardella et al. (2021). DIVIDEND_PAYER is an indicator set to 1 if common dividends are positive, and 0 otherwise. HIGH HP INDEX is an indicator set to 1 if it corresponds to the top tercile of the HP INDEX, and 0 otherwise. HIGH WW INDEX is an indicator set to 1 if it corresponds to the top tercile of the WW INDEX, and 0 otherwise. HIGH HM INDEX is an indicator set to 1 if it corresponds to the top tercile of the HM INDEX, and 0 otherwise. All variables are defined in the Appendix.

	HEDGE		COMMODITY_HEDGE		FX_HEDGE		INTEREST_RATE_HEDGE	
Constraint Measure	Constrained	Unconstrained	Constrained	Unconstrained	Constrained	Unconstrained	Constrained	Unconstrained
	1	2	3	4	5	6	7	8
INVESTMENT GRADE$_{t-1}$	0.305	0.770	0.044	0.148	0.166	0.579	0.188	0.610
Difference (N = 40,066)	−0.465***		−0.104***		−0.413***		−0.422***	
CREDIT LINE$_{t-1}$	0.175	0.434	0.025	0.067	0.112	0.248	0.089	0.296
Difference (N = 40,066)	−0.259***		−0.042***		−0.136***		−0.207***	
DIVIDEND_PAYER$_{t-1}$	0.288	0.561	0.040	0.102	0.158	0.366	0.175	0.413
Difference (N = 40,066)	−0.273***		−0.062***		−0.208***		−0.238***	
HP INDEX$_{t-1}$	0.099	0.541	0.025	0.082	0.050	0.340	0.039	0.381
Difference (N = 27,009)	−0.442***		−0.057***		−0.290***		−0.342***	
WW INDEX$_{t-1}$	0.210	0.516	0.030	0.084	0.113	0.318	0.125	0.361
Difference (N = 25,899)	−0.306***		−0.054***		−0.205***		−0.236***	
HM INDEX$_{t-1}$	0.320	0.408	0.061	0.059	0.176	0.232	0.197	0.273
Difference (N = 16,920)	−0.088***		0.002		−0.056***		−0.076***	

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We next consider whether the difference in the propensity to hedge using derivative securities is driven by one particular type of hedging or if the difference exists across commodity, FX, and interest rate risk hedges. The vast majority of differences in hedging across the three measures of hedging and the six measures of financial constraints demonstrate that financially unconstrained firms have a significantly higher propensity to hedge than financially constrained firms, and the economic magnitude of the difference between financially unconstrained and constrained firms is large for all three types of hedging. The only exception is that there is no significant difference in commodity hedging for firms when the HM index is used as the measure of financial constraints. It appears that each of the three types of hedging contributes to the higher propensity to hedge by financially unconstrained firms.

IV. Empirical Results

A. The Effect of Anti-Recharacterization Laws on Corporate Hedging

The empirical predictions of the paper based on the theoretical literature suggest that the difference in hedging practices between constrained and unconstrained firms stems from the difference in the use of collateral assets for these two groups of firms. We first test the mechanism underlying this theoretical prediction that hedging increases with an increase in the value of collateral by estimating the model in equation (1). Table 4 tabulates the results.

In model 1, we run a linear probability model and regress the hedging indicator variable on the indicator variable that takes the value of 1 if a firm is incorporated in a state that has enacted an anti-recharacterization law, and 0 otherwise. This model includes HQ state-by-year, industry-by-year, and firm fixed effects and no control variables. We initially omit control variables to ensure that our findings are not the product of bias in our variable of interest because of the presence of endogenous controls. The coefficient on the law enactment indicator variable is positive and significant at the 1% level, suggesting that firms increase hedging activity as a result of the enactment of anti-recharacterization laws.

In model 2, we run the full model specification by adding firm-level control variables to ensure that the result is robust to the inclusion of firm-level characteristics that might correlate to hedging practices. We continue to find a positive and significant relation between hedging and the laws' enactment. In the presence of firm-level controls, the coefficient on the ARLs indicator variable in model 2 suggests that firms' average propensity to hedge using derivative securities increases by 2.7% relative to control firms following the enactment of the law. This represents an increase of 7.8% relative to the pooled unconditional average of 34.5%. In other words, the effect of the laws' enactment on the propensity to hedge with derivative securities is both statistically and economically meaningful.

In unreported tests, we assess whether our results are driven by the distribution of firms' states of incorporation as most treated companies in the sample are Delaware-incorporated firms, which specialized in corporate bankruptcies. While any heterogeneity between non-Delaware-incorporated firms and Delaware-incorporated firms is differenced away by our use of firm fixed effects, we follow

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TABLE 4

Anti-Recharacterization Laws and Risk Management

Table 4 documents the results from ordinary least squares (OLS) regressions relating corporate risk management to the adoption of the anti-recharacterization laws for Compustat industrial firms between 1996 and 2003 and consists of 40,066 firm-year observations. This table presents results relating HEDGE to the adoption of the anti-recharacterization laws. The dependent variable HEDGE in models 1–4 is an indicator set to 1 if a firm discusses either commodity, foreign exchange, or interest rate hedging contracts in its annual 10-K filings at least once in a year, and 0 otherwise. ARLs is an indicator set to 1 if the state where a firm is incorporated has adopted the anti-recharacterization laws by year t and 0 otherwise. $ARLs^{-3}$, $ARLs^{-2}$, and $ARLs^{-1}$ is an indicator set to 1 if the state where a firm is incorporated will adopt the anti-recharacterization laws in 3 years, 2 years, and 1 year, and 0 otherwise, respectively. $ARLs^{0}$, $ARLs^{+1}$, $ARLs^{+2}$, and $ARLs^{3+}$ is an indicator set to 1 if the state where a firm is incorporated has adopted the anti-recharacterization laws in the current year, 1 year ago, 2 years ago, and 3 or more years ago, and 0 otherwise, respectively. All variables are defined in the Appendix. HQ state-by-year fixed effects are based on the state of headquarter. Industry-by-year fixed effects are based on the Fama–French 49-industry classification codes. t-statistics in parentheses are clustered by state of incorporation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: HEDGE			
	1	2	3	4
$ARLs_t$	0.029***	0.027***		
	(5.022)	(4.221)		
$ARLs^{-3}$			0.004	0.001
			(0.543)	(0.212)
$ARLs^{-2}$			0.004	0.001
			(0.458)	(0.150)
$ARLs^{-1}$			0.016	0.011
			(1.624)	(1.279)
$ARLs^{0}$			0.017	0.012
			(1.482)	(1.240)
$ARLs^{+1}$			0.039***	0.034***
			(4.427)	(4.632)
$ARLs^{+2}$			0.044***	0.039***
			(4.247)	(3.789)
$ARLs^{3+}$			0.044**	0.032*
			(2.295)	(1.895)
$FIRM\_SIZE_{t-1}$		0.059***		0.059***
		(15.578)		(15.538)
$FIRM\_AGE_{t-1}$		0.004		0.004
		(0.608)		(0.592)
$LEVERAGE_{t-1}$		0.021***		0.021***
		(4.642)		(4.659)
MTB_{t-1}		0.001***		0.001***
		(2.936)		(2.926)
$CAPEX_{t-1}$		0.043		0.043
		(1.348)		(1.339)
ROA_{t-1}		−0.006***		−0.006***
		(−3.517)		(−3.492)
RD_{t-1}		0.000		0.000
		(0.016)		(0.021)
RD_MISS_{t-1}		−0.009		−0.009
		(−0.849)		(−0.855)
$TANGIBILITY_{t-1}$		−0.032*		−0.032*
		(−1.745)		(−1.741)
$DIVIDEND\_PAYER_{t-1}$		−0.007		−0.007
		(−0.624)		(−0.657)
$CASH\_HOLDING_{t-1}$		−0.068***		−0.068***
		(−4.434)		(−4.391)
HQ state-by-year FEs	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
No. of obs.	40,066	40,066	40,066	40,066
Adj. R^2	0.635	0.639	0.635	0.639

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the approach in Favara, Gao, and Giannetti (2021) and keep Delaware-incorporated firms as the only treated firms. We keep the entire control sample. We continue to find a positive and significant relation between ARLs and corporate hedging. Borusyak, Jaravel, and Spiess (2021) suggest that a staggered difference-in-differences specification may bias estimates, so this test, which is not staggered, suggests this is not a concern in our sample.[8]

The parallel trends assumption suggests that hedging behavior of treatment and control firms would be similar absent the treatment. This assumption implies that the effect of the laws should have an effect on the propensity to hedge only after the law's adoption. We next test the timing of the main result by decomposing our anti-recharacterization indicator variable into the following seven indicator variables: ARLs^{-3}, ARLs^{-2}, ARLs^{-1}, ARLs^{0}, ARLs^{+1}, ARLs^{+2}, and ARLs^{3+}. These seven indicator variables take the value of 1 if the state in which the firm is incorporated will enact the law in 3, 2, or 1 year, enacted the laws in the current year or enacted the laws 1, 2, or 3 or more years ago, respectively, and 0 otherwise.

The results are tabulated in models 3 and 4 of Table 4 (without and with lagged firm-level controls, respectively). We find no significant increase in hedging activity prior to the enactment of the laws. In fact, the effect of the laws is only statistically significant in the year after the enactment of the law and remains significantly positive for all remaining years after the enactment. Consistent with the parallel trends assumption, the difference in the propensity to hedge using derivative securities between treatment and control firms shifts only after the laws' enactment.

Another potential threat to the parallel trends assumption is that firms are not randomly assigned into treatment and control groups. Instead, states decide whether and when to enact anti-recharacterization laws. The enactment of these laws may vary in ways that correlate with firm-level characteristics that determine risk management practices, which would be a violation of balance between treatment and control firms. Notably, as documented in column 1 of Panel A of Table 5, we find that the treatment firms in our sample differ from the control firms in several ways.

We use three different approaches to address the differences between treatment and control firms. Our first approach is a propensity score matched sample analysis. We match our treatment firms to a control group of firms in the year prior to treatment based on observable, firm-level characteristics. We match by estimating a propensity score based on the nine characteristics that differ prior to the match (firm size, firm age, capital expenditures, return on assets, R&D expenditures, whether a firm has a missing value for R&D expenditures in Compustat, tangible assets, whether a firm pays dividends, and cash holdings). We use a logit model to estimate the propensity scores. We then perform a one-to-one match of treatment to control firms. In other words, we keep the control firm with the propensity score

[8]Favara et al. (2021) also include robustness specifications in which they drop all Delaware-incorporated firms from the treatment group after the law was incorporate in that state (i.e., 2002). As Delaware constitutes a major proportion of treated firms, the authors match non-Delaware-incorporated treated firms on propensity scores to up to 5 companies in the same industry in states that did not pass the laws to control firms. We omit this test because the main finding in our paper is highly sensitive to the matching approach taken.

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TABLE 5

Anti-Recharacterization Laws, Risk Management, and Matching

Table 5 documents the results using a matched sample and the ±1-year window around the adoption of the laws. Panel A presents matching diagnostics based on a propensity match where a logit model is used to estimate propensity scores based on FIRM_SIZE, FIRM_AGE, CAPEX, ROA, RD, RD_MISS, TANGIBILITY, DIVIDEND_PAYER, and CASH_HOLDING. Each treatment firm is one-to-one matched to a control firm with replacement, matching on year, the Fama–French 49-industry classification codes, and closest propensity score with a maximum difference in the propensity score between the treatment firm and control firm is less than or equal to 0.01. Column 2 (3) of Panel A reports the means of the matched variables for the treatment (control) group in year $t-1$. To control for repeated measurement due to some control firms being matched multiple times to different treatment firms, standard errors are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Models 1–5 of Panel B tabulate the results assessing the influence of the adoption of the anti-recharacterization on HEDGE utilizing the sample in which each treatment firm is matched to one control firm. Model 1 is based on a propensity score matched sample. Model 2 (3) is based on an inverse propensity score weighted analysis using the full (matched) sample. All sample firms for which a propensity score is estimated are retained then our initial results from Table 4 with regression observations being weighted by the inverse of the estimated propensity score are re-estimated. Model 4 (5) is based on the nearest-neighbor matching procedure with the Mahalanobis distance scaled by control (pooled) covariance matrix. In Panel B, the dependent variable HEDGE in models 1–4 is an indicator set to 1 if a firm discusses either commodity, foreign exchange, or interest rate hedging contracts in its annual 10-K filings at least once in a year, and 0 otherwise. ARLs is an indicator set to 1 if the state where a firm is incorporated has adopted the anti-recharacterization laws by year t and 0 otherwise. All variables are defined in the Appendix. HQ state-by-year fixed effects are based on the state of headquarter. Industry-by-year fixed effects are based on the Fama–French 49-industry classification codes. t-statistics in parentheses are clustered by state of incorporation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Comparison of Treatment and Control Group Means

	Pre-Match Difference	Propensity Score Matched Sample Year $t-1$: Treatment Group (Obs. = 2,675)	Control Group (Obs. = 2,675)	Post-Match Difference (Treatment – Control)
	1	2	3	4
Propensity score	0.067***	0.308	0.308	−0.000
FIRM_SIZE	0.514***	5.225	5.021	0.204*
FIRM_AGE	−0.071***	1.873	1.964	−0.091*
CAPEX	−0.012***	0.057	0.053	0.005*
ROA	−0.152***	−0.264	−0.445	0.181***
RD	0.174***	0.375	0.291	0.085
RD_MISS	−0.031***	0.366	0.389	−0.023
TANGIBILITY	−0.043***	0.255	0.253	0.002
DIVIDEND_PAYER	−0.062***	0.169	0.166	0.003
CASH_HOLDING	0.058***	0.218	0.205	0.013

Panel B. Anti-Recharacterization Laws and Risk Management for the Matched Sample

	Dependent Variable: HEDGE				
	1	2	3	4	5
$ARLs_t$	0.026**	0.023***	0.018*	0.032**	0.034***
	(2.477)	(2.832)	(1.741)	(2.582)	(2.860)
Controls	No	No	No	No	No
HQ state-by-year FEs	Yes	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
No. of obs.	15,424	36,487	15,424	14,904	14,832
Adj. R^2	0.785	0.628	0.784	0.804	0.801

closest in magnitude to the treatment firm. The match is done with replacement. We only keep matches if the difference in the estimated propensity score between the treatment firm and control firm is less than or equal to 0.01. The match results in a sample of 2,675 treatment firms and the same number of control firms.

The matching procedure is partially successful in pairing treatment and control firms that have similar observable characteristics. As tabulated in column 4 of Panel A of Table 5, there is no significant difference between treatment and control firms in R&D expenditures, missing R&D indicator, tangible assets, dividend payer indicator, or cash holdings after the match is performed. However, the difference in values for firm size, firm age, and capital expenditures (return on assets) between

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the treatment and control firms is still significant at the 10 (1)% level. We note that the propensity scores between the treatment and control firms are nearly identical.

In Panel B of Table 5, we re-estimate our main models from Table 4 using the propensity matched sample. In model 1, we continue to find a significantly positive relation between the enactments of anti-recharacterization laws and hedging for the propensity score matched sample. However, one concern is that we are unable to perfectly match on some firm-level characteristics, and differences in these characteristics explain our results. As a first attempt to alleviate this concern, we re-estimate our model after including firm-level control variables. The results are reported in Table A5 of the Supplementary Material, and we continue to find significant results.[9]

We consider the robustness of our matching procedure by using two additional approaches. First, we perform an inverse propensity score weighted analysis. For this analysis, we keep all sample firms for which a propensity score is estimated. We then re-estimate our initial results from Table 4 with regression observations being weighted by the inverse of the estimated propensity score. The results are tabulated in models 2–3 of Panel B of Table 5. For model 2, we keep the full sample of firms. For model 3, we keep only the matched sample of firms, following Crane and Koch (2018). We continue to find a significant effect of the laws using this approach. Last, we perform a nearest neighbor matched analysis. We match each treatment firm to the closest neighbor firm based on the Mahalanobis distance. In model 4 (5) of Panel B of Table 5, we scale the distance measure by the control firms' (pooled) covariance matrix. In these models, we again find an increase in hedging following the enactment of the laws, and the magnitude of the coefficients is similar to, though slightly larger than, those in model 1 of Table 4. Collectively, Table 5 documents that the main results are unlikely to be a result of differences between treatment and control firms.

A final threat to the parallel trends assumption that we consider is that some omitted industry- or state-level variable affects the relation between the enactment of anti-recharacterization laws and hedge using derivative securities. However, we note that all models throughout the paper include industry-by-year fixed effects[10] and HQ state-by-year fixed effects based on the state of headquarter[11] (in addition to firm fixed effects). These fixed effects suggest that our results are

[9]The decision to include of firm-level control variables centers on a tradeoff. The inclusion of firm-level characteristics that are affected by the enactment of the laws may bias the coefficients of interest. However, the omission of firm-level control variables may raise concerns of omitted correlated variables. To address this tradeoff, for several tables in the paper we tabulate regression results without firm-level control variables in the main paper and with firm-level control variables in the Supplementary Material.

[10]The positive relation between the enactment of anti-recharacterization laws is robust to using 2-, 3-, or 4-digit SIC codes as the industry definitions for fixed effects. This relation is also robust to the changing the level of standard error clusters from the state level to either the state and year level, firm level, or firm and year level. These robustness tests are tabulated in Panels A and B of Table A2 in the Supplementary Material.

[11]In Table A3 of the Supplementary Material, we show that the relation between the enactment of anti-recharacterization laws and hedging is robust to replacing HQ state-by-year fixed effects with either census division- or census region-by-year fixed effects.

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not driven by industry-level, time varying factors (such as shifts in industry production technology, etc.) or state-level, time varying factors (such as GDP growth, etc.). In sum, while we cannot completely rule out endogeneity concerns, the timing tests, matching tests, and use of fixed effects that rule out a number of potential omitted, correlated variables are consistent with our findings not being in violation of the parallel trends assumption.

We next shift from addressing endogeneity to consider which types of hedging are impacted by the laws. We separate our dependent variable into three separate types of hedging activity: indicator variables based on commodity hedging, FX hedging, and interest rate hedging. We run our linear probability models (without and with control variables) on each of these dependent variables separately. The results are tabulated in Panel A of Table 6. Odd-numbered models exclude firm-level control variables, and even-numbered models include the full set of firm-level control variables used in model 2 of Table 4. We find a positive and significant relation between the enactment of anti-recharacterization laws and each type of hedging, suggesting that our results are not unique to one type of hedging.

We next consider whether the shift in hedging activity is driven by firms that are likely to have an underlying exposure to the risk that is managed by the derivative security. This test has two purposes. First, any finding that the result is more pronounced for firms that have an exposure to the cash flow risk increases the reliability of our interpretations as any potential omitted variables would need to correlate to the documented cross-sectional variation in our main effect. Second, to this point, we have presumed that the documented use of derivative securities is evidence of hedging, though there is some evidence that firms use derivatives to speculate (e.g., Chernenko and Faulkender (2011)). We posit that, if the average effect is evidence of hedging, then firms are more likely to be using derivative securities when they have an underlying exposure to the risk. For these models and all other models with interaction terms, we estimate equation (2).

We first consider commodity hedging. For this type of hedging, we proxy for exposure by firms operating in the airline industry. Airline firms are commonly discussed in the context of hedging because of their tendency to hedge their fuel exposures (Carter, Rogers, and Simkins (2006), Rampini et al. (2014)). Notably, Rampini et al. (2014) document that airlines discuss collateral as an important determinant to be able to hedge. In model 1 in Panel B of Table 6, we define SIC codes 4512 or 4513 as the airline industry, as in Rampini et al. (2014). In model 2, we expand our definition of airline firms to be those in SIC codes 4500–4599 to include all airline firms based on the Fama–French 49-industry classification codes. We interact an indicator variable that takes the value of 1 if a firm is assigned these SIC codes and 0 otherwise, with ARLs, effectively running a triple difference linear probability model. We note that the cross terms in the triple difference are held constant by fixed effects. We find a significantly positive coefficient on the interaction term suggesting that airline firms, those that commonly hedge with commodities contracts because of their high exposure to fuel costs, are more likely to increase commodity hedging with derivative securities after the enactment of anti-recharacterization laws.

We next consider firms that likely have FX exposure. We again use two proxies to capture this exposure. First, in model 3, we classify firms as having a

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TABLE 6

Anti-Recharacterization Laws and Types of Risk Management

Table 6 documents the results from OLS regressions relating corporate risk management to the adoption of the anti-recharacterization laws for Compustat industrial firms between 1996 and 2003. Panel A consists of 40,066 firm-year observations. The dependent variable HEDGE in models 1–2 is an indicator set to 1 if a firm discusses either commodity, foreign exchange, or interest rate hedging contracts in its annual 10-K filings at least once in a year, and 0 otherwise. COMMODITY_HEDGE in models 3–4, FX_HEDGE in models 5–6, and INTEREST_RATE_HEDGE in models 7–8 are defined similarly. ARLs is an indicator set to 1 if the state where a firm is incorporated has adopted anti-recharacterization laws by year t and 0 otherwise. Unreported controls include FIRM_SIZE, FIRM_AGE, LEVERAGE, MTB, CAPEX, ROA, RD, RD_MISS, TANGIBILITY, DIVIDEND_PAYER, and CASH_HOLDING. Panel B tests for cross-sectional variation using a cohort approach. AIRLINE INDUSTRY 1 is an indicator set to 1 if a firm belongs to SIC code of 4512 or 4513, and 0 otherwise. AIRLINE INDUSTRY 2 is an indicator set to 1 if a firm belongs to SIC codes between 4500 and 4599, and 0 otherwise, as in the Fama–French 49-industry classification codes. HIGH FOREIGN SALES is an indicator set to 1 if it corresponds to the top tercile of the ratio of foreign sales to total sales (set as 0 if missing), and 0 otherwise. GR is an indicator set to 1 if a firm reveals foreign assets, income, or sales in the Compustat geographic segment file or reveals positive values of deferred foreign taxes, exchange rate effect, foreign currency adjustment, or foreign income taxes in the Compustat annual file, and 0 otherwise. LOW TOTAL DEBT is an indicator set to 1 if it corresponds to the bottom tercile of LEVERAGE, and 0 otherwise. ZERO DEBT is an indicator set to 1 if LEVERAGE equals 0, and 0 otherwise. All variables are defined in the Appendix. HQ state-by-year fixed effects are based on the state of headquarter. INC State-by-year fixed effects are based on the state of incorporation. Industry-by-year fixed effects are based on the Fama–French 49-industry classification codes. *t*-statistics in parentheses are clustered by state of incorporation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable					
	COMMODITY_HEDGE		FX_HEDGE		INTEREST_RATE_HEDGE	
	1	2	3	4	5	6
Panel A. Anti-Recharacterization Laws and Types of Risk Management						
ARLs$_t$	0.008**	0.007*	0.023***	0.022***	0.019**	0.017**
	(2.022)	(1.916)	(3.767)	(3.670)	(2.624)	(2.181)
Controls	No	Yes	No	Yes	No	Yes
HQ state-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	40,066	40,066	40,066	40,066	40,066	40,066
Adj. R^2	0.491	0.491	0.653	0.655	0.594	0.598
Panel B. Anti-Recharacterization Laws, Types of Risk Management, and Underlying Exposure						
Underlying Exposure Measure	AIRLINE INDUSTRY 1_{t-1}	AIRLINE INDUSTRY 2_{t-1}	HIGH FOREIGN SALES$_{t-1}$	GR$_{t-1}$	LOW TOTAL DEBT$_{t-1}$	ZERO DEBT$_{t-1}$
	1	2	3	4	5	6
ARLs$_t$ × UNDERLYING EXPOSURE$_{t-1}$	0.158***	0.116***	0.037***	0.025***	−0.032***	−0.032***
	(7.032)	(5.281)	(12.297)	(7.935)	(−4.964)	(−4.772)
Controls	No	No	No	No	No	No
Year-by-cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm-by-cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
INC State-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	86,449	86,449	86,350	86,449	86,255	86,255
Adj. R^2	0.578	0.578	0.716	0.716	0.666	0.666

high FX exposure if the firm has foreign sales corresponding to the top cross-sectional tercile in a given year. In model 4, we classify a firm as having high FX exposure based on the firm's GR. GR is an indicator set to 1 if a firm reveals foreign assets, income, or sales in the Compustat geographic segment file or reveals positive values of deferred foreign taxes, exchange rate effect, foreign currency adjustment, or foreign income taxes in the Compustat annual file, and 0 otherwise (Graham and Rogers (2002), Qiu (2019)). We find that the increase in FX hedging following the enactment of the laws is significantly more pronounced for firms with a higher exposure based on these proxy variables.

Last, we consider the underlying exposure to interest rates. This exposure is difficult to identify as firms with higher leverage may not be more exposed to

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fluctuations in interest rate fluctuations. Yet, firms with little or no debt balances are unlikely to have a direct exposure to interest rates (Bretscher, Schmid, and Vedolin (2018)). As such, the interaction in this model captures firms that are *unlikely* to have exposure to interest rate risk. In model 5, firms with low interest rate exposure are those with leverage corresponding to the bottom cross-sectional tercile in a given year. In model 6, we define firms with low exposure as those with zero debt, as a significant number of firms are financed completely with equity (Strebulaev and Yang (2013)).

We find that the increase in interest rate hedging is significantly lower for firms that have little to no debt exposure through debt financing, as proxied by low or zero debt in the firm's capital structure. In sum, the enactment of anti-recharacterization laws results in an increase across all three hedging types considered and this main effect varies with proxies for the underlying exposure of the cash flow risk faced by the firm.

The theory in Rampini and Viswanathan (2010), (2013) predicts that increases in collateral value will lead to greater hedging activity. The use of anti-recharacterization laws allows us to test this theory, but it only applies to one particular type of collateral (securitization through SPVs). We next consider a validation test of the main result by testing whether the effects of ARLs on hedging is most prevalent for firms that use SPVs. We note that Ayotte and Gaon (2011) document that certain types of assets are likely to be held in SPVs, so this cross-sectional variation is not exogenous. However, significant results in this test provide validity of the mechanism underlying the paper's main test.

To perform this test, we utilize data that estimates firm usage of SPVs (Demeré, Donohoe, and Lisowsky (2020)).[12] These data are collected following the procedure developed in Feng et al. (2009). Specifically, a text processing script counts the number of a firm's subsidiaries that are likely to be SPVs. A firm's subsidiaries are found in Exhibit 21, a mandatory filing in a firm's 10-K. A subsidiary is classified as an SPV if the listed name contains "Limited Partnership," "Limited Liability Partnership," "Limited Liability Corporation," "trust," or the legal acronyms associated with these organization structures. These are the most common ways to organize an SPV.

While this method may slightly over-identify firms with SPVs, it has advantages over other methods because it identifies virtually all SPVs, avoids selection bias by using a mandatory disclosure, and is collected efficiently. We create a variable called High SPV Usage, which is an indicator variable that takes the value of 1 if the total number of SPVs (as based on the aforementioned approach) for a given firm-year is in the top tercile and 0 otherwise. Firms that are classified as having High SPV Usage have a mean of 7.8 subsidiaries that are classified as SPVs. Other firms have a mean of less than 0.1 subsidiaries that are classified as SPVs.

We next use these data and independently regress each of the hedging variables on the anti-recharacterization laws interacted with High SPV Usage. The results are tabulated in Table 7, which uses indicator variables as hedging measures. Model 1 utilizes the aggregate hedging measure, while models 2, 3, and 4 use the indicator

[12]We are grateful to Paul Demeré for providing the SPV usage data.

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TABLE 7

Anti-Recharacterization Laws, Risk Management, and SPV Usage

Table 7 documents the results from OLS regressions relating corporate risk management to the adoption of the anti-recharacterization laws for Compustat industrial firms with treatment and controls based on a cohort approach. The dependent variable HEDGE in model 1 is an indicator set to 1 if a firm discusses either commodity, foreign exchange, or interest rate hedging contracts in its annual 10-K filings at least once in a year, and 0 otherwise. COMMODITY_HEDGE in model 2, FX_HEDGE in model 3, and INTEREST_RATE_HEDGE in model 4 are defined similarly. ARLs is an indicator set to 1 if the state where a firm is incorporated has adopted the anti-recharacterization laws by year *t* and 0 otherwise. HIGH SPV USAGE is an indicator set to 1 if the total number of SPV subsidiaries corresponds to the top tercile of the annual cross-sectional distribution, and 0 otherwise. All variables are defined in the Appendix. INC state-by-year fixed effects are based on the state of incorporation. Industry-by-year fixed effects are based on the Fama–French 49-industry classification codes. *t*-statistics in parentheses are clustered by state of incorporation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable			
	HEDGE	COMMODITY _HEDGE	FX_HEDGE	INTEREST_RATE_HEDGE
	1	2	3	4
$ARLs_t \times$ HIGH SPV $USAGE_{t-1}$	0.020***	0.018***	0.028***	0.015***
	(5.186)	(10.707)	(13.471)	(2.831)
Controls	No	No	No	No
Year-by-cohort FEs	Yes	Yes	Yes	Yes
Firm-by-cohort FEs	Yes	Yes	Yes	Yes
INC state-by-year FEs	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes
No. of obs.	86,449	86,449	86,449	86,449
Adj. R^2	0.696	0.578	0.716	0.666

variable capturing commodity, FX, and interest rate hedging, respectively. Across all four models, the positive relation between hedging activity using derivative securities and the enactment of anti-recharacterization laws is most pronounced for firms that likely utilize SPVs. Also, the results are robust to including firm-level controls in the regressions (see Table A7 of the Supplementary Material). This series of tests provides validity that firms using SPVs, the particular type of collateral affected by anti-recharacterization laws, are the same firms most impacted by the laws.

B. Anti-Recharacterization Laws, Corporate Hedging, and External Financing Needs

The finding we have documented is consistent with the theoretical literature suggesting that the value of collateral is an important determinant of corporate risk management. An important distinction between the past theoretical literature on corporate risk management and this more recent literature incorporating collateral constraints is that the more recent literature emphasizes that it is firms that do not need collateral for external financing to meet valuable investment opportunities that are more likely to hedge. As such, we predict that firms that are most likely to use collateral for external financing needs are least likely to increase hedging in response to increased collateral value. We examine this prediction by testing for cross-sectional variation in the main finding first across financial constraints and then other proxies of external financing needs.

The cross-sectional financial constraints tests are reported in Table 8. We interact ARLs with an indicator variable that takes the value of 1 if the firm is financially constrained and 0 otherwise. We use the same six proxies for financial constraints that are used in Table 3. Across all six measures, we find that the

TABLE 8

Anti-Recharacterization Laws, Risk Management, and Financial Constraints

Table 8 documents the results from OLS regressions relating corporate risk management to the adoption of the anti-recharacterization laws for Compustat industrial firms with treatment and controls based on a cohort approach. The dependent variable HEDGE is an indicator set to 1 if a firm discusses either commodity, foreign exchange, or interest rate hedging contracts in its annual 10-K filings at least once in a year, and 0 otherwise. ARLs is an indicator set to 1 if the state where a firm is incorporated has adopted the anti-recharacterization laws by year t and 0 otherwise. A firm is classified as financially constrained if the firm is not INVESTMENT GRADE, does not have a CREDIT LINE, DIVIDEND_PAYER equal to 0, or if the HP INDEX, WW INDEX, or HM INDEX is in the top tercile of the annual cross-sectional distribution, and 0 otherwise. All variables are defined in the Appendix. INC state-by-year fixed effects are based on the state of incorporation. Industry-by-year fixed effects are based on the Fama–French 49-industry classification codes. t-statistics in parentheses are clustered by state of incorporation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: HEDGE					
Financial Constraint Measure	INVESTMENT GRADE$_{t-1}$	CREDIT LINE$_{t-1}$	DIVIDEND_ PAYER$_{t-1}$	HP INDEX$_{t-1}$	WW INDEX$_{t-1}$	HM INDEX$_{t-1}$
	1	2	3	4	5	6
ARLs$_t$ × FINANCIALLY CONSTRAINED$_{t-1}$	−0.015**	−0.024***	−0.015**	−0.025***	−0.038***	−0.021***
	(−2.035)	(−5.692)	(−2.511)	(−6.625)	(−3.981)	(−9.813)
Controls	No	No	No	No	No	No
Year-by-cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm-by-cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
INC state-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	86,449	86,449	86,449	86,320	86,185	77,232
Adj. R^2	0.696	0.696	0.696	0.697	0.697	0.715

sensitivity between hedging activity and ARLs is significantly diminished for financially constrained firms. The models in Table 8 do not include firm-level controls. In Table A8 of the Supplementary Material, we add controls to the models and continue to find a negative sign on the interactions. Further, the coefficient is significant in all models except the model that uses investment grade bond rating as a proxy for financial constraints.

We next consider other proxies for external financing needs. First, to capture the nearness to default, we estimate the distance to default using the functional form of the Merton (1974) model and another measure that does require solving non-linear equations (see Bharath and Shumway (2008)). Second, following Rampini et al. (2014), we use the firm's net worth based on both book and market values, with the bottom tercile net worth firms having more need for external financing. The results are presented in Table 9. Consistent with Table 8, we find that the main effect is less pronounced for firms that have high external financing needs, and the results are robust to the inclusion of control variables as tabulated in Table A9 of the Supplementary Material. Tables 8 and 9 collectively suggest that the increased propensity to hedge following a plausibly exogenous increase in the value of collateral is less pronounced in firms that value collateral for external financing, consistent with Rampini and Viswanathan (2010), (2013).

C. Anti-Recharacterization Laws and Corporate Hedging Phrase Counts

To this point, results are based on an indicator dependent variable that takes the value of 1 if a firm has *any* discussion of positive hedging activity with derivative securities in its 10-K filing. We next consider whether there is also variation in the frequency at which firms discuss hedging activity. Following past literature

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TABLE 9

Anti-Recharacterization Laws, Risk Management, and External Financing Needs

Table 9 documents the results from OLS regressions relating corporate risk management to the adoption of the anti-recharacterization laws for Compustat industrial firms with treatment and controls based on a cohort approach. The dependent variable HEDGE is an indicator set to 1 if a firm discusses either commodity, foreign exchange, or interest rate hedging contracts in its annual 10-K filings at least once in a year, and 0 otherwise. ARLs is an indicator set to 1 if the state where a firm is incorporated has adopted the anti-recharacterization laws by year t and 0 otherwise. HIGH $\pi_{\text{naïve}}$ and π_{Merton} are indicator variables set to 1 if they correspond to the top tercile of the annual cross-sectional distribution $\pi_{\text{naïve}}$ and π_{Merton}, respectively, and 0 otherwise. LOW NET WORTH [BOOK] is an indicator set to 1 if it corresponds to the bottom tercile of the stockholders' equity/1,000, and 0 otherwise. LOW NET WORTH [MARKET] is an indicator set to 1 if it corresponds to the bottom tercile of the book value of assets + market value of equity − book equity − deferred taxes − total liabilities, and 0 otherwise. All variables are defined in the Appendix. INC state-by-year fixed effects are based on the state of incorporation. Industry-by-year fixed effects are based on the Fama–French 49-industry classification codes. t-statistics in parentheses are clustered by state of incorporation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: HEDGE			
Financing Needs Measure	HIGH $\pi_{\text{naïve}_{t-1}}$	HIGH $\pi_{\text{Merton}_{t-1}}$	LOW NET WORTH [BOOK]$_{t-1}$	LOW NET WORTH [MARKET]$_{t-1}$
	1	2	3	4
ARLs$_t$ × FINANCING NEEDS$_{t-1}$	−0.042***	−0.034***	−0.038***	−0.038***
	(−13.658)	(−10.965)	(−8.304)	(−9.963)
Controls	No	No	No	No
Year-by-cohort FEs	Yes	Yes	Yes	Yes
Firm-by-cohort FEs	Yes	Yes	Yes	Yes
INC state-by-year FEs	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes
No. of obs.	54,494	54,494	86,359	83,102
Adj. R^2	0.684	0.684	0.697	0.692

TABLE 10

Anti-Recharacterization Laws and Risk Management: Count of Mentions

Table 10 documents the results from OLS regressions relating corporate risk management to the adoption of the anti-recharacterization laws for Compustat industrial firms between 1996 and 2003 and consists of 40,066 firm-year observations. The dependent variable ln(1 + HEDGE_COUNT) in models 1–2 is the natural logarithm of 1 plus the total number of textual discussion of either commodity, foreign exchange, or interest rate hedging contracts by the firm in its annual 10-K filings in a given year. ln(1 + COMMODITY_COUNT) in models 3–4, ln(1 + FX_COUNT) in models 5–6, and ln(1 + INTEREST_RATE_COUNT) in models 7–8 are defined similarly. ARLs is an indicator set to 1 if the state where a firm is incorporated has adopted the anti-recharacterization laws by year t and 0 otherwise. Unreported controls include FIRM_SIZE, FIRM_AGE, LEVERAGE, MTB, CAPEX, ROA, RD, RD_MISS, TANGIBILITY, DIVIDEND_PAYER, and CASH_HOLDING. All variables are defined in the Appendix. HQ state-by-year fixed effects are based on the state of headquarter. Industry-by-year fixed effects are based on the Fama–French 49-industry classification codes. t-statistics in parentheses are clustered by state of incorporation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable							
	ln(1 + HEDGE_COUNT)		ln(1 + COMMODITY_COUNT)		ln(1 + FX_COUNT)		ln(1 + INTEREST_RATE_COUNT)	
	1	2	3	4	5	6	7	8
ARLs$_t$	0.051***	0.047***	0.009**	0.009**	0.021**	0.019**	0.038***	0.035**
	(3.961)	(3.381)	(2.360)	(2.257)	(2.301)	(2.151)	(2.905)	(2.418)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
HQ state-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	40,066	40,066	40,066	40,066	40,066	40,066	40,066	40,066
Adj. R^2	0.708	0.713	0.537	0.537	0.713	0.716	0.661	0.665

(e.g., Hoberg and Moon, (2017), Qiu (2019)), this test incorporates variation beyond whether or not a firm discusses hedging.

In Table 10, we change our dependent variable from an indicator variable capturing any hedging activity to the natural logarithm of 1 plus the count of mentions of hedging phrases. The approach picks up variation in both whether or not a firm mentions hedging activity and the extent to which the firm mentions hedging activity. We also note that the inclusion of firm fixed effects ensures that we capture within firm variation in these 10-K discussions. In models 1 and 2, we use the count of any types of hedging activity without and with control variables, respectively. We find a positive and significant association. Based on the coefficient in model 2, the number of mentions in a firm's 10-K increases by 4.7% following the enactment of anti-recharacterization laws. While the economic impact of this model is smaller than that in Table 4 (7.8%), it continues to be nontrivial.

We next repeat these models but replace the dependent variable to the count of mentions of commodity, FX, and interest rate hedging activity in models 3 and 4, 5 and 6, and 7 and 8, respectively. Across all three types of hedging, we continue to find a positive and significant relation between the enactment of anti-recharacterization laws and the count of hedging mentions. The models in Table 10 suggest that firms discuss hedging with derivative securities more frequently following the enactment of the laws.

D. Robustness Tests

We run a number of robustness tests. We first consider robustness to our sample period. We end our sample in 2003 because, in that year, an influential federal case (*Reaves Brokerage Company, Inc v. Sunbelt Fruit & Vegetable Company, Inc.* (336 F.3d 410, 413 (5th Cir. 2003))) ignored the effect of the anti-recharacterization laws in Texas, which precluded lenders from seizing assets while the firm was in bankruptcy protection. This federal law, amongst others, raised questions as to the effect of state-level anti-recharacterization laws, motivating the selected end of our sample period.

However, Chu (2020) suggests that some interpret this federal precedent to only have an impact on agricultural cases. To ensure that our results are not a product of the end of the sample period, which assumes that the *Reaves Brokerage Company* case limited the effect of state-level laws generally, we re-estimate our main regressions after extending our sample period to 2006. A result of this change is that firms incorporated in South Dakota, Virginia, and Nevada take the value of 1 beginning in 2003, 2004, and 2005, respectively, as these states enacted anti-recharacterization laws in these years.

These results are tabulated in Table 11. In Panel A, we tabulate results in which the dependent variables are indicator variables that capture whether the firm discusses hedging activity in its 10-K. We include the aggregate measure as well as indicator variables based on commodity, FX, and interest rate hedging. For each variable, we include both models without and with control variables. We find a positive coefficient on the indicator variable for the enactment of anti-recharacterization laws for all measures of hedging, and these coefficients are statistically significant for all measures except for the hedging with derivative securities of commodity risk.

In Panel B of Table 11, we tabulate models in which the dependent variable is a continuous measure based on the count of hedging mentions. We tabulate the same models described for Panel A. Again, all coefficients on our variable of interest are positive and significant for all measures of hedging except for interest rate risk.

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TABLE 11

Anti-Recharacterization Laws and Risk Management: Removing Effect of Federal Preemption

Table 11 documents the results from OLS regressions relating corporate risk management to the adoption of the anti-recharacterization laws for Compustat industrial firms between 1996 and 2006 and consists of 52,569 firm-year observations after removing effect of federal preemption. In Panel A, the dependent variable HEDGE in models 1–2 is an indicator set to 1 if a firm discusses either commodity, foreign exchange, or interest rate hedging contracts in its annual 10-K filings at least once in a year, and 0 otherwise. COMMODITY_HEDGE in models 3–4, FX_HEDGE in models 5–6, and INTEREST_RATE_HEDGE in models 7–8 are defined similarly. In Panel B, the dependent variable ln(1 + HEDGE_COUNT) in models 1–2 is the natural logarithm of 1 plus the total number of textual discussion of either commodity, foreign exchange, or interest rate hedging contracts by the firm in its annual 10-K filings in a given year. ln(1 + COMMODITY_COUNT) in models 3–4, ln(1 + FX_COUNT) in models 5–6, and ln(1 + INTEREST_RATE_COUNT) in models 7–8 are defined similarly. ARLs is an indicator set to 1 if the state where a firm is incorporated has adopted the anti-recharacterization laws by year *t* and 0 otherwise. Controls included in the regression but are not reported consist of FIRM_SIZE, FIRM_AGE, LEVERAGE, MTB, CAPEX, ROA, RD, RD_MISS, TANGIBILITY, DIVIDEND_PAYER, and CASH_HOLDING. All variables are defined in the Appendix. HQ state-by-year fixed effects are based on the state of headquarter. Industry-by-year fixed effects are based on the Fama–French 49-industry classification codes. *t*-statistics in parentheses are clustered by state of incorporation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Hedging Indicator Variables

	Dependent Variable							
	HEDGE		COMMODITY_HEDGE		FX_HEDGE		INTEREST_RATE_HEDGE	
	1	2	3	4	5	6	7	8
$ARLs_t$	0.022***	0.018**	0.004	0.004	0.024***	0.022***	0.016**	0.013*
	(3.190)	(2.481)	(1.231)	(1.120)	(4.721)	(4.214)	(2.366)	(1.722)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
HQ state-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	52,569	52,569	52,569	52,569	52,569	52,569	52,569	52,569
Adj. R^2	0.629	0.634	0.498	0.498	0.647	0.649	0.598	0.602

Panel B. Hedging Count Variables

	Dependent Variable							
	ln(1 + HEDGE_COUNT)		ln(1 + COMMODITY_COUNT)		ln(1 + FX_COUNT)		ln(1 + INTEREST_RATE_COUNT)	
	1	2	3	4	5	6	7	8
$ARLs_t$	0.032***	0.024**	0.006**	0.006*	0.027***	0.024***	0.016	0.010
	(2.884)	(2.068)	(2.018)	(1.861)	(3.920)	(3.455)	(1.448)	(0.846)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
HQ state-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	52,569	52,569	52,569	52,569	52,569	52,569	52,569	52,569
Adj. R^2	0.646	0.652	0.523	0.523	0.638	0.640	0.586	0.591

These results suggest that the findings that firms hedge more with derivative securities after the enactment of anti-recharacterization laws are largely robust to including years after federal law that raises questions regarding the efficacy of state-level laws.

Anti-recharacterization laws are governed by a firm's state of incorporation. We next consider the robustness of our results to potential noise in the assignment of firms' state of incorporation. The general approach we take for these tests is to remove firm-years that may have questionable assignments for the state of incorporation. Because Compustat backfills the state of incorporation to the firms' current state, we largely use incorporation information from firms' 10-K filing headers. This information is time varying and captures historical states of incorporation. However, this information is unavailable for 5.6% of the sample firms in

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Compustat. Throughout the paper, for this group of firms we rely on Compustat incorporation information.

To ensure that this choice does not influence our results, we re-estimate the results without these firm-years. The results are included in Panels A and B of Table 12. Panel A (B) includes models with a dependent variable that is an indicator variable (based on the count of hedging mentions). Across all measures of hedging and specifications, we continue to find a positive and significant relation between hedging with derivative securities and the enactment of anti-recharacterization laws.

We next remove firms that change its state of incorporation at any point in the sample period. This robustness test has two purposes. First, to the extent that the change in state of incorporation results from noise in the assignment of incorporation location, we ensure that the noise does not influence our results. Second, if the change in the assigned state of incorporation reflects an actual change, this is indicative that the firm has selected a state with a more advantageous business environment. If that change also correlates to hedging activity, this may signify omitted variables that influence the results.

However, the findings suggest that this is not a significant issue. First, only 351 firms have a state of incorporation that changes during the sample period. This corresponds to 4.7% (5.3%) of sample firms (firm-years). Second, the removal of these firms has little effect on our results. Specifically, in Panels C and D of Table 12, we continue to find a positive and significant relation between hedging and the enactment of anti-recharacterization laws, regardless of whether the dependent variable is an indicator variable or continuous, the type of hedging being tested, and whether the models include control variables. In sum, the paper's results are not materially affected by the assignment of the state of incorporation.

The robustness tests in Tables 11 and 12 result in a different sample than our main results. As a result of this change, the magnitudes of the coefficients also change. As a benchmark, we compare these tables to the model 2 in Table 4 using the aggregate hedge indicator variable and including control variables. We see a reduction in the magnitude of the coefficient in model 2 of Panel A of Table 11 from 0.027 to 0.018. The coefficients in model 2 of Panels A and C of Table 12 remain relatively consistent with Table 4 (0.028 and 0.027, respectively). Importantly, all coefficients retain statistical significance.

V. Conclusion

We directly test the underlying mechanism in the theoretical models that predict that the value of collateral impacts the propensity of firms to hedge cash flow risk (Rampini and Viswanathan (2010), (2013)). To test these models, we use the staggered enactment of anti-recharacterization laws as a plausibly exogenous shock to the value of a particular type of collateral: assets securitized in SPVs. These laws make it easier for lenders to reclaim collateral when the firm enters bankruptcy, increasing SPV assets' usefulness as collateral. We find that, following the enactment of the laws, firms significantly increase hedging commodities, FX, and interest rate risk with the use of derivative securities. The increase in hedging of each of these risks is more pronounced for firms that have a more significant

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TABLE 12

Anti-Recharacterization Laws and Risk Management: State of Incorporation Robustness

Panels A and B (C and D) of Table 12 document the results from OLS regressions relating corporate risk management to the adoption of the anti-recharacterization laws for Compustat industrial firms between 1996 and 2003 and consists of 37,829 (37,920) firm-year observations after removing Compustat incorporation information (firms that change states of incorporation). In Panels A and C, the dependent variable HEDGE in models 1–2 is an indicator set to 1 if a firm discusses either commodity, foreign exchange, or interest rate hedging contracts in its annual 10-K filings at least once in a year, and 0 otherwise. COMMODITY_HEDGE in models 3–4, FX_HEDGE in models 5–6, and INTEREST_RATE_HEDGE in models 7–8 are defined similarly. In Panels B and D, the dependent variable ln(1 + HEDGE_COUNT) in models 1–2 is the natural logarithm of 1 plus the total number of textual discussion of either commodity, foreign exchange, or interest rate hedging contracts by the firm in its annual 10-K filings in a given year. ln(1 + COMMODITY_COUNT) in models 3–4, ln(1 + FX_COUNT) in models 5–6, and ln(1 + INTEREST_RATE_COUNT) in models 7–8 are defined similarly. ARLs is an indicator set to 1 if the state where a firm is incorporated has adopted the anti-recharacterization laws by year *t* and 0 otherwise. Controls included in the regression but are not reported consist of FIRM_SIZE, FIRM_AGE, LEVERAGE, MTB, CAPEX, ROA, RD, RD_MISS, TANGIBILITY, DIVIDEND_PAYER, and CASH_HOLDING. All variables are defined in the Appendix. HQ state-by-year fixed effects are based on the state of headquarter. Industry-by-year fixed effects are based on the Fama–French 49-industry classification codes. *t*-statistics in parentheses are clustered by state of incorporation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Hedging Indicator Variables

	Dependent Variable							
	HEDGE		COMMODITY_ HEDGE		FX_HEDGE		INTEREST_RATE_ HEDGE	
	1	2	3	4	5	6	7	8
$ARLs_t$	0.030***	0.028***	0.008*	0.008*	0.025***	0.024***	0.019**	0.017*
	(4.349)	(3.549)	(1.940)	(1.833)	(3.832)	(3.669)	(2.320)	(1.887)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
HQ state-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	37,829	37,829	37,829	37,829	37,829	37,829	37,829	37,829
Adj. R^2	0.628	0.632	0.491	0.492	0.650	0.652	0.591	0.594

Panel B. Hedging Count Variables

	Dependent Variable							
	ln(1 + HEDGE_ COUNT)		ln(1 + COMMODITY_ COUNT)		ln(1 + FX_COUNT)		ln(1 + INTEREST_ RATE_COUNT)	
	1	2	3	4	5	6	7	8
$ARLs_t$	0.052***	0.047***	0.010**	0.009**	0.024**	0.022**	0.038***	0.035**
	(3.835)	(3.233)	(2.245)	(2.148)	(2.460)	(2.292)	(2.745)	(2.263)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
HQ state-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	37,829	37,829	37,829	37,829	37,829	37,829	37,829	37,829
Adj. R^2	0.705	0.710	0.539	0.539	0.712	0.715	0.659	0.663

Panel C. Hedging Indicator Variables

	Dependent Variable							
	HEDGE		COMMODITY_ HEDGE		FX_HEDGE		INTEREST_ RATE_HEDGE	
	1	2	3	4	5	6	7	8
$ARLs_t$	0.027***	0.027***	0.010***	0.010***	0.022***	0.021***	0.019***	0.018**
	(4.621)	(3.912)	(3.021)	(2.903)	(4.475)	(4.230)	(2.726)	(2.353)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
HQ state-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	37,920	37,920	37,920	37,920	37,920	37,920	37,920	37,920
Adj. R^2	0.637	0.641	0.494	0.494	0.656	0.658	0.597	0.601

(continued on next page)

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TABLE 12 (continued)

Anti-Recharacterization Laws and Risk Management: State of Incorporation Robustness

Panel D. Hedging Count Variables

	Dependent Variable							
	ln(1 + HEDGE_COUNT)		ln(1 + COMMODITY_COUNT)		ln(1 + FX_COUNT)		ln(1 + INTEREST_RATE_COUNT)	
	1	2	3	4	5	6	7	8
$ARLs_t$	0.046***	0.044***	0.012***	0.011***	0.021**	0.019**	0.035***	0.034**
	(3.824)	(3.299)	(3.422)	(3.310)	(2.461)	(2.343)	(2.829)	(2.463)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
HQ state-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	37,920	37,920	37,920	37,920	37,920	37,920	37,920	37,920
Adj. R^2	0.712	0.717	0.543	0.543	0.715	0.718	0.665	0.669

exposure to the risk and firms that are likely to rely heavily on SPVs. Importantly, consistent with the theoretical risk management literature including collateral constraints, the effect is driven by firms that are less likely to use collateral to fund external financing, such as financially unconstrained firms. Our findings provide causal evidence that increases in collateral values result in greater propensity to hedge, especially for firms that face relatively low costs in accessing the external capital markets, complementing the broader body of work considering how collateral constraints impact firms' financing policies. The empirical findings in this article support the theoretical rationale for why financially unconstrained firms are more likely to hedge.

Appendix. Variable Definitions

This Appendix documents variable definitions. The sample includes Compustat industrial firms (excluding financials and utilities) between 1996 and 2003 and consists of 40,066 firm-year observations. Continuous variables are winsorized at their 1st and 99th percentiles and all dollar values are expressed in 2009 dollars. Corporate accounting data are from the Compustat database on the Wharton Research Data Services server. Compustat variable names are denoted by their Xpressfeed mnemonic in bold.

AIRLINE INDUSTRY 1: An indicator set to 1 if a firm belongs to SIC code of 4512 or 4513, and 0 otherwise, as in Rampini et al. (2014).

AIRLINE INDUSTRY 2: An indicator set to 1 if a firm belongs to SIC codes between 4500 and 4599, and 0 otherwise, as in the Fama–French 49-industry classification codes.

ARLs: An indicator set to 1 if the state where a firm is incorporated has adopted the anti-recharacterization laws by year *t*, and 0 otherwise.

CAPEX: Capital expenditures/book value of assets [**capex**/**at**].

CASH_HOLDING: Cash and short-term investments/book value of assets [**che**/**at**].

COMMODITY_HEDGE: An indicator set to 1 if a firm discusses commodity hedging contracts in its annual 10-K filings at least once in a year, and 0 otherwise.

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CREDIT LINE: An indicator set to 1 if a firm has credit line information, and 0 otherwise, as in Cardella et al. (2021).

DIVIDEND_PAYER: An indicator set to 1 if common dividends (**dvc**) are positive, and 0 otherwise.

FIRM_AGE: The natural logarithm of 1 plus the number of years a firm has been publicly traded.

FIRM_SIZE: The natural logarithm of book value of assets [ln(**at**)], adjusted to 2009 dollars.

FX_HEDGE: An indicator set to 1 if a firm discusses foreign exchange hedging contracts in its annual 10-K filings at least once in a year, and 0 otherwise.

GR: An indicator set to 1 if a firm reveals foreign assets, income, or sales in the Compustat geographic segment file or reveals positive values of deferred foreign taxes, exchange rate effect, foreign currency adjustment, or foreign income taxes in the Compustat annual file, and 0 otherwise, as in Graham and Rogers (2002).

HEDGE: An indicator set to 1 if a firm discusses either commodity, foreign exchange, or interest rate hedging contracts in its annual 10-K filings at least once in a year, and 0 otherwise.

HIGH π_{Merton}: An indicator set to 1 if it corresponds to the top tercile of the implied default probability based on the distance to default model by Merton (1974), and 0 otherwise.

HIGH $\pi_{\text{naïve}}$: An indicator set to 1 if it corresponds to the top tercile of the implied default probability based on the distance to default model by Merton (1974) but that does not solve nonlinear equations to estimate market value and volatility of the firm, and 0 otherwise, as in Bharath and Shumway (2008).

HIGH FOREIGN SALES: An indicator set to 1 if it corresponds to the top tercile of the ratio of foreign sales to total sales (set as 0 if missing), and 0 otherwise, as in Qiu (2019).

HIGH HM INDEX: An indicator set to 1 if it corresponds to the top tercile of HM INDEX, and 0 otherwise, as in Hoberg and Maksimovic (2015) (see http://faculty.marshall.usc.edu/Gerard-Hoberg/).

HIGH HP INDEX: An indicator set to 1 if it corresponds to the top tercile of HP INDEX, and 0 otherwise, as in Hadlock and Pierce (2010).

HIGH SPV USAGE: An indicator set to 1 if it corresponds to the top tercile of the natural logarithm of 1 plus the total number of Special Purpose Vehicle subsidiaries, and 0 otherwise, as in Demeré et al. (2020).

HIGH WW INDEX: An indicator set to 1 if it corresponds to the top tercile of WW INDEX, and 0 otherwise, as in Whited and Wu (2006).

INTEREST_RATE_HEDGE: An indicator set to 1 if a firm discusses interest rate hedging contracts in its annual 10-K filings at least once in a year, and 0 otherwise.

INVESTMENT GRADE: An indicator set to 1 if S&P domestic long-term issuer credit rating falls between AAA and BBB−, and 0 otherwise.

LEVERAGE: (Book value of long-term debt + debt in current liabilities) / book value of assets [(**dlc** + **dltt**)/**at**].

ln(1 + COMMODITY_COUNT): The natural logarithm of 1 plus the total number of textual discussion of commodity hedging contracts by the firm in its annual 10-K filings in a given year.

ln(1 + FX_COUNT): The natural logarithm of 1 plus the total number of textual discussion of foreign exchange hedging contracts by the firm in its annual 10-K filings in a given year.

ln(1 + HEDGE_COUNT): The natural logarithm of 1 plus the total number of textual discussion of either commodity, foreign exchange, or interest rate hedging contracts by the firm in its annual 10-K filings in a given year.

ln(1 + INTEREST_RATE_COUNT): The natural logarithm of 1 plus the total number of textual discussion of interest rate hedging contracts by the firm in its annual 10-K filings in a given year.

LOW NET WORTH [BOOK]: An indicator set to 1 if it corresponds to the bottom tercile of the stockholders' equity/1,000, and 0 otherwise, as in Rampini et al. (2014).

LOW NET WORTH [MARKET]: An indicator set to 1 if it corresponds to the bottom tercile of the book value of assets + market value of equity − book equity − deferred taxes − total liabilities, and 0 otherwise, as in Rampini et al. (2014).

LOW TOTAL DEBT: An indicator set to 1 if it corresponds to the bottom tercile of LEVERAGE, and 0 otherwise.

MTB (market to book ratio): (market value of equity + book value of assets − book equity)/book value of assets [(**prcc_f** + **csho** + **at** − **ceq)/at**].

RD: Research and development expense/sales [**xrd/sale**] (set as 0 if missing).

RD_MISS: An indicator set to 1 if research and development expense (**xrd)** is missing, and 0 otherwise.

ROA: Net income/book value of assets [**ni/at**].

TANGIBILITY: Property, plant, and equipment/book value of assets [**ppent/at**].

ZERO DEBT: An indicator set to 1 if LEVERAGE equals 0, and 0 otherwise.

Supplementary Material

Supplementary Material for this article is available at https://doi.org/10.1017/S0022109022000254.

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