The real effects of rating actions: Evidence from corporate asset sales

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Abstract

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Keywords: Credit ratings, asset sales, financial constraints, asset allocation, managerial discipline

JEL Classifications: G34

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March 5, 2020

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1. Introduction

In this paper, we empirically study whether rating actions by credit rating agencies (CRA) have real effects on corporate decisions. In particular, we investigate whether credit rating actions impose or facilitate monitoring and discipline by public creditors. The monitoring role of CRAs may be important, since public debt typically contains relatively few clauses to protect creditors from agency conflicts, compared to private credit agreements (Billett et al., 2007). Similarly, Diamond (1991), argues that dispersed ownership or ownership by information insensitive investors of public debt allows for free-riding in monitoring and information production. This would further inhibit monitoring at the individual investor's level. CRAs may fill this void by acting as delegated monitors and tacitly improving corporate decisions (Boot et al., 2005).[1] However, rating actions may also unintentionally tighten financial constraints, raise the cost of capital, and deteriorate the firm's financial condition (Kisgen, 2007; Manso, 2013). Accordingly, rating actions may have an alternative effect and induce corporate decisions aimed at relaxing these additional financial constraints. We label these channels as the discipline and the financial constraints channel, respectively.

Understanding whether and how rating actions affect corporate decisions, is important for corporate executives, financial investors, and other stakeholders alike. Survey evidence consistently reveals that corporate executives consider credit ratings important in their decision making (Graham and Harvey, 2001). Moreover, only scant research is available on the effectiveness of creditor governance in the case of dispersed public debt, despite ample evidence of creditor governance induced by private creditors (*e.g.*, covenants in bank loans). Yet, a continued increase in focus on market-based financing and diminished reliance on banks warrants more research in this area.[2] In fact, even for bank debt, there has been a recent emergence of credit agreements sans protective covenants, referred to as "cov-lite" loans, which may erode the effectiveness and relative importance of private credit monitoring *vis-a-vis* public credit monitoring (Becker and Ivashina, 2016).

Empirically, we use corporate asset sales as a laboratory to identify real effects of credit rating actions and their underlying channels. Among several material corporate decisions through which firms may respond to ratings actions, asset sales provide an attractive background for our research question for several reasons. First, in order to identify real effects of downgrades, discrete, more irreversible, and stock-based events, such as asset sales, gen-

[1] Ramakrishnan and Thakor (1984) and Millon and Thakor (1985) further argue that actions by CRAs could improve informational efficiency in public debt markets at issuance.

[2] See, *e.g.*, the European Commission through the Capital Markets Union Initiative: `https://ec.europa.eu/info/business-economy-euro/growth-and-investment/capital-markets-union/what-capital-markets-union_en`

erate superior signal-to-noise ratios compared to continuous flow variables. Second, asset sales are meaningful corporate responses under either channel and hence, we have power to identify either if present.[3]

As a first step in guiding our empirical analyses, we set up a simple static agency model that yields several testable predictions with respect to real effects of rating actions. In the model, we derive optimal responses of corporate executives to rating changes in the context of managerial agency problems and traditional capital structure tradeoff theory considerations. Depending on model parameters, negative rating actions (such as downgrades and negative watchlists) may impose discipline on managers, resulting in a more efficient allocation of the firm's productive assets. This happens when private benefits of opportunistic behavior are small compared to the associated productivity losses. However, the model also shows that in response to negative rating actions managers may optimally undertake actions aimed at relaxing financial constraints through asset sales. This happens when private benefits of opportunistic behavior are large compared to the associated productivity losses. The model provides several other empirical predictions, for example with respect to asset liquidity, which help to distinguish between these two non-mutually exclusive channels.

Our model yields several testable implications, which guide our empirical tests. One of the main predictions is that firms respond to negative ratings actions through, among other things, corporate asset sales. We show empirically that the incidence of asset sales indeed increases sharply in response to rating downgrades for the sample period 1990-2015. In terms of economic significance, our base model estimation shows that asset sale are 45% more likely to occur after a rating downgrade. These results continue to hold when we control for prior credit watchlist placements.[4] Interestingly, negative watchlist placements also increase the incidence of asset sales significantly (39%). Following Chava and Roberts (2008) and Roberts and Sufi (2009), we include covenant violations as an additional control and find that these violations are another strong predictor of assets sales, even for firms with access to the public debt market. However, their inclusion leaves the effect of rating downgrades intact, showing that they affect corporate actions over and beyond the effects of private creditor monitoring. These results are robust to the inclusion of a comprehensive set of credit risk-related variables, other firm and deal characteristics, and various fixed effects.

[3]Alternative responses to rating actions, such as capital expenditures (CAPEX) and payout policies, are difficult to interpret in terms of asset allocation decisions within and across firms. For example, CAPEX within a firm may be sub-optimal even when they occur under the most efficient owner. Payout policies may reflect financial constraints, but are difficult to interpret in terms of asset allocations within a firm.

[4]Watchlists are indications of planned rating changes in the absence of improvements (negative watch) or adverse events (positive watch). As such, negative watch events may be more closely tied to monitoring than rating changes. Failure to account for watchlist events may bias against finding evidence for the discipline hypothesis.

The model also provides several insights that help alleviate identification and robustness concerns. Most importantly, the model shows that negative rating actions still cause asset sales in the presence of a deterioration in creditworthiness, which in itself could lead to discipline and tighter financial constraints. This theoretical result mitigates concerns about endogeneity and biases caused by omitted variables. The necessary conditions for this result are that ratings deteriorate together with credit quality, ratings are coarse, and that ratings have institutional importance (all of which are easily met).

We also perform several empirical tests to alleviate endogeneity concerns. Our specification with covenant violations also addresses omitted variables. Omitted variables which would affect the likelihood of asset sales would arguably also affect the likelihood of covenant violations. Covenant violations then proxy for such omitted variables, even if these omitted variables themselves are unobservable. Similarly, we would expect these omitted variables to correlate with market-based measures of credit risk, such as Moody's KMV Expected Default Frequencies$^{\text{TM}}$ (EDFs) and credit spreads.[5] Yet, our results continue to be statistically and economically significant when we include these measures as controls.

The last empirical test to alleviate omitted variable concerns is a novel type of placebo test. In this test we exploit the sluggishness and conservatism in rating updates (Altman and Rijken, 2004). The through-the-cycle approach employed by CRAs combined with conservatism in rating migrations makes it highly likely that an important part of the information underlying rating changes was already publicly available earlier. Accordingly, we define placebo downgrade and upgrade indicator variables, which we shift one year prior to the actual rating change (see Fig. 1). Based on the premise that downgrades cause asset sales (which typically take less than a year to organize), we should not see an increase in asset sales in the year prior to the rating change, but only in the period following the rating change.[6] Alternatively, if omitted public information drives our results, we expect to see an increase in asset sales in the year before the rating change, and not per se for the year after. We find a robust increase in asset sales (45%) in the post-downgrade period, but no material increase (1%) in the pre-downgrade period. The placebo results are robust to excluding larger asset sales, which arguably would take longer to organize, or to excluding asset sales announced within a half year after the placebo. These additional tests support

[5] We are grateful to Moody's Analytics for sharing the data on EDFs with us.

[6] Sluggishness in corporate actions results from the need for shareholder approval or when state-level corporate statutes contain provisions that permit shareholders to dissent from certain corporate actions or to seek a court directed appraisal of their shares under certain circumstances by following specified procedures. However, because contract law and the business judgment rule govern regular asset sales, as opposed to corporate law, asset sales are a relatively quick divestiture mechanism with few disclosure requirements and minimal need for shareholder approval or participation (*e.g.*, Hege et al., 2008). Firms are able to conduct (partial) asset sales typically in a matter of just a few months and much quicker than other forms of corporate divestitures. See, *e.g.*, `https://corpgov.law.harvard.edu/2017/07/27/when-a-piece-of-your-company-no-longer-fits-what-boards-need-to-know-about-divestitures/`

the finding that downgrades positively affect the incidence of subsequent asset sales.

In the remainder of the paper, we investigate whether rating downgrades induce firms to sell assets to improve asset allocation, relax financial constraints, or both. As before, the model implications drive our empirical tests. In the context of the discipline hypothesis, asset sales are an opportunity for a firm to reallocate assets more efficiently and improve its fundamentals through changes on the asset side of the balance sheet (Hite et al., 1987). In the context of the financial constraints hypothesis, asset sales provide the firm with an opportunity to raise cash and address financing frictions through changes on the liability side of the balance sheet (Lang et al., 1995). Our first test considers the reported use of the proceeds of the asset sale. We find that asset sales are particularly more likely (156%) after a rating downgrade if the firm intents to use the proceeds to relax financial constraints. In fact, depending on the specification, the sign on the coefficient for a rating downgrade turns negative for discipline-based asset sales. When we include negative watchlist placements, we find that they are positively associated with the incidence of asset sales motivated by financial constraints. In contrast, we find no association between negative watchlists and the incidence of discipline-based asset sales.

We conduct a second test that involves a sample of pure-stock spinoffs as an alternative method to divest assets.[7] Since these transactions do not involve a cash infusion for the firm or its shareholders they would not be a logical response to a downgrade in the context of financial constraints, but could be in the context of discipline and asset reallocation. Consistent with the financial constraint hypothesis, we find that the average rating for firms that announce spinoffs and for firms that announce asset sales with the purpose of asset reallocation are similar, and three notches higher than for firms announcing asset sales aimed at relaxing financial constraints. This difference is economically and statistically significant. Moreover, we find no relation between downgrades and the likelihood of subsequent spinoffs, irrespective of whether we consider negative watchlists. Importantly, negative watchlists also do not predict subsequent spinoffs.

Our third test is a corollary of the financial constraints hypothesis. Our model differentiates the effect of transaction costs between the two channels. If the goal of the asset sale is to relax financial constraints, transaction costs are particularly undesirable because the firm's marginal utility of cash is high. In contrast, if the goal of the asset sale is to only improve the allocation of assets, the marginal utility of cash is unaffected. Therefore, there is a positive interaction effect between asset liquidity and negative rating actions on the likelihood of conducting asset sales under the financial constraints channel. There is

[7]We are grateful to our AFA discussant, Mariassunta Giannetti, for this suggestion.

no such interaction effect under the discipline channel. Note that the interaction effect is over and beyond the baseline effect that illiquid assets are more difficult and costly to sell irrespective of what motivates the asset sale (Shleifer and Vishny, 1992).[8] In line with the financial constraints channel, we find that the relation between rating downgrades and the likelihood for asset sales is stronger when asset redeployability is higher. For example, the marginal impact of a recent downgrade on the likelihood of announcing an asset sale is roughly four times higher in the highest than in the lowest decile of asset redeployability.

In the last section, we ask if rating actions matter for which assets the firm sells. We match asset sales to segment data and conduct inter- and intra-firm analyses. We find no relation between downgrades and the likelihood of selling non-core segments or segments that underperform their industry peers, irrespective of prior watchlists. However, downgrades increase the likelihood of selling segments with high asset redeployability, poor cash flow performance, and high growth opportunities by 10 percentage points. This suggests that firms respond to financial constraints, but not necessarily seek to improve the allocation of productive assets after negative rating actions. While it may be challenging to distinguish unambiguously between the financial constraints and disciplinary channels based on any test alone, in concert the evidence suggests that financial constraints is the more dominant explanation for why firms respond with asset sales after negative rating actions.

We contribute to several strands of literature. First, we add to the literature on creditor governance, which primarily focuses on private credit agreements and discipline imposed by debt covenants (Chava and Roberts, 2008; Roberts and Sufi, 2009). For dispersed public debt, we find that rating actions matter in explaining assets sales over and beyond covenants, but are poor substitutes for monitoring actions around covenant breaches.

Our findings also complement a growing literature on the real effects of credit ratings. On the theory side, there are models that relate to the discipline channel (e.g., Boot et al., 2005) and models that relate to the financial constraints channel (e.g., Goldstein and Huang, 2018). We contribute by providing a model that integrates both channels and derives testable implications to delineate between these two channels. The empirical literature on the real effects of credit ratings is divided on the underlying channels. Kisgen (2006) and Kisgen (2009) show that ratings affect capital structure decisions and the cost of capital. Bannier et al. (2012), find that CAPEX reduces after downgrades and attribute this to managerial discipline. By contrast, Begley (2015), however, finds that firms boost EBITDA prior to bond issues close to key Debt/EBITDA thresholds, as emphasized by

[8]The interaction effect may be negative for severely distressed firms that conduct fire sales of even their more illiquid assets. Because of the illiquidity, they would need to sell more of them. We exclude severely distressed firms in from or sample. To the extent that such firms remain in the sample, our positive interaction effect would understate the true effect.

CRAs. This happens at the expense of long-term performance and value, which suggests a financial constraints channel. We contribute to this empirical literature and provide additional evidence that, on balance, the financial constraints channel dominates the discipline channel. In doing so, we use changes in stock rather than flow variables, which (arguably) provide us with a better signal-to-noise ratio.

Two related papers also use stock variables (M&As) in the context of credit rating effects. Harford and Uysal (2014) show that not having a credit rating leads to underinvestment in acquisitions. Aktas et al. (2017) show that rating levels and changes affect corporate acquisitiveness. Our focus on asset sales and spinoffs, which exploits firm and segment level data, provides us with a more direct way to analyze whether ratings affect financing and asset allocation decisions and if so, which channel dominates.

Our paper also contributes methodologically to the literature on the real effects of credit ratings by developing novel strategies to mitigate identification concerns. The model we put forward can also be used in other studies that investigate effects of credit ratings on operating, allocation, or financing decisions. Moreover, to the best of our knowledge, the type of placebo test we use has not been used before and can also be used by other studies that investigate effects of ratings.

Finally, our paper contributes to the asset sales literature, which shows that firms sell small, liquid, and non-core assets, which leads to improved firm performance and reduced costs associated with cross-subsidization.[9] As such, the motivation for asset sales can originate from discipline or financial constraints. We provide evidence that in context of rating changes, the financial constraints channel is strongest.

2. A simple model

In this section, we introduce a simple static agency model of real effects of rating actions on asset allocation and capital structure decisions (proofs in appendix). This framework yields testable implications that steer our subsequent empirical analysis.

2.1. Intuition of the model

We set up a simple static agency model with a manager who makes investment decisions while facing financial frictions. The manager can choose to invest in two types of assets: core and non-core assets. Non-core assets offer private benefits to the manager, but the firm cannot efficiently use them. Crucially, operating non-core assets also impairs the firm's credit rating. The manager's compensation is partially performance-based. He trades off

[9] Eckbo et al. (2013) provide a detailed summary of this literature.

private benefits from holding non-core assets with lower performance-based compensation resulting from inefficient use of non-core assets. If private benefits are sufficiently large, the manager optimally invests in non-core assets at the expense of investors.[10]

In our model, the manager also makes financing decisions under the conventional tradeoff theory. Financing decisions affect the manager's utility through the cost of capital. As the credit rating exogenously decreases, the cost of capital increases.[11] The manager optimally responds by either lowering leverage (the financial constraint channel) or by selling non-core assets (the discipline channel).[12] Assuming that asset sales are the most cost-effective way to reduce leverage, both channels predict an increase in assets sales following negative rating actions. We also derive under which conditions the discipline or financial constraint channel are at work following negative rating actions.

We derive additional predictions by enriching the model with transaction costs and confounding variables (both affect financial constraints channel more than discipline channel), as well as omitted variables (we show that rating actions matter over and beyond).

2.2. Model setup

Consider a multi-segment firm with a core and a non-core segment, indexed by c and nc, respectively. We also assume that the risk of both segments is identical, for expositional purposes. Finally, we assume that the firm is fully proficient in its core activity, but receives a discount $\delta \in (0, 1)$ on the profits of its non-core activities, such that $IRR_c = \delta IRR_{nc}$, where IRR_x refers to the internal rate of returns for a segment x. The (expected) internal rate of return for the company (IRR) is given by

$$IRR = \frac{IC_c}{IC} IRR_c + \frac{IC_{nc}}{IC} IRR_{nc}, \tag{1}$$

where IC_x refers to segment-specific invested capital and $IC = IC_c + IC_{nc}$. The cost of capital r is defined as

$$r = r_a - \frac{D}{V} Tr_d + \gamma \left(a\frac{D}{V} + bCR \right)^2, \tag{2}$$

where T is the corporate tax rate, r_a is the cost of capital for an unlevered firm, $\frac{D}{V}$ is the leverage ratio, CR is the rating level (where a higher value for CR corresponds to a worse

[10]This is line with Boot (1992), who argues that misaligned managerial incentives result in managers rationally holding on to incompatible assets for too long.

[11]Several papers (see *e.g.*, Bongaerts et al., 2012; Ellul et al., 2011; Kisgen and Strahan, 2010) empirically show that ratings, through regulatory importance, influence yield spreads. Opp et al. (2013) and Goldstein and Huang (2018) analyze the role of such regulatory importance of ratings theoretically.

[12]The latter is in line with Boot et al. (2005) who shows theoretically that ratings can act as coordination mechanisms and that negative watch list procedures of CRAs serve as implicit monitoring contracts.

rating), r_d is the pre-tax cost of debt, and γ is a weighting parameter on financial distress costs. The second term in Eq. (2) refers to the tax shield and the third to financial distress costs. The firm creates economic value

$$EVA = (IRR - r)IC \tag{3}$$

per annum. We assume the following expected utility function of the CEO:

$$U_m = \beta IC_{nc} + EVA, \tag{4}$$

where β reflects private benefits of non-core operations (e.g., empire building). The EVA term reflects performance-based CEO incentives (normalized to 1 without loss of generality). For the moment, we assume transaction costs to be zero for asset sales and to be strictly positive for any other means of adjusting leverage.

2.3. CEO private value maximization

We derive the (privately) optimal financing structure as well as conditions under which the CEO invests in the non-core segment. Investing in the non-core segment may be privately optimal if private benefits from doing so exceed the associated loss in EVA.

Lemma 1. *Given a rating, the optimal leverage ratio is given by*

$$\left(\frac{D}{V}\right)^* = \frac{-2abCR + \gamma^{-1}Tr_d}{2a^2}. \tag{5}$$

The CEO optimally holds on to the non-core segment if

$$r^* \leq IRR_{nc} + \beta, \tag{6}$$

where r^* is given by (2) evaluated at $\left(\frac{D}{V}\right)^*$.

Now assume that $IRR_{nc} < r^*$, but that the CEO holds on to segment nc ((6) satisfied). Moreover, assume that owning segment nc would initially be irrelevant for the credit rating due to rating coarseness (see Goel and Thakor, 2015). Now exogenous economic adversity causes the rating to deteriorate to $CR' > CR$. Moreover, assume that this shock just puts the firm over a rating threshold, such that the negative rating action can be undone by selling segment nc to a better user. We can now derive whether the CEO optimally sells the non-core segment or reduces leverage in response of the changed rating.

Proposition 1. *In response to the rating deterioration, the CEO lowers leverage to*

$$\left(\frac{D}{V}\right)^{*'} = \frac{-2abCR' + \gamma^{-1}Tr_d}{2a^2}, \tag{7}$$

if

$$r^{*'} \leq \frac{(\beta + IRR_{nc})IC_{nc} + IC_c r^*}{IC_{nc} + IC_c'}, \tag{8}$$

where $r^{*'}$ *is given by (2) evaluated at* $\left(\frac{D}{V}\right)^{*'}$ *and* CR' *and* IC_c' *is the invested capital of segments c after the leverage reduction. Otherwise the CEO sells segment nc and leaves leverage unchanged.*

Proposition 1 shows that if Condition (8) is satisfied (i.e., the financial constraints channel dominates), negative rating actions lead to leverage reductions, which in this case are funded by asset sales.[13] Proposition 1 also shows that the negative rating action increases pressure to sell segment nc in two ways. Even if financial constraints are partially alleviated by reducing leverage, the reduced tax-deductability further impairs the profitability of segment nc, thereby tightening condition (6). The reduced tax-deductability also gives rise to an intra-firm spillover effect by making segment c less profitable. These effects are broadly consistent with Boot et al. (2005), who shows theoretically that ratings can act as coordination mechanisms and that negative watch lists of CRAs serve as implicit monitoring contracts. By assumption transaction costs are zero for asset sales and strictly positive for other ways of reducing leverage. Therefore, we get the following testable implications:

Implication 1. *Negative rating actions increase the likelihood of asset sales, irrespective of whether the financial constraints or discipline channel is at work.*

Implication 2. *Under the discipline channel, non-core, and poorly performing segments are more likely to be sold following negative rating actions.*

Under the assumption that companies truthfully report the purpose of their asset sales we immediately get another implication:

Implication 3. *Negative rating actions primarily induce asset sales with leverage reduction purpose when the financial constraints channel dominates and primarily induce asset sales with restructuring purpose when the discipline channel dominates.*

[13] Empirically, Lang et al. (1995) show that asset sales are an important source of financing when firms are otherwise financially constrained and Officer (2007) show that firms who announce asset sales have lower bond ratings and are financially more constrained than firms that do not.

2.4. Transaction costs and other ways of reducing leverage

Now assume that there are two core segments, $c1$ and $c2$. Denote the asset liquidity of segments x by l_x. Liquidity l_x is defined as the proportional secondary market value (relative to true value), such that proportional transaction cost are given by $1 - l_x$. For tractability, assume that segments are infinitely divisible, such that the desired reduction in leverage can be exactly achieved. Also assume that there is an outside option to reduce leverage, such as a Seasoned Equity Offering (SEO), denoted by s with proportional transaction cost $1 - l_s$.

A crucial insight of our analysis is that the *effective* transaction costs for selling assets aimed at reducing leverage are higher than those for other asset sales. The reason is that transaction costs reduce transaction revenue and therefore require to be larger to achieve the desired leverage reduction. This size increment is costly since it involves additional transaction costs.

Lemma 2. *The effective transaction costs for selling assets from segment k to generate a unit of cash equal $(\frac{1}{l_k} - 1) > (1 - l_k)$.*

Lemma 2 immediately implies that liquidity-induced transactions have higher effective transaction costs than other transactions.

Implication 4. *Transaction costs matter for asset sales aimed to reduce leverage over and beyond to how they matter for other types of asset sales.*

We now derive the main proposition of this section.

Proposition 2. *In response to the rating deterioration, the CEO lowers leverage to*

$$\left(\frac{D}{V}\right)^{**} = \min\left(\frac{D^*}{V}, \frac{-2abCR' + \gamma^{-1}(Tr_d + l_{k^*}^{-1} r_f V)}{2a^2}\right), \tag{9}$$

if

$$r^{**} \leq \frac{(\beta + IRR_{nc})IC_{nc} + r^* IC_c + IRR_c(IC_c' - IC_c) + (1 - l_{nc})IC_{nc} r_f}{IC_{nc} + IC_c'}, \tag{10}$$

where

$$r^{**} = r_a - \frac{D^{**}}{V} Tr_d + \frac{V r_f |\frac{D^{**}}{V} - \frac{D^*}{V}|}{l_x} + \gamma\left(a\frac{D^{**}}{V} + bCR'\right)^2, \tag{11}$$

$$k^* = \arg \max_{k \in \{c1, c2, nc, s\}} l_k, \tag{12}$$

V is firm value, r_f is the risk-free rate, and IC'_c is the invested capital of segments $c1$ and $c2$ together after the leverage reduction. Otherwise the CEO sells segment nc and leaves leverage unchanged.

Proposition 2 shows that if Condition (10) is violated, the non-core segment is sold and leverage is unaffected. An efficient way to achieve this is by doing a spinoff.

Implication 5. *The likelihood of spinoffs following negative rating actions is higher only under the discipline channel.*

Proposition 2 accounts for other ways to reduce leverage than asset sales. Hence, our focus on asset sales may only allow us to capture part of the real effect of rating changes. This leads to the following robustness result.

Robustness Result 1. *Transaction costs would prevent some assets sales from happening. This works against finding empirical evidence for Implication 1.*

2.5. Incorporating other characteristics

Now assume that financial distress costs are not only driven by ratings and leverage, but also by another characteristic X. To focus on the effect of X, we assume markets to be perfectly liquid and no outside options to be available. We have that

$$r = r_a - \frac{D}{V}Tr_d + \gamma\left(a\frac{D}{V} + bCR + cX\right)^2, \tag{13}$$

$$= r_a - \frac{D}{V}Tr_d + \gamma\left(\left(a\frac{D}{V}\right)^2 + b^2CR^2 + c^2X^2 + 2ab\frac{D}{V}CR + 2ac\frac{D}{V}X + 2bcCRX\right). \tag{14}$$

We derive the optimal leverage and the condition keep the non-core asset as before.

Lemma 3. *Given a rating, the optimal leverage ratio is given by*

$$\left(\frac{D}{V}\right)^{***} = \frac{-2a(bCR + cX) + \gamma^{-1}Tr_d}{2a^2}. \tag{15}$$

In this setting, the CEO optimally holds on to the non-core segment if

$$r^{***} \leq IRR_{nc} + \beta, \tag{16}$$

where r^{***} is given by (13) evaluated at $\left(\frac{D}{V}\right)^{***}$.

Other characteristics may be important as these could give rise to omitted variables concerns or interfere with the predictions derived before (confounding characteristics effects). We first address the omitted variable concern. Because ratings are coarse, a deterioration in X to a level X' affects the credit rating with strictly positive probability. It follows from (15) that under the financial constraints channel, the optimal leverage adjustment is larger if X' results in a rating deterioration. It follows from (16) that under the discipline channel, the sale of the under-performing segment is also more likely if X' results in a rating deterioration (as selling the non-core asset offsets a larger negative utility effect).

Proposition 3. *In response to the rating deterioration induced by X', the CEO lowers leverage to*

$$\left(\frac{D}{V}\right)^{***'} = \frac{-2a(b(CR + \Delta CRI_{ch}) + cX') + \gamma^{-1}Tr_d}{2a^2}, \tag{17}$$

if

$$r^{***'}_{I_{ch}=1} \leq \frac{(\beta + IRR_{nc})IC_{nc} + IC_c r^{***'}_{I_{ch}=0}}{IC_{nc} + IC'_c}, \tag{18}$$

where I_{ch} is an indicator function that equals 1 in case of a rating change and 0 otherwise, $\Delta CR = CR' - CR$, and $r^{***'}_{I_{ch}}$ is given by (13) evaluated at $\left(\frac{D}{V}\right)^{***'}$, X' and I_{ch}.

Hence, even if a rating change is induced by a change in credit quality that matters by itself for financial distress costs, there is an incremental effect on the likelihood of asset sales under both channels caused by the rating change.

Robustness Result 2. *Rating changes driven by deteriorations in credit risk induce asset sales over and above the effect of credit risk deteriorations on their own, irrespective of the channel at work.*

Next, we address the confounding characteristics effect. We show the effect of confounding characteristics for both the discipline channel and the financial constraints channel. In the financial distress component of Eq. (14), there is an interaction term with leverage, which influences leverage choices. As a result, asset sales that attenuate financial distress by improving other firm characteristics require smaller leverage decreases than asset sales that worsen financial distress through their effect on firm characteristics. Since leverage reductions are costly due to the loss of tax shields, the financial constraints channel predicts that assets are sold that aggravate financial distress and that assets are kept that mitigate it. Yet, the sale of the non-core segment involves similar effects (it may require additional leverage reduction with associated costs). Yet, Eq. (14) also contains the interaction term $2bcCRX$. Under the financial constraints hypothesis, the rating is likely to stay poor, so the effect of this interaction term is large. By contrast, under the discipline channel the asset sale is likely to improve the rating, and hence, these characteristics are likely to matter less. We work this out formally below.

Proposition 4. *Assume that selling (from) segment k induces X to change to X_{-k}. In response to the rating deterioration, the CEO lowers leverage to*

$$\left(\frac{D}{V}\right)^{***''} = \frac{-2ab(CR + \Delta CRI_{ch} + cX_{-k^*}) + \gamma^{-1}Tr_d}{2a^2}, \tag{19}$$

if

$$r^{***''} \leq \frac{(\beta + IRR_{nc})IC_{nc} + r^{***}_{-nc}IC_c + IRR_c(IC'_c - IC_c)}{IC_{nc} + IC'_c}, \tag{20}$$

where $r^{***''}$ is given by (13) evaluated at $\left(\frac{D}{V}\right)^{***''}$ and X_{-k^*}, r^{***}_{-nc} is given by (13) evaluated at $\left(\frac{D}{V}\right)^{***''}$ with $k = nc$ and $I_{ch} = 0$, and

$$k^* = \arg \min_{k \in \{c1, c2, nc, s\}} X_{-k}. \tag{21}$$

Otherwise the CEO sells segment nc and changes leverage to a level that incorporates X_{-nc}.

Implication 6. *Confounding characteristics matter more for leverage-reducing assets sales than for asset sales aimed at improving asset configurations.*

In summary, our model predicts that negative rating actions lead to an increase in asset sales. It also generates several robustness results that mitigate concerns about omitted variables and alternative responses to negative rating actions in our subsequent empirical estimations. Finally, the model generates several predictions that can help us delineate between a discipline channel and a tightening of financial constraints channel.

3. Data and sample design

In this section we describe the data sources and explain the formation of the full sample (containing all U.S. listed corporates), the asset sale sample, and the sample with segment data.

3.1. Full sample

We begin with a sample that includes the Compustat universe of listed corporates in the U.S., excluding firms with total book assets less than $75 million (measured in 1990 inflation-adjusted dollars), financial firms (SIC 6000 to 6999) and regulated utilities (SIC 4900 to 4999) during the period 1990-2015. We collect accounting data from Compustat and data on the top-5 executive shareholdings (in %) excluding options from ExecuComp. We collect S&P long-term credit ratings from Compustat Ratings and use the CRSP database to collect data to construct the size-age (SA) index to proxy for financial constraints following Hadlock and Pierce (2010).

We use the asset redeployability measure from Kim and Kung (2016) as a proxy for liquidity to test Implication 4.[14] Asset redeployability is an important determinant of liquidation values and debt capacity (Williamson, 1988). Their measure is also a good proxy for liquidity as there is likely more asymmetric information about segments that employ specific assets, search costs are likely to be higher due to fewer potential buyers, and industry shocks translate into more correlated 'funding liquidity' shocks for potential buyers. The academic literature has identified asymmetric information (Glosten and Milgrom, 1985; Kyle, 1985), search costs (Duffie et al., 2005), and funding liquidity shocks (Brunnermeier and Pedersen, 2008) as key drivers for liquidity in securities markets. Specifically, we include in all our tests the baseline measure of Kim and Kung (2016) that uses the market capitalization of firms in a given Bureau of Economic Analysis (BEA) industry. However, we note that we generally find even stronger results when we use their alternative definition of redeployability that incorporates both across and within industry correlation of firm-level output, but for brevity do not report these results except for Appendix Fig. B.1 described in Section 4.3.3.[15] While this alternative measure has less cross-sectional variation, we believe this result is important because it shows that the extent to which credit rating downgrades exacerbate financial constraints is higher in periods of industry distress.

Finally, we collect watchlist data from Bloomberg for our entire sample period. Since Bloomberg does not have identifiers that can easily be matched to our company data, we match these data by name. We manage to automate this process for a sizeable fraction of rated firms in our sample. For the remaining rated firms we compose a set of suitable candidate matches (if any), which we match by hand. Only if we are certain about a manual match we include it. We also cross-check with the letter rating. Naturally, this procedure is far from ideal. Consistently, we only match a subset of rated firms. Therefore, the specifications with only rating changes are our baseline specifications and we use the specifications that also include watchlist placements as robustness checks, which we report in Appendix B (except for Table 4, which includes watchlists).

Our sample contains 835,926 firm-month observations, with 8,980 unique firms (i.e.,

[14] An advantage of this measure is that it captures both asset specificity and liquidity, but is not transaction based. Given that our dependent variable is transaction based and to avoid potential endogeneity, we prefer the Kim and Kung (2016) measure as an independent variable instead of transaction-based measures, such as the asset liquidity measure in Schlingemann et al. (2002).We are grateful to Hyunseob Kim and Howard Kung for making these data available to us.

[15] The results are available upon request from the authors.

with unique GVKEY identifiers in Compustat). Out of these, 3,253 firms (36.2%) have an S&P credit rating at any point of time in the sample period. Of the firms with a credit rating, 58% (47.8%) experience at least one credit rating downgrade (upgrade) during the sample period. Table 1 provides definitions of the variables we use in our analysis and the first four columns in Table 2 provide summary statistics for our full sample.

3.2. Asset sales sample

We collect corporate asset sales announced during the period 1990-2015 from the Securities Database Corporation Refinitiv (SDC) Special Mergers Sectors Database. We include all target firms where the ultimate parent is a publicly listed firm in the U.S. and the restructuring event is completed and listed as a restructuring, equity carve-out, subsidiary acquisitions, or divestiture according to SDC. We also include deals labeled by SDC as seeking buyer, but exclude stock swaps, pooling of interest, reverse take-overs and reverse Morris trusts. We remove observations if the transaction value is less than $10 million (measured in 1990 inflation-adjusted dollars), or if we are unable to match the ultimate or immediate parent of the target with the comprehensive sample described above. We collect a separate sample of spinoffs from SDC based on the same criteria as for our sample of asset sales and verify that they do not coincide with the issuance of securities to outside investors or the sale of other assets for cash. We use this sample of alternative restructurings in a separate analysis to test whether we find similar results as we find for asset sales. Since spinoffs typically do not involve a cash infusion for the firm, it is unlikely that financing needs motivate these transactions.

These criteria result in an initial sample of 16,304 completed assets sales. We match these deals to parent companies as follows. We take the target immediate parent and ultimate parent CUSIP from SDC and match those to the PERMNO and PERMCO identifiers from the CRSP file in the fiscal year before the announcement. Usually the immediate parent and ultimate parent coincide. If they do not coincide, we take the immediate parent. We delete deals that match only on the Target CUSIP field in SDC. We then match each SDC deal number to the acquirer PERMNO and PERMCO identifiers and merge in the deal numbers, deal characteristics, acquirer and target parent identifiers (PERMNO/PERMCO) into our sample of firm fundamentals. Our final sample includes 4,974 asset sales, performed by 1,657 firms (*i.e.*, with unique GVKEY identifiers in Compustat).

For this sample, we collect data on the use of proceeds from SDC. We label the asset sales as financial constraints motivated if the firm (seller) intends to use the proceeds of the asset sale to pay down existing debt or to raise cash (247 deals or 5%). We label the asset sale as disciplinary if the firm reports the intent to concentrate on core business or assets or if the sale involves a loss making or bankrupt operation (431 deals or 9%). For all remaining cases (over 80%), SDC reports no data on the seller's purpose (either no data or only buyer purpose), only other seller purposes (approximately 5% of asset sales), or includes both financial constraints and disciplinary purposes (<0.5% of asset sales).[16] We label those asset sale as ambiguous.

We also collect data on rumored, uncompleted, pending, intended, partially completed deals and deals with seeking buyer announcements. We label these as 'failed deals' and use these in a robustness test to mitigate concerns regarding selection bias or limited external validity.

We also include non-rated firms and asset sales by non-rated firms as a control or benchmark sample and include rating fixed effects (having a rating at all or the particular rating) with rating fixed effects. Moreover, these observations help with estimating the effect of other covariates more precisely. Columns (4) to (8) in Table 2 show summary statistics for this sample.

3.3. Asset sales with segment-level data

Finally, we construct a sub-sample firms that conduct asset sales for which we have matching segment data. To do so, we match each asset sale by a multi-segment firm to a corporate segment using the Compustat Segment File. In total, there are 2,023 asset sales done by multi-segment firms. As SDC does not contain segment identifiers, we proceed as follows. First, we check whether the 4-digit SIC code for the asset sale (reported by SDC) uniquely matches the primary or secondary 4-digit SIC code in the Compustat segment file. If so, we keep this match. This procedure yields 625 unique matches. For the remaining observations, we repeat this procedure based on a 3-digit SIC code match. This gives us 118 additional matches. We match the remaining observations manually, where we compare the deal synopsis, as reported in SDC, with the 10-K filings in EDGAR. This procedure produces another 867 matches for a total of 1,610 observations.[17]

We match the event, as reported in SDC, with a specific segment for 1,610 assets sales. For these firms, we collect the following additional data items from the Compustat Segment File: Total Identifiable Assets (IAS), Operating Profit (OPS), Sales (SALES), Capital Expenditures (CAPEX), and Depreciation and Amortization (DPS) of all segments of the seller firm in the year before the asset sale, and the number of operating segments. These

[16] Most of these "other motivations" are either regulatory or classified as general purposes.

[17] EDGAR only provides data on filings from 1994 onward. Because of this, we lose a few observations in the beginning of our sample period.

data fields have the best coverage at the segment level. We construct for each segment the following performance measures: operating profitability (OPS/IAS), profit margin (OPS / SALES), turnover (SALES / IAS), Cash Flow ratio ((OPS + DPS) / IAS), and Net Cash Flow ratio ((OPS + DPS – CAPEX) / IAS). For each segment, we determine whether it is the highest or lowest, or in the upper or lower half within the firm with respect to each of the performance and CAPEX measures. In addition, we compare each sold segment to other segments in the same 2-digit SIC industry for all performance measures and record whether it is in the top or bottom half of that industry.

The final four columns in Table 2 present summary statistics for the segment sample. A comparison of firm characteristics, between the asset sale sample and the sub-sample with segment data, shows that firms in the asset sales sample experience more credit rating downgrades and have higher S&P credit rating. They are also larger, have more short-term debt (Rollover), higher profitability and ROA, lower capital expenditures and investments in R&D, and a higher financial constraints index (SA index).

4. Results

4.1. Credit rating changes as a determinant of asset sales

Our first empirical prediction is that negative rating actions have real effects. Specifically, we predict that the incidence of asset sale announcements increases in response to negative rating actions (Implication 1). To this end, we estimate a Cox proportional hazard model on the time it takes (duration) for an asset sale to take place. A duration model is in our view the ideal methodology to get at this question. Our baseline model is as follows,

$$\lambda(s|\mathbf{X}_{i,t}) = \lambda_0(s)\exp\Big(\beta_1 \times \textit{Rating downgrade}\,(0,1) + \beta_2 \times \textit{Rating upgrade}\,(0,1) + \gamma'\mathbf{Y}_{i,t} + \mathbf{z}'_{i,t}\Big), \quad (22)$$

where $\lambda(s|\mathbf{X}_{i,t})$, is the asset sale hazard rate (or intensity) for a firm i at time t that has survived for s periods and with covariates collected in vector $\mathbf{X}_{i,t}$. $\lambda_0(s)$ is the (common) baseline hazard rate for a firm that has not seen an asset sale for s periods.[18] The vector $\mathbf{X}_{i,t}$ collects the following covariates: *Rating downgrade* $(0,1)$ (*Rating upgrade* $(0,1)$) is a dummy that equals 1 in case of an S&P credit rating downgrade (upgrade) over the last 12 months, and 0 otherwise; $\mathbf{Y}_{i,t}$ is a vector that contains time-varying firm-specific and potentially industry-wide control variables; $\mathbf{z}_{i,t}$ is a vector of fixed effects. Our spells in

[18] The Cox proportional hazard model is convenient, as the baseline hazard rate $\lambda_0(s)$ falls out, which facilitates estimation (Cox, 1972, 1975).

which firms are at risk start at the first observation of the firm in question, or in case of multiple events per firm the month after the previous event.

We estimate our Cox model on the whole universe of US corporates, properly accounting for the effects of censoring and truncation. Our key explanatory variable is *Rating downgrade* $(0, 1)$. Since several downgrades are preceded by negative watchlist placements, we also include specifications which include watchlist placements and also look at the effects of negative credit watches. Since our rating data are of better quality than our credit watch data, our main specification does not include watchlist placements. Our specifications include a comprehensive set of controls for credit risk, firm performance, leverage, alternative forms of credit monitoring, and several fixed effects (see Table 1 for variable definitions). In our main hazard specification, we include levels of all controls. To rule out that it is not levels, but changes in credit risk that could drive both rating changes as well as asset sales, we also include a specification in which we include changes rather than levels of all our control variables. Depending on the specification, we include industry, time, industry-time fixed effects, and industry medians of the firm-specific covariates. We update all covariates on a monthly basis and make sure that for an observation in month t, we measure the covariates before month $t-1$, to ensure that all information we include was available to management and investors in month t. We first estimate this baseline model, but to make a causal interpretation more plausible, we propose in the next sections a comprehensive identification strategy, which, we believe, mitigates potential biases from omitted unobservable variables.

Table 3 presents the baseline results of our duration analysis based on Eq. (22). In model (1), we include the respective dummy variables for a credit rating downgrade and upgrade, a dummy for whether the firm has a bond rating, and an ordinal variable that assigns higher integer numbers to better credit ratings. In this model, β_1 is positive and highly significant, which indicates that rating downgrades significantly increase the hazard rate of asset sales and hence accelerate them. Rating upgrades on the other hand have a negative significant coefficient and lead to a significant delay in the time it takes for a corporate to announce an asset sale. In model (2), we include a large set of control variables related to firm's credit risk profile and financial performance. Specifically, we add variables previously used in the literature as proxies for credit risk, such as profitability, leverage, size, tangibility, asset redeployability, financial constraints, governance, executive ownership, cash buffers, cash flow, growth opportunities, capital expenditures, R&D, and debt maturity structure. We continue to find a strong positive (negative) relation between the hazard rate of asset sales and credit rating downgrades (upgrades). In model (3) we add time fixed effects, in model (4) we add industry fixed effects (2-digit SIC), and in Model (5) we add both industry and time fixed effects as well as industry covariates (industry medians of the firm level covariates). In each specification the relation credit rating changes and the hazard rate of asset sales continues to be economically and statistically significant. For example, in model (5), a rating downgrade increases the hazard rate of an asset sale by about 45% ($\exp(0.369) - 1$). Finally, in model (6) we see that the coefficient on our rating downgrade indicator variable (β_1) remains positive and highly significant when we include time$\times$industry fixed effects.

The coefficient estimates for many of the control variables are consistent with tighter financial constraints. For example, higher leverage and more severe financial constraints trigger asset sales, while high ROA, a high Altman z-score and high cash holdings lower the incidence rate of asset sales. In model (7), we repeat the specification of model (5), but include only the first asset sale by a specific firm in the sample. After all, the occurrence of an asset sale could influence the likelihood of other asset sales going forward, and treating all asset sales the same irrespective of their order might lead to biases. The coefficient on the credit rating downgrade remains statistically and economically similar to the coefficient estimated in model (5), but the coefficient on the credit rating upgrade switches signs and is no longer significant. In model (8), we address the issue that credit rating up- or downgrades constitute changes, whereas the covariates in models (1) through (6) relate to levels. To the extent that changes rather than the level of credit risk matter, we may inadequately control for credit risk. The results for specification (6) are qualitatively similar to the first six specifications in Table 3. The effect of rating downgrades is also quantitatively similar.

We next consider the impact of being placed on a credit watchlist by a CRA. CRAs may put a firm on a watchlist, which indicates that they intend to downgrade a firm if creditworthiness does not improve (deteriorate). Firms may act following negative watchlist placements (for example by selling non-performing assets), thereby preventing downgrades (Boot et al., 2005). Hence, an analysis that focuses solely on actual rating changes may be biased against finding evidence for the discipline channel. Therefore, we also run our analysis controlling for recent watchlist placements.

In models (1) through (4) of Table 4, we re-estimate models (2) through (5) from Table 3, where we include indicator variables for a negative watchlist and a positive watchlist in addition to the rating downgrade and upgrade indicator variables. For brevity, we suppress the remaining covariates in all subsequent tables with Cox regressions. For each model, we find that the coefficients on the negative watchlist indicator variable are positive and significant at the one percent level. In other words, a negative watchlist, like a rating downgrade, increases the likelihood for an asset sale. In terms of economic significance, the estimated coefficient from model (4), for example, translates into an increased likelihood of an asset sales after a negative watchlist of 39%. The inclusion of the watchlist indicator variables reduces the coefficients on the rating downgrade variable a little bit compared to the ones reported in Table 3. This is natural given the positive correlation (0.36) between the two. However, each coefficient on the rating downgrade variable (β_1) remains statistically and economically highly significant. For example, based on model (4), for example, the likelihood of an asset sales still increases by 31% after a rating downgrade over and above the effect on the likelihood based on watchlists. Therefore, our evidence shows that rating downgrades and credit watchlists are far from perfect substitutes and that downgrade decisions matter over and beyond the relation between credit watchlists and asset sales. In models (5) and (6), we confirm these conclusions based on the specifications with only the first asset sale event and in terms of changes (as opposed to levels) in the covariates, respectively.

4.2. Alternative forms of creditor governance and identification

Overall, the duration analysis reported in Tables 3 and 4 shows that rating downgrades are positively associated with subsequent asset sales announcements. This is consistent with results reported in the literature that show that ratings correlate with strategic decisions at the corporate level over and above the effect of credit risk itself (e.g., Aktas et al., 2017; Kisgen, 2006, 2009). In this section, we address two important issues that facilitate the interpretation of this association as relevant and, conceivably, causal. First, we analyze whether credit ratings have an impact over and beyond other established forms of creditor governance. Second, we address the role of omitted variables and present several approaches to mitigate identification concerns.

4.2.1. Creditor governance from covenants

We start with the issue of alternative mechanisms for creditor governance and the question whether our results are incrementally relevant. The literature on creditor governance focuses primarily on private credit agreements and finds that covenants constitute binding constraints (e.g., Chava and Roberts, 2008; Roberts and Sufi, 2009). While firms with access to the public debt market typically satisfy their long-term financing needs with bonds rather than loans, some exposure to private credit arrangements may remain such as through short-term revolving credit facilities. To the extent this is the case, covenant breaches may render credit rating downgrades redundant and ineffective in terms of affecting corporate behavior. To address this question, we download the updated covenant violation data from Michael Roberts' website and re-estimate Eq. (22), where we include a dummy variable that equals one if a covenant took place during the last 12 months and equal to zero otherwise. Since the covenant violation data covers a shorter sample period than our baseline sample, we shorten our sample for this analysis and also run a specification without the covenant violation data to exclude the possibility of sample differences driving results.

Table 5 presents the results of this analysis. Model (1) shows that shortening the sample period to cover the covenant data leaves the coefficient on the rating downgrade and upgrade indicator variables (β_1 and β_2) unaffected. Models (2) to (5) include a control variable for recent covenant violations and show that covenant violations are statistically and economically significant. These results corroborate the findings by Chava and Roberts (2008) and Roberts and Sufi (2009) even for a sample with access to the public debt market. Moreover, including covenant violations leaves the effect of rating downgrades intact in all specifications. In short, rating downgrades seem to matter over and beyond covenant violations.

4.2.2. Identification

Our model yields two important results alleviating identification concerns: (i) the fact that there may be other ways to alleviate financial constraints would, if anything, work against us finding effects of rating changes on asset sales (Robustness Result 1) and (ii) even if a rating change is induced by a credit risk characteristic that matters by itself for financial distress costs, the rating change would still yield an incremental effect on the likelihood of asset sales under both channels (Robustness Result 2). Notwithstanding these two arguments derived from our model, we present four empirical approaches which, we believe, will further help mitigate identification concerns, specifically with respect to omitted variables.

First, we note that the addition of the covenant violations to our main specification, as we described in the previous section, also diminishes omitted variables concerns. Omitted variables related to unobservable credit risk, would arguably also affect the likelihood of covenant violations. Therefore, covenant violations serve as a proxy for such omitted variables, even if these omitted variables are not directly observable or even known. The results in Table 5 show that omitted variables that induce both credit rating downgrades and covenant violations do not appear to drive our results.

Second, and similar to the argument with respect to covenant violations, we include market-based measures of credit risk as controls in estimating Eq. (22). To the extent that omitted variables related to credit risk affect rating changes and asset sales, these should also affect the market-based measures of credit risk. Since these measures are market-based, they reflect information in a forward looking way (as opposed to backward looking controls such as accounting ratios). The market-based measures we consider are Moody's KMV Expected Default Frequencies (EDF) and credit spreads. Conceptually, we prefer credit spreads as these are more direct measures of credit risk. While widely accepted and used as measures of credit risk, Moody's KMV EDFs require more assumptions. Yet, an important advantage of Moody's KMV EDF data is that these are available for the full sample, as opposed to credit spread data, which only start in 2002.

We begin with the specifications that include credit spreads. We download bond yields from the WRDS Bond Return Data (based on the TRACE Enhanced database). These data include all bond trades conducted in the U.S. bond markets and are cleaned by WRDS. We limit the data to senior unsecured corporate debentures and corporate medium-term notes. We require bonds to have at least one year to maturity left, have a strictly positive yield, and discard any observations with yields larger than 30%. For each bond, we construct the yield of a hypothetical treasury bond, as a weighted average of the yields of the two treasury bonds from the CRSP constant maturity indices for which the (modified) durations bracket the (modified) duration of the corporate bond in question. The weights on these treasuries are inversely proportional to the absolute difference in modified durations between the respective treasuries and the corporate bond, and add to one. The WRDS Bond Return Data include a matching table, which allows us to match individual bonds to issuers using PERMCO identifiers. Finally, for every firm $\times$ time observation, we create an issue-size-weighted average credit spread and use this as a control variable.

Since TRACE Enhanced data is only available from July 2002 onwards, we provide results with and without credit spreads as controls over the part of the sample that starts in July 2002. We report the results in Table 6. Model (1) shows that the results of our baseline estimation of Eq. (22) are robust for the sub-sample from July 2002 onwards. In models (2) to (4) we include credit spreads ($avgCS$). We add an indicator variable that equals 1 if the credit spread is missing to models (3) and (4). The coefficients on ($avgCS$) are insignificant and while on rating downgrades (β_1) remain significant. These results further mitigates omitted variable concerns.

Moody's KMV EDFs represent expected default frequencies, which are generated a modified version of the Merton (1974) model, as laid out in Crosbie and Bohn (2003). The model behind the EDFs is calibrated to stock prices and and stock return volatilities. Because of the calibration to stock prices, the forward looking nature of stock prices is inherited. Several publications by Moody's KMV show the usefulness of their EDF measure in predicting defaults.[19]

For our analysis with Moody's KMV EDFs, we download one- and five-year expected default frequencies from Moody's KMV and match these with our other data using CUSIPs. We run specifications with the one-year EDFs, five-year EDFs, and with both. For brevity, we only report the most parsimonious model with both EDFs (the others are similar) in Table 7. The results of this specification are consistent with our baseline results. The coefficients on the EDFs are largely insignificant, which further mitigates omitted variables concerns.

Third, we conduct a placebo test where we exploit the empirical fact that CRAs are relatively sluggish and conservative in their rating updates (Altman and Rijken, 2004). The through-the-cycle approach employed by CRAs combined with their conservatism in rating migrations make it highly likely that a material part of the information underlying rating changes would have been publicly available before the rating changes. In contrast, firms are able to conduct (partial) asset sales relatively quickly, especially compared to other forms of corporate divestitures. To illustrate, a recent study by PricewaterhouseCoopers LLP reports that organizing an asset sale typically takes only a few months to a year, which is faster than for alternative forms of corporate divestments. This agility in asset sale decisions is important for our placebo design and avoids spuriousness, because if asset sales are sluggish too, downgrades may still not cause the asset sale *even* if the asset sale occurs after the downgrade. To implement this strategy, we define a placebo downgrade and placebo upgrade indicator variable set equal to one year prior ($t-1$) to the corresponding rating change in time t (see Figure 1).[20] Based on our hypothesis that asset sales are caused by downgrades and field evidence that asset sales typically take less than a year to organize, we should not see an increase in asset sales in the period from $t-1$ to t, but only for the period from t to t+1. Alternatively, if omitted public information drives our results, we expect to see an increase in asset sales in the period from $t-1$ to t and not, or at least much less so, for the period from t to t+1.

We report the results for the placebo test in Table 8. In model (1) we replicate model (5)

[19] https://www.moodys.com/sites/products/productattachments/riskcalc%203.1%20whitepaper.pdf

[20] The period of twelve months in our placebo test is arguably arbitrary. However, there are good reasons for choosing a shift of this length. First, most companies review financial budgets and strategies annually, which means this would be the minimal plausible shift. Second, credit ratings within CRAs tend to be reviewed (at least) annually (S&P Global, 2018). Third, ideally we have no overlap between our regular measurements of rating changes and our placebos for these to be true placebos. Since the dummies for our regular measurements range from one to twelve months after the rating downgrade, a twelve months shift is the minimum shift that preserves this mutual exclusivity condition. If the period of twelve months in some cases would be too long, we would still capture the full effect, but our coefficient estimate would suffer from an attenuation bias. In this case, we would still expect to see a sizable positive coefficient on placebo downgrades (albeit somewhat smaller than when the 12 months period would be 'spot on').

from Table 3, but replace the rating change indicator variables with their placebo counterparts. The coefficients on the placebo indicator variables are economically and statistically insignificant and considerably smaller than the coefficient reported in the baseline regression (0.008 versus 0.369). This suggests that information available prior to the downgrade does not drive the relation between downgrades and assets sales. Even if a 12-month shift is too large, we would still expect a much larger and more significant coefficient here if our results were driven by omitted variables. In model (2) we add the actual downgrade and upgrade indicator variables and find that the coefficient on the actual downgrade indicator variable (β_1) continues to be positive and highly significant. In contrast, the coefficient on the placebo version of the downgrade indicator variable loads insignificant with a negative sign. To put these coefficients in perspective, this translates into a 45% increase in the likelihood for an asset sale to occur based on an actual downgrade versus a 3% decrease based on the placebo downgrade. In model (3), we drop asset sales announced within a half year after the downgrade and a half year after the placebo date to avoid potential misclassification caused by sluggishness in asset sales. In model (4), we only consider below median-size asset sales ($\approx$ 2.7% relative to the seller's book value of assets). We expect these smaller asset sales to take less time to organize, which would also avoid potential misclassification caused by sluggishness in asset sales. For both specifications, we continue to find insignificant coefficients on the placebo rating action indicator variables and positive significant coefficients on the actual rating downgrade variable. Finally, in models (5) and (6) we confirm these conclusions based on a specification with only the first asset sale and for the specification based on changes in the covariates. In other words, consistent with the idea that downgrades lead to asset sales, we find a sharp and robust increase in the post-downgrade period, but no increase in asset sales in the period prior to the downgrade.

Finally, we strengthen our identification by showing that our results are stronger when ratings matter more. Kisgen and Strahan (2010) and Bongaerts et al. (2012) show that the effect of ratings on the cost of capital is larger among bonds around the Investment Grade-High Yield (IG-HY) boundary. We exploit this prediction as a fourth way to help assure that our duration models, in fact, capture the effects of credit rating downgrades on the likelihood of an asset sale. Accordingly, we expect a stronger effect on the incidence of asset sales for rating downgrades around the IG-HY boundary. To test this prediction, we weigh the rating downgrade variable by the distance in (absolute) number of notches between the firm's rating and the IG-HY boundary. Non-rated firms receive the minimum weight among the rated firms. We normalize the weights such that the average weight over the whole sample equals 1. We report the results in Table B.1 of the appendix. In models

(1) and (2) this is done symmetrically. In models (3) and (4), weights on the HY side of the spectrum are multiplied by 2 and in models (5) and (6) these are multiplied by 5.[21] On par with our prediction, the coefficients on the downgrade indicator variable are larger, and statistically substantially stronger than those reported in Table 3.

4.3. Channels through which firms respond to rating downgrades

The next sections of the paper present various tests of the predictions derived from our model on the hypothesized channels through which asset sales are a response to a downgrade. We seek to understand whether, on average, managerial discipline or financial constraints is the predominant channel. We analyze the use of proceeds asset sales (Implication 3), equity-based spinoffs (Implication 5), asset liquidity (Implication 4), and the choice of assets to divest based on inter-firm and intra-firm comparisons (Implications 2 and 6).

4.3.1. Use of proceeds

In this section we test whether negative ratings actions associate more with an increase in asset sales with the purpose to reduce leverage as predicted by the financial constraints channel, or with asset sales with the purpose to restructure assets as predicted by the discipline channel (Implication 3). We use information on the expected use of proceeds (purpose) of asset sales (relax financial constraints or efficient reallocation of productive assets) from SDC to estimate purpose-specific hazard rates. We estimate two types of specifications. First, we assume that the occurrence of an asset sale of any type does not affect the future occurrence of other asset sales of any type. In this case, we estimate purpose-specific hazard rate functions, where other types of events are assumed censored data points. We report the results for this analysis in Table 9 in models (1) to (3). Alternatively, we account for the possibility that the occurrence of an asset sale could affect the hazard rate of any other type of event afterwards. To prevent any estimation bias, we only consider the first asset sale that occurs, as we did in model (7) of Table 3. Yet, a by-product of this specification is that events become mutually exclusive, which we incorporate explicitly. To do so, we follow the competing risk framework of Fine and Gray (1999) and estimate purpose-specific sub-hazard functions while explicitly accounting for mutual exclusivity of events. We report the estimates according to this approach in models (4) to (6) of Table 9. Without mutual exclusivity, the coefficient on the credit rating downgrade (β_1) is positive and significant in each hazard rate function. However, the coefficient for the financial constraints hazard rate, reported in model (1), is 30% larger and statistically more significant than the coefficient

[21]The asymmetric weights account for the fact that in the HY spectrum, a rating notch represents a larger increase in default probability than in the IG spectrum.

for the discipline hazard rate, reported in model (2). The results from the competing risk model show even more pronounced effects: Credit rating downgrades are associated with a higher likelihood for asset sales motivated by financial constraints, but not if efficient reallocation motivates asset sales.

4.3.2. Spinoffs

In this section, we provide corollary evidence that credit rating downgrades are associated with additional financial constraints and asset sales represent a response to this. We expect that we should see an increase in the likelihood of non-cash generating spinoffs only through the discipline channel (Implication 5) and interpret an increase in spinoffs after a negative rating action as evidence for the discipline channel. However, the absence of an increase in spinoffs after negative rating actions is at most inconsistent with the predictions from discipline channel, but does not allow us to completely reject the channel as firms may respond in ways other than through a spinoff. We re-estimate the hazard rates with our sample to which we add 268 spinoffs collected from SDC. These spinoffs, like asset sales, are restructuring events, but unlike asset sales, do not generate cash for the firm or for its shareholders.[22] We report the results in Table 10. Model (1) implicitly assumes that multiple events can happen to a subject and that hazard rates are unaffected by past events. We find that β_1 is insignificant for the hazard rate of spinoffs compared to a consistently positive and significant estimate for β_1 for the hazard rate of asset sales. Models (2) to (5) present sub-hazard estimates for spinoffs and asset sales by their intended use of proceeds using the competing risk model by Fine and Gray (1999). Consistent with financial constraints, we find that rating downgrades significantly increase the likelihood for cash generating asset sales for the purpose to relax financial constraints, but do not affect the likelihood for spinoffs or for asset sales with the purpose of allocating assets more efficiently. We re-estimate all our models with the inclusion of the watchlist indicator variables and report the results in Appendix Table B.2. The results remain mostly the same, with the exception that negative watchlist placements now load positively and significantly, at the expense of downgrades (but β_1 is economically still large and with a z-statistic of 1.600 close to significant).

[22]Spinoffs sometimes coincide with issuance of new shares or include monetization and recapitalization techniques that would result in raising cash. To the extent we are able to identify these techniques based on the information provided in SDC, we exclude such spinoffs.

4.3.3. Asset liquidity

In this section we test whether transaction costs matter for asset sales aimed at reducing leverage over and beyond to how they matter for other types of asset sales (Implication 4). Asset liquidity as a measure of transaction costs is an important variable in the contexts of the financial constraint and discipline channels. Intuitively, the sale of an illiquid asset, all else equal, is less desirable irrespective of which channel motivates the asset sale, or whether there is a prior downgrade. Our model (Implication 4) shows that asset sales become less attractive when assets are more illiquid compared to alternatives, such as debt rescheduling or issuance of new securities (also in line with Shleifer and Vishny, 1992). Our model shows in particular that liquidity is less pertinent if efficient asset reallocation more so than financing constraints motivates the asset sale. In the latter case, a downgrade further tightens the firm's financial constraints and increases the relative cost of illiquidity (or equivalently the firm's relative value of cash). As a result, we expect a positive interaction of asset liquidity with downgrades if the firm aims to relax financial constraints by doing an asset sale, but not if the asset sale is a manifestation of increased discipline.

To test whether liquidity creates an interaction effect with rating downgrades, we sort the sample in deciles of asset redeployability and estimate Eq. (22) separately for each liquidity-decile sub-sample. Figure 2 shows the coefficients on the credit rating downgrade for the specification of Model (2) from Table 3 for each of ten sub-samples, based on deciles of asset redeployability within the full sample. The impact of a credit rating downgrade on the likelihood of an asset sale announcement increases gradually across the asset redeployability deciles, as shown by the coefficient, β_1, which quadruples from the lowest to the highest liquidity decile. When we compare the top and bottom deciles on the basis of their economic impact, we find that the likelihood an asset sale after a rating downgrade increases by 19% for the bottom-decile in asset liquidity, but increases by 128% for the top-decile in asset liquidity. We also confirm that the difference in β_1 between the top and bottom decile is statistically significant (p-value=0.034). The results in Fig. 2 are consistent with the financial constraints channel, where the marginal value of cash increases as rating downgrades tighten the firm's financial constraints and asset sales serve to relax these. For robustness, Appendix Fig. B.1 yields he same conclusions based on the alternative asset redeployability definition that incorporates both across and within industry correlation of firm-level output (Kim and Kung, 2016).

4.3.4. Asset selection

We next explore whether rating actions affect which assets the firms sell. Our tests are based on the prediction that (*i*) under the discipline channel, firms would choose to sell off poorly performing or non-core segments following negative rating actions (Implication 2), and (*ii*) under the financial constraints channel firms would be more inclined to sell segments that impair creditworthiness more (Implication 6). We start with an inter-firm segment-level analysis, where we compare several ex-ante performance measures of the divested segments to those of their industry peers to see whether under-performing assets are sold to better users leading to a better allocation of resources. Next, we present the intra-firm analysis based on performance measures of the divested segment relative to all non-divested segments within the same firm and whether the segment is a core versus a non-core segment. To implement this strategy, we estimate cross-sectional logit regressions, each with a dummy variable as the dependent variable based on both inter-firm and intra-firm comparisons. The main variable of interest is the indicator variable, which is equal to one if the firm experienced a recent credit rating downgrade, and zero otherwise. We include the same control variables used in the previous tests.[23] More specifically, we match each asset sale to a business segment using Compustat segment level data. For each asset sale we construct a dummy variable for whether the corresponding segment is core or non-core and dummy variables for whether a particular accounting or performance measure is above or below the median segment compared to the firm's industry peers (inter-firm analysis) and compared to its own firm-level median across all its segments (intra-firm analysis). We define a segment as non-core if the primary and secondary 2, 3, or 4-digit SIC codes differ from the parent's respective SIC codes. We define five performance measures at the segment level: Profitability (Operating Profit/Identifiable Assets), Profit Margin (Operating Profit/Sales), Asset Turnover (Sales/Identifiable Assets), Operating Cash Flow ((Operating Profit + Depreciation)/Identifiable Assets), and Net Cash Flow (Operating Cash Flow − Capital Expenditures/Identifiable Assets). We also measure asset liquidity (redeployability) at the segment level, where we match the industry average redeployability measure to the primary segment SIC code. Finally, we estimate a segment level proxy for growth opportunities based on the median value of Tobin's Q of specialized firms in the industry (Shin and Stulz, 1998).

In Table 11, we report the marginal effects for logit regression models for each of five

[23]Hence, this analysis is conditional on observing an asset sale. Alternatively, one could specify a model where the dependent variable is the decision to sell and the independent variables include all the segment-level variables in order to assess the relative importance of each variable. However, we believe this approach is problematic due to mechanical correlations among the segment variables, particularly for firms with fewer segments.

performance measures. The dependent variable is an indicator variable equal to 1 if the performance measure is below the median of its industry peers, where industry peers are defined as all segments in multi-segment firms, excluding the sample firm, that have the same two-digit primary SIC code as the primary SIC code for the divested segment. In Models (1) through (5), we focus on (Operating) Profitability, Profit Margin, Asset Turnover, Operating Cash Flow, and Net Cash Flow (all defined in Table 1). The discipline hypothesis predicts a positive and significant marginal effect of a credit rating downgrade, which suggests a higher likelihood for a firm to divest a segment with below-industry performance following a downgrade. However, the results in Table 11 show that the marginal effects of the credit rating downgrade indicator variable are insignificant for each performance measure and even have the opposite sign for Profitability and Profit Margin. Interestingly, the marginal effects for a credit rating upgrade are mostly negative and significant, which suggests a reduction in managerial discipline after a credit rating upgrade. In terms of the effects of a credit rating downgrade, our main variable of interest in this paper, the results in Table 11 do not support the discipline hypothesis.

The financial constraints hypothesis is ambiguous in terms of predicting a sign on the rating downgrade indicator variable in the inter-firm analysis. Firms who seek to relax financial constraints are more likely to consider liquidity (asset redeployability) and internal, as opposed to external, relative performance in terms of current cash flow generation and contribution to collateral than to compare the segment's performance to their industry peers (Implication 6).

Table 12 presents the intra-firm analysis. For each logit model, the dependent variable is an indicator variable based on a performance measure of the divested segment relative to all non-divested segments within the same firm. We begin with Implication 4 on liquidity. In model (1), we find that segments with relatively high asset redeployability are significantly more likely to be divested following a credit rating downgrade (controlling for average firm-level asset redeployability). High asset redeployability is measured as an indicator variable equal to one if the divested segment's asset redeployability exceeds the median asset redeployability over all of the firm's segments in the same year, and zero otherwise. The probability of divesting a segment with above median liquidity (asset redeployability) is nearly ten percentage points higher if the asset sale follows a rating downgrade. We continue with Implication 6 and the prediction of Shleifer and Vishny (1992) that financially constrained firms would be more likely to sell off segments that are valuable, but do not contribute to current cash flow generation. This way, debt relief inhibits the servicing of near-term debt obligations as little as possible. In model (2), we use an indicator variable equal to one if the Operating Cash Flow of the divested segment is below the median among all of the firm's segments. We show that the probability of divesting a segment with below median operating cash flows is more than ten percentage points higher if the asset sale follows a rating downgrade. The coefficient on the downgrade indicator variable in model (3) indicates that the probability of divesting a segment with the highest Tobin's Q is almost ten percentage points higher if the asset sale follows a rating downgrade. This result is also consistent with Implication 6 and the predictions of Shleifer and Vishny (1992) regarding firms asset sales decisions motivated by relaxing financial constraints. Firms with high growth opportunities typically require substantial investments in intangible assets that would provide little to no collateral and would not contribute to current cash flow generation. Moreover, it is easier to convert high growth opportunity segments into cash and are therefore prime candidates to divest in case of tighter financial constraints. The result from model (3) is inconsistent with the predictions from the discipline hypothesis insofar as firms cherish high growth segments in favor of low growth opportunity segments that the firm can sell to a more efficient user of these assets. Note that we use the highest Q rather than the above-median Q in model (3) because of the relatively flat distribution among the segments' industry-median Q values. The coefficient on the rating downgrade variable is insignificant when we use the above-median Q instead (unreported). The results for models (1) through (3) support the financial constraints hypothesis and show that firms prefer to sell assets that are most liquid, generate low current cash flows and have high growth opportunities.

In model (4), we test another prediction of the discipline hypothesis: If credit rating downgrades motivate firms to conduct asset sales to achieve a more efficient allocation of their assets, we would expect a higher likelihood for selling non-core segments. We define a segment as a non-core if the primary 2-digit SIC code of the segment is different from the firm 2-digit SIC code. Inconsistent with this prediction, we find no evidence that the likelihood of selling a non-core segment is significantly higher after a credit rating downgrade. We re-estimate, but do not tabulate, model (4) where we use a more granular definition of a non-core segment, (based on 3- and 4-digit SIC code). These more granular definitions of core segments confirm that negative rating actions do not increase the probability of selling non-core segments. In models (5)-(7), we test if the segment with below-median performance based on profitability, profit margin, or asset turnover are more likely to be divested in an asset sale following a rating downgrade. Similar to the results from the inter-firm segment analysis, for the first two performance measures, we cannot reject the null hypothesis that the coefficient on the credit rating downgrade indicator in these models is equal to zero. We do find a positive and significant coefficient for the rating downgrade variable for low asset turnover. This is the lone evidence we can find in the segment analyses consistent with a discipline channel. Yet, it is also consistent with a financial constraints channel insofar higher asset turnover allows for more efficient working capital management.[24] Taken together, the results in Models (5) through (7) provide little support the discipline hypothesis.[25]

Finally, we estimate all models in Tables 11 and 12 and include the watchlist indicator variables. The results are in Appendix Tables B.3 and B.4 and remain unchanged for the inter-firm comparisons. The watchlist variables also do not load in any of the models. The results for the rating downgrade variable in the intra-firm analysis strengthen with the inclusion of the watchlist variables. Interestingly, we find that both negative and positive watchlist events have a negative relation with our first two performance measures (high asset redeployability and low operating cash flow) in models (1) and (2).

4.4. Alternative channels and robustness

In this section, we ask whether our results can be explained by historical acquisition activity.[26] Kaplan and Weisbach (1992), for example, show that a substantial fraction of their sample of large acquisitions subsequently divests. Firms may divest certain parts of recently acquired companies for disciplinary reasons especially if these assets do not provide a good fit with the new owners (Hite et al., 1987). Similarly, acquisitions may trigger rating downgrades, especially if they are associated with cash payments, significant increases in debt, or other outcomes that deteriorate the growth prospects of the firm. In this sense, asset sales may simply be a disciplinary or financial constraints-induced response to acquisitions, rather than caused by credit rating downgrades per se.

To address these alternative mechanisms, we collect all majority acquisitions from SDC and match these with our sample used in the duration analysis. We then construct the following monthly variables for acquisition activity for each sample firm. First, for each firm i in month t in our sample period, we calculate the ratio of aggregated deal values with firm i as a buyer from month $t-24$ to $t-6$ to the most recent book value of assets prior to month t (Acquisition spending). We also define an indicator variable (Acquisition) equal to one if Acquisition spending > 0 and zero otherwise. Similarly, we calculate the aggregated dollars spent with cash [equity] on acquisitions as a fraction of the most recent

[24] E.g., for the same collection period, a larger volume of outstanding invoices could be delayed on.

[25] We recognize that failing to reject the null hypothesis (β_1=0) may be caused by a lack of power of the test and/or an attenuation bias in the presence of measurement error and/or multicollinearity. Yet, the results in models (1) to (3) should suffer from the same problem.

[26] We thank Jean Helwege for this suggestion.

book value of assets prior to month t (Cash [Equity] acquisition spending). The coefficients on all these acquisition-related variables are positive and significant (see Appendix Table B.5). When we include both the cash and equity variables we find that both are significant. An F-test indicates that the coefficient for equity used in acquisitions is marginally higher than the coefficient for cash spending on acquisitions (p-value = 0.085). Hence, acquisition activity helps to explain the likelihood for asset sales, but does not change our conclusions with respect to rating downgrades. We also run a sub-sample analysis where we split the sample into observations with no prior acquisition activity (Acquisition spending=0) and with prior acquisition activity (Acquisition spending > 0 and find that the coefficient on the rating downgrade indicator variable is positive and significant in both models.

Leveraged buy-outs (LBO) are another example of events where the corporate structure of a firm is heavily affected. Asset sales and rating changes may occur concurrently as a result of the LBO. To make sure LBOs do not drive our results, we re-estimate our duration analysis where we exclude all deals that are part of an LBO transaction. This includes straight up LBOs and deals conducted by an LBO firm, where the parent firm is an LBO firm, or deals where the acquirer is an LBO firm. The results are qualitatively and quantitatively similar to our baseline results and reported in Table B.6 in the Appendix.

Since we only consider completed deals in our analyses, there is a potential concern about selection bias. In particular, there may be endogenous selection effects that impair the external validity of our results. To alleviate such concerns, we provide a robustness test in Table B.7 in the Appendix in which we re-estimate our duration analysis and include deals that never (fully) completed. These deals include rumored, pending, intended, and partially completed deals. We label these as 'failed deals' and include these as a specific type of deals in the same way we do with spin-offs. We re-estimate separate sub-hazards for these deal types, both in an unconstrained setting as well as in a competing risk setting (similar to the analysis in Table 9). We conclude that the degree of such bias, if any, is small. The coefficient on downgrades is positive and significant, albeit a bit smaller than for the financial constraint or mixed category.

Finally, reverse-causality may become an issue if a rating change already incorporates an expected asset sale. We would expect this potential problem to be most relevant for rumored deals and for cases with a prior "seeking a buyer" announcement. Therefore, we re-run our duration analysis where we exclude completed deals that before completion had rumors, seeking buyer announcements, or both. We report our results in Table B.8 in the Appendix. These are qualitatively and quantitatively similar as our baseline results.

5. Conclusion

Compared to private credit agreements and bank debt, public corporate debt typically contains few clauses to protect creditors from agency conflicts and free-riding among dispersed investors prevents effective monitoring at the individual level. CRAs may fill this void and provide a monitoring role. At the same time, rating actions may result in financial constraints feedback effects, to which firms would want to respond. In this paper, we provide strong and novel evidence on the existence of real effects of credit rating downgrades on asset sales. We show that firms, on balance, respond to rating actions primarily in accordance to a financial constraints hypothesis, while we hardly find any evidence for responses in accordance to a discipline hypothesis.

Identification is a prime concern in the absence of a strong instrument or natural experiment. Yet, our model as well as a battery of robustness tests mitigate these concerns significantly. Moreover, the different tests in concert paint a coherent picture. While one could challenge each of our tests individually, it would be more challenging to come up with alternative mechanisms that would predict similar empirical patterns jointly.

While comprehensive, our findings leave room for future research as we are only able to analyze real effects of ratings to the extent that asset sales are not prohibitively expensive. As our model shows and the results on liquidity interactions confirm, firms resort to other means to relax financial constraints (or foster discipline) following rating downgrades as their asset liquidity deteriorates. Hence, our findings are particularly relevant for firms with sufficiently high asset liquidity. One would need to investigate other ways of relaxing financial constraints (or fostering discipline) to say more about the external validity of our results in case of highly illiquid assets. Similarly, discipline could manifest itself in other forms than asset sales (e.g., cost-cutting and layoffs; see Denis and Kruse, 2000). Yet, our empirical tests imply that private benefits are high, which suggests that these other forms of discipline are also less likely.

Our results are also relevant in a regulatory context. Boot et al. (2005) links the monitoring role of CRAs explicitly to regulatory (or institutional) importance. We, however, find little evidence that this monitoring role is indeed adequately performed, which seems to make the recent reduction in regulatory reliance on credit ratings to be well guided.

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Figures

Figure 1: Placebo timeline
This figure shows the time-line around month t, during which the rating downgrade occurs and how the indicator variable for a (placebo) rating downgrade, (Placebo) Rating downgrade (0, 1), is set equal to one during the 12 months period following (prior to) month t and set to zero elsewhere.

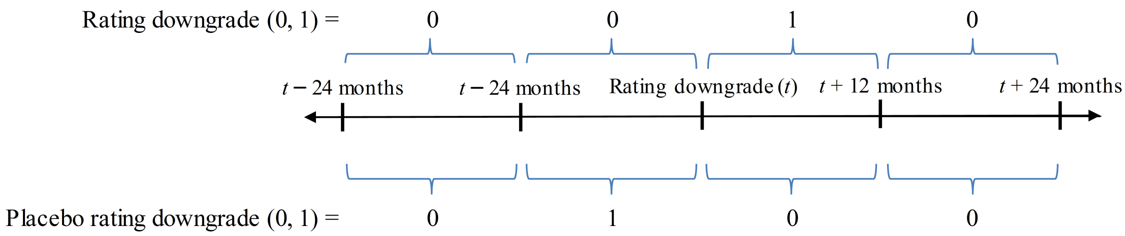

Figure 2: Coefficients on Credit Rating Downgrade (0, 1) Indicator Variable by Asset Redeployability Deciles

Tables

Table 1: Variable definitions

Variable	Description
Segment profitability	Segment ROA (operating income over identifiable assets)
Segment turnover	Segment sales over identifiable assets
Segment profit margin	Segment operating income over sales
Segment operating cash flow	Segment operating income plus depreciation over identifiable assets
Segment net cash flow	Segment operating income plus depreciation minus CAPEX over identifiable assets
Rating downgrade (0,1)	Indicator variable=1 if downgraded by S&P in the past year (=0 otherwise)
Rating upgrade (0,1)	Indicator variable=1 if upgraded by S&P in the past year (=0 otherwise)
S&P credit rating	S&P credit rating (AAA=22; declining by 1 per notch)
Assets – Total (1990 $ billion)	Total (book) assets (inflation-adjusted, in 1990 $ billions)
Ln(Assets)	Natural logarithm of Total (book) assets (in 1990 $ millions)
Asset redeployability	Defined as in Kim and Kung (2016)
Cash holdings	Cash over total assets
Interest coverage	Operating income before depreciation over interest expense
Leverage	Total debt over total assets
Rollover	Short-term debt over total assets
Tangibility	PPE over total assets
Altman Z-score	Altman's Z-score
Tobin's Q	(Equity market cap + book assets – book equity and deferred taxes) / total assets
Profitability	Operating profit over total assets
ROA	Net income over total assets
Cash Flow	(EBIDA – interest expense, dividends and taxes) / total assets
CAPEX	Capital expenditures over total assets
PPE growth	Growth rate of PPE over the past year
Sales growth	Growth rate of sales over the past year
R&D/assets	R&D expense over total assets
Number of segments	Number of business or operating segments
Stock ownership	Ownership top-5 compensated executives excluding options (in % points)
SA index	SA index of financial constraints (Hadlock and Pierce, 2010)
All Cash (0,1)	Dummy deal 100% cash
All Stock (0,1)	Dummy deal 100% stock
Same 2-digit SIC (0,1)	Divested segment same industry as target parent (2-d SIC)

Table 2: Summary statistics

The table presents the number of observations (n), mean, standard deviation (SD) and median for the variables used in the analysis for the three samples used in the analysis. The 'Full Sample' consists of the universe of Compustat firms over the period 1990 to 2015, the 'Asset Sale Sample' consists of all matched asset sales over our sample period, and the 'Segment Sample' consists of all asset sales over our sample period that could be traced back to one of the segments in the Compustat Segment file. Variable descriptions are in Table 1.

	Full sample				Asset sales				Segment-matched subsample			
	n	Mean	SD	Median	n	Mean	SD	Median	n	Mean	SD	Median
Rating downgrade (0, 1)	835,926	0.048	0.213	0.000	4,974	0.144	0.351	0	1,610	0.157	0.363	0
Rating upgrade (0, 1)	835,926	0.038	0.192	0.000	4,974	0.050	0.217	0	1,610	0.045	0.207	0
Changed to positive watch	835,926	0.009	0.094	0.000	4,974	0.020	0.140	0	1,610	0.026	0.159	0
Changed to negative watch	835,926	0.028	0.164	0.000	4,974	0.093	0.290	0	1,610	0.114	0.318	0
S&P credit rating	322,911	12.550	3.619	12.000	3,793	14.022	4.165	14.000	1,381	14.825	4.028	15
Average asset redeployability	808,271	0.419	0.135	0.416	4,872	0.379	0.128	0.403	1,593	0.391	0.115	0.406
Assets - Total	835,926	5,797	27,572	736	4,974	40,392	122,473	4,472	1,610	59,424	146,904	9,310
Cash holdings	825,999	0.094	0.107	0.052	4,825	0.062	0.072	0.037	1,555	0.058	0.063	0.038
Interest coverage	697,121	20.980	35.633	6.955	4,824	12.016	21.693	5.405	1,580	13.440	22.068	6.489
Leverage	832,365	0.244	0.194	0.222	4,967	0.320	0.179	0.305	1,608	0.313	0.170	0.292
Rollover	834,526	0.039	0.058	0.014	4,972	0.050	0.067	0.021	1,610	0.052	0.068	0.024
Tangibility	834,835	0.287	0.237	0.222	4,973	0.335	0.233	0.278	1,610	0.320	0.221	0.268
Altman Z-score	689,412	3.828	3.561	2.996	4,422	2.624	2.380	2.319	1,412	2.707	2.055	2.484
Tobin's Q	736,461	1.774	1.019	1.432	4,743	1.602	0.762	1.370	1,542	1.636	0.732	1.406
Profitability	835,926	0.077	0.114	0.079	4,974	0.075	0.093	0.075	1,609	0.089	0.083	0.085
ROA	835,926	0.026	0.117	0.038	4,974	0.014	0.109	0.030	1,609	0.035	0.087	0.041
Operating cash flow	717,149	0.075	0.102	0.081	4,792	0.068	0.078	0.068	1,570	0.072	0.066	0.071
CAPEX/assets	762,354	0.070	0.065	0.048	4,888	0.070	0.064	0.047	1,594	0.062	0.056	0.044
PPE growth	832,570	0.142	0.335	0.052	4,967	0.078	0.295	0.023	1,607	0.072	0.273	0.025
Sales growth	830,970	0.136	0.274	0.084	4,972	0.085	0.256	0.047	1,609	0.074	0.222	0.049
R&D/assets	434,303	0.058	0.084	0.024	3,001	0.038	0.057	0.017	1,055	0.032	0.045	0.015
Number of segments	763,933	2.175	1.537	2.000	4,933	3.129	1.991	3.000	1,610	3.973	1.868	4.000

Continued on next page

Table 2 – *continued from previous page*

	Full sample				Asset sales				Segment-matched subsample			
	n	Mean	SD	Median	n	Mean	SD	Median	n	Mean	SD	Median
Stock ownership	255,248	4.557	6.912	1.300	1,741	2.876	5.318	0.688	618	2.754	5.379	0.475
SA index	835,926	-3.702	0.635	-3.593	4,974	-3.939	0.642	-3.997	1,610	-4.119	0.594	-4.437
dealval	-	-	-	-	4,974	324	875	92	1,610	565	1,041	220
Relative Size	-	-	-	-	4,974	0.082	0.153	0.027	1,542	0.070	0.127	0.021
Same 2-D Industry as parent	-	-	-	-	-	-	-	-	1,610	0.620	0.485	1
Segment profitability	-	-	-	-	-	-	-	-	1,192	0.112	0.220	0.097
Segment asset turnover	-	-	-	-	-	-	-	-	1,472	1.223	1.316	0.973
Segment profit margin	-	-	-	-	-	-	-	-	1,293	0.059	1.892	0.110
Segment operating cash flow	-	-	-	-	-	-	-	-	1,134	0.164	0.225	0.143
Segment net cash flow									1,068	0.104	0.224	0.091
Segment CapEx over assets	-	-	-	-	-	-	-	-	1,347	0.065	0.075	0.042
Segment CapEx over sales	-	-	-	-	-	-	-	-	1,409	0.161	0.534	0.042

Table 3: Basic Cox regressions

The coefficients in the table represent estimates of hazard rates of an asset sale event using Cox proportional hazard regressions on a monthly basis over the entire sample. R&D missing (0, 1) and Stock ownership missing (0, 1) are equal to one if, respectively, R&D intensity or executive ownership is missing, and zero otherwise. We define all other covariates in Table 1. We cluster standard errors by firm and report t-statistics in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	Levels						1st Event	Changes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rating downgrade (0, 1)	0.597***	0.392***	0.355***	0.401***	0.369***	0.360***	0.412***	0.446***
	[9.75]	[5.92]	[5.49]	[6.11]	[5.77]	[5.62]	[4.16]	[6.75]
Rating upgrade (0, 1)	-0.264***	-0.208**	-0.224***	-0.191**	-0.183**	-0.160*	0.0644	-0.177**
	[-3.16]	[-2.46]	[-2.64]	[-2.30]	[-2.17]	[-1.87]	[0.48]	[-2.07]
Rated (0, 1)	0.0244	-0.191	0.144	-0.124	0.246	0.224	0.270	0.507***
	[0.11]	[-1.11]	[0.83]	[-0.74]	[1.47]	[1.33]	[1.45]	[3.10]
S&P credit rating	0.106***	0.0640***	0.0222	0.0573***	0.0126	0.0158	0.00608	0.0368***
	[5.80]	[4.76]	[1.62]	[4.34]	[0.95]	[1.18]	[0.41]	[2.97]
Redeployability		-1.394***	-1.728***	-0.821*	-1.223**	-1.533***	-1.330***	0.670
		[-3.65]	[-4.62]	[-1.69]	[-2.52]	[-3.00]	[-2.66]	[0.75]
Altman Z-score		-0.0583***	-0.0877***	-0.0358*	-0.0589***	-0.0592***	-0.0312	0.00106
		[-2.92]	[-4.19]	[-1.76]	[-2.74]	[-2.80]	[-1.50]	[0.06]
Cash holdings		-2.914***	-2.286***	-2.476***	-1.790***	-1.652***	-1.857***	0.248
		[-7.27]	[-5.70]	[-6.42]	[-4.80]	[-4.39]	[-4.37]	[0.73]
Interest coverage		-0.00333**	-0.00106	-0.00379***	-0.00107	-0.00129	-0.000680	0.00109
		[-2.21]	[-0.75]	[-2.66]	[-0.82]	[-1.07]	[-0.47]	[1.05]
Rollover		-0.732	-1.101**	-0.232	-0.647	-0.719	-0.753	0.498
		[-1.34]	[-1.97]	[-0.42]	[-1.18]	[-1.35]	[-1.32]	[1.11]
Leverage		-0.0387	0.0453	-0.0786	0.125	0.151	0.420*	0.988***
		[-0.17]	[0.20]	[-0.35]	[0.56]	[0.68]	[1.73]	[3.42]
Tangibility		-0.760***	-0.852***	-0.723***	-0.965***	-0.973***	-0.796***	-1.065**
		[-3.58]	[-3.91]	[-3.40]	[-4.33]	[-4.40]	[-3.61]	[-2.10]
Tobin's Q		0.0428	0.120**	-0.00883	0.0312	0.0445	-0.0772	-0.0890*
		[0.93]	[2.52]	[-0.19]	[0.65]	[0.93]	[-1.52]	[-1.84]
Profitability		0.981*	0.192	1.083**	0.00798	-0.00816	-0.694	-0.133
		[1.80]	[0.33]	[2.02]	[0.01]	[-0.01]	[-1.07]	[-0.25]
ROA		-1.594***	-1.457***	-1.830***	-1.692***	-1.649***	-1.675***	-0.227
		[-4.85]	[-4.37]	[-5.74]	[-5.17]	[-5.04]	[-4.05]	[-0.70]
Operating cash flow		-0.551	-0.265	-0.493	0.104	0.189	0.954*	-0.317
		[-1.10]	[-0.50]	[-1.05]	[0.22]	[0.38]	[1.72]	[-0.72]
CAPEX/assets		3.104***	2.668***	2.585***	1.469**	1.199*	0.449	-0.308
		[5.11]	[4.30]	[4.23]	[2.34]	[1.90]	[0.64]	[-0.63]
PPE growth		-0.511***	-0.460***	-0.456***	-0.395***	-0.359***	-0.292**	-0.228
		[-4.46]	[-3.99]	[-4.11]	[-3.67]	[-3.35]	[-2.28]	[-1.50]
Sales growth		-0.307**	-0.393***	-0.332***	-0.459***	-0.519***	-0.399***	-0.389***
		[-2.50]	[-3.00]	[-2.86]	[-3.71]	[-4.21]	[-2.78]	[-2.63]
R&D/assets		0.570	-0.00185	0.240	-0.372	-0.503	-0.149	-0.186
		[0.94]	[-0.00]	[0.42]	[-0.64]	[-0.85]	[-0.26]	[-0.26]
R&D missing (0, 1)		-0.0221	-0.0252	0.0823	0.0593	0.0447	0.115	-0.0208
		[-0.33]	[-0.39]	[1.08]	[0.80]	[0.60]	[1.56]	[-0.28]
Number of segments		0.102***	0.109***	0.105***	0.105***	0.113***	0.106***	0.150***
		[5.84]	[6.16]	[6.05]	[5.99]	[6.38]	[5.23]	[8.12]
Ln(Assets)		0.297***	0.374***	0.290***	0.374***	0.363***	0.175***	0.131
		[10.71]	[13.27]	[9.65]	[12.51]	[12.34]	[5.54]	[0.67]
SA index		0.292***	0.412***	0.247***	0.383***	0.381***	0.510***	2.196***
		[4.36]	[6.86]	[3.78]	[6.68]	[6.76]	[8.75]	[3.01]
Stock ownership		-0.0149*	-0.0256***	-0.0127*	-0.0243***	-0.0252***	-0.0241***	-0.00831
		[-1.67]	[-2.80]	[-1.68]	[-3.14]	[-3.21]	[-2.67]	[-0.53]
Stock ownership		-0.145**	-0.231***	-0.138**	-0.222***	-0.240***	-0.341***	-0.0363
missing (0, 1)		[-2.41]	[-3.86]	[-2.31]	[-3.76]	[-4.05]	[-4.37]	[-0.55]
Industry fixed effects	No	No	No	Yes	Yes	No	Yes	Yes
Time fixed effects	No	No	Yes	No	Yes	No	Yes	Yes
Industry covariates	No	No	No	No	Yes	No	Yes	Yes
Industry-Time FEs	No	No	No	No	No	Yes	No	No
Number of observations	835,269	587,043	587,043	586,055	578,306	586,055	453,546	495,144
Pseudo R2	0.037	0.055	0.074	0.063	0.085	0.104	0.065	0.069
Number of clusters	8,980	6,406	6,406	6,401	6,364	6,401	6,302	5,472

Table 4: Cox regressions including watchlist placements.
The coefficients in the table represent estimates of hazard rates coefficient estimates of an asset sale event using Cox proportional hazard regressions on a monthly basis over the entire sample. Negative (Positive) watchlist (0,1) refers to a dummy variable that equals 1 in case the firm was put on negative (positive) watch during the 12 months preceding the observation. The same covariates are included as in Table 3. We cluster standard errors by firm and report t-statistics in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	Levels				1st Event	Changes
	(1)	(2)	(3)	(4)	(5)	(6)
Rating downgrade (0,1)	0.291***	0.267***	0.293***	0.270***	0.326***	0.343***
	[4.38]	[4.11]	[4.43]	[4.16]	[3.10]	[4.86]
Rating upgrade (0,1)	-0.223**	-0.239***	-0.208**	-0.200**	0.0523	-0.209**
	[-2.57]	[-2.75]	[-2.42]	[-2.32]	[0.37]	[-2.36]
Negative watchlist (0,1)	0.337***	0.283***	0.366***	0.329***	0.259*	0.357***
	[4.13]	[3.42]	[4.47]	[3.96]	[1.93]	[4.17]
Positive watchlist (0,1)	0.220	0.188	0.236	0.208	0.202	0.290*
	[1.49]	[1.27]	[1.63]	[1.45]	[0.82]	[1.90]
Other covariates	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	No	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes	Yes	Yes
Industry covariates	No	No	No	Yes	Yes	Yes
Number of observations	586,927	586,927	585,939	578,190	453,522	495,164
Pseudo R2	0.054	0.072	0.062	0.083	0.064	0.07
Number of clusters	6,406	6,406	6,401	6,364	6,302	5,472

Table 5: Cox regressions including covenants.
The coefficients in the table represent estimates of hazard rates coefficient estimates of an asset sale event using Cox proportional hazard regressions on a monthly basis over the sample up to 2011. Covenant violation (0,1) is a dummy variable that equals 1 in case of a covenant violation during the 12 months prior to the observation in question. The same covariates are included as in Table 3. We cluster standard errors by firm and report t-statistics in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	Levels			1st Event	Changes
	(1)	(2)	(3)	(4)	(5)
Rating downgrade (0, 1)	0.382***	0.421***	0.374***	0.388***	0.479***
	[5.29]	[5.77]	[5.18]	[3.67]	[6.42]
Rating upgrade (0, 1)	-0.212**	-0.221**	-0.213**	0.0399	-0.143
	[-2.24]	[-2.33]	[-2.25]	[0.27]	[-1.48]
Covenant violation (0,1)		0.569***	0.587***	0.522***	0.567***
		[4.52]	[4.58]	[3.65]	[4.47]
Other covariates	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	No	Yes	Yes	Yes
Time fixed effects	Yes	No	Yes	Yes	Yes
Industry covariates	Yes	No	Yes	Yes	Yes
Number of observations	441,230	447,415	441,230	355,205	383,490
Pseudo R2	0.084	0.06	0.085	0.063	0.066
Number of clusters	5,807	5,844	5,807	5,760	5,011

Table 6: Cox regressions including credit spreads.

The coefficients in the table represent estimates of hazard rates coefficient estimates of an asset sale event using Cox proportional hazard regressions on a monthly basis over the sample from July 2002 onwards. avgCS is the average credit spread observed in the TRACE corporate bond market trading data and CS Missing (0,1) is a dummy variable that equals 1 if there is no credit spread for the particular firm in that month and 0 otherwise. The same covariates are included as in Table 3. We cluster standard errors by firm and report t-statistics in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)
Rating downgrade (0,1)	0.261***	0.252***	0.257***	0.249***
	[2.76]	[2.62]	[2.71]	[2.59]
Rating upgrade (0,1)	-0.287**	-0.269**	-0.278**	-0.262**
	[-2.58]	[-2.43]	[-2.48]	[-2.36]
avgCS			-2.873	-2.257
			[-1.46]	[-1.17]
CS missing (0,1)			-0.838***	-0.654***
			[-6.84]	[-5.44]
Other covariates	Yes	Yes	Yes	Yes
Industry Fes	No	Yes	No	Yes
Time Fes	No	Yes	No	Yes
Industry covariates	No	No	No	No
Observations	292,840	292,518	292,840	292,518
Pseudo R-squared	0.071	0.097	0.071	0.097
N_clust	3,946	3,944	3,946	3,944

Table 7: Cox regressions including Moody's KMV EDFs.
The coefficients in the table represent estimates of hazard rates coefficient estimates of an asset sale event using Cox proportional hazard regressions on a monthly basis over the entire sample. EDF1 and EDF5 are the 1 and 5 year Moody's KMV EDFs, respectively. The same covariates are included as in Table 3. We cluster standard errors by firm and report t-statistics in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)
Rating downgrade (0,1)	0.321***	0.316***
	[4.61]	[4.66]
Rating upgrade (0,1)	-0.253***	-0.217**
	[-2.76]	[-2.39]
EDF1	-0.00471	-0.00113
	[-0.47]	[-0.11]
EDF5	0.0103	0.00962
	[0.53]	[0.48]
Other covariates	Yes	Yes
Time Fes	No	Yes
Indusrty Fes	No	Yes
Industry covariates	No	Yes
Observations	406,837	400,809
Pseudo R-squared	0.066	0.092
Number of clusters	4,973	4,938

Table 8: Cox hazard regressions with placebo indicator variables for rating changes
The coefficients in the table represent estimates of hazard rates coefficient estimates of an asset sale event using Cox proportional hazard regressions on a monthly basis over the entire sample. We cluster standard errors by firm and report t-statistics in brackets. The same covariates are included as in Table 3. In specification (3) the placebo dummies are set to zero between $t - 12$ and $t - 6$. In specification (4), only asset sales with a relative size smaller than the median of 2.7% are classified as events. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	Levels				1st Event	Changes
			Excluding 1st half year	Small deals only		
	(1)	(2)	(3)	(4)	(5)	(6)
Placebo Rating downgrade (0, 1)	0.00801	-0.0321	-0.0283	0.0776	-0.144	0.0338
	[0.11]	[-0.44]	[-0.35]	[0.77]	[-1.23]	[0.42]
Placebo Rating upgrade (0, 1)	-0.0707	-0.0322	-0.0506	-0.239**	-0.0291	0.0215
	[-0.91]	[-0.42]	[-0.54]	[-2.13]	[-0.22]	[0.26]
Rating downgrade (0, 1)		0.370***	0.305***	0.263***	0.419***	0.444***
		[5.81]	[4.16]	[2.99]	[4.20]	[6.80]
Rating upgrade (0, 1)		-0.184**	-0.211**	-0.348***	0.0564	-0.176**
		[-2.19]	[-1.96]	[-2.95]	[0.42]	[-2.05]
Other covariates	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry covariates	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	578,306	578,306	578,306	578,190	453,546	495,144
Pseudo R2	0.084	0.085	0.084	0.195	0.065	0.069
Number of clusters	6,364	6,364	6,364	6,364	6,302	5,472

Table 9: Hazard rate regressions by purpose

The coefficients in the table represent hazard rate estimates of asset sales events by self-reported purposes: Relaxing credit constraints (Relax), Discipline, or Ambiguous. Specification (1) to (3) are Cox proportional hazard regressions on a monthly basis over the entire sample. These specifications assume that multiple events can happen to a subject and that hazard rates are unaffected by such events. Specifications (4) to (6) present sub-hazard estimates for asset sales using the competing risk model by Fine and Gray (1999), where subjects leave the sample after the first event takes place. The same covariates are included as in Table 3. We cluster standard errors by firm and report t-statistics in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	Multiple events with others as censored			Competing risk (1st only) subhazard		
	Relax	Discipline	Ambiguous	Relax	Discipline	Ambiguous
	(1)	(2)	(3)	(4)	(5)	(6)
Rating downgrade (0, 1)	0.559***	0.430**	0.379***	0.868**	-0.122	0.441***
	[2.88]	[2.41]	[5.26]	[2.19]	[-0.31]	[4.14]
Rating upgrade (0, 1)	-0.269	-0.629**	-0.178**	0.488	-1.006	0.103
	[-0.82]	[-2.24]	[-2.03]	[0.77]	[-1.39]	[0.74]
Other covariates	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	No	No	No
Time fixed effects	No	No	No	No	No	No
Industry covariates	No	No	No	No	No	No
Number of observations	606,620	606,620	606,620	475,654	475,654	475,654
Pseudo R2	0.117	0.045	0.055	-	-	-
Number of clusters	6,550	6,550	6,550	6,489	6,489	6,489

Table 10: Spinoff hazard rate regressions

The coefficients in the table represent hazard rate estimates of spinoff events and asset sales events by self-reported purposes: Relaxing credit constraints (Relax), Discipline, or Ambiguous. Specification (1) refers to Cox proportional hazard regressions on a monthly basis over the entire sample for spinoffs. This specification implicitly assumes that multiple events can happen to a subject and that hazard rates are unaffected by past events. Specifications (2) to (5) present sub-hazard estimates for spinoffs and asset sales by purpose using the competing risk model by Fine and Gray (1999). The same covariates are included as in Table 3. We cluster standard errors by firm and report t-statistics in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	Multiple events with others as censored	Competing risk (1st only) subhazard			
	Spinoff	Relax	Disicpline	Ambiguous	Spinoff
	(1)	(2)	(3)	(4)	(5)
Rating downgrade (0, 1)	0.188	0.941**	-0.166	0.382***	-1.028
	[0.68]	[2.29]	[-0.40]	[3.44]	[-1.44]
Rating upgrade (0, 1)	-0.814**	0.572	-0.921	0.119	-0.714
	[-2.12]	[0.90]	[-1.27]	[0.83]	[-1.20]
Other covariates	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	No	No
Time fixed effects	No	No	No	No	No
Industry covariates	No	No	No	No	No
Number of observations	606,620	470,476	470,476	470,476	470,476
Pseudo R2	0.058	-	-	-	-
Number of clusters	6,550	6,482	6,482	6,482	6,482

Table 11: Inter-firm segment performance analysis
The table presents average marginal effects of logit regressions of dummy variables equal to 1 for inter-firm segment underperformance and 0 otherwise, in comparison to medians of peer segments in other multi-segment firms with matching 2-digit SIC codes for Profitability, Profit Margin, Asset Turnover, Operating Cash Flow, and Net CF using the Segment Sale sample. t-statistics are in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level. Variable descriptions are in Table 1.

VARIABLES	Profitability (1)	Profit Margin (2)	Asset Turnover (3)	Operating CF (4)	Net CF (5)
Rating downgrade (0, 1)	0.00143	-0.0243	0.0122	0.0219	0.0329
	[0.034]	[-0.592]	[0.288]	[0.511]	[0.761]
Rating upgrade (0, 1)	-0.154**	-0.112*	0.0270	-0.110	-0.118*
	[-2.315]	[-1.708]	[0.357]	[-1.516]	[-1.656]
Altman Z-score	0.00892	0.00167	-0.0526***	-0.0109	-0.0138
	[0.494]	[0.106]	[-3.032]	[-0.558]	[-0.695]
Cash holdings	0.430	0.255	-0.480	-0.0252	0.356
	[1.280]	[0.836]	[-1.557]	[-0.073]	[1.064]
Interest coverage	-0.000534	0.000604	0.00158*	-6.20e-05	-0.000274
	[-0.476]	[0.653]	[1.763]	[-0.053]	[-0.212]
Rollover	0.475	0.413	0.0286	0.444	0.702**
	[1.478]	[1.325]	[0.088]	[1.398]	[2.228]
Leverage	-0.378***	-0.554***	-0.0327	-0.384***	-0.344**
	[-2.659]	[-4.005]	[-0.227]	[-2.642]	[-2.334]
Tangibility	0.210**	0.0165	0.0229	0.0135	-0.0615
	[1.987]	[0.158]	[0.224]	[0.127]	[-0.574]
Tobin's Q	-0.0954**	-0.0373	0.0304	-0.132***	-0.0816*
	[-2.327]	[-1.029]	[0.891]	[-3.114]	[-1.930]
ROA	-1.077***	-0.996***	0.243	-0.569**	-0.775***
	[-4.006]	[-3.881]	[0.955]	[-2.030]	[-2.739]
Operating cash flow	-0.341	0.157	-0.819***	-0.894**	0.00209
	[-1.238]	[0.556]	[-2.768]	[-2.490]	[0.007]
CAPEX/assets	-0.388	0.740*	-0.308	-0.233	1.455***
	[-0.926]	[1.798]	[-0.784]	[-0.536]	[3.563]
PPE growth	0.147**	-0.00254	0.0898	0.101	-0.0221
	[2.271]	[-0.040]	[1.340]	[1.518]	[-0.326]
Sales growth	-0.138*	-0.0907	0.0840	0.0506	0.00644
	[-1.812]	[-1.213]	[1.108]	[0.629]	[0.082]
R&D/assets	-1.072*	-1.105**	-1.457***	-0.493	-0.302
	[-1.912]	[-2.172]	[-3.033]	[-0.741]	[-0.470]
R&D missing (0, 1)	0.0483	0.00234	0.0238	0.0856**	0.0412
	[1.326]	[0.068]	[0.670]	[2.282]	[1.130]
Number of segments	0.00516	0.00334	-0.0226**	-0.00633	0.0201*
	[0.447]	[0.310]	[-2.226]	[-0.549]	[1.768]
Ln(Assets)	0.0328**	-0.00703	0.0249*	0.0471***	0.0232
	[2.037]	[-0.455]	[1.649]	[2.871]	[1.377]
SA index	0.00390	0.0409	-0.00710	0.0381	0.0555*
	[0.129]	[1.414]	[-0.238]	[1.241]	[1.863]
Stock ownership	-0.00161	0.00445	-0.00904**	0.00103	0.00162
	[-0.403]	[1.128]	[-2.045]	[0.256]	[0.424]
Stock ownership missing (0, 1)	-0.0306	-0.0418	-0.0266	-0.0225	0.00777
	[-0.747]	[-1.059]	[-0.647]	[-0.550]	[0.198]
Rating FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	874	978	1,113	853	801
Pseudo R2	0.124	0.109	0.0829	0.150	0.161

Table 12: Intra-firm segment performance analysis

The table presents average marginal effects of logit regressions of dummy variables indicating intra-firm segment under- or over-performance on covariates described in Table 1 using the Segment Sale sample. In specification (4) we include a variable indicating the fraction of segments that are core segments to correct for mechanical effects. The same covariates are included as in Table 11. t-statistics are in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

VARIABLES	High Asset Redeployability (1)	Low Operating Cash flow (2)	Highest Tobin's q (3)	Non-Core Segment (4)	Low Profitability (5)	Low Profit Margin (6)	Low Asset Turnover (7)
Rating downgrade (0, 1) = 1	0.0981***	0.104**	0.0977***	0.0209	0.0495	0.0193	0.0704*
	[2.776]	[2.262]	[2.651]	[0.457]	[1.063]	[0.431]	[1.760]
Rating upgrade (0, 1) = 1	0.0461	0.167**	-0.0463	-0.0179	0.105	-0.0310	-0.0829
	[0.760]	[2.159]	[-0.688]	[-0.243]	[1.375]	[-0.391]	[-1.186]
Other covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,259	908	1,308	989	957	1,046	1,185
Pseudo R2	0.0668	0.0478	0.0988	0.164	0.0384	0.0424	0.0491

Appendix

A. Proofs

Proof of Lemma 1. Minimizing the discount rate r with respect to $\frac{D}{V}$ yields the first-order condition

$$0 = \gamma \left(2a^2 \frac{D}{V} + 2abCR \right) - Tr_d. \tag{23}$$

Solving w.r.t. $\frac{D}{V}$ yields (5).

Now we denote (2) evaluated at $\left(\frac{D}{V}\right)^*$ as r^*. We can write the utility function of the CEO as

$$\begin{aligned} U_m &= \beta IC_{nc} + (IRR_{nc} - r^*)IC_{nc} + (IRR_c - r^*)IC_c, & (24) \\ &= (\beta + (IRR_{nc} - r^*))IC_{nc} + (IRR_c - r^*)IC_c. & (25) \end{aligned}$$

This is maximized by holding on to segment nc when

$$\begin{aligned} (\beta + (IRR_{nc} - r^*)) &\geq 0, & (26) \\ r^* &\leq IRR_{nc} + \beta. & (27) \end{aligned}$$

□

Proof of Proposition 1. If segment nc is held on to, Lemma 1 provides the new optimal leverage ratio in (7). If segment nc is sold, optimal leverage is unchanged as the rating is reverted to level CR in that case. To find the optimal solution, we need to compare CEO utility when selling with keeping segment nc. We have that keeping nc is optimal when

$$\begin{aligned} (IRR_c - r^*)IC_c &\leq (\beta + IRR_{nc} - r^{*'})IC_{nc} + (IRR_c - r^{*'})IC'_c, \Rightarrow & (28) \\ r^{*'}(IC_{nc} + IC'_c) &\leq (\beta + IRR_{nc})IC_{nc} + r^* IC_c, \Rightarrow & (29) \\ r^{*'} &\leq \frac{(\beta + IRR_{nc})IC_{nc} + IC_c r^*}{IC_{nc} + IC'_c}. & (30) \end{aligned}$$

□

Proof of Lemma 2. Assume that $l_x \in (0, 1)$. In order to generate a unit of cash one needs to liquidate $\frac{1}{l_x}$ units of asset. The (long term) value of a unit of asset is 1, so is the value of a unit of cash. Hence, the transaction cost equals $\frac{1}{l_x} - 1$. Dividing by $(1 - l_x)$, we get

$$\left(\frac{1}{l_x} - 1\right)\frac{1}{1 - l_x} = \frac{1 - l_x}{l(1 - l_x)} = \frac{1}{l} > 1. \tag{31}$$

□

Proof of Proposition 2. We can transform one-off transaction costs to a perpetuity. Since there is no uncertainty about these costs, the discount rate is the risk-free rate. We have that

$$\frac{(D^{**} - D^*)}{l_x} = \frac{r_f(D^{**} - D^*)}{l_x r_f} = \frac{V r_f(\frac{D^{**}}{V} - \frac{D^*}{V})}{l_x r_f}, \tag{32}$$

$$(1 - l_{nc})IC_{nc} = \frac{(1 - l_{nc})r_f IC_{nc}}{r_f}. \tag{33}$$

Hence, per period transaction costs for reducing leverage are $\frac{V r_f(\frac{D^{**}}{V} - \frac{D^*}{V})}{l_x}$ and for selling segment nc they equal $(1 - l_{nc})r_f IC_{nc}$. We now have that the cost of capital accounting for transaction costs of adjusting leverage is given as a function of leverage by

$$r = r_a - \frac{D}{V}Tr_d + \frac{V r_f|\frac{D}{V} - \frac{D^*}{V}|}{l_x} + \gamma\left(a\frac{D}{V} + bCR'\right)^2. \tag{34}$$

Imposing a first-order condition and minimizing w.r.t. $\frac{D}{V}$ yields (9) for a given l_x. Since r is decreasing in l_x, r is minimized by maximizing l_x, giving rise to (12). It is optimal for the CEO to keep nc when

$$(IRR_c - r^*)IC_c - (1 - l_{nc})r_f IC_{nc} \leq (\beta + IRR_{nc} - r^{**})IC_{nc} + (IRR_c - r^{**})IC_c'. \tag{35}$$

Re-writing yields (10). □

Proof of Lemma 3. Minimizing the discount rate r with respect to $\frac{D}{V}$ yields the first-order condition

$$0 = \gamma\left(2a^2\frac{D}{V} + 2a(bCR + cX)\right) - Tr_d. \tag{36}$$

Solving w.r.t. $\frac{D}{V}$ yields (15).

Now we denote (13) evaluated at $\left(\frac{D}{V}\right)^{***}$ as r^{***}. The utility function of the CEO is given by

$$U_m = \beta IC_{nc} + (IRR_{nc} - r^{***})IC_{nc} + (IRR_c - r^{***})IC_c, \tag{37}$$

$$= (\beta + (IRR_{nc} - r^{***}))IC_{nc} + (IRR_c - r^{***})IC_c. \tag{38}$$

This is maximized by holding on to segment nc when

$$(\beta + (IRR_{nc} - r^{***})) \geq 0, \tag{39}$$

$$r^{***} \leq IRR_{nc} + \beta. \tag{40}$$

□

Proof of Proposition 3. If segment nc is held on to, Lemma 3 provides the new optimal leverage ratio in (15) given rating level CR'. If segment nc is sold, optimal leverage Lemma 3 provides the new optimal leverage ratio in (15) with rating level CR as the rating is reverted to level CR in that case. To find the optimal action for the CEO, we need to compare CEO utility when selling with keeping segment nc. We have that keeping segment nc is optimal when

$$(IRR_c - r^{***'}_{I_{ch}=0})IC_c \leq (\beta + IRR_{nc} - r^{***'}_{I_{ch}=1})IC_{nc} + (IRR_c - r^{***'}_{I_{ch}=1})IC'_c, \Rightarrow \tag{41}$$

$$r^{***'}_{I_{ch}=1}(IC_{nc} + IC'_c) \leq (\beta + IRR_{nc})IC_{nc} + r^{***'}_{I_{ch}=0}IC_c, \Rightarrow \tag{42}$$

$$r^{***'}_{I_{ch}=1} \leq \frac{(\beta + IRR_{nc})IC_{nc} + IC_c r^{***'}_{I_{ch}=0}}{IC_{nc} + IC'_c}. \tag{43}$$

□

Proof of Proposition 4. The optimal leverage with characteristics X_{-k} is given by Lemma 3. Since a smaller X_{-k} leads to a lower discount rate and therefore higher EVA, this is optimized by choosing the k that minimizes X_{-k}. This gives rise to (21). When segment nc is sold, the optimal new leverage is given by Lemma 3.

It is then optimal for the CEO to keep segment nc when

$$(IRR_c - r^{***}_{-nc})IC_c \leq (\beta + IRR_{nc} - r^{***''})IC_{nc} + (IRR_c - r^{***''})IC'_c. \tag{44}$$

Re-writing yields (10). □

B. Supplementary Tables and Figures

Figures

Figure B.1: Coefficients on Credit Rating Downgrade (0, 1) Indicator Variable by alternative Asset Redeployability Deciles

Tables

Table B.1: Cox hazard regressions using distance-weighted credit rating downgrades
The coefficients in the table represent hazard rate coefficient estimates of an asset sale event using Cox proportional hazard regressions on a monthly basis over the entire sample. In each specification, we weigh all observations of a firm by the sample-period average of the absolute inverse distance of that firm's rating relative to the IG-HY boundary (in notches). Non-rated firms receive the minimum weight among the rated firms. We re-scale all weights to get a sample average weight of 1. In specifications (1) and (2) this is done symmetrically. In specifications (3) and (4), weights on the HY side of the spectrum are multiplied by 2 and in specifications (5) and (6) these are multiplied by 5. The same covariates are included as in Table 3. We cluster standard errors by firm and report t-statistics in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Rating downgrade (0,1)	0.433***	0.393***	0.436***	0.402***	0.435***	0.410***
	[11.16]	[9.91]	[11.28]	[10.17]	[11.31]	[10.38]
Rating upgrade (0,1)	-0.220***	-0.175***	-0.240***	-0.185***	-0.257***	-0.195***
	[-4.11]	[-3.22]	[-4.45]	[-3.40]	[-4.77]	[-3.58]
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed effects	No	Yes	No	Yes	No	Yes
Time Fixed effects	No	Yes	No	Yes	No	Yes
Industry covariates	No	Yes	No	Yes	No	Yes
Ratio HY vs IG weights	1	1	2	2	5	5
Observations	634,319	624,012	640,069	629,820	646,724	636,542
Pseudo R-squared	0.038	0.076	0.036	0.076	0.034	0.077

Table B.2: Hazard rate regressions by purpose including watchlist placements

The coefficients in the table represent hazard rate estimates of asset sales events by self-reported purposes: Relaxing credit constraints (Relax), Discipline, Ambiguous, or spinoff. Specification (1) to (4) are Cox proportional hazard regressions on a monthly basis over the entire sample. These specifications assume that multiple events can happen to a subject and that hazard rates are unaffected by such events. Specifications (5) to (8) present sub-hazard estimates for asset sales using the competing risk model by Fine and Gray (1999), where subjects leave the sample after the first event takes place. The same covariates are included as in Table 3. We cluster standard errors by firm and report t-statistics in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	Multiple events with others as censored				Competing risk (1st only) subhazard			
	Relax	Discipline	Ambiguous	Spinoff	Relax	Discipline	Ambiguous	Spinoff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rating downgrade (0, 1)	0.333*	0.311*	0.280***	0.123	0.655	-0.312	0.335***	-0.864
	[1.71]	[1.78]	[3.82]	[0.41]	[1.60]	[-0.76]	[2.84]	[-1.15]
Rating upgrade (0, 1)	-0.167	-0.579*	-0.206**	-0.710*	0.716	-0.888	0.0751	-0.725
	[-0.51]	[-1.94]	[-2.29]	[-1.90]	[1.12]	[-1.19]	[0.50]	[-1.30]
Negative watchlist (0,1)	0.779***	0.422**	0.322***	0.275	0.831**	0.458	0.193	-0.913
	[3.81]	[2.00]	[3.58]	[0.81]	[2.13]	[1.08]	[1.27]	[-0.86]
Positive watchlist (0,1)	-0.357	-0.0644	0.284*	-1.133	-13.00***	-0.168	0.393	-0.0239
	[-0.71]	[-0.14]	[1.88]	[-1.16]	[-35.59]	[-0.16]	[1.57]	[-0.02]
Other covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	No	No	No	No	No
Time fixed effects	No	No	No	No	No	No	No	No
Industry covariates	No	No	No	No	No	No	No	No
Number of observations	606,503	606,503	606,503	606,503	470,476	470,476	470,476	470,476
Pseudo R2	0.119	0.045	0.054	0.058	-	-	-	-
Number of clusters	6,550	6,550	6,550	6,550	6,482	6,482	6,482	6,482

Table B.3: Inter-firm segment performance analysis including watchlist placements
The table presents average marginal effects of logit regressions of dummy variables equal to 1 for inter-firm segment underperformance and 0 otherwise, in comparison to medians of peer segments in other multi-segment firms with matching 2-digit SIC codes for Profitability, Profit Margin, Asset Turnover, Operating Cash Flow, and Net CF using the Segment Sale sample. Negative (Positive) watchlist (0,1) refers to a dummy variable that equals 1 in case the firm was put on negative (positive) watch during the 12 months preceding the observation. t-statistics are in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level. Variable descriptions are in Table 1.

VARIABLES	Profitability (1)	Profit Margin (2)	Asset Turnover (3)	Operating CF (4)	Net CF (5)
Rating downgrade (0, 1) = 1	-0.00894	-0.0383	0.0468	0.0315	0.0556
	[-0.195]	[-0.861]	[1.005]	[0.662]	[1.138]
Rating upgrade (0, 1) = 1	-0.170**	-0.110	0.00760	-0.103	-0.128*
	[-2.522]	[-1.616]	[0.099]	[-1.336]	[-1.819]
Negative watchlist (0,1)	0.0338	0.0384	-0.0784	-0.0273	-0.0530
	[0.665]	[0.761]	[-1.597]	[-0.537]	[-1.013]
Positive watchlist (0,1)	0.0785	-0.00547	0.116	-0.0410	0.0569
	[0.790]	[-0.056]	[1.342]	[-0.407]	[0.603]
Other covariates	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	874	978	1,113	853	801
Pseudo R2	0.125	0.109	0.0859	0.150	0.162

Table B.4: Intra-firm segment performance analysis including watchlist placements

The table presents average marginal effects of logit regressions of dummy variables indicating intra-firm segment under- or over-performance on covariates described in Table 1 using the Segment Sale sample. In specification (4) we include a variable indicating the fraction of segments that are core segments to correct for mechanical effects. The same covariates are included as in Table B.3. t-statistics are in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	High Asset Redeployability	Low Operating Cash flow	Highest Tobin's q	Non-Core Segment	Low Profitability	Low Profit Margin	Low Asset Turnover
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rating downgrade (0, 1) = 1	0.124***	0.139***	0.112***	0.0345	0.0766	-0.0174	0.0845**
	[3.347]	[2.861]	[2.817]	[0.697]	[1.545]	[-0.350]	[1.982]
Rating upgrade (0, 1) = 1	0.0481	0.204***	-0.0484	-0.0318	0.136*	0.00593	-0.0900
	[0.784]	[2.754]	[-0.712]	[-0.430]	[1.790]	[0.074]	[-1.270]
Negative watchlist (0,1)	-0.0867*	-0.118**	-0.0419	-0.0240	-0.0917	0.0823	-0.0373
	[-1.923]	[-2.011]	[-0.931]	[-0.471]	[-1.602]	[1.493]	[-0.774]
Positive watchlist (0,1)	-0.0704	-0.281**	-0.00996	0.100	-0.214*	-0.206*	0.0486
	[-0.933]	[-2.413]	[-0.124]	[1.106]	[-1.912]	[-1.953]	[0.542]
Other covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,259	908	1,308	989	957	1,046	1,185
Pseudo R2	0.0696	0.0554	0.0993	0.165	0.0430	0.0468	0.0497

Table B.5: Cox hazard regressions and acquisition activity

The coefficients in the table represent hazard rate coefficient estimates of an asset sale event using Cox proportional hazard regressions on a monthly basis over the entire sample. Acquisition spending is the monthly ratio of aggregated deal values for firm i from month t–24 to t–6 to the most recent book value of assets prior to month t. Acquisition activity is an indicator variable equal to one if Acquisition spending > 0 and zero otherwise. We define Cash (equity) acquisition spending as the aggregate dollars spent with cash (equity) on acquisitions for firm i from month t–24 to t–6 to the most recent book value of assets prior to month t. All acquisition activity and spending is from SDC. Models (1) to (5) utilize the full sample of observations. Model (6) is for the sub-sample where Acquisition activity equals one and model (7) is for the sub-sample where Acquisition activity equals zero. The same covariates are included as in Table 3. We cluster standard errors by firm and report t-statistics in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

						Acquisition Activity	
						Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rating downgrade (0,1)	0.360***	0.335***	0.352***	0.352***	0.344***	0.333***	0.317***
	[5.61]	[5.18]	[5.52]	[5.48]	[5.40]	[3.78]	[3.76]
Rating upgrade (0,1)	-0.161*	-0.190**	-0.158*	-0.167**	-0.163**	-0.231**	-0.115
	[-1.95]	[-2.27]	[-1.91]	[-2.03]	[-1.98]	[-1.97]	[-1.02]
Recent M&A Activity	0.926***		0.866***	0.878***	0.817***		
	[19.27]		[15.38]	[17.81]	[14.37]		
Aggregate value Recent M&A Activity		2.476***					
		[16.95]					
Aggregate cash in Recent M&A Activity			0.747**		0.751**		
			[2.49]		[2.56]		
Aggregate stock in Recent M&A Activity				1.534***	1.540***		
				[4.26]	[4.34]		
Other covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	No	No	No	No
Time fixed effects	No	No	No	No	No	No	No
Industry covariates	No	No	No	No	No	No	No
Observations	587,043	587,043	587,043	587,043	587,043	134,596	452,447
Pseudo R-squared	0.066	0.061	0.067	0.067	0.067	0.083	0.053
Number of clusters	6,406	6,406	6,406	6,406	6,406	3,305	6,087

Table B.6: Cox hazard regressions excluding LBOs

The coefficients in the table represent hazard rate coefficient estimates of an asset sale event using Cox proportional hazard regressions on a monthly basis over the entire sample. We exclude asset sale events that are LBO deals (model (1)), where the seller is an LBO firm (model (2)), where the seller parent is an LBO firm (model (3)), and where the acquirer is an LBO firm (model (4)). The same covariates are included as in Table 3. We cluster standard errors by firm and report t-statistics in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	No LBO (1)	Target no LBO (2)	Target parent no LBO (3)	Acquirer no LBO (4)
Rating downgrade (0, 1)	0.391***	0.392***	0.396***	0.399***
	[5.71]	[5.92]	[5.97]	[5.94]
Rating upgrade (0, 1)	-0.252***	-0.207**	-0.216**	-0.209**
	[-2.83]	[-2.46]	[-2.54]	[-2.44]
Other covariates	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	No
Time fixed effects	No	No	No	No
Industry covariates	No	No	No	No
Number of observations	587,043	587,043	587,043	587,043
Pseudo R2	0.055	0.055	0.055	0.056
Number of clusters	6,406	6,406	6,406	6,406

Table B.7: Cox hazard regressions for failed asset sales and asset sales by purpose
The coefficients in the table represent hazard rate estimates for failed asset sale events and asset sales events by self-reported purposes: Relaxing credit constraints (Relax), Discipline, or Ambiguous. Specification (1) presents Cox proportional hazard regressions on a monthly basis over the entire sample for never completed deals that were rumored, intended, pending, were seeking a buyer or only partially completed (failed deals). This specification implicitly assumes that multiple events can happen to a subject and that hazard rates are unaffected by past events. Specifications (2) to (5) present sub-hazard estimates for failed deals and asset sales by purpose using the competing risk model by Fine and Gray (1999). The same covariates are included as in Table 3. We cluster standard errors by firm and report t-statistics in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

		Competing risk (1st only) subhazard			
	Failed asset sale	Relax	Discipline	Ambiguous	Failed asset sale
	(1)	(2)	(3)	(4)	(5)
Rating downgrade (0, 1)	0.301***	0.830	-0.336	0.381***	0.223
	[3.03]	[1.56]	[-0.70]	[3.02]	[1.26]
Rating upgrade (0, 1)	-0.313**	0.998	-0.777	0.204	-0.0639
	[-2.23]	[1.49]	[-1.07]	[1.32]	[-0.27]
Other covariates	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	No	No
Time fixed effects	No	No	No	No	No
Industry covariates	No	No	No	No	No
Number of observations	606,620	444,579	444,579	444,579	444,579
Pseudo R2	0.036	-	-	-	-
Number of clusters	6,550	6,467	6,467	6,467	6,467

Table B.8: Cox hazard regression excluding anticipated deals

The coefficients in the table represent hazard rate coefficient estimates of an asset sale event using Cox proportional hazard regressions on a monthly basis over the entire sample. We exclude asset sale events that were rumored before completion (model (1)), that had announced that they were seeking a buyer prior to completion (model (2)), and both (model (3)). The same covariates are included as in Table 3. We cluster standard errors by firm and report t-statistics in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)
	Excluding Rumors	Excluding seeking buyer	Excluding both
Rating downgrade (0, 1)	0.379***	0.357***	0.355***
	[5.81]	[5.32]	[5.23]
Rating upgrade (0, 1)	-0.188**	-0.145	-0.158*
	[-2.19]	[-1.63]	[-1.76]
Other covariates	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Industry covariates	Yes	Yes	Yes
Number of observations	578,306	578,306	578,306
Pseudo R2	0.084	0.082	0.081
Number of clusters	6,364	6,364	6,364

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