The real effects of credit ratings: Evidence from corporate asset sales*

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Abstract:
Credit rating agencies (CRAs) have been accused of exacerbating financial distress through downgrades, but are also perceived as dedicated monitors when debt holdings are widely dispersed. In this paper, we investigate the relative contribution of credit rating downgrades on financial distress and managerial discipline. We show that firms are more likely to conduct an asset sale following a credit rating downgrade, particularly if firms indicate that the purpose is to pay down outstanding debt or raise cash. We find a smaller or no effect of downgrades on the likelihood of asset sales with the purpose of concentrating on core assets or selling loss-making or bankrupt operations. In a placebo test we find that downgrades do not affect the likelihood of spinoffs, which do not involve a cash infusion for the firm. Stock price reactions to asset sales following a credit rating downgrades are consistent with financial distress relief for sellers and a way for buyers to benefit from fire-sale prices. Asset sales following a downgrade are concentrated in segments that are most liquid, generate lowest current cash flows, and have highest growth opportunities. Peer-based performance, intra-firm performance rank, or relatedness to core activities, do not explain the choice of divested segments. Our results suggest that firms respond to credit rating downgrades with asset sales in an attempt to reduce financial distress and that downgrades, at the margin, exacerbate financial distress rather than induce managerial discipline.

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In the aftermath of the sub-prime and the European sovereign debt crises, policy makers have introduced a large body of regulation and legislation to prevent misbehavior by Credit Rating Agencies (CRAs). A substantial part of this aims at preventing CRAs from inflating ratings, as they had allegedly done at the onset of the sub-prime crisis (Griffin and Tang, 2012). Yet, other parts, such as 'rating calendars' in Europe, aim at insulating government budgets from distress enhancing effects due to the tightening of capital constraints following downgrades. Global efforts to reduce regulatory reliance on ratings also fit these goals of reducing ratings-induced financial distress. In contrast, CRAs are also often referred to as dedicated monitors when debt holdings are widely dispersed or held by information insensitive investors. In this capacity, credit rating downgrades could be an important governance device in enforcing managerial discipline.

In this paper, we investigate whether credit rating downgrades of corporate debt, at the margin, exacerbate financial distress (the financial distress hypothesis) or improve the allocation of productive assets through managerial discipline (the discipline hypothesis). Disentangling the effect of credit rating downgrades is important because distress effects at the corporate level are pro-cyclical and are likely to exacerbate distress at an aggregate level. In contrast, if credit rating downgrades improve the allocation of productive assets they would be counter-cyclical and would alleviate distress at an aggregate level.

We focus on the relative importance of the distress and disciplining effects of credit rating downgrades, since these effects are not mutually exclusive. In fact, any discipline from credit rating downgrades over and above the discipline induced by financial distress will more likely materialize if credit rating downgrades amplify financial distress to some degree. Understanding whether, at the margin, credit rating downgrades exacerbate financial distress or improve the allocation of productive assets is important to corporate decision makers, financial investors, and other stakeholders. Corporate executives, for example, have been shown to consider credit rating as an important aspect in their decision making process (Graham and Harvey, 2001). At a macro level, it is important to understand whether and how CRAs affect corporate decision making in the context of proposed legislation and regulation with respect to CRAs.

Our identification strategy is based on analyzing corporate asset sales. We acknowledge that we do not conduct a natural experiment and, frankly, are skeptical on finding a convincing instrument for a credit rating downgrade in the context of our cross-sectional analyses, where the instrument would have to be uncorrelated with credit risk. Naturally, this implies that endogeneity may affect our analyses. Nonetheless, we believe that studying corporate asset sales mitigates these concerns, for example, due to a high signal-to-noise ratio. Studying asset sales allows us to analyze four distinct channels through which we predict that credit rating downgrades affect corporate decision-making. This mitigates identification concerns, as alternative channels would have to be consistent with the results we report for each of these four dimensions. We note that our results consistently point in one direction across these different channels.

The four channels we consider are as follows. First, we analyze whether credit rating downgrades affect the likelihood of an asset sale occurring. Understanding whether downgrades result in firms conducting more asset sales beyond the commonly known determinants of distress and asset sales, such as poor firm performance and leverage, is important as it validates our subsequent analysis where we study the effects of credit rating changes. We also consider whether downgrades affect the likelihood for an asset sale differently depending on the self-reported purpose of the deal. We distinguish asset sales based on whether the proceeds will be used to alleviate distress (e.g., pay down existing outstanding debt or raise cash), or to improve the allocation of productive assets (e.g., focus on core operations or divestiture of loss making or bankrupt operations). As expected, we find that the difference in the average credit rating for the first group (distress motivated) of firms is three notches lower than for the second group (discipline motivated). This is economically large and statistically significant at the one percent level. Similarly, we analyze whether downgrades affect the likelihood for an asset sale depending on the asset redeployability of the firm, which proxies for liquidity or the cost of conducting an asset sale as a response to an increase in financial distress (Shleifer and Vishny, 1992). Second we consider the effects of credit rating downgrades on the wealth effects for shareholders around the announcement of an asset sale for the seller, buyer, and for the seller and buyer combined (aggregate welfare effects). Third, to understand the role of credit rating downgrades on the allocation of productive assets we conduct intra- and inter-firm analyses where we analyze which assets are sold off using segment-level data. Finally, we consider an important deal characteristic, the form of payment, of the asset sales to corroborate the results from our other analyses. In the next section we develop specific testable predictions based on the financial distress and discipline hypotheses for each of the four channels. In addition to the above reasons, analyzing asset sales provides another potential advantage for our empirical setting because they involve financial stock, not flow variables (such as capital expenditures). Stock variables are known to be less noisy in terms of isolating real effects of credit rating changes that occur at a particular point in time. Compared to capital expenditures, asset sales are also more informative events as they deal more directly with the question of efficient allocation of assets both within the firm and across owners. Capital expenditures, in contrast, could be suboptimal but could be so even under the most efficient owner.

Our results highlight the unique role CRAs play in the economy. We summarize the real effects that CRAs have on corporate finance decisions as follows. For each test the evidence points in the direction of a financial distress inducing effect of credit rating downgrades. Collectively, our results suggest that the financial distress inducing effect of credit rating downgrades outweighs the potential improvements in the allocation of productive assets or other decision making reminiscent of improved managerial discipline. More specifically, for a comprehensive sample of corporate assets sales by U.S. corporations, spanning the period 1990-2015, the duration analysis provides robust evidence that credit rating downgrades are associated with a higher likelihood of an asset sale, over and above the effect of credit risk-related variables. This relation is particularly relevant for asset sales self-reported as distress motivated and when average asset redeployability of the firm is high. In fact, the marginal impact on the likelihood of announcing an asset sale is approximately four times as high in the highest decile of average asset redeployability, compared to the marginal impact on the likelihood in the lowest decile. We also conduct a placebo test with a sub-sample of spinoffs, which represent primarily stock transactions among the current shareholders of the firm without a cash infusion for the firm or its shareholders. Spinoffs, therefore, present a cleaner example of discipline-driven events. Interestingly, the duration analysis shows that downgrades are not associated with a higher likelihood of spinoffs.[1] The average credit ratings for firms announcing spinoffs and for firms announcing discipline-motivated asset sales are similar and both economically and statistically higher than for firms announcing a distress-motivated asset sale.

Cross-sectional regression analyses shows that the cumulative abnormal announcement returns (CAR) to seller shareholders around asset sales of recently downgraded firms are both positive and statistically and economically larger than for firms that have not experienced recent downgrades.[2] For example, the 3-day announcement CAR of an asset sale with a preceding credit rating downgrade within the previous year is 74 to 125 basis points (bps) higher than without, which is economically significant. Furthermore, we find that the announcement CAR for sellers is significantly, both economically and statistically, more negative for sellers with a credit rating around the Investment Grade – High Yield (IG-HY) boundary. Asset sales by sellers with a credit rating of BBB or BB are accompanied with a roughly 90 bps lower announcement return than other asset sales. This result is consistent with the intuition that distress-induced assets sales

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

[2] Our results differ from those reported by Sicherman and Pettway (1992). They report lower CARs for asset sales following a rating downgrade in the period 1981-1987, which they interpret as evidence for reduced bargaining power. Lasfer, Sudarsanam, and Tafller (1996) report positive announcement returns for a sample of U.K. asset sales that are higher for financially distressed firms.

would be more likely to involve the sale of well performing assets at fire-sale prices as these would bring more relief of financial distress for the seller. Asset redeployability is an important determinant of liquidation values and debt capacity (Williamson, 1988). In this context, we find that after a credit rating downgrade, only firms with high asset redeployability, exhibit a positive CAR, while firms with low asset redeployability exhibit a significantly lower and negative CAR.[3] Consistent with the likelihood analysis of the Cox regressions, the event study results are consistent with the idea that for lower asset redeployability and more illiquid assets the cost of an asset sale increases relative to some alternative choices for alleviating financial distress (Shleifer and Vishny, 1992).[4]

We also document that the buyer CAR associated with an asset sale is 103 to 154 basis points higher after a recent rating downgrade of the seller. This result is consistent with the prediction that distress-induced asset sales are typically conducted at fire-sale prices, which is expected to benefit the buyers of these assets. This suggests that cash-in-the-market pricing contributes to the fire-sale discounts realized over and beyond any discount due to the buyer being a potentially less efficient user of the assets.[5]

Interestingly, based on combined buyer and seller CAR as a proxy for aggregate welfare effects, we find that positive effects only materialize for asset sales by recently downgraded firms with high asset redeployability, but not for recently downgraded firms with low asset redeployability. This suggests that welfare gains of asset sales following rating downgrades are solely due to relief of financial distress and

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[3] We thank Hyunseob Kim and Howard Kung for graciously making their data on asset redeployability available to us. For a detailed description of their measures and its applications, we refer to Kim and Kung (*forthcoming*).

[4] Favara and Giannetti (2016) and Giannetti and Saidi (2016) find that negative externalities associated with forced asset sales are attenuated when the market for lenders is more concentrated. Our interest is in firms that have experienced downgrades on their public long-terms debt, which typically trades in a dispersed market.

[5] The term cash-in-the-market pricing was first introduced by Allen and Gale (1994) and subsequently connected to financial crises in several of their works. In Allen and Gale (2004), for example, they refer to cash-in-the-market pricing as "how asset prices depend on the liquidity of the market participants' portfolios, as well as on the traditional factors of productivity and thrift (p. 538)".

relaxing financial constraints and that acquirers in those asset sales are worse rather than better users of those assets. In fact, the event study analyses help us for identification, but we believe that the real economic implications of our results are severely understated because the decision to sell assets is endogenous. The real welfare losses following downgrades are very likely to be concentrated in the firms not in our event study sample, as these firms found themselves incapable of resolving the ratings-induced financial distress by selling assets that are too specific. This would have lead them to continue incurring financial distress costs or to engage in more costly ways of alleviating financial distress.

Our segment analysis also generally supports the distress hypothesis. We find that segments with poor intra-firm cash flow performance and high asset redeployability are associated with a higher likelihood of being divested after a credit rating downgrade. Similarly, segments with the best intra-firm growth opportunities are more likely to be divested. In contrast, we find little support for improvements in the allocation of productive assets after a credit downgrade. For example, the likelihood of divesting non-core segments or segments that underperform their industry is unaffected by credit rating downgrades. Finally, we find that asset sales following a credit rating downgrade are more likely to involve 100% cash transactions, which we interpret as consistent with the idea that on average these transactions appear to be motivated by reducing financial distress.

Our paper contributes to several strands in the finance literature. First, it contributes to the literature on how credit ratings affect corporate strategic decision making and governance. Credit ratings have been shown to affect capital structure decisions (e.g. Kisgen (2006, 2009)), but it is unclear to which extent these effects are welfare enhancing or welfare deteriorating. Begley (2015) shows that firms boost EBITDA prior to bond issues when they are near key Debt/EBITDA thresholds, emphasized by credit rating agencies, at the expense of long-term performance and value. Moreover, while credit ratings have been shown to reflect corporate governance (e.g., Ashbaugh-Skaife, Collins and LaFond, 2006 and Bhojraj and

Sengupta, 2003), the disciplining effect of credit ratings has only been explored theoretically (Boot et al, 2006). Our paper also relates to the recent work by Harford and Uysal (2014) and Aktas, Karampatsas, Petmezas, and Servaes (2015), who show that credit ratings affect the acquisition process in terms of acquisitiveness and announcement returns. Focusing on asset sales allows us to analyze whether credit ratings affect efficient allocation of capital within firms.

The paper also contributes to the literature on asset sales. The literature has focused on financial constraints and distress as well as on efficient asset allocation as likely determinants of the occurrence and valuation effects of assets sales.[6] The empirical evidence suggests that firms divest assets that are liquid, small, unrelated to the firm's core activities, and lead to increased performance in the remaining firm and reduced costs associated with cross-subsidization. In line with this, sellers benefit from assets as has been shown using several event studies in the literature.[7] Our evidence on the role of credit rating agencies corroborates these findings in terms of financial constraints and distress, but not in terms of improved asset allocation. Our paper complements Meier and Servaes (2015), who are the first to study the shareholder wealth effects of fire sales from the buyers' point of view and find that gains are significantly higher in the case of fire sales. They define asset sales as fire sales if categorized by SDC as a bankruptcy, liquidation, or debt restructuring. Given that these transactions are so clearly distress induced and relatively rare, we believe it is unlikely in those instances for credit ratings to have a marginal impact on corporate decision making and valuations.[8] Therefore, we exclude these pure fire sales from our analysis and focus on assets sales where a change in credit ratings may still marginally affect corporate behavior and shareholder wealth in ways similar to those of ex-ante defined fire sales.

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[6] Eckbo and Thorburn (2013) provide a detailed summary of this literature.

[7] Alternatively, asset sales could be a manifestation of managerial entrenchment where through an asset lockup the firm sells off certain assets, such as the firm's crown jewels to a buyer to prevent an unsolicited takeover attempt by an alternative buyer. However, these asset lockups are mostly extinct (Coates and Subramanian, 2000).

[8] Meier and Servaes (2015) report 367 (3%) asset fire sales for their sample of 12,341 asset sales for the period 1982-2012. We find a similar low proportion of fire sales (according to their definition) in our sample.

The paper also contributes to the literature on the intersection of financial distress and asset liquidity. Asset sales could provide additional liquidity or reduce the scale and diversity of the firm, affecting the creditworthiness of the firm positively or negatively ex-post. In this context, Venkiteshwaran (2014) finds that increased industry-level turnover of assets improves subsequent credit quality, but provides no analysis or evidence with respect to our research question of whether credit rating downgrades exacerbate financial distress or have a disciplinary effect on corporate decision making.

1. Hypotheses and empirical methodology

Our research is motivated by the recent skepticism on the role of CRAs in the real economy and their potential effects on corporate decision making, specifically. We ask whether credit rating downgrades of corporate debt, at the margin, exacerbate financial distress (the financial distress hypothesis) or improve the allocation of productive assets and hence, on average, induce managerial discipline (the discipline hypothesis). While the hypotheses are not mutually exclusive, we are interested in which of these effects, if any, dominates empirically.

A fundamental question is why credit ratings would cause additional distress over and beyond the distress caused by poor fundamentals. Several papers (see e.g., Bongaerts et al., 2012; Ellul et al., 2011; Kisgen and Strahan, 2009) empirically show that ratings, through regulatory importance, influence yield spreads. Opp et al., (2013) show this in a theoretical model. Given the regulatory effect of ratings, there may be a feedback loop where rating downgrades negatively affect an issuer's fundamentals, which in turn trigger further downgrades (Manso, 2013). Moreover, when CRAs employ sovereign ceilings, a sovereign downgrade can trigger downgrades of corporates and financials domiciled in that country, hence triggering contagion of financial distress mechanically (Almeida et al., 2014).

The literature has also proposed and identified positive effects associated with credit rating downgrades. For example, Boot, et al., (2006) show theoretically that ratings can act as coordination mechanisms and that being placed on a negative watch list by the CRA serves as an implicit monitoring contract. Bannier, et al., (2012) find that corporations reduce their investment levels significantly after credit rating downgrades and vice versa after upgrades, while Kisgen (2006, 2009) finds that ratings factor into the decision to get further away from financial distress.[9] While these findings indeed could be interpreted as in line with a disciplining effect of credit rating changes, the results may also indicate rational firm responses to a change in financial distress as induced by a credit rating change.

The analyses that follow are based on tests that would allow us to delineate between the two hypotheses by testing their respective empirical predictions. Specifically, our empirics focus on four types of tests. We first analyze whether the likelihood of an asset sale is affected by a credit rating downgrade. This duration analysis is motivated by various distress and discipline arguments made in the literature. For example, Lang, Stulz, and Poulsen (1996) show that asset sales are an important source of financing when firms are otherwise financially constrained. Similarly, Officer (2007) finds that firms who announce asset sales have lower ex-ante bond ratings and are more financially distressed compared to firms that do not. To the extent that credit rating downgrades exacerbate financial distress, they would be expected to lead to more asset sales. Boot (1992), in contrast, argues that misaligned incentives between managers and shareholders with respect to the firm's assets in place result in managers rationally holding on to incompatible assets for too long. To the extent that credit rating downgrades result in increased managerial discipline (i.e., better aligned with shareholders' interests) they would also be expected to lead to more asset sales. Several papers provide support for this view and show an increased likelihood

[9] Similarly, de Jong, Verbeek, and Verwijmeren (2012) find that firms with less financial flexibility, measured as the difference between the maximum leverage without losing its investment grade rating and the firm's actual leverage, invest less than firms with more financial flexibility.

of divestitures after hostile takeovers and management turnover (e.g., Bhide, 1989; Ravenscraft and Scherer, 1989; Bhagat, Shleifer, and Vishny, 1990).

For our duration analysis, we specify a Cox proportional hazard model for the whole universe of U.S. corporates to estimate the hazard rate of an asset sale event as a function of covariates (Cox, 1972, 1975). The Cox proportional hazard rate model has the advantage that one can separate out the effect of covariates (by using a partial likelihood function) from the effect of the time span in which no event has taken place (i.e., the baseline hazard rate). Our spells in which subjects are at risk start at the first observation, or in case of multiple events per subject the month after the previous event. To avoid any truncation biases, we correct for right censoring.

To identify the effect of rating downgrades as cleanly as possible, we control for a variety of confounding effects. Of particular importance is the credit risk profile of the corporate because credit risk may also have a disciplining effect, while we are interested in the marginal disciplining effect as caused by the credit rating change. We include measures of 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 predict that if rating downgrades cause or amplify distress we would see more asset sales following rating downgrades. However, to the extent that asset sales following credit rating downgrades are motivated by improved discipline causing firms to sell off unproductive assets, we would also expect to see more asset sales following credit rating downgrades.

Our goal is to better understand whether asset sales following a credit rating downgrade are more likely to be explained by distress versus discipline motivations. A direct way of addressing this question comes from the information firms provide when they announce an asset sale. For example, firms typically provide information with respect to the purpose of an asset sale. We collect this data from SDC and sort the sample based on the purpose of the asset sale reported by the company filings. We label the purpose of an asset sale as distress if the proceeds are used to pay down existing outstanding debt [DBT] or by raising cash through the sale of assets [CSH], as disciplinary if the sale is motivated by concentrating on core business or assets [COR] or involves the sale of a loss making or bankrupt operation [SEL], or ambiguous if either no purpose, both distress and disciplinary purposes, or other ambiguous purposes are reported in SDC. Out of 4,690 assets sales, we label 255 deals as distress motivated, 420 deals as disciplinary, and the rest as ambiguous. This information we then incorporate in our duration models. The distress hypothesis predicts a positive significant coefficient on the credit rating downgrade dummy for asset sales where the purpose is labeled as distress, and a zero coefficient for asset sales motivated by discipline. The discipline hypothesis makes the opposite prediction.

Shleifer and Vishny (1992), propose that an asset sale becomes a relatively less attractive way in which a firm would respond to an increase in financial distress when assets are illiquid, compared, for example, to a debt rescheduling or the issue of new securities. In contrast, the attractiveness of conducting an asset sale when motivated by increased managerial discipline would be less subject to asset liquidity, as the liquidity of the assets is less pertinent to the firm. We use the asset redeployability measure from Kim and Kung (2016) as a proxy for liquidity.[10] Their measure is 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 (Kyle, 1985, Glosten and Milgrom 1985), search costs (Duffie, Garleanu and Pedersen, 2005), and funding liquidity shocks (Brunnermeier and Pedersen, 2009) as key drivers for liquidity in securities markets. Specifically, we use the baseline measure of Kim and Kung (2016) that uses the market capitalization of firms in a given

[10] An advantage of this measure is that it captures both asset specificity and liquidity, but is not based on transactions. Given that our dependent variable is transaction based, 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, Stulz, and Walkling (2002).

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. While this measure has less cross-sectional variation, we believe this result is important because it corroborates the hypothesis that the extent to which credit rating downgrades exacerbate financial distress should be more pronounced during periods of industry distress. We report the results of our main analyses using the within and across industry measure of asset redeployability in Tables A1 to A3 of the Appendix.

Next, we sort the sample in deciles of asset redeployability and run the Cox regressions separately for each decile sub-sample. When asset redeployability is particularly low, we predict that asset sales become relatively more expensive vis-à-vis alternatives for dealing with financial distress, such as debt renegotiation or issuance of new securities (Shleifer and Vishny, 1992). Consequently, the distress hypothesis predicts significant coefficients on the credit rating downgrade indicator variable for sub-samples with high asset redeployability, but not for low asset redeployability where assets are too illiquid for asset sales to be the optimal response to the increase in financial distress as caused by the downgrade. The discipline hypothesis, in contrast, makes no specific predictions with respect to asset redeployability as the primary objective of the asset sale would not be to raise cash in this context.

Second, we conduct an event study analysis. The purpose of this analysis is to test whether shareholder reactions to the announcement of an asset sale following a credit rating downgrade are, on average, consistent with the predictions from the distress or discipline hypotheses. For each asset sale we identify the target's immediate or ultimate parent and label the announcement date as the event date. We shift this date forward if the announcement date is a weekend day or public holiday. To delineate a financial distress effect from a potential disciplining effect, we focus on the diverging predictions with respect to the sign and significance of the coefficients on the credit rating downgrade indicator variable and its interactions of this indicator variable with other covariates, such as asset redeployability. We estimate OLS regressions where, respectively, the seller, buyer, and combined CAR are the dependent variables and our covariates include different variables measuring the recent occurrence of rating up- and downgrades. In each model, we control for a host of credit risk proxies to better capture the marginal impact of the credit rating downgrade.

The distress hypothesis is ambiguous in terms of its predictions regarding the seller CAR. We expect to see more negative announcement returns for firms with lower credit ratings or credit ratings close to important (regulatory) boundaries as those are more likely to conduct fire-sales. On the other hand, an asset sale in this context may also relief financial distress and be viewed positively by the market, especially if fire-sale discounts turn out to be (unexpectedly) low. To better understand the role of the credit rating downgrade in explaining seller CAR, we separately consider sellers with a credit rating around the Investment Grade – High Yield boundary (IG-HY) and sellers with high versus low asset redeployability. We predict a lower or negative CAR for sellers with a credit rating around the IG-HY boundary and for sellers with low asset redeployability. The discipline hypothesis, predicts a significant and positive coefficient on the credit rating downgrade indicator variable, as we expect a higher CAR if a credit rating downgrade results in selling of assets to improve the firm's overall efficiency.

We also consider the degree of asset redeployability in our event study. Insofar as asset sales after a credit rating downgrade are driven more by financial distress and resemble fire sales, we expect that the cost of conducting an asset sale decreases in asset redeployability (Shleifer and Vishny, 1992). The financial distress hypothesis predicts a stronger positive relation between asset redeployability and seller CAR after an asset sale following a credit rating downgrade than for asset sales not following a credit rating downgrade. Alternatively, if asset sales, on average, are motivated by managerial discipline aiming to improve the allocation of assets to their most efficient users, we expect there to be no, or at least a less pronounced relation between asset redeployability and the cost of conducting an asset sale. The discipline hypothesis makes no prediction with respect to the relation between asset redeployability and seller CAR regardless of whether the asset sale follows a credit rating downgrade or not.

With respect to the buyer CAR, the distress hypothesis predicts a positive coefficient on the indicator variable for a credit rating downgrade. Distress-induced asset sales, to the extent that they involve selling assets at fire-sale prices, are expected to benefit the buyer, especially in the presence of cash-in-the-market pricing (Meier and Servaes, 2015). In contrast, the discipline hypothesis makes no specific prediction with respect to the buyer CAR.

Our final event study analysis focuses on the combined seller and buyer returns, defined as the value-weighted average of the seller and buyer CAR, which allows us to focus on welfare implications. Negative combined returns indicate sales to less efficient users, whereas positive combined returns indicate either the sale to more efficient users or relief of financial distress.

We next develop a set of predictions derived from the distress and discipline hypotheses with respect to the assets selected in an asset sale following a credit rating downgrade. This segment-level analysis and its corresponding predictions are motivated by financial distress and discipline arguments proposed in the literature. In general, insofar as credit rating downgrades exacerbate financial distress (the distress hypothesis), we predict that firms are more likely to sell segments that are most liquid (i.e., have the highest asset redeployability) among their segments (e.g., Shleifer and Vishny, 1992; Schlingemann, Stulz, and Walkling, 2002). The distress hypothesis also predicts that firms should be more likely to sell segments in growth industries or segments that are most likely to affect collateral negatively. Similarly, segments that generate higher current cash flows should be less likely to be divested. Alternatively, the discipline hypothesis predicts that credit rating downgrades will improve the allocation of productive assets. To that end, firms would be expected to divest assets that underperform relative to their peers and thus appear to not be the most efficient user. Similarly, the discipline hypothesis predicts an increased likelihood for non-core segments to be divested, as their sale would be the least disruptive to the core business of the firm or otherwise hurting the firm's operating performance. Segments with high performance and the best growth opportunities would also be less likely to be sold if the asset sale following a credit rating downgrade is motivated by increased managerial discipline. Finally, asset redeployability would be expected to be a less important factor if assets sales are driven by improving allocative efficiency, unless the asset sale is motivated by the firm's lack of liquidity.

To test our predictions, we match each asset sale to a business segment using Compustat segment level data. For each asset sale we construct a dummy variable indicating whether the corresponding segment is core or non-core and dummy variables based on 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. For the segment performance measures we focus on 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). As before, we measure asset liquidity with the redeployability measure in Kim and Kung (2016) but now at the segment level, where we match their industry average redeployability measure to the primary segment SIC code. Similar to Shin and Stulz (1994) we estimate a segment level proxy for growth opportunities based on the median value of Tobin's Q of specialized firm in the industry (Shin and Stulz, 2001).

We estimate cross-sectional logit regressions with each of the dummy variables as the dependent variable based on both inter-firm and intra-firm comparisons. The main covariate of interest is the indicator variable equal to one if the firm experienced a recent credit rating downgrade. We include the same control variables used in the previous tests.[11]

The final channel we consider in delineating between the financial distress hypothesis and the discipline hypothesis considers whether the form of payment in the asset sale is affected by a credit rating downgrade. We predict that firms would prefer pure cash transactions if an asset sale is motivated by financial distress. Insofar credit rating downgrades lead to an increase in financial distress and trigger assets sales, we predict that these should be pure cash transactions. Insofar as asset sales following a credit rating downgrade are motivated by improving the firm's efficiency in asset allocation (discipline hypothesis), we would predict that if anything, there are benefits of (at least a partial) payment in acquirer stock. This way, the seller can also benefit from improvements in operational efficiency going forward and would be able to negotiate a lower information-asymmetry-induced discount (if any).

We include non-rated firms and asset sales by non-rated firms essentially as a control or benchmark sample. Any effect of ratings (having a rating at all or the particular rating) is controlled for by rating fixed effects. Moreover, these observations help us to estimate the effect of other covariates more precisely.

2. Data and Sample Design

The analyses described in the previous sections are conducted on three different samples. The most comprehensive sample 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. This sample

[11] 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.

allows us to test whether credit ratings and changes therein (i.e., upgrades and downgrades) affect the likelihood for asset sales to occur. To implement these tests, we collect accounting data from Compustat. In addition, we collect data on the top 5 executive shareholdings (in %) excluding options from ExecuComp, S&P long-term credit ratings from Compustat Ratings, Asset Redeployability data from Kim and Kung (2016), and use the CRSP database to collect data to construct the size-age (SA) index to proxy for financial constraints from Hadlock and Pierce (2010). [12] Our sample contains 832,281 firm-month observations, with 8,975 unique firms (i.e., with unique GVKEY identifiers in Compustat). Out of these, 3,240 firms (36.1%) have an S&P credit rating at any point of time in the sample period. Of the firms with a credit rating, 57.7% (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 three columns in Table 2 provide summary statistics for our full sample.

From the Securities Database Corporation Thomson Reuters (SDC) Special Mergers Sectors database we collect a comprehensive sample of corporate asset sales announced during the period 1990-2015. 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, spinoff, equity carve-out, subsidiary acquisitions, or divestiture according to SDC. We also include deals labeled by SDC as seeking buyer, but exclude stock swaps, poolings of interest, reverse take-overs and reverse Morris trusts. We remove observations if the percent of shares owned after the transaction is less than 95 or more than 100 percent, 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. For the main analyses, we also exclude spinoffs. However, 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

[12] We are grateful to Hyunseob Kim and Howard Kung for making these data available to us.

issuance of securities to outside investors or the sale of other assets for cash. We use this sample to conduct a placebo test since doing a spinoff is an alternative disciplinary-driven restructuring mechanism to asset sales, but typically does not involve a cash infusion for the firm. These criteria result in an initial sample of 4,777 assets sales observations, performed by 1,644 firms (i.e., with unique GVKEY identifiers in Compustat). 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. Similarly, we match each SDC deal number to the acquirer PERMNO and PERMCO identifiers. For each deal we collect the announcement date and effective date from SDC. Where necessary, we roll these dates forward by one or two days if they coincide with weekend days or public holidays. Finally, we merge in the deal numbers, deal characteristics, acquirer and target parent identifiers (PERMNO/PERMCO) into our sample of firm fundamentals.

For our event study analysis, we collect stock price data from CRSP and use Eventus and construct 3- and 5-day cumulative abnormal announcement returns (CAR) for the seller, the buyer, and seller and buyer combined around asset sale announcements. We follow standard event-study methodology and use the market-model specification with the CRSP value-weighted index as the market portfolio. The market model parameters are estimated over the window from 379 to 127 trading days prior to the announcement date. We merge these with the SDC deal characteristics and seller fundamentals. This yields 4,690 observations by 1,617 asset sellers (a seller may conduct multiple asset sales). Of these asset sales, 75.9% were conducted by a seller that has a credit rating, where 13.9% (4.9%) experienced a credit rating downgrade (upgrade) during the fiscal year prior to and not overlapping the announcement data of the asset sale. The summary statistics for our event-study sample are reported in columns 4 through 6 in Table 2. One feature of these summary statistics that stands out is that the average combined CAR is much smaller than either the average seller CAR or the average buyer CAR. Upon closer inspection, this is caused by the fact that high seller CARs are associated with small buyer CARs and that the relative size of the buyers in these cases is high. Similarly, low seller CARs are associated with high buyer CARs and the relative size of the buyers in these cases is small. Consistently, the standard deviation of combined CARs is much smaller than the standard deviations of either seller or buyer CARs.[13]

Finally, we construct our third sample for our intra- and inter-firm segment-level analyses. We match each asset sale conducted 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, as 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 gives us 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. The remaining observations are matched manually, where we compare the deal synopsis, as reported in SDC, with the 10-K filings in EDGAR. This procedure produces another 1,009 matches.[14]

We are able to match the event, as reported in SDC, with a specific segment for 1,716 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 (CAPXS), 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 are the data fields with the best coverage at the segment level. We then construct for each segment the following performance measures: operating profitability

[13] While surprising at first glance, one can work out a simple numerical example to show that this is possible. Consider a sample of two deals. One deal has a seller CAR of 5% with a seller size of 1000 and a buyer CAR of 10% and a buyer size of 10. The other one has a seller CAR of 10% and a buyer CAR of 5% where seller and buyer both have size 100. The average buyer and seller CARs are 7.5%, but the average combined CAR is 6.27%.

[14] EDGAR only provides filings that are filed from 1994 onwards, and hence, we lose some observations in the beginning of our sample.

(OPS/IAS), profit margin (OPS/SALES), turnover (SALES/IAS), Cash Flow ratio ((OPS+DPS)/IAS), and Net Cash Flow ratio ((OPS+DPS-CAPXS)/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 also 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 three columns in Table 2 present the 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 (S&P credit rating). They are also larger, have more short-term debt (Rollover), more profitability and higher ROA, lower capital expenditures and investments in R&D, and a higher governance index (SA index).

3. Results

3.1. Credit rating changes as a determinant of asset sales

Our first test serves to validate our reliance on asset sales to study the effects of credit rating changes on corporate decision making. Specifically, we test whether credit ratings and credit rating downgrades are relevant and incremental determinants of assets sales beyond the commonly known determinants of asset sales, such as poor firm performance and leverage.

Table 3 presents the results of our duration analysis using the Cox proportional hazard model on the universe of US listed corporates. The dependent variable in each specification is occurrence of an asset sale in month t where the covariates are measured before month t – 1. 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, 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 credit risk and financial performance and 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 industry covariates. In each of the specifications 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 recent downgrade increases the hazard rate of an asset sale by about 47%.[15]

Interestingly, the coefficient estimates for many of the control variables are also consistent with a distress effect of credit risk. For example, higher leverage and more severe financial constraints trigger asset sales, while high profitability, a high Altman *z*-score and high cash holdings lower the incidence rate of asset sales. In model (6) we repeat the specification of model (5), but only include the first asset sale by a specific firm as the hazard rate structure may change after the first event. 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 (7) we address the issue that credit rating up- or downgrades constitute changes, whereas the covariates considered in specifications (1) to (6) relate to levels. Therefore, we also estimate a specification with changes of all our covariates. The results for the specification with all change variables are qualitatively unaffected when compared to the first six specifications in Table 3.

[15] This is calculated as $e^{0.386} - 1 = 0.47$ due to the proportional hazard assumption.

Overall, the results of the duration analysis reported in Table 3 are consistent with those reported in several studies in the literature that show that ratings affect strategic decisions at the corporate level over and above the effect of credit risk itself (e.g., Kisgen, 2006, 2009; Aktas et al., 2015).

To further distinguish the predictions from the discipline and distress hypotheses we use information on the purpose of our asset sale events to estimate purpose-specific hazard rates. There are two ways of doing this in a comprehensive way. First, we can assume that the occurrence of an asset sale event of any type does not affect the future occurrence of other asset sale events of any type. In this case, we can estimate purpose specific hazard rate functions where other types of events are simply assumed to be censored data points. The purpose specific hazard rate estimates according to this method are reported in Table 4 in specifications (1) to (3). The second way of doing this does take account of the fact that the occurrence of an asset sale could affect the hazard rate of any other type of event afterwards. To prevent any estimation bias, only the first asset sale that occurs is considered, as before in specification (6) of Table 3. Yet, a by-product is that events become mutually exclusive and that this mutual exclusivity should be incorporated explicitly. With the competing risk framework of Fine and Gray (1999) we can estimate purpose-specific sub-hazard functions while explicitly accounting for mutual exclusivity of events. The estimates according to this approach are reported in Table 4 specifications (4) to (6). For the model without mutual exclusivity, the coefficient on the credit rating downgrade is positive and significant in each hazard rate function. However, the coefficient for the distress hazard rate is twice as high as the coefficient for the discipline hazard rate. The coefficient for the hazard rate labeled as ambiguous, model (3), lies in between the coefficients reported for the pure distress and discipline hazard rates. Similar to the results without mutual exclusivity, the results from the competing risk model show that credit rating downgrades are particularly associated with an increased likelihood for asset sales motivated by financial distress, but not for asset sales motivated by managerial discipline.

Kisgen and Strahan (2010), show that the effect of credit ratings on the cost of capital is larger among bonds around the IG-HY boundary. Similarly, to the extent that our duration models indeed capture the effects of credit rating downgrades on the likelihood of an asset sale, we expect that these effects are stronger for rating downgrades around the IG-HY boundary. In order to test this prediction, we weigh the credit rating downgrade variable by the distance in (absolute) number of notches between the firm's rating and the IG-HY boundary. The results we show in Table A4 of the Appendix are consistent with this expectation. The coefficients on the downgrade indicator variable are consistently larger, by approximately ten percent, than those reported in Table 3.

Our next analysis with respect to the effect of a credit rating downgrade on the likelihood of an asset sale announcement and to what extent this effect can be attributed, on average, to increased financial distress or increased managerial discipline is provided in Figure 1. This figure 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 a decile of asset redeployability within the full sample. The impact of a credit rating downgrade on the likelihood of an asset sale announcement is gradually increasing across the asset redeployability deciles. When we compare the top and bottom deciles, the effect of a credit rating downgrade on the likelihood of announcing an asset sale is four times as high as the effect for the bottom decile. In an unreported specification using decile indicator variables, we find that the difference in the coefficient between the top and bottom decile is not only economically large, but also statistically significant with a *p*-value of 0.076. The results shown in Figure 1 are consistent with the predictions from the financial distress hypothesis, where firms use asset sales as a response to financial distress, but less so when asset redeployability is low and alternative ways to deal with financial distress become relatively more attractive (Shleifer and Vishny, 1992).

The financial distress hypothesis predicts that credit rating downgrades lead to more asset sales insofar as these transactions alleviate distress through the infusion of cash. In contrast, the discipline hypothesis predicts that credit rating downgrades lead to more asset sales insofar as these transactions improve the allocation of productive assets. As a placebo test, we conduct our duration analysis using a sample of 268 spinoffs collected from SDC. Spinoffs, like asset sales, are corporate divestiture events, but unlike asset sales, do typically not generate cash for the firm or for its shareholders.[16] We report the results for this analysis in Table A5 in the Appendix. We show that for each specification, the coefficient on the downgrade indicator variable is economically and statistically insignificant and of substantially smaller magnitude compared to the coefficients based on asset sales reported in Table 4. Consistent with the distress hypothesis, our analyses show that credit rating downgrades significantly increase the likelihood for cash generating asset sales, but do not affect the likelihood for spinoffs where there is no direct cash infusion.

3.2. Event study analysis

The duration results in the previous section show that credit rating changes are economically important determinants of asset sales, particularly for those that are most likely motivated by financial distress and generate cash. In this section, we investigate the valuation effects of credit rating changes in asset sales. We use standard event study methodology to measure these valuation effects and present the results separately from the perspective of the seller (target), the buyer (acquirer), and for combined returns. As before, we control for financial distress indicators and firm performance in our specifications using the same set of covariates as in the duration analysis. In addition, we control for a number of typical deal

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

characteristics, such as the relative size of the asset sale, the form of payment, and whether the divested assets are the in the same industry as the seller's (core assets), and include a variety of fixed effects.

The results of the event study analysis from the perspective of the target are presented in Table 5. We are primarily interested in learning whether we observe valuation effects consistent with the idea that corporations that experienced credit rating downgrades may be forced into more fire-sale type behavior (financial distress hypothesis) or sell non-core, non-productive, and loss-generating assets where the assets are being reallocated to a more efficient owner of such assets (discipline hypothesis). Model (1) presents the baseline regression, which shows that recent credit rating downgrades are associated with higher (more positive) 3-day CARs (around 83 basis points) around asset sale announcements. This effect could be interpreted as being consistent with both a financial distress inducing effect and a disciplining role of credit downgrades. For example, the positive valuation effect may come from reducing financial distress and increasing liquidity through the sale of productive assets at a substantial discount, or from selling non-productive and loss-generating assets to better users. We return to this issue in our segment-level analysis.

In Model (2) we add industry, time, and credit rating fixed effects, which increases the coefficient on the downgrade indicator variable to 87 basis points. Interestingly, the coefficients on the rating indicators show that the valuation effects for sellers close to the investment grade-high yield (BB and BBB) boundary (IG-HY) are significantly lower than for other sellers. This may point to an increased propensity of firms to sell productive assets in order to try to qualify for IG, which could be interpreted as additional evidence of a distress effect for at least a sub-set of firms close to the IG-HY boundary.

In Model (3) we add two indicator interaction variables based on whether the divested asset is in the same 2-digit SIC industry as the parent for a down or upgrade. In this specification, downgrades are associated with positive CARs when non-core assets are sold (125 basis points), but not when core assets are sold

(57 basis points, with a *p*-value of 0.250). This result is more in line with the discipline hypothesis where firms divest assets that can be deployed more efficiently within another firm. However, insofar as core assets provide better collateral or have a lower degree of asset redeployability, the result could be in line with the distress hypothesis as well. In Model (4) we add industry medians of firm-specific covariates already included to the specification (suppressed in the table) and continue to find similar results for the coefficient on the credit rating downgrade (93 basis points). In Model (5) we add an interaction between asset redeployability at the firm level and credit rating downgrade indicator variable. The results from this model suggest that asset redeployability plays a significant and positive role in explaining the valuation effects for asset sales following a credit rating downgrade, but not for other asset sales. The interaction variable itself, which captures the difference in coefficients between asset sales following a credit rating downgrade and those that do not, is also significant at the five percent level. We interpret this as evidence in line with the financial distress hypothesis, which predicts that asset sales become a more attractive mechanism for dealing with financial distress when asset redeployability is higher. Apparently, the positive effect of asset sales following a downgrade is concentrated in firms with liquid assets. Hence, it is likely that the main motivation for doing an asset sale is the opportunity to reduce financial distress at a low cost, rather than intrinsically improving operations or improving allocative efficiency by selling under-performing segments to better users.

Surprisingly, in each specification so far, we obtain a positive and mostly significant coefficient on the credit rating upgrade indicator variable as well. However, in Model (6), we substitute a 5-day measure of CAR instead for the 3-day measure and find that the coefficient on credit rating upgrades is economically much smaller, opposite in sign, and no longer significant. There appears to be no robust relation between credit rating upgrades and stock price reactions for asset sales. In contrast, the coefficient for credit rating downgrades for 5-day CAR remains significant and similar to the estimates based on the 3-day CAR. Finally, in Model (7) we repeat Model (5) with asset redeployability interacted with the credit rating downgrade indicator variable and find similar results irrespective of using the three- or five-day measure of abnormal announcement period returns.

The results of the event study analysis from the perspective of the acquirer are presented in Table 6. In Model (1) the coefficient on the credit rating downgrade indicator variable is positive and significant. The impact of a credit rating downgrade for the acquirer return is 125 basis points, which is economically a large number, given the that the size of the assets purchased relative to the size of the acquirer is on average six percent. In Model (2) we add fixed effects for the seller's credit rating and find that the impact of the credit rating downgrade on the acquirer CAR drops to 103 basis points, which is still economically large, but statistically insignificant. In model (3) and (4), we add, respectively, time and target and acquirer industry fixed effects to Model (1) and find that the impact of the credit rating downgrade on the acquirer CAR remains economically large and varies between being significant at the five percent level and just below the ten percent threshold. In model (5) we include time, industry, and credit rating fixed effects in the same model. The coefficient on the credit rating downgrade remains similar in magnitude, but is again just below the ten percent significance threshold with a *t*-statistic of 1.551. In Model (6) we assess the impact of asset redeployability of the seller and find no evidence that it affects the acquirer returns, irrespective of a recent credit rating downgrade. Finally, in Models (7) and (8) we repeat Models (5) and (6) where we substitute our five-day return measure for the three-day return measure. Even with all the fixed effects included, the impact of a credit rating downgrade on the acquirer returns is 175 basis points, which is significant at the five-percent level. Seller asset redeployability continues to be mostly irrelevant for the acquirer return in Model (8). Overall, the results are in line with the financial distress hypothesis and corroborate the results reported in Meier and Servaes (2015). Asset sales following a credit rating downgrade, on average, resemble fire sales, which are beneficial to the buyer of these assets when sold at fire-sale prices. This also suggests that the fire-sale prices paid reflect cash-in-the-market pricing over and above any effect of buyers being less efficient users than the sellers.

We present the results of the event study analysis for combined seller and buyer returns in Table 7. We follow the same specifications as those reported in Table 6 where the dependent variable is the buyer CAR, but only report a sub-set of the coefficients in the table for brevity. The results in Table 6 are generally in line with the results shown for seller and buyer CARs. Specifically, we find that the coefficients on the credit rating downgrade indicator variable are positive and range from 69 to 85 basis points. While they are economically non-trivial, they are not statistically significant, except for the coefficient reported in Model (2). In Models (5) and (7), we show that the positive welfare effects of asset sales are concentrated in firms with high asset redeployability. If rating downgrades induce discipline, reallocation of productive assets to better users should lead to aggregate welfare improvements irrespective of the level of asset redeployability. In contrast, if asset sales reduce distress and are mainly driven by minimization of transaction costs, firms will even sell to worse users if needs be. This will be reflected in negative combined CARs for low asset redeployability firms following downgrades and positive combined CARs for high asset redeployability firms following downgrades. Our results confirm this.

Taken together, the event-study analysis provides novel evidence of the role credit rating agencies, through rating changes, play in corporate asset sales, as manifested by the impact these rating changes have on seller, buyer, and combined abnormal announcement returns. In particular, the evidence on the interactions with asset redeployability suggests that rating downgrades exacerbate financial distress, which firms respond to through selling off assets at fire-sale prices. While it appears that asset sales are important as a channel through which firms can mitigate financial distress, we note that this channel would likely not be as available for firms with assets with low asset redeployability. Consequently, we are only able to identify the distress effects from credit rating downgrades for the least affected firms that have access to the asset sale channel. Any effects we cannot observe are likely to be much more severe as their hurdle for asset sales is higher. Being unable to relieve ratings-induced capital constraints through the sale of liquid assets, such firms would continue to incur financial distress costs or turn to more costly ways of resolving distress.

3.3. Segment-level analysis

In the previous sections we present evidence, which suggests that firms are more likely to announce an asset sale after a credit rating downgrade, particularly for asset sales where the purpose of the asset sales is to use the proceeds to pay down outstanding debt or to raise cash. We also present evidence of a marginal impact on announcement period returns for both the sellers and buyers based on a credit rating downgrade. We next explore how a credit rating downgrade impacts the choice of assets to be sold in an asset sale. To do so, 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. In Table 8 we report a marginal effects for logit regression models for each of five performance measures, where the dependent variable is an indicator variable equal to 1 if the performance measure is below the median of its industry peers, where the industry is defined as all firms, excluding the sample firm, in the same two-digit SIC code as the primary SIC code for the divested segment and zero otherwise. 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 would suggest that there is a higher likelihood that a segment with below-industry performance is divested following a downgrade. However, the results in Table 8 show that the marginal effects of the credit rating downgrade indicator variable are insignificant for each of the five performance measures and even have the opposite sign for Profitability and the Profit Margin. Interestingly, the marginal effects for a credit rating upgrade are mostly negative and significant, which may be interpreted as 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 8 do not support the discipline hypothesis.

The financial distress hypothesis is more ambiguous in terms of a predicted sign on the credit rating downgrade indicator variable in the inter-firm analysis. Firms in financial distress 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.

In Table 9 we present the intra-firm analysis based on logit regressions. For each 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 the predictions of Shleifer and Vishny (1992) that firms in financial distress would be more likely to sell off segments that are valuable, but do not contribute to current cash flow generation so that debt relief and servicing near-term debt obligations are uninhibited. In Model (1) we find that, controlling for the average firm-level asset redeployability, segments with relatively high asset redeployability are significantly more likely to be divested following a credit rating downgrade. High asset redeployability is measured as an indicator variable equal to one if the divested segment's asset redeployability is above the median across the asset redeployability of all of the firms segments in the same year and zero otherwise. In Models (2) we use an indicator variable equal to one if the Operating Cash Flow of the divested segment is above the median among all of the firm's segments. The coefficient on the credit rating downgrade indicator variable is negative and significant, which is consistent with the predictions of Shleifer and Vishny (1992) that firms under distress are less likely to divest assets that contribute the most to current cash flow generation. In Model (3), we find that firms are significantly more likely to sell segments with the highest growth opportunities among all its segments. This result is consistent with the predictions of Shleifer and Vishny (1992) regarding firms asset sales decisions motivated by financial distress. Firms with high growth opportunities typically require substantial investments in intangible assets that do provide little to no collateral and do not contribute to current cash flow generation. Moreover, high growth opportunity segments are likely to be more easily converted to cash and are therefore prime candidates to be divested in case of distress. The result from Model (3) is inconsistent with the predictions from the discipline hypothesis insofar as high growth segments should be cherished, while low growth opportunity segments should be sold 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 credit rating downgrade indicator variable is insignificant when we use the above-median Q instead (unreported). The results for Models (1) through (3) are supportive of the financial distress hypothesis and are consistent with the idea that if asset sales following a credit rating downgrade are motivated by increased financial distress, firms prefer to sell assets that are most liquid to avoid deep discounts, do not generate current cash flows, have high growth opportunities and require substantial investments in intangible assets and replacement investment.

In Model (4) we test another prediction of the discipline hypothesis with respect to the choice of a segment being divested. If credit rating downgrades motivate firms to conduct asset to achieve a more efficient allocation of their assets, we would expect to observe an increased likelihood for non-core segments to be divested. We define a segment as a non-core segment based on whether 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 finer measure of a core versus non-core segment, where we define a core segment based on 3- and 4-digit SIC matching. These finer level definitions of core segments do not alter our conclusion from Model (4) that a credit rating downgrade does not appear to affect the decision to sell a core or non-core segment. In Models (5) through (7) we test whether the segment with below-median performance based on Profitability, Profit Margin, Asset Turnover are more likely to be divested in an asset sale following a credit rating downgrade. Similar to the results from the inter-firm segment analysis, we cannot reject the null hypothesis that in either of these models the coefficient on the credit rating downgrade indicator is equal to zero. Taken together, we interpret the results in Models (5) through (7) as unsupportive of the discipline hypothesis.[17]

3.4. Alternative mechanisms and robustness

In this section, we provide corollary evidence consistent with the argument that credit rating downgrades exacerbate financial distress and asset sales represent a response to this. We argue that insofar as these asset sales are motivated by financial distress, firms would prefer cash transactions. Insofar as asset sales following a credit rating downgrade are motivated by improving the firm's efficiency in asset allocation (discipline hypothesis), we would predict there is no preference in the form of payment. In fact, the seller can also benefit from improvements in operational efficiency and would need to accept a lower information-asymmetry-induced discount if at least part of the payment was done in acquirer stock. Similarly, one can think of other mechanisms, besides the distress and discipline channels, where a credit rating downgrade may lead to an asset sale. For example, a downgrade may provide useful information with respect to worsening growth prospects for the firm. However, a unique aspect of the distress channel, relative to the discipline or other channels is the importance of raising cash through the transaction. We already confirm there is no increased likelihood of conducting a non-cash generating spinoff after a credit rating downgrade, which supports the distress hypothesis. In addition, we test the prediction that within the sample of asset sales there is a preference for cash transactions. In Table 10, we estimate logit regression specifications where the dependent variable is equal to one if the form of

[17] We recognize that failing to reject the null hypothesis of a zero coefficient on the credit rating downgrade indicator variable may be because of a lack of power of the test and/or an attenuation bias in the presence of measurement error and/or multicollinearity.

payment is pure cash and zero otherwise. Model (1) shows that the coefficient on the credit rating downgrade indicator variable is positive, but insignificant. The *t*-statistic of 1.601 shows that the coefficient is close to a ten-percent significance level, but given the relatively low use of equity as a form of payment in asset sales, there is likely lack of power in this specification.[18] In Model (2), we add two binary indicator variables for whether the purpose of the deal using the SDC classifications is Discipline or Ambiguous. The coefficient on the credit rating downgrade indicator variable remains similar to the coefficient reported in Model (1). However, consistent with the idea that raising cash is most important for deals where the purpose of the asset sales is to relieve financial distress, we find that the coefficients on the indicator variables for Discipline and Ambiguous are negative and significant, suggesting more acceptance of alternative forms of payment beyond pure cash.

We also consider the possibility that historical acquisition activity may explain some of the observed patterns.[19] 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. Similarly, acquisitions may trigger credit rating downgrades, especially if they are associated with cash payments, significant increases in debt, or otherwise outcomes that deteriorate the growth prospects of the firm. In this sense, asset sales may simply be a disciplinary or distress-induced response to acquisitions, rather than caused by credit rating downgrades per se. In order to address these alternative mechanisms, we collect all majority acquisitions from the SDC universe 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 for firm i from month $t - 24$ to $t - 6$ to the most recent book value of assets prior to month t (*Acquisition spending*). We

[18] In contrast to merger and acquisition samples where approximately 40% of deals are pure cash deals (e.g., Moeller, Schlingemann, and Stulz, 2004), in our sample of asset sales, approximately 84% of deals are pure cash deals.
[19] We thank Jean Helwege for this suggestion.

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 book value of assets prior to month *t* (*Cash* (*Equity*) *acquisition spending*). When we include various combinations of these variables in our duration analyses, we find that the coefficients on *Acquisition* and *Acquisition spending* are both positive and significant. The coefficients on *Cash acquisition spending* and *Equity acquisition spending*, controlling for whether there is acquisition activity are also positive and significant in separate regressions. When we include both the cash and equity variables in the same specification, 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=0.093). Hence, acquisition activity helps explain the likelihood for asset sales to occur in an economically and statistically significant manner, irrespective of the financing method, but does not change our conclusions with respect to credit rating downgrades. We also run a sub-sample analysis where we split the sample into observation with no prior acquisition activity (*Acquisition spending* = 0) and with prior acquisition activity (*Acquisition spending* > 0). Regardless of prior acquisition activity, we find that the coefficient on the credit rating downgrade indicator variable remains positive and significant. To conserve space, we report these results in Table A6 in the Appendix.

4. Conclusion

In this paper we provide evidence on the relative contribution of credit rating downgrades on financial distress and managerial discipline. We propose that asset sales provide a unique background to test whether credit rating downgrades, at the margin, exacerbate the effects of financial distress (distress hypothesis) or result in more efficient allocation decisions within a firm (the discipline hypothesis). The ongoing debate on the role credit rating agencies play in the real economy motivates our research.

We test our hypotheses along three dimensions and conclude the following. First, we show that firms are more likely to conduct asset sales following a credit rating downgrade, particularly so if firms indicate the purpose is to use the proceeds to pay down outstanding debt or to raise cash. We find a smaller or no effect if the sale is motivated by concentrating on core assets or involves the sale of a loss making or bankrupt operation. Second, we show that asset sales are an important channel through which credit rating downgrades affect seller and acquirer shareholder wealth and have welfare implications. Specifically, we show that shareholder perceive asset sale following a credit rating downgrade as a successful mechanism by the seller to mitigate financial distress caused by the downgrade. We also show that buyers benefit from fire-sale prices and from selling assets with greater asset redeployability. We also find evidence that credit rating downgrades affect which assets the firm choses to sell. Asset sales following a downgrade are more likely to involve segments that are the most liquid (highest asset redeployability), generate the least current cash flows, and have the highest growth opportunities. Peer-based performance, intra-firm performance, or relatedness to core activities, do not explain which segments are divested. Consistent with the distress hypothesis, we find that receiving all cash in an asset sale is most important for deals where the purpose of the asset sales is given by the firm as to relieve financial distress. For asset sales where the stated purpose is more in line with discipline or ambiguous, we find a higher willingness to accept alternative forms of payment.

Taken together, our results suggest that firms respond to credit rating downgrades through asset sales in ways that are consistent with mitigating financial distress. At the margin, we show that downgrades exacerbate financial distress in lieu of enhancing managerial discipline or allocative efficiency. Our results offer new perspectives on recently proposed regulatory changes regarding sovereign ratings in the aftermath of the European sovereign debt crisis. Our findings may have additional policy implications with respect to the role of credit rating agencies in the real economy as our results expose new channels through which CRAs affect corporate decision making consistent with the distress amplifying argument.

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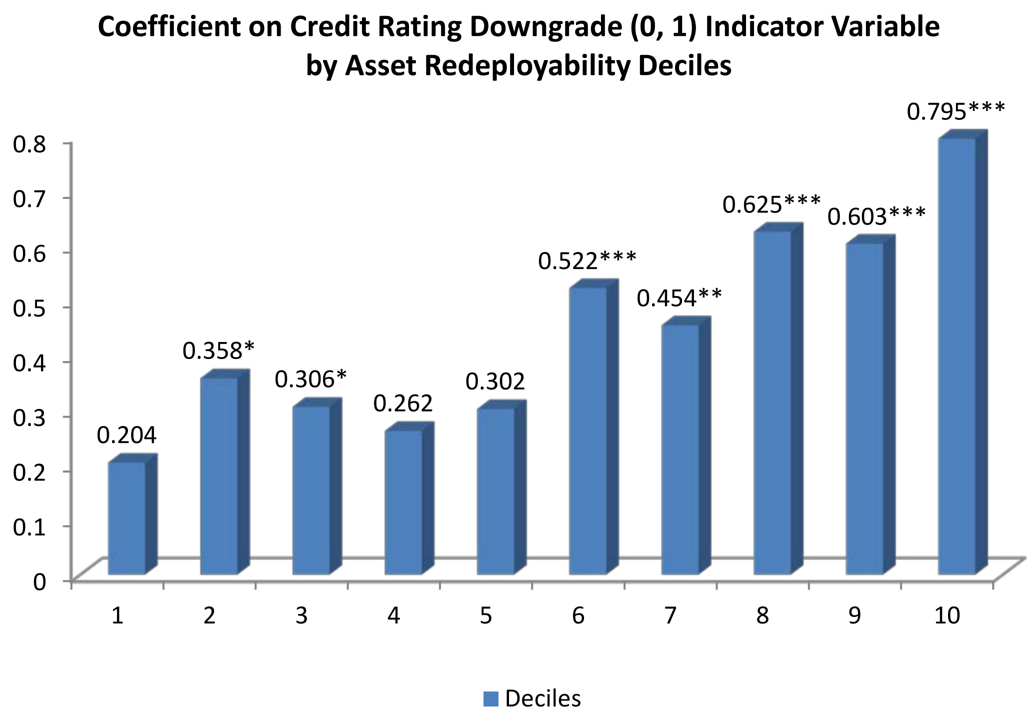

Figure 1: Each bar shows the magnitude and statistical significance of the coefficient on the Credit rating downgrade (0, 1) indicator variable based on Model (2) from Table 2 for each sub-sample based on deciles of asset redeployability. Statistical significance of each coefficient is indicated with ***, **, and * to denote significance at the 1%, 5%, and 10% level.

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
Segment net cash flow	Segment operating profit 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 (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 assets
Rollover	Short-term debt over total assets
Tangibility	PPE over total assets
Altman Z-score	Altman's Z-score
Tobin's Q	(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	CAPEX 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)
CAR(-1,+1)	3-day seller CAR
CAR(-2,+2)	5-day seller CAR
ACAR(-1,+1)	3-day acquirer CAR
ACAR(-2,+2)	5-day acquirer CAR
SCAR(-1,+1)	3-day value-weighted combined seller and acquirer CAR
SCAR(-2,+2)	5-day value-weighted combined seller and acquirer CAR
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 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 sale sample				Segment sample			
	n	mean	sd	Median	*n*	mean	sd	Median	*n*	mean	sd	Median
Segment profitability	-	-	-	-	-	-	-	-	1,290	0.1103	0.2133	0.0958
Segment asset turnover	-	-	-	-	-	-	-	-	1,577	1.2142	1.2845	0.9766
Segment profit margin	-	-	-	-	-	-	-	-	1,392	0.0615	1.8239	0.1095
Segment operating cash flow	-	-	-	-	-	-	-	-	1,229	0.1632	0.2177	0.1431
Segment net cash flow	-	-	-	-	-	-	-	-	1,163	0.1018	0.2174	0.0898
Segment CapEx over assets	-	-	-	-	-	-	-	-	1,450	0.0658	0.0742	0.0441
Segment CapEx over sales	-	-	-	-	-	-	-	-	1,512	0.1600	0.5371	0.0425
Rating downgrade (0, 1)	832,281	0.0471	0.2119	-	4,690	0.1390	0.3460	-	1,716	0.1573	0.3642	-
Rating upgrade (0, 1)	832,281	0.0382	0.1917	-	4,690	0.0486	0.2151	-	1,716	0.0478	0.2134	-
S&P credit rating	319,436	12.5549	3.6187	12.000	3,562	14.0410	4.1695	14.0000	1,476	14.8713	4.0228	15
Assets - Total (1990 $ billion)	832,281	5.6922	26.9024	0.7306	4,690	37.0229	11.5059	4.2306	1,716	56.9602	14.209	9.310
Cash holdings	822,457	0.0940	0.1072	0.052	4,546	0.0617	0.0714	0.0358	1,653	0.0575	0.0621	0.0373
Interest coverage	693,476	21.0372	35.7024	6.960	4,544	12.0980	21.7288	5.4858	1,686	13.071	21.524	6.363
Leverage	828,730	0.2433	0.1940	0.221	4,680	0.3170	0.1791	0.3009	1,714	0.313	0.169	0.292
Rollover	830,882	0.0386	0.0582	0.014	4,685	0.0494	0.0666	0.0209	1,716	0.054	0.068	0.026
Tangibility	831,194	0.2872	0.2373	0.222	4,688	0.3357	0.2327	0.2787	1,716	0.323	0.220	0.270
Altman Z-score	686,243	3.8350	3.5626	3.001	4,176	2.6583	2.3629	2.3564	1,501	2.711	2.043	2.471
Tobin's Q	732,966	1.774	1.0194	1.4321	4,690	1.6138	0.7839	1.3724	1,645	1.6317	0.742	1.3953
Profitability	832,281	0.077	0.1137	0.0789	4,590	0.0759	0.0929	0.0754	1,715	0.0886	0.082	0.0836
ROA	832,281	0.026	0.1166	0.0375	4,592	0.0157	0.1072	0.0306	1,715	0.0345	0.087	0.0386
Operating cash flow	713,504	0.075	0.1021	0.0813	4,419	0.0688	0.0775	0.0691	1,675	0.0710	0.065	0.0699
CAPEX/assets	758,702	0.070	0.0655	0.0479	4,507	0.0695	0.0638	0.0473	1,698	0.0627	0.055	0.0447

Table 2: Summary statistics - *continued*

	Full sample				Asset sale sample				Segment sample			
	n	mean	sd	Median	*n*	mean	sd	Median	*n*	mean	sd	Median
PPE growth	828,937	0.142	0.3350	0.0525	4,584	0.0776	0.2927	0.0223	1,713	0.0705	0.269	0.0254
Sales growth	827,330	0.137	0.2738	0.0839	4,588	0.0834	0.2540	0.0467	1,715	0.0726	0.220	0.0484
R&D/assets	432,462	0.059	0.0842	0.0244	2,776	0.0390	0.0579	0.0175	1,134	0.0317	0.044	0.0147
Number of segments	760,318	2.171	1.5333	2.0000	4,555	3.1155	1.9738	3.0000	1,716	3.9545	1.858	4.0000
Stock ownership	246,794	4.656	7.0397	1.3155	1,613	2.9420	5.4599	0.6890	632	2.7823	5.514	0.4595
SA index	832,281	-3.702	0.6335	-3.5920	4,690	-3.9430	0.6392	-3.9969	1,716	-4.1333	0.592	-4.4899
Deal Value (1990 $ million)	-	-	-	-	4,690	298.13	756.66	90.000	1,716	552.95	1018	215.99
Relative Size	-	-	-	-	4,690	0.0602	0.1149	0.0182	1,645	0.0695	0.127	0.0206
All Cash (0, 1)	-	-	-	-	4,690	0.8382	0.3683	-	1,716	0.8421	0.365	-
All Stock (0, 1)	-	-	-	-	4,690	0.0117	0.1077	-	1,716	0.0076	0.087	-
Same 2-digit SIC (0, 1)	-	-	-	-	4,690	0.4962	0.5000	-	1,716	0.6177	0.4860872	-
CAR (-1, +1)	-	-	-	-	4,690	0.0133	0.0628	0.0037	-	-	-	-
CAR (-2, +2)	-	-	-	-	4,668	0.0144	0.0718	0.0045	-	-	-	-
ACAR (-1, +1)	-	-	-	-	1,405	0.0189	0.0655	0.0075	-	-	-	-
ACAR (-2, +2)	-	-	-	-	1,404	0.0211	0.0738	0.0103	-	-	-	-
SCAR (-1, +1)	-	-	-	-	1,405	0.0059	0.0382	0.0033	-	-	-	-
SCAR (-2, +2)	-	-	-	-	1,400	0.0070	0.0429	0.0041	-	-	-	-

Table 3: Cox hazard regressions

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. 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)
Rating downgrade (0, 1)	0.639***	0.419***	0.373***	0.431***	0.386***	0.447***	0.495***
	[10.72]	[6.53]	[5.91]	[6.76]	[6.18]	[4.46]	[7.69]
Rating upgrade (0, 1)	-0.278***	-0.217***	-0.233***	-0.201**	-0.190**	0.0376	-0.215**
	[-3.33]	[-2.60]	[-2.77]	[-2.44]	[-2.28]	[0.27]	[-2.57]
Rated (0, 1)	0.0288	-0.122	0.217	-0.0648	0.311*	0.258	0.462***
	[0.11]	[-0.71]	[1.25]	[-0.39]	[1.88]	[1.37]	[2.85]
S&P credit rating	0.107***	0.0585***	0.0159	0.0521***	0.00668	0.00619	0.0413***
	[5.44]	[4.36]	[1.16]	[3.96]	[0.51]	[0.40]	[3.38]
Altman Z-score		-0.0639***	-0.0932***	-0.0405**	-0.0642***	-0.0361*	0.00777
		[-3.22]	[-4.49]	[-2.02]	[-3.03]	[-1.69]	[0.43]
Leverage		-0.104	-0.0276	-0.132	0.0597	0.457*	0.939***
		[-0.46]	[-0.12]	[-0.59]	[0.27]	[1.86]	[3.36]
Ln(Assets)		0.311***	0.386***	0.306***	0.387***	0.164***	0.124
		[11.21]	[13.71]	[10.12]	[12.95]	[5.13]	[0.64]
Redeployability		-1.344***	-1.684***	-0.850*	-1.249***	-1.416***	
		[-3.57]	[-4.58]	[-1.77]	[-2.61]	[-2.82]	
Cash holdings		-2.933***	-2.273***	-2.481***	-1.762***	-1.964***	0.197
		[-7.25]	[-5.62]	[-6.35]	[-4.67]	[-4.61]	[0.59]
Interest coverage		-0.00346**	-0.00111	0.00395**	-0.00113	-0.000454	0.000911
		[-2.29]	[-0.79]	[-2.76]	[-0.86]	[-0.31]	[0.92]
Rollover		-0.642	-1.045*	-0.137	-0.591	-0.953	0.385
		[-1.17]	[-1.86]	[-0.25]	[-1.08]	[-1.64]	[0.88]
Tangibility		-0.732***	-0.858***	-0.686***	-0.975***	-0.833***	-1.020**
		[-3.53]	[-4.01]	[-3.28]	[-4.43]	[-3.77]	[-2.02]
Tobin's Q		0.0573	0.131***	0.00742	0.0450	-0.0841*	-0.0895*
		[1.25]	[2.78]	[0.16]	[0.95]	[-1.67]	[-1.80]
Profitability		1.048*	0.355	1.116**	0.137	-0.913	-0.437
		[1.94]	[0.62]	[2.10]	[0.25]	[-1.41]	[-0.85]

Table 3: Cox hazard regressions – *continued*

	Levels					1st Event	Changes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ROA		-1.659***	-1.542***	-1.889***	-1.773***	-1.592***	-0.354
		[-5.02]	[-4.62]	[-5.95]	[-5.46]	[-3.83]	[-1.12]
Operating cash flow		-0.598	-0.320	-0.530	0.0670	1.068*	-0.0765
		[-1.21]	[-0.61]	[-1.14]	[0.14]	[1.95]	[-0.17]
CAPEX/assets		3.151***	2.791***	2.652***	1.628***	0.394	-0.263
		[5.27]	[4.56]	[4.39]	[2.63]	[0.57]	[-0.56]
PPE growth		-0.537***	-0.481***	-0.483***	-0.417***	-0.221*	-0.253*
		[-4.61]	[-4.13]	[-4.26]	[-3.82]	[-1.79]	[-1.66]
Sales growth		-0.356***	-0.425***	-0.385***	-0.492***	-0.369***	-0.394***
		[-2.91]	[-3.26]	[-3.34]	[-4.00]	[-2.58]	[-2.64]
R&D/assets		0.500	-0.0886	0.161	-0.462	-0.358	-0.387
		[0.83]	[-0.14]	[0.28]	[-0.79]	[-0.62]	[-0.53]
R&D missing (0, 1)		-0.0305	-0.0345	0.0749	0.0515	0.105	-0.0331
		[-0.46]	[-0.53]	[0.98]	[0.69]	[1.41]	[-0.43]
Number of segments		0.105***	0.111***	0.108***	0.107***	0.101***	0.148***
		[5.97]	[6.25]	[6.18]	[6.09]	[4.90]	[8.27]
SA index		0.280***	0.412***	0.236***	0.383***	0.512***	1.957***
		[4.10]	[6.70]	[3.50]	[6.49]	[8.40]	[2.67]
Stock ownership		-0.0173**	-0.0256***	-0.0156**	-0.0245***	-0.0244***	-0.00851
		[-2.00]	[-2.90]	[-2.12]	[-3.26]	[-2.71]	[-0.61]
Stock ownership missing (0, 1)		-0.221***	-0.238***	-0.221***	-0.227***	-0.337***	-0.0663
		[-3.83]	[-4.04]	[-3.83]	[-3.89]	[-4.26]	[-1.02]
Industry fixed effects	No	No	No	Yes	Yes	Yes	No
Time fixed effects	No	No	Yes	No	Yes	Yes	Yes
Industry covariates	No	No	No	No	Yes	Yes	No
Number of observations	832,213	584,773	584,773	583,785	576,124	444569	518,257
Pseudo R^2	0.038	0.058	0.075	0.066	0.086	0.065	0.069
Number of clusters	8,975	6,402	6,402	6,397	6,361	6221	5,654

Table 4: Cox hazard regressions by purpose

The coefficients in the table represent hazard rate estimates of an asset sales event by self-reported purposes: Distress, 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). 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. Industry covariates are the industry medians of the same firm covariates we report; these are suppressed (when included) for brevity. 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		
	Distress	Disicpline	Ambiguous	Distress	Disicpline	Ambiguous
	(1)	(2)	(3)	(4)	(5)	(6)
Rating downgrade (0, 1)	0.590***	0.419**	0.389***	1.058***	-0.0833	0.470***
	[3.12]	[2.39]	[5.57]	[2.67]	[-0.23]	[4.37]
Rating upgrade (0, 1)	-0.293	-0.664**	-0.191**	0.812	-1.025	0.0383
	[-0.89]	[-2.37]	[-2.19]	[1.46]	[-1.42]	[0.26]
Rated (0, 1)	0.757*	0.547	-0.237	1.031	1.374**	-0.291
	[1.66]	[1.51]	[-1.32]	[1.22]	[2.38]	[-1.51]
S&P credit rating	-0.0599*	-0.0187	0.0756***	-0.146**	-0.115**	0.0732***
	[-1.71]	[-0.66]	[5.54]	[-2.04]	[-2.53]	[4.82]
Altman Z-score	-0.269***	-0.0721	-0.0633***	-0.278**	-0.0197	-0.0168
	[-3.10]	[-1.42]	[-3.24]	[-2.25]	[-0.25]	[-0.92]
Cash holdings	-6.908***	-0.311	-3.050***	-1.195	-2.122*	-2.879***
	[-3.95]	[-0.42]	[-7.26]	[-0.61]	[-1.96]	[-6.46]
Interest coverage	-0.00290	-0.00289	-0.00379**	-0.0151	-0.0106	-0.00102
	[-0.40]	[-0.96]	[-2.46]	[-0.63]	[-1.42]	[-0.72]
Rollover	-2.682	-0.837	-0.546	-1.014	-1.117	-1.124*
	[-1.59]	[-0.62]	[-0.94]	[-0.47]	[-0.54]	[-1.94]
Leverage	1.153*	-0.553	-0.239	0.868	0.0259	0.428*
	[1.74]	[-1.08]	[-1.01]	[0.81]	[0.03]	[1.77]
Tangibility	0.313	-0.716*	-0.426**	0.460	-1.407**	-0.538***
	[0.77]	[-1.70]	[-2.23]	[0.66]	[-2.51]	[-2.99]
Tobin's Q	-0.686***	0.127	0.0576	-0.660**	0.224	-0.0764
	[-3.11]	[1.17]	[1.22]	[-2.23]	[1.48]	[-1.60]
Profitability	1.895	0.997	0.970*	2.205	-2.858	-0.191
	[1.20]	[0.72]	[1.72]	[0.96]	[-1.42]	[-0.29]
ROA	-0.240	-2.976***	-1.266***	-0.782	-1.682	-1.182***
	[-0.25]	[-3.73]	[-3.51]	[-0.69]	[-1.26]	[-2.73]
Operating cash flow	-0.781	1.514	-1.074**	1.227	2.737*	0.184
	[-0.67]	[1.30]	[-2.18]	[0.61]	[1.77]	[0.33]

Table 4: Cox hazard regressions by purpose - *continued*

	Multiple events with others as censored			Competing risk (1^{st} only) subhazard		
	Distress	Disicpline	Ambiguous	Distress	Disicpline	Ambiguous
	(1)	(2)	(3)	(4)	(5)	(6)
CAPEX/assets	5.427***	3.741**	3.097***	0.372	2.590	1.288*
	[3.51]	[2.45]	[4.92]	[0.15]	[1.17]	[1.91]
PPE growth	-0.912**	-0.838**	-0.505***	0.0416	-0.717	-0.220*
	[-2.23]	[-2.45]	[-4.10]	[0.11]	[-1.39]	[-1.71]
Sales growth	0.246	-0.704**	-0.326**	0.0452	-0.941*	-0.280*
	[0.78]	[-1.96]	[-2.42]	[0.10]	[-1.81]	[-1.95]
R&D/assets	-0.297	0.999	0.882	-0.669	-1.978	0.869
	[-0.13]	[0.64]	[1.44]	[-0.25]	[-0.91]	[1.64]
R&D missing (0, 1)	-0.0135	-0.0656	-0.0757	-0.391	-0.346	0.113*
	[-0.08]	[-0.46]	[-1.06]	[-1.40]	[-1.53]	[1.73]
Number of segments	0.134***	0.112***	0.0978***	0.159**	0.105**	0.0751***
	[3.26]	[3.40]	[5.30]	[2.00]	[2.11]	[3.79]
Ln(Assets)	0.246***	0.314***	0.286***	0.175*	0.249***	0.0449
	[4.24]	[5.87]	[9.99]	[1.79]	[2.85]	[1.46]
SA index	0.506***	0.246*	0.297***	0.895***	0.126	0.336***
	[3.33]	[1.75]	[3.93]	[3.51]	[0.59]	[5.47]
Stock ownership	-0.0402*	-0.0672***	-0.00984	0.0165	-0.0534	-0.0218**
	[-1.79]	[-2.78]	[-1.03]	[0.58]	[-1.21]	[-2.30]
Stock ownership missing (0, 1)	-0.684***	-0.673***	-0.164***	-0.605**	-0.885***	-0.323***
	[-4.09]	[-4.62]	[-2.58]	[-1.98]	[-3.58]	[-3.96]
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	604049	604049	604049	468,848	468,665	466,137
Pseudo R^2	0.115	0.049	0.058	-	-	-
Number of clusters	6545	6545	6545	6,407	6,407	6,406

Table 5: Seller wealth effects

The table presents the coefficient estimates from OLS regressions where the 3-day, CAR (–1, +1), and 5-day, CAR (–2, +2), cumulative abnormal announcement returns of the sellers in the asset sales are the dependent variables. We define all other covariates in Table 1. We cluster standard errors by firm and report *t*-statistics in brackets. Industry covariates are the industry medians of the same firm covariates we report. Industry covariates and industry, time, and credit rating fixed effects are indicated when included in the specification, but not reported and *p*-values for indicated F-tests in Models (3), (5), and (7) are reported. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	CAR (–1, +1)					CAR (–2, +2)	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rating downgrade (0, 1) [A]	0.0083**	0.0087**	0.0125**	0.0093***	-0.0168	0.0095**	-0.0144
	[2.344]	[2.482]	[2.483]	[2.649]	[-1.632]	[2.337]	[-1.199]
Rating upgrade (0, 1) [B]	0.0057	0.0081**	0.0068	0.0081**	0.0082**	-0.0018	0.0008
	[1.575]	[2.123]	[1.430]	[2.091]	[2.083]	[-0.411]	[0.180]
Redeployability [C]					-0.0178		-0.0193
					[-0.916]		[-0.886]
Redeployability × Rating downgrade (0, 1) [D]					0.0707**		0.0633**
					[2.549]		[2.012]
Same down (0, 1) [E]			-0.0068				
			[-0.991]				
Same up (0, 1) [F]			0.0023				
			[0.322]				
Altman Z-score	-0.0008	-0.0015	-0.0015	-0.0016	-0.0020*	-0.0004	-0.0017
	[-0.752]	[-1.350]	[-1.363]	[-1.408]	[-1.744]	[-0.374]	[-1.199]
Cash holdings	0.0091	0.0078	0.0079	0.0090	0.0083	0.0075	0.0036
	[0.526]	[0.411]	[0.417]	[0.460]	[0.423]	[0.382]	[0.168]
Interest coverage	0.0002***	0.0001*	0.0001*	0.0001*	0.0001*	0.0001*	0.0001
	[2.703]	[1.891]	[1.893]	[1.811]	[1.835]	[1.708]	[0.928]
Rollover	0.0085	-0.0033	-0.0033	-0.0111	-0.0097	0.0008	-0.0057
	[0.329]	[-0.120]	[-0.120]	[-0.403]	[-0.351]	[0.028]	[-0.186]
Leverage	0.0221**	0.0143	0.0141	0.0128	0.0094	0.0226*	0.0110
	[2.057]	[1.179]	[1.159]	[1.030]	[0.744]	[1.852]	[0.771]
Tangibility	0.0031	-0.0086	-0.0083	-0.0098	-0.0110	0.0004	-0.0084
	[0.433]	[-0.856]	[-0.824]	[-0.965]	[-1.067]	[0.047]	[-0.730]
Tobin's Q	-0.0028	-0.0038	-0.0037	-0.0028	-0.0017	-0.0031	-0.0024
	[-1.358]	[-1.529]	[-1.523]	[-1.128]	[-0.686]	[-1.313]	[-0.837]
Profitability	-0.0093	-0.0262	-0.0263	-0.0299	-0.0368	-0.0288	-0.0547
	[-0.290]	[-0.754]	[-0.760]	[-0.849]	[-1.026]	[-0.840]	[-1.427]
ROA	-0.0477**	-0.0394	-0.0394	-0.0374	-0.0302	-0.0376	-0.0141
	[-1.976]	[-1.600]	[-1.598]	[-1.533]	[-1.219]	[-1.384]	[-0.500]
Operating cash flow	0.0395	0.0606*	0.0611*	0.0629*	0.0687**	0.0402	0.0596
	[1.281]	[1.880]	[1.895]	[1.909]	[2.018]	[1.207]	[1.638]
CAPEX/assets	-0.0276	-0.0109	-0.0111	-0.0110	-0.0192	-0.0201	-0.0177
	[-0.936]	[-0.318]	[-0.324]	[-0.308]	[-0.528]	[-0.619]	[-0.464]
PPE growth	0.0023	0.0025	0.0025	0.0039	0.0056	0.0041	0.0072
	[0.400]	[0.406]	[0.408]	[0.630]	[0.882]	[0.633]	[1.040]
Sales growth	-0.0052	-0.0066	-0.0067	-0.0059	-0.0066	-0.0050	-0.0070
	[-0.945]	[-1.087]	[-1.101]	[-0.970]	[-1.079]	[-0.811]	[-1.016]

Table 5: Seller wealth effects – *continued*

VARIABLES	CAR (-1, +1) (1)	(2)	(3)	(4)	(5)	CAR (-2, +2) (6)	(7)
R&D/assets	0.0103	0.0275	0.0278	0.0211	0.0151	0.0095	0.0180
	[0.340]	[0.805]	[0.812]	[0.613]	[0.433]	[0.255]	[0.415]
R&D missing (0, 1)	0.0006	0.0040	0.0041	0.0035	0.0035	-0.0014	-0.0001
	[0.262]	[1.290]	[1.339]	[1.117]	[1.125]	[-0.486]	[-0.014]
Number of segments	0.0005	0.0010	0.0010	0.0007	0.0009	0.0003	0.0008
	[0.968]	[1.572]	[1.613]	[1.232]	[1.455]	[0.505]	[1.154]
Ln(Assets)	-0.0013	-0.0014	-0.0014	-0.0012	-0.0010	-0.0018**	-0.0025*
	[-1.563]	[-1.214]	[-1.207]	[-0.980]	[-0.813]	[-1.966]	[-1.867]
SA index	0.0033*	0.0021	0.0022	0.0020	0.0021	0.0032	0.0017
	[1.707]	[0.973]	[0.999]	[0.904]	[0.965]	[1.442]	[0.694]
Stock ownership	-0.0005	-0.0007*	-0.0007*	-0.0008**	-0.0008**	-0.0005	-0.0008*
	[-1.587]	[-1.891]	[-1.905]	[-2.011]	[-2.123]	[-1.298]	[-1.777]
Stock ownership missing (0, 1)	-0.0022	-0.0037	-0.0038	-0.0038	-0.0043	-0.0014	-0.0030
	[-1.007]	[-1.220]	[-1.245]	[-1.244]	[-1.398]	[-0.534]	[-0.854]
Relative Size	0.1110***	0.1043***	0.1045***	0.1067***	0.1043***	0.1110***	0.1031***
	[6.389]	[5.932]	[5.934]	[6.103]	[5.997]	[6.120]	[5.663]
All cash (0, 1)	0.0031	0.0027	0.0027	0.0028	0.0025	0.0040	0.0032
	[1.020]	[0.858]	[0.872]	[0.874]	[0.766]	[1.189]	[0.906]
All stock (0, 1)	0.0068	0.0050	0.0049	0.0047	0.0042	0.0018	0.0007
	[0.791]	[0.574]	[0.554]	[0.542]	[0.475]	[0.196]	[0.076]
Core segment	-0.0023	-0.0016	-0.0007	-0.0012	-0.0015	-0.0028	-0.0018
	[-1.107]	[-0.702]	[-0.298]	[-0.511]	[-0.656]	[-1.204]	[-0.684]
Rating=CC		0.0088	0.0834***		0.0187	0.0684	0.0201
		[0.122]	[9.245]		[0.266]	[1.069]	[0.292]
Rating=CCC		0.0006	-0.0086		0.0034	0.0009	0.0041
		[0.032]	[-0.459]		[0.172]	[0.041]	[0.202]
Rating=B		-0.0034	-0.0055		-0.0019	-0.0046	-0.0031
		[-0.633]	[-0.982]		[-0.341]	[-0.750]	[-0.567]
Rating=BB		-0.0109**	-0.0081**		-0.0091**	-0.0092*	-0.0095**
		[-2.549]	[-1.972]		[-2.072]	[-1.720]	[-2.152]
Rating=BBB		-0.0091**	-0.0084**		-0.0083**	-0.0128**	-0.0097**
		[-2.324]	[-2.296]		[-1.981]	[-2.365]	[-2.286]
Rating=A		-0.0042	-0.0045		-0.0029	-0.0064	-0.0041
		[-0.991]	[-1.145]		[-0.645]	[-1.053]	[-0.907]
Rating=AA		-0.0004	-0.0011		0.0019	-0.0039	0.0004
		[-0.082]	[-0.224]		[0.336]	[-0.440]	[0.076]
Rating=AAA		0.0088	0.0095*		0.0101	0.0219	0.0085
		[1.461]	[1.732]		[1.511]	[1.568]	[1.268]
F-test (*p* -value): [A] + [E] = 0			*0.250*				
F-test (*p* -value): [B] + [F] = 0			*0.102*				
F-test (*p* -value): [C] + [D] = 0					*0.097*		*0.217*
Industry fixed effects	No	Yes	Yes	Yes	Yes	No	Yes
Time fixed effects	No	Yes	Yes	Yes	Yes	No	Yes
Industry covariates	No	No	No	Yes	Yes	No	No
Observations	3,916	3,913	3,913	3,874	3,801	3,894	3,816
Adjusted R-squared	0.078	0.084	0.084	0.086	0.084	0.065	0.072

Table 6: Acquirer wealth effects

The table presents the coefficient estimates from OLS regressions where the 3-day, ACAR (–1, +1), and 5-day, ACAR (–2, +2), cumulative abnormal announcement returns of the acquirers in the asset sales are the dependent variables. We define all other covariates in Table 1. We cluster standard errors by firm and report *t*-statistics in brackets. Target and acquirer industry covariates are the respective target and acquirer industry medians of the same firm covariates we report. Industry covariates and industry, time, and credit rating fixed effects are indicated when included in the specification, but not reported and *p*-values for indicated F-tests in Models (3), (5), and (7) are reported. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	ACAR (–1, +1)					ACAR (–2, +2)	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rating downgrade (0,1)	0.0125*	0.0154**	0.0118	0.0122	-0.0148	0.0175**	-0.0220
	[1.832]	[2.202]	[1.597]	[1.551]	[-0.595]	[2.030]	[-0.819]
Rating upgrade (0,1)	0.0037	0.0036	-0.0051	-0.0069	-0.0086	-0.0049	-0.0055
	[0.276]	[0.256]	[-0.350]	[-0.456]	[-0.543]	[-0.295]	[-0.317]
Asset Redeployability Target [A]					0.0070		0.0383
					[0.137]		[0.718]
Redeployability × Rating downgrade (0, 1) [B]					0.0624		0.0901
					[1.015]		[1.396]
Cash holdings target	0.0399	0.0308	0.0144	-0.0026	-0.0053	-0.0136	-0.0159
	[0.974]	[0.738]	[0.354]	[-0.060]	[-0.123]	[-0.308]	[-0.357]
Interest coverage target	0.0002	0.0002	0.0003*	0.0003	0.0003	0.0002	0.0002
	[1.568]	[1.618]	[1.835]	[1.534]	[1.639]	[1.166]	[1.277]
Rollover target	0.0023	-0.0001	-0.0274	-0.0340	-0.0265	0.0005	0.0073
	[0.065]	[-0.003]	[-0.727]	[-0.895]	[-0.684]	[0.011]	[0.156]
Leverage target	-0.0184	-0.0152	-0.0130	-0.0205	-0.0171	-0.0279	-0.0240
	[-1.096]	[-0.883]	[-0.683]	[-0.952]	[-0.775]	[-1.125]	[-0.946]
Tangibility target	0.0061	0.0020	-0.0129	-0.0277	-0.0206	-0.0383	-0.0255
	[0.357]	[0.115]	[-0.544]	[-1.106]	[-0.806]	[-1.524]	[-0.970]
Tobin's Q target	-0.0030	-0.0017	-0.0024	-0.0027	-0.0029	0.0015	0.0016
	[-0.808]	[-0.450]	[-0.587]	[-0.554]	[-0.579]	[0.320]	[0.323]
Profitability target	0.1365**	0.1306**	0.1536**	0.1209	0.1142	0.1133	0.0995
	[2.226]	[2.075]	[2.174]	[1.587]	[1.440]	[1.426]	[1.203]
ROA target	-0.1193***	-0.1177***	-0.1101**	-0.0866*	-0.0814*	-0.0988*	-0.0929*
	[-2.889]	[-2.775]	[-2.464]	[-1.904]	[-1.794]	[-1.931]	[-1.820]
Operating cash flow target	-0.0000	-0.0037	-0.0146	0.0059	0.0016	0.0392	0.0386
	[-0.000]	[-0.063]	[-0.210]	[0.079]	[0.021]	[0.522]	[0.495]
CAPEX/assets target	-0.0001	0.0032	0.0276	0.0199	0.0096	0.1046	0.0908
	[-0.002]	[0.046]	[0.332]	[0.226]	[0.107]	[1.069]	[0.922]
PPE growth target	0.0025	0.0012	0.0064	0.0074	0.0112	0.0036	0.0072
	[0.297]	[0.142]	[0.687]	[0.793]	[1.184]	[0.311]	[0.613]
Sales growth target	-0.0054	-0.0008	-0.0109	-0.0059	-0.0060	-0.0088	-0.0075
	[-0.515]	[-0.074]	[-0.971]	[-0.509]	[-0.508]	[-0.752]	[-0.621]
R&D/assets target	-0.0165	0.0002	-0.0084	0.0156	0.0224	-0.0317	-0.0211
	[-0.239]	[0.003]	[-0.105]	[0.198]	[0.280]	[-0.409]	[-0.269]

Table 6: Acquirer wealth effects – *continued*

	ACAR (–1, +1)					ACAR (–2, +2)	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R&D missing (0, 1) target	-0.0031	-0.0021	-0.0002	-0.0008	-0.0020	0.0028	0.0013
	[-0.578]	[-0.376]	[-0.024]	[-0.111]	[-0.281]	[0.350]	[0.157]
Number of segments target	-0.0012	-0.0006	-0.0022	-0.0014	-0.0016	-0.0016	-0.0020
	[-0.894]	[-0.420]	[-1.539]	[-0.894]	[-1.014]	[-0.858]	[-1.017]
Ln(Assets) target	0.0022	0.0024	0.0014	0.0019	0.0018	0.0016	0.0017
	[1.487]	[1.435]	[0.747]	[0.684]	[0.633]	[0.505]	[0.525]
SA index target	-0.0054	-0.0034	-0.0096*	-0.0086	-0.0100*	-0.0058	-0.0072
	[-1.200]	[-0.733]	[-1.881]	[-1.563]	[-1.822]	[-0.949]	[-1.171]
Stock ownership target	-0.0002	-0.0001	-0.0003	-0.0006	-0.0008	-0.0009	-0.0009
	[-0.173]	[-0.115]	[-0.332]	[-0.555]	[-0.679]	[-0.832]	[-0.726]
Stock ownership missing (0, 1) target	0.0043	0.0050	0.0047	0.0055	0.0057	0.0101	0.0113
	[0.833]	[0.765]	[0.818]	[0.844]	[0.847]	[1.395]	[1.495]
Relative Size	0.0092	0.0098	0.0079	0.0016	-0.0012	0.0037	-0.0001
	[0.408]	[0.413]	[0.371]	[0.066]	[-0.048]	[0.133]	[-0.003]
All Cash (0, 1)	-0.0122*	-0.0112	-0.0119*	-0.0126*	-0.0115	-0.0213**	-0.0206**
	[-1.702]	[-1.518]	[-1.660]	[-1.685]	[-1.511]	[-2.310]	[-2.212]
All Stock (0, 1)	0.0046	0.0051	0.0127	0.0130	0.0133	0.0342	0.0330
	[0.149]	[0.169]	[0.353]	[0.365]	[0.371]	[1.069]	[1.007]
Same 2-digit SIC (0, 1)	-0.0041	-0.0022	-0.0067	-0.0027	-0.0013	-0.0054	-0.0033
	[-0.976]	[-0.499]	[-1.339]	[-0.540]	[-0.266]	[-0.943]	[-0.569]
Cash holdings acquirer	0.0340	0.0214	0.0314	0.0102	0.0113	-0.0426	-0.0376
	[1.103]	[0.707]	[0.866]	[0.279]	[0.304]	[-1.144]	[-1.008]
Interest coverage acquirer	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001
	[0.528]	[0.528]	[0.810]	[0.826]	[0.718]	[1.277]	[1.101]
Rollover acquirer	-0.0855**	-0.1000**	-0.0791	-0.0899*	-0.0852	-0.0335	-0.0248
	[-2.005]	[-2.321]	[-1.570]	[-1.697]	[-1.567]	[-0.548]	[-0.396]
Leverage acquirer	0.0386**	0.0399**	0.0392**	0.0401**	0.0335*	0.0512**	0.0455**
	[2.112]	[2.208]	[2.014]	[2.112]	[1.745]	[2.356]	[2.066]
Tobin's Q acquirer	-0.0036	-0.0034	-0.0013	-0.0012	-0.0019	-0.0011	-0.0018
	[-1.130]	[-1.054]	[-0.362]	[-0.319]	[-0.501]	[-0.283]	[-0.443]
Profitability acquirer	-0.0472	-0.0479	-0.0763	-0.0801	-0.0620	-0.1517*	-0.1366
	[-0.681]	[-0.682]	[-0.978]	[-1.021]	[-0.787]	[-1.760]	[-1.579]
ROA acquirer	0.1147***	0.1205***	0.1190***	0.1377***	0.1396***	0.1507***	0.1546***
	[2.709]	[2.681]	[2.669]	[2.971]	[2.952]	[3.152]	[3.180]
Operating cash flow acquirer	-0.0658	-0.0751	-0.0545	-0.0644	-0.0856	0.0161	-0.0056
	[-0.924]	[-1.044]	[-0.677]	[-0.795]	[-1.063]	[0.171]	[-0.060]
CAPEX/assets acquirer	0.0115	0.0076	0.0452	0.0358	0.0353	-0.0632	-0.0677
	[0.228]	[0.152]	[0.854]	[0.665]	[0.646]	[-0.955]	[-1.007]
Sales growth acquirer	-0.0091	-0.0076	-0.0073	-0.0057	-0.0031	-0.0049	-0.0005
	[-0.830]	[-0.687]	[-0.631]	[-0.473]	[-0.254]	[-0.345]	[-0.031]

Table 6: Acquirer wealth effects – *continued*

	ACAR (–1, +1)					ACAR (–2, +2)	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of segments acquirer	-0.0018	-0.0013	-0.0018	-0.0016	-0.0021	-0.0032*	-0.0038**
	[-1.525]	[-1.042]	[-1.156]	[-0.967]	[-1.204]	[-1.692]	[-1.988]
SA index acquirer	0.0099***	0.0098***	0.0060	0.0060	0.0055	0.0087*	0.0078
	[2.670]	[2.595]	[1.439]	[1.342]	[1.221]	[1.785]	[1.579]
Time FE	No	Yes	No	Yes	Yes	Yes	Yes
Target and acquirer Indusrty FE	No	No	Yes	Yes	Yes	Yes	Yes
Target Rating FE	No	No	No	Yes	Yes	Yes	Yes
F-test (*p* -value): [A] + [B] = 0					*0.338*		*0.090*
Observations	835	835	834	834	818	834	818
Adjusted R-squared	0.054	0.053	0.095	0.106	0.106	0.113	0.116

Table 7: Combined seller and acquirer wealth effects

The table presents the coefficient estimates from OLS regressions where the 3-day, SCAR (–1, +1), and 5-day, SCAR (–2, +2), market-value weighted average cumulative abnormal announcement returns of the sellers and acquirers in the asset sales are the dependent variables. We define all other covariates in Table 1. We cluster standard errors by firm and report *t*-statistics in brackets. Each specification includes the same covariates as those reported in Table 6, but only reports a sub-set. Industry covariates and industry, time, and credit rating fixed effects are indicated when included in the specification, but not reported and *p*-values for indicated F-tests in Models (3), (5), and (7) are reported. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	SCAR (–1, +1)					SCAR (–2, +2)	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rating downgrade (0,1)	0.0071	0.0085*	0.0069	0.0080	-0.0356*	0.0097	-0.0266
	[1.564]	[1.825]	[1.457]	[1.465]	[-1.825]	[1.637]	[-1.251]
Rating upgrade (0,1)	0.0032	0.0046	0.0036	-0.0007	-0.0010	-0.0069	-0.0067
	[0.448]	[0.624]	[0.481]	[-0.075]	[-0.101]	[-0.721]	[-0.672]
Asset Redeployability Target [A]					-0.0027		0.0280
					[-0.086]		[0.857]
Redeployability × Rating downgrade (0, 1) [B]					0.1074**		0.0869*
					[2.293]		[1.700]
Covariates from Table 6	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	Yes	Yes	Yes
Target Rating FE	No	No	Yes	Yes	Yes	Yes	Yes
Target and acquirer Indusrty FE	No	No	No	Yes	Yes	Yes	Yes
F-test (*p* -value): [A] + [B] = 0					*0.0476*		*0.0437*
Observations	835	835	835	834	818	830	814
Adjusted R-squared	0.044	0.061	0.055	0.087	0.095	0.044	0.048

Table 8: 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, based on comparison to medians of peer segments in 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. Standard errors are robust to heteroscedasticity and *t*-statistics are in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level. Variable descriptions are in Table 1.

	Profitability	Profit Margin	Asset Turnover	Operating CF	Net CF
VARIABLES	(1)	(2)	(3)	(4)	(5)
Rating downgrade (0, 1)	-0.00650	-0.0423	0.0275	0.0114	0.0115
	[-0.160]	[-1.080]	[0.671]	[0.281]	[0.282]
Rating upgrade (0, 1)	-0.1690***	-0.1370**	0.0598	-0.1660***	-0.1690***
	[-2.839]	[-2.319]	[0.846]	[-2.739]	[-2.893]
Altman Z-score	0.00578	-0.000661	-0.0553***	-0.0144	-0.0116
	[0.323]	[-0.041]	[-3.223]	[-0.747]	[-0.589]
Cash holdings	0.548*	0.250	-0.469	0.0680	0.387
	[1.671]	[0.832]	[-1.565]	[0.202]	[1.176]
Interest coverage	-0.0003	0.0007	0.0016*	0.0001	-0.0002
	[-0.298]	[0.728]	[1.764]	[0.080]	[-0.182]
Rollover	0.384	0.543*	-0.270	0.305	0.496
	[1.259]	[1.840]	[-0.875]	[1.006]	[1.641]
Leverage	-0.412***	-0.591***	-0.0533	-0.436***	-0.348**
	[-2.996]	[-4.372]	[-0.383]	[-3.126]	[-2.449]
Tangibility	0.199**	-0.00772	0.00521	0.0245	-0.0701
	[1.966]	[-0.076]	[0.053]	[0.240]	[-0.679]
Tobin's Q	-0.0965**	-0.0416	0.0255	-0.136***	-0.0968**
	[-2.407]	[-1.180]	[0.774]	[-3.230]	[-2.279]
ROA	-1.037***	-0.9880***	0.2490	-0.587**	-0.758***
	[-4.099]	[-4.052]	[1.029]	[-2.244]	[-2.880]
Operating cash flow	-0.474*	0.0731	-0.842***	-0.961***	-0.104
	[-1.742]	[0.266]	[-2.917]	[-2.753]	[-0.340]
CAPEX/assets	-0.5020	0.7770*	-0.3520	-0.3860	1.4850***
	[-1.225]	[1.921]	[-0.916]	[-0.906]	[3.711]
PPE growth	0.1580**	0.00532	0.1050	0.1190*	-0.0201
	[2.537]	[0.087]	[1.612]	[1.867]	[-0.307]
Sales growth	-0.114	-0.0787	0.0804	0.0559	-0.00150
	[-1.530]	[-1.065]	[1.086]	[0.711]	[-0.019]
R&D/assets	-1.270**	-1.091**	-1.553***	-0.792	-0.410
	[-2.285]	[-2.194]	[-3.313]	[-1.216]	[-0.655]
R&D missing (0, 1)	0.0441	-0.00121	0.0163	0.0768**	0.0295
	[1.247]	[-0.036]	[0.471]	[2.100]	[0.834]
Number of segments	0.00404	0.00366	-0.0223**	-0.00742	0.0195*
	[0.360]	[0.348]	[-2.245]	[-0.663]	[1.756]

Table 8: Inter firm segment performance analysis – *continued*

	Profitability	Profit Margin	Asset Turnover	Operating CF	Net CF
VARIABLES	(1)	(2)	(3)	(4)	(5)
Ln(Assets)	0.0327**	-0.00733	0.0229	0.0444***	0.0262
	[2.097]	[-0.486]	[1.563]	[2.788]	[1.602]
SA index	0.00197	0.0287	-0.00387	0.0379	0.0536*
	[0.067]	[1.006]	[-0.133]	[1.268]	[1.832]
Stock ownership	-0.00221	0.00486	-0.00969**	0.0008	0.0005
	[-0.568]	[1.249]	[-2.241]	[0.023]	[0.122]
Stock ownership missing (0, 1)	-0.0286	-0.0462	-0.0229	-0.0196	0.0051
	[-0.716]	[-1.176]	[-0.569]	[-0.488]	[0.132]
Rating FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	949	1,055	1,194	926	874
Pseudo R^2	0.122	0.106	0.0842	0.148	0.157

Table 9: 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. CoreFrac2 is a variable indicating the fraction of segments that are core segments and is meant to correct for mechanical effects. Standard errors are robust to heteroscedasticity and *t*-statistics are in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level. Variable descriptions are in Table 1.

VARIABLES	High Asset Redeployability (1)	High 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	0.0594*	-0.0841*	0.0844**	0.0471	0.0324	-0.000153	0.0559
	[1.653]	[1.881]	[2.336]	[1.075]	[0.718]	[-0.004]	[1.431]
Rating upgrade (0, 1) = 1	0.0339	0.158**	-0.0261	-0.00501	0.0557	-0.0544	-0.0490
	[0.573]	[2.163]	[-0.410]	[-0.071]	[0.753]	[-0.736]	[-0.743]
Altman Z-score	0.00197	-0.00149	0.0136	0.0183	-0.00989	0.00102	0.00136
	[0.145]	[-0.075]	[0.968]	[1.173]	[-0.540]	[0.063]	[0.086]
Cash holdings	-0.334	-0.0984	-0.585**	0.0116	0.335	0.245	-0.112
	[-1.387]	[-0.289]	[-2.362]	[0.041]	[1.032]	[0.801]	[-0.415]
Interest coverage	0.0007	0.00151	-0.0010	0.0004	0.00230*	0.000444	-0.000374
	[0.890]	[1.231]	[-1.413]	[0.531]	[1.910]	[0.471]	[-0.477]
Rollover	0.283	-0.272	0.457	-0.544	-0.205	0.169	-0.872***
	[0.978]	[-0.790]	[1.584]	[-1.604]	[-0.609]	[0.542]	[-2.937]
Leverage	0.187	-0.0807	0.0850	-0.0847	-0.0616	-0.0106	-0.0479
	[1.481]	[-0.520]	[0.665]	[-0.591]	[-0.410]	[-0.075]	[-0.355]
Tangibility	-0.0290	0.0104	0.252***	0.00125	0.0282	-0.147	0.0400
	[-0.302]	[0.090]	[2.712]	[0.012]	[0.254]	[-1.388]	[0.412]
Tobin's Q	0.0169	-0.0220	0.0367	-0.0199	-0.0309	-0.0306	0.0220
	[0.606]	[-0.595]	[1.286]	[-0.616]	[-0.860]	[-0.912]	[0.716]
ROA	-0.167	-0.0565	0.0854	-0.765***	0.111	0.105	0.133
	[-0.775]	[-0.196]	[0.398]	[-2.855]	[0.416]	[0.426]	[0.579]
Operating cash flow	0.566**	0.440	0.575**	0.401	0.439	0.600**	0.283
	[2.356]	[1.237]	[2.301]	[1.311]	[1.488]	[2.038]	[1.124]
CAPEX/assets	-0.664*	-0.575	-0.347	-0.702*	-0.438	-0.433	0.0607
	[-1.930]	[-1.223]	[-0.954]	[-1.659]	[-0.980]	[-0.995]	[0.160]
PPE growth	0.0762	0.0530	0.0822	0.0715	0.105	0.0332	0.0650
	[1.304]	[0.714]	[1.379]	[1.059]	[1.490]	[0.510]	[1.031]

Table 9: Intra firm segment performance analysis – *continued*

VARIABLES	High Asset Redeployability (1)	High Cash Flow (2)	Highest Tobin's Q (3)	Non-core segment (4)	Low Profitability (5)	Low Profit Margin (6)	Low Asset Turnover (7)
Sales growth	-0.0389	0.0646	-0.152**	-0.157*	-0.0486	0.00215	-0.0895
	[-0.565]	[0.719]	[-2.121]	[-1.957]	[-0.591]	[0.027]	[-1.249]
R&D/assets	0.530	0.354	1.637***	-0.0834	-0.355	-0.473	-0.301
	[1.325]	[0.527]	[3.498]	[-0.145]	[-0.630]	[-0.927]	[-0.664]
R&D missing (0, 1) = 1	0.00314	0.0331	-0.0639**	0.0192	-0.0214	0.00114	-0.00354
	[0.096]	[0.856]	[-1.988]	[0.530]	[-0.566]	[0.032]	[-0.105]
Number of segments	0.0105	-0.0101	-0.00534	0.0181*	-0.00467	-0.00914	-0.0257***
	[1.230]	[-0.909]	[-0.622]	[1.804]	[-0.424]	[-0.885]	[-2.811]
Ln(Assets)	-0.0258*	-0.00161	-0.0365***	0.00331	-0.0161	0.0197	0.0134
	[-1.911]	[-0.094]	[-2.705]	[0.208]	[-0.980]	[1.262]	[0.943]
SA index	0.0688**	-0.0477	0.112***	-0.0641**	0.0232	0.0221	0.0337
	[2.515]	[-1.446]	[4.180]	[-2.009]	[0.734]	[0.729]	[1.186]
Stock ownership	0.000323	-0.00304	-0.00314	0.00531	-0.00168	-0.00316	-0.00248
	[0.082]	[-0.679]	[-0.816]	[1.290]	[-0.389]	[-0.750]	[-0.618]
Stock ownership missing (0, 1) = 1	-0.00920	-0.0417	0.0684*	0.108**	0.00603	0.0484	-0.0574
	[-0.252]	[-0.963]	[1.858]	[2.562]	[0.141]	[1.186]	[-1.503]
Redeployability	-0.0370						
	[-0.255]						
CoreFrac2				-0.914***			
				[-12.452]			
Credit rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,343	984	1,394	1,058	1,035	1,126	1,270
Pseudo R2	0.0592	0.0736	0.0904	0.155	0.0427	0.0347	0.0427

Table 10: Form of payment analysis

The table presents average marginal effects of logit regressions of dummy variables indicating whether the assets sale is paid for in 100% cash using the Segment Sale sample. Each model includes, but does not report marginal effects, for indicator variables equal to one if R&D is missing, stock ownership is missing, and time and industry fixed effect. Standard errors are robust to heteroscedasticity and *t*-statistics are in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level. Variable descriptions are in Table 1.

	All Cash (0, 1)	
VARIABLES	(1)	(2)
Rating downgrade (0, 1)	0.0419	0.0421
	[1.601]	[1.608]
Rating upgrade (0, 1)	-0.0143	-0.0151
	[-0.289]	[-0.307]
purpose = Discipline (0, 1)		-0.136***
		[-3.439]
purpose = Missing or Ambiguous (0, 1)		-0.0987***
		[-3.632]
Redeployability	-0.0142	-0.00455
	[-0.123]	[-0.040]
Altman Z-score	-0.0377***	-0.0386***
	[-3.492]	[-3.577]
Cash holdings	-0.232	-0.196
	[-1.216]	[-1.028]
Interest coverage	0.00152**	0.00159**
	[2.185]	[2.298]
Rollover	0.245	0.251
	[1.071]	[1.097]
Leverage	-0.0415	-0.0565
	[-0.434]	[-0.591]
Tangibility	-0.0166	-0.0115
	[-0.224]	[-0.154]
Tobin's Q	0.0490**	0.0517**
	[2.160]	[2.280]
ROA	0.427***	0.434***
	[2.660]	[2.717]
Operating cash flow	-0.171	-0.225
	[-0.868]	[-1.128]
CAPEX/assets	0.165	0.127
	[0.619]	[0.476]
PPE growth	-0.0602	-0.0549
	[-1.422]	[-1.288]
Sales growth	0.0602	0.0571
	[1.140]	[1.081]

Table 10: Form of payment analysis – *continued*

	All Cash (0, 1)	
VARIABLES	(1)	(2)
R&D/assets	-0.302	-0.279
	[-0.967]	[-0.896]
Number of segments	-0.00151	-0.00207
	[-0.230]	[-0.314]
Ln(Assets)	-0.00436	-0.00262
	[-0.414]	[-0.249]
SA index	0.0192	0.0205
	[0.916]	[0.977]
Stock ownership	-0.000753	-0.000572
	[-0.257]	[-0.196]
Observations	1,375	1,375
Pseudo R^2	0.0689	0.0776

The real effects of credit ratings: Evidence from corporate asset sales

Appendix

A. Supplemental figure

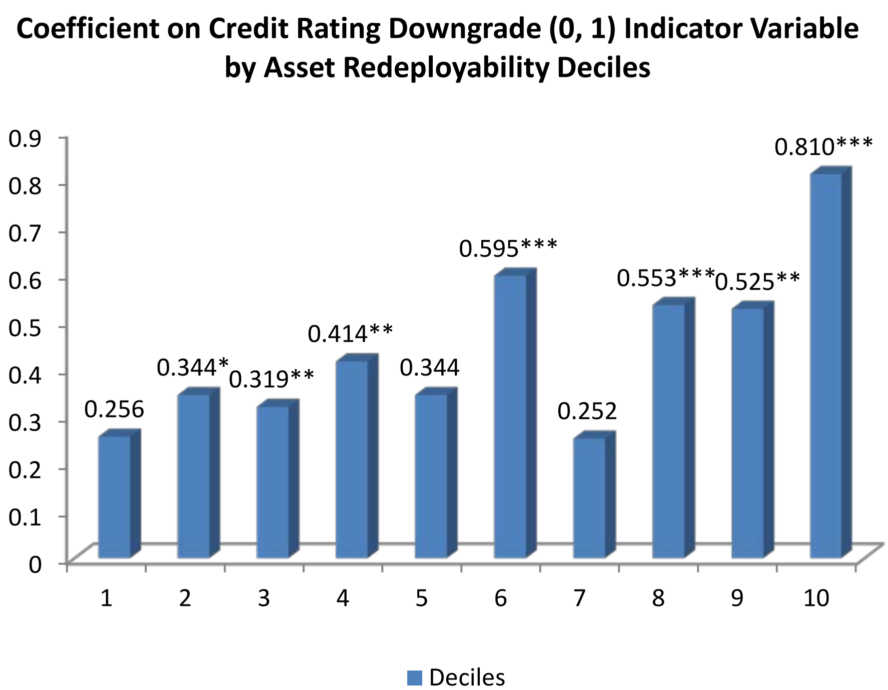

Figure A1: Each bar shows the magnitude and statistical significance of the coefficient on the Credit rating downgrade (0, 1) indicator variable based on Model (2) from Table 2 for each sub-sample based on deciles of asset redeployability. The asset redeployability measure incorporates both across and within industry correlation of firm-level output and is from Kim and Kung (2016). Statistical significance of each coefficient is indicated with ***, **, and * to denote significance at the 1%, 5%, and 10% level.

B. Supplemental tables

Table A1: Cox hazard regressions using alternative asset redeployability measure

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. Asset redeployability incorporates both across and within industry correlation of firm-level output and is from Kim and Kung (2016). We define all other covariates in the paper. 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
	(1)	(2)
Rating downgrade (0, 1)	0.370***	0.424***
	[5.90]	[4.34]
Rating upgrade (0, 1)	-0.185**	0.0187
	[-2.20]	[0.14]
Rated (0, 1)	0.317*	0.273
	[1.90]	[1.48]
S&P credit rating	0.00670	0.00833
	[0.51]	[0.56]
Altman Z-score	-0.0632***	-0.0320
	[-2.97]	[-1.54]
Leverage	0.0817	0.416*
	[0.37]	[1.72]
Ln(Assets)	0.386***	0.169***
	[12.82]	[5.38]
Redeployability	-1.864**	-2.376**
	[-2.12]	[-2.54]
Cash holdings	-1.799***	-1.929***
	[-4.77]	[-4.53]
Interest coverage	-0.00111	-0.000640
	[-0.86]	[-0.44]
Rollover	-0.600	-0.712
	[-1.10]	[-1.26]
Tangibility	-0.944***	-0.817***
	[-4.30]	[-3.75]
Tobin's Q	0.0458	-0.0701
	[0.96]	[-1.40]
Profitability	0.0999	-0.584
	[0.18]	[-0.91]

Table A1: Cox hazard regressions using alternative asset redeployability measure - *Continued*

		1st Event
	(5)	(6)
ROA	-1.742***	-1.756***
	[-5.42]	[-4.29]
Operating cash flow	0.0809	0.879
	[0.17]	[1.60]
CAPEX/assets	1.597**	0.599
	[2.57]	[0.87]
PPE growth	-0.433***	-0.301**
	[-4.01]	[-2.36]
Sales growth	-0.484***	-0.422***
	[-3.90]	[-2.94]
R&D/assets	-0.391	-0.270
	[-0.67]	[-0.47]
R&D missing (0, 1)	0.0502	0.0959
	[0.68]	[1.32]
Number of segments	0.105***	0.108***
	[5.97]	[5.36]
SA index	0.384***	0.501***
	[6.49]	[8.61]
Stock ownership	-0.0246***	-0.0252***
	[-3.22]	[-2.79]
Stock ownership missing (0, 1)	-0.218***	-0.333***
	[-3.71]	[-4.28]
Industry fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Industry covariates	Yes	Yes
Number of observations	577,273	450,562
Pseudo R^2	0.086	0.065
Number of clusters	6,349	6,286

Table A2: Wealth effects using alternative asset redeployability measure

The table presents the coefficient estimates from OLS regressions. The dependent variables are, respectively, the 3- and 5-day cumulative abnormal announcement return of the sellers (CAR (–1, +1) and CAR (–2, +2)), acquirers (ACAR (–1, +1) and ACAR (–2, +2), and the market-value weighted average cumulative abnormal announcement returns of the sellers and acquirers (SCAR (–1, +1) and SCAR (–2, +2)). Asset redeployability incorporates both across and within industry correlation of firm-level output and is from Kim and Kung (2016). We define all other covariates in Table 1. We cluster standard errors by firm and report *t*-statistics in brackets. We indicate when industry covariates, industry, time, and credit rating fixed effects are included in the specification, but do not report coefficients. We report *p*-values for the F-tests in Models (3), (5), and (7). Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Seller		Acquirer		Combined	
	CAR (-1,+1)	CAR (-2,+2)	ACAR (-1,+1)	ACAR (-2,+2)	SCAR (-1,+1)	SCAR (-2,+2)
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Rating downgrade (0, 1)	-0.0225**	-0.0211*	-0.0059	-0.0173	-0.0274	-0.0213
	[-2.152]	[-1.748]	[-0.243]	[-0.655]	[-1.415]	[-0.983]
Rating upgrade (0, 1)	0.0082**	0.0008	-0.0089	-0.0060	-0.0011	-0.0070
	[2.093]	[0.184]	[-0.562]	[-0.351]	[-0.112]	[-0.697]
Redeployability [A]	-0.0457	-0.0539	0.0764	0.1527	0.0017	0.0513
	[-1.181]	[-1.239]	[0.680]	[1.251]	[0.027]	[0.796]
Redeployability × Rating downgrade (0, 1) [B]	0.1663***	0.1576**	-0.0090	0.0180	0.1651*	0.1403
	[3.031]	[2.554]	[-0.092]	[0.176]	[1.865]	[1.420]
Altman Z-score	-0.0021*	-0.0017				
	[-1.803]	[-1.243]				
Cash holdings	0.0083	0.0034	-0.0063	-0.0182	0.0156	0.0004
	[0.420]	[0.158]	[-0.146]	[-0.409]	[0.617]	[0.015]
Interest coverage	0.0001*	0.0001	0.0003	0.0002	0.0002*	0.0001
	[1.813]	[0.913]	[1.632]	[1.267]	[1.808]	[0.742]
Rollover	-0.0104	-0.0065	-0.0244	0.0102	-0.0383	-0.0218
	[-0.377]	[-0.212]	[-0.629]	[0.217]	[-1.320]	[-0.623]
Leverage	0.0078	0.0096	-0.0183	-0.0260	0.0237	0.0260
	[0.619]	[0.676]	[-0.829]	[-1.022]	[1.522]	[1.505]
Tangibility	-0.0108	-0.0086	-0.0233	-0.0297	-0.0258	-0.0366**
	[-1.037]	[-0.746]	[-0.890]	[-1.114]	[-1.573]	[-2.010]
Tobin's Q	-0.0017	-0.0023	-0.0028	0.0018	-0.0035	-0.0055*
	[-0.670]	[-0.812]	[-0.555]	[0.366]	[-1.141]	[-1.681]
Profitability	-0.0334	-0.0521	0.1132	0.0983	0.0070	-0.0296
	[-0.935]	[-1.362]	[1.416]	[1.176]	[0.134]	[-0.491]
ROA	-0.0301	-0.0138	-0.0811*	-0.0913*	-0.0566*	-0.0362
	[-1.214]	[-0.490]	[-1.784]	[-1.786]	[-1.716]	[-0.944]
Operating cash flow	0.0651*	0.0567	0.0031	0.0397	0.0395	0.0877*
	[1.922]	[1.565]	[0.040]	[0.503]	[0.898]	[1.735]
CAPEX/assets	-0.0224	-0.0210	0.0096	0.0895	0.0746	0.0940
	[-0.615]	[-0.548]	[0.106]	[0.901]	[1.200]	[1.360]
PPE growth	0.0059	0.0076	0.0111	0.0075	-0.0030	-0.0012
	[0.941]	[1.103]	[1.176]	[0.641]	[-0.408]	[-0.138]
Sales growth	-0.0067	-0.0071	-0.0060	-0.0075	-0.0052	-0.0134
	[-1.096]	[-1.030]	[-0.506]	[-0.618]	[-0.596]	[-1.383]

Table A2: Wealth effects using alternative asset redeployability measure – *Continued*

	Seller		Acquirer		Combined	
	CAR (-1,+1)	CAR (-2,+2)	ACAR (-1,+1)	ACAR (-2,+2)	SCAR (-1,+1)	SCAR (-2,+2)
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
R&D/assets	0.0147	0.0173	0.0196	-0.0275	-0.0555	-0.0915
	[0.423]	[0.399]	[0.245]	[-0.350]	[-1.006]	[-1.515]
R&D missing (0, 1)	0.0036	0.0000	-0.0019	0.0015	-0.0017	-0.0031
	[1.157]	[0.009]	[-0.256]	[0.184]	[-0.346]	[-0.561]
Number of segments	0.0009	0.0008	-0.0015	-0.0019	0.0008	0.0009
	[1.423]	[1.137]	[-0.954]	[-0.942]	[0.876]	[0.819]
Ln(Assets)	-0.0010	-0.0025*	0.0017	0.0015	-0.0006	-0.0013
	[-0.814]	[-1.869]	[0.609]	[0.487]	[-0.293]	[-0.638]
SA index	0.0022	0.0018	-0.0098*	-0.0070	-0.0038	-0.0025
	[1.007]	[0.720]	[-1.780]	[-1.137]	[-1.048]	[-0.639]
Stock ownership	-0.0008**	-0.0008*	-0.0008	-0.0009	-0.0003	-0.0004
	[-2.112]	[-1.773]	[-0.665]	[-0.720]	[-0.440]	[-0.363]
Stock ownership missing (0, 1)	-0.0044	-0.0031	0.0057	0.0114	0.0037	0.0044
	[-1.443]	[-0.883]	[0.854]	[1.503]	[0.816]	[0.818]
Relative Size	0.1043***	0.1032***	-0.0012	-0.0005	0.0177	0.0158
	[6.002]	[5.675]	[-0.052]	[-0.016]	[0.873]	[0.723]
All cash (0, 1)	0.0024	0.0031	-0.0116	-0.0210**	-0.0044	-0.0057
	[0.751]	[0.894]	[-1.538]	[-2.255]	[-0.943]	[-1.065]
All stock (0, 1)	0.0039	0.0004	0.0138	0.0343	-0.0178	-0.0134
	[0.440]	[0.045]	[0.385]	[1.058]	[-1.092]	[-0.916]
Core segment	-0.0015	-0.0018	-0.0015	-0.0035	0.0022	0.0027
	[-0.655]	[-0.683]	[-0.294]	[-0.610]	[0.668]	[0.715]
Acquirer covariates	No	No	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Target Credit rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry covariates	Yes	No	No	No	No	No
F-test (p-value): [A] + [B] = 0	*0.045*	*0.144*	*0.618*	*0.236*	*0.100*	*0.084*
Observations	3,800	3,816	818	818	818	814
Adjusted R-squared	0.086	0.072	0.105	0.115	0.092	0.046

Table A3: Intra-firm segment performance analysis using alternative asset redeployability measure

The table presents average marginal effects of a logit regression where the dependent variable, High asset redeployability, is an indicator variable equal to one if the divested segment's asset redeployability is above the median across the asset redeployability of all of the firms segments in the same year and zero otherwise. Asset redeployability incorporates both across and within industry correlation of firm-level output and is from Kim and Kung (2016). All the covariates described in Table 1 using the Segment Sale sample. Standard errors are robust to heteroscedasticity and *t*-statistics are in brackets. Respectively, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level.

	High Asset Redeployability		
VARIABLES	(1)	VARIABLES - *continued*	(1) - *continued*
Rating downgrade (0, 1) = 1	0.0461	PPE growth	0.0836
	[1.240]		[1.404]
Rating upgrade (0, 1) = 1	0.0190	Sales growth	-0.0487
	[0.311]		[-0.702]
Altman Z-score	-0.00950	R&D/assets	0.437
	[-0.652]		[1.092]
Cash holdings	-0.306	R&D missing (0, 1) = 1	-0.0264
	[-1.173]		[-0.777]
Interest coverage	0.000747	Number of segments	0.00574
	[0.992]		[0.665]
Rollover	0.387	Ln(Assets)	-0.0211
	[1.268]		[-1.512]
Leverage	0.215	SA index	0.0686**
	[1.629]		[2.446]
Tangibility	-0.0117	Stock ownership	-0.00296
	[-0.120]		[-0.727]
Tobin's Q	0.0309	Stock ownership missing (0, 1) = 1	-0.0465
	[1.059]		[-1.262]
ROA	-0.0887	Redeployability	0.0699
	[-0.401]		[0.243]
Operating cash flow	0.675***	Credit rating FE	Yes
	[2.771]	Year FE	Yes
CAPEX/assets	-0.640*	Observations	1,267
	[-1.851]	Pseudo R2	0.0672

Table A4: 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 the credit rating downgrade variable by the distance between the firm's rating and the IG-HY boundary. We define all other covariates in the paper. 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				
	(1)	(2)	(3)	(4)	(5)
Rating downgrade (0, 1)	0.694***	0.469***	0.414***	0.478***	0.412***
	[11.68]	[6.82]	[5.97]	[6.89]	[5.85]
Rating upgrade (0, 1)	-0.255***	-0.226**	-0.230**	-0.207**	-0.176*
	[-2.96]	[-2.34]	[-2.38]	[-2.15]	[-1.80]
Rated (0, 1)	-0.00341	-0.114	0.463**	-0.0240	0.642***
	[-0.02]	[-0.62]	[2.44]	[-0.13]	[3.21]
S&P credit rating	0.0957***	0.0470***	-0.00604	0.0390***	-0.0210
	[11.47]	[3.71]	[-0.46]	[2.99]	[-1.50]
Altman Z-score		-0.0798***	-0.101***	-0.0437	-0.0526*
		[-3.00]	[-3.76]	[-1.50]	[-1.79]
Leverage		-0.324	-0.292	-0.309	-0.139
		[-1.39]	[-1.25]	[-1.27]	[-0.56]
Ln(Assets)		0.343***	0.427***	0.342***	0.447***
		[14.66]	[17.72]	[13.25]	[16.22]
Redeployability		-1.640***	-1.851***	-0.700*	-1.015**
		[-6.39]	[-7.19]	[-1.67]	[-2.37]
Cash holdings		-2.879***	-2.175***	-2.218***	-1.430***
		[-6.22]	[-4.64]	[-4.75]	[-2.97]
Interest coverage		-0.0061***	-0.0030	-0.0063***	-0.0026
		[-2.81]	[-1.45]	[-2.87]	[-1.24]
Rollover		-0.512	-0.869	-0.0507	-0.770
		[-0.93]	[-1.53]	[-0.09]	[-1.31]
Tangibility		-0.630***	-0.812***	-0.671***	-0.983***
		[-3.72]	[-4.66]	[-3.21]	[-4.46]
Tobin's Q		0.0565	0.1340**	-0.0212	-0.0009
		[1.06]	[2.44]	[-0.36]	[-0.01]
Profitability		1.606***	0.820	1.748***	0.612
		[2.65]	[1.28]	[2.86]	[0.92]
ROA		-1.686***	-1.448***	-1.947***	-1.747***
		[-4.25]	[-3.55]	[-4.74]	[-4.15]
Operating cash flow		-1.068*	-0.682	-1.217**	-0.423
		[-1.94]	[-1.16]	[-2.18]	[-0.69]
CAPEX/assets		3.184***	3.285***	2.165***	1.570**
		[5.32]	[5.40]	[3.21]	[2.22]

Table A4: Cox hazard regressions using distance-weighted credit rating downgrades – *Continued*

	Levels				
	(1)	(2)	(3)	(4)	(5)
PPE growth		-0.375***	-0.343***	-0.287**	-0.242**
		[-3.03]	[-2.74]	[-2.37]	[-1.99]
Sales growth		-0.414***	-0.542***	-0.428***	-0.622***
		[-3.02]	[-3.71]	[-3.20]	[-4.32]
R&D/assets		1.086	0.548	0.808	0.189
		[1.60]	[0.78]	[1.11]	[0.25]
R&D missing (0, 1)		-0.00952	-0.0224	0.122*	0.111
		[-0.17]	[-0.40]	[1.80]	[1.60]
Number of segments		0.0960***	0.101***	0.0939***	0.0942***
		[6.78]	[7.10]	[6.19]	[6.14]
SA index		0.254***	0.360***	0.188***	0.319***
		[5.25]	[7.69]	[3.64]	[6.23]
Stock ownership		-0.0078	-0.0168**	-0.0065	-0.0139*
		[-1.11]	[-2.32]	[-0.87]	[-1.77]
Stock ownership missing (0, 1)		-0.126**	-0.171***	-0.127**	-0.140**
		[-2.01]	[-2.59]	[-1.98]	[-2.04]
Industry fixed effects	No	No	No	Yes	Yes
Time fixed effects	No	No	Yes	No	Yes
Industry covariates	No	No	No	No	Yes
Observations	239081	181805	181805	181563	178875
Pseudo R-squared	0.022	0.050	0.077	0.062	0.095

Table A5: Cox hazard regressions for spinoffs and asset sales by purpose

The coefficients in the table represent hazard rate coefficient estimates of a spinoff and asset sales event by self-reported purposes: Distress, Discipline, or Ambiguous. Specification (1) is Cox proportional hazard regressions on a monthly basis over the entire sample for spinoffs. This specifications 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). We define all covariates in the paper. 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	Spinoff	Distress	Disicpline	Ambiguous
	(1)	(2)	(3)	(4)	(5)
Rating downgrade (0, 1)	0.152	-0.984	0.938**	-0.139	0.417***
	[0.56]	[-1.38]	[2.18]	[-0.35]	[3.85]
Rating upgrade (0, 1)	-0.724**	-0.670	0.643	-0.931	0.0677
	[-2.04]	[-1.13]	[1.01]	[-1.29]	[0.47]
Rated (0, 1)	0.00254	-0.307	1.113	1.630***	-0.221
	[0.00]	[-0.52]	[1.24]	[2.70]	[-1.14]
S&P credit rating	0.0472	0.0691	-0.172**	-0.146***	0.0704***
	[1.04]	[1.57]	[-2.31]	[-3.11]	[4.69]
Altman Z-score	-0.0517	-0.0396	-0.258*	0.0294	-0.0216
	[-0.88]	[-0.62]	[-1.95]	[0.45]	[-1.19]
Cash holdings	-1.032	-0.619	-0.266	-1.531	-2.903***
	[-0.93]	[-0.50]	[-0.14]	[-1.41]	[-6.45]
Interest coverage	-0.0080*	-0.0051	-0.0092	-0.0166**	-0.0009
	[-1.69]	[-0.88]	[-0.53]	[-2.04]	[-0.64]
Rollover	-0.226	-0.489	-1.145	-0.225	-1.193**
	[-0.15]	[-0.22]	[-0.50]	[-0.11]	[-2.08]
Leverage	-0.830	-0.344	1.924*	-0.204	0.278
	[-1.04]	[-0.39]	[1.75]	[-0.22]	[1.16]
Tangibility	-0.436	-0.832	0.468	-1.311**	-0.490***
	[-0.73]	[-1.12]	[0.65]	[-2.23]	[-2.76]
Tobin's Q	0.159	0.207	-0.770**	0.0550	-0.0617
	[1.38]	[1.28]	[-2.44]	[0.35]	[-1.28]
Profitability	2.097	0.256	0.826	-2.667	0.392
	[1.32]	[0.13]	[0.35]	[-1.35]	[0.60]
ROA	0.332	2.050	0.113	-1.173	-1.515***
	[0.28]	[1.63]	[0.09]	[-0.93]	[-3.63]
Operating cash flow	-0.289	-0.307	2.587	3.634**	-0.192
	[-0.21]	[-0.23]	[1.30]	[2.11]	[-0.35]

Table A5: Cox hazard regressions for spinoffs and asset sales by purpose – *Continued*

	Multiple events with others as censored	Competing risk (1^{st} only) subhazard			
	Spinoff	Spinoff	Distress	Disicpline	Ambiguous
	(1)	(2)	(3)	(4)	(5)
CAPEX/assets	1.868	2.394	-0.880	3.310	1.379**
	[0.77]	[0.96]	[-0.31]	[1.53]	[2.06]
PPE growth	-1.151***	-1.429**	-0.0399	-0.794	-0.256*
	[-3.05]	[-2.32]	[-0.10]	[-1.47]	[-1.93]
Sales growth	0.207	0.207	-0.222	-0.826	-0.351**
	[0.44]	[0.35]	[-0.44]	[-1.57]	[-2.46]
R&D/assets	1.694	2.075	0.632	-0.424	0.833
	[1.05]	[1.03]	[0.23]	[-0.20]	[1.56]
R&D missing (0, 1)	-0.0895	-0.0584	-0.196	-0.336	0.0752
	[-0.51]	[-0.22]	[-0.68]	[-1.44]	[1.16]
Number of segments	0.168***	0.174***	0.156**	0.0985*	0.0890***
	[5.20]	[3.36]	[1.98]	[1.85]	[4.54]
Ln(Assets)	0.332***	0.255***	0.147	0.289***	0.0348
	[3.95]	[2.72]	[1.46]	[3.37]	[1.14]
SA index	0.532***	0.322	0.651***	0.0848	0.271***
	[3.00]	[1.45]	[2.61]	[0.39]	[4.50]
Stock ownership	-0.00348	-0.0156	0.00432	-0.0602	-0.0208**
	[-0.21]	[-0.65]	[0.17]	[-1.26]	[-2.16]
Stock ownership missing (0, 1)	-0.526***	-0.944***	-0.680**	-0.988***	-0.307***
	[-2.98]	[-3.71]	[-2.21]	[-3.95]	[-3.72]
Industry fixed effects	no	no	no	no	no
Time fiixed effects	no	no	no	no	no
Industry covariates	no	no	no	no	no
Number of observations	604049	466628	466628	466628	466628
Pseudo R^2	0.061				
Number of clusters	6545	6476	6476	6476	6476

Table A6: 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. We define all other covariates in the paper. 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)	0.374***	0.350***	0.366***	0.367***	0.358***	0.344***	0.335***
	[5.96]	[5.54]	[5.87]	[5.84]	[5.74]	[3.91]	[4.13]
Rating upgrade (0,1)	-0.166**	-0.193**	-0.162*	-0.171**	-0.167**	-0.244**	-0.115
	[-2.01]	[-2.31]	[-1.96]	[-2.08]	[-2.03]	[-2.08]	[-1.02]
Acquisition activity	0.886***		0.820***	0.836***	0.771***		
	[18.63]		[14.57]	[17.14]	[13.57]		
Acquisition spending		2.444***					
		[16.72]					
Cash acquisition spending			0.815***		0.812***		
			[2.69]		[2.75]		
Equity acquisition spending				1.575***	1.577***		
				[4.39]	[4.46]		
Rated (0,1)	-0.0276	-0.139	-0.0303	-0.0436	-0.0465	0.204	-0.0811
	[-0.17]	[-0.82]	[-0.19]	[-0.27]	[-0.29]	[0.90]	[-0.40]
S&P credit rating	0.0435***	0.0574***	0.0438***	0.0447***	0.0450***	-0.00567	0.0601***
	[3.42]	[4.31]	[3.43]	[3.52]	[3.52]	[-0.32]	[3.82]
Redeployability	-1.039***	-1.130***	-1.007***	-1.031***	-0.999***	-1.794***	-0.837**
	[-2.81]	[-2.98]	[-2.70]	[-2.79]	[-2.69]	[-3.60]	[-2.23]
Altman Z-score	-0.0570***	-0.0561***	-0.0550***	-0.0578***	-0.0559***	-0.0708**	-0.0463*
	[-2.93]	[-2.88]	[-2.83]	[-2.98]	[-2.88]	[-2.53]	[-1.96]
Cash holdings	-2.443***	-2.658***	-2.416***	-2.427***	-2.401***	-2.048***	-2.508***
	[-6.40]	[-6.83]	[-6.33]	[-6.39]	[-6.32]	[-3.66]	[-5.69]
Interest coverage	-0.0034**	-0.0033**	-0.0035**	-0.0032**	-0.0033**	-0.0028*	-0.0031*
	[-2.46]	[-2.29]	[-2.51]	[-2.33]	[-2.38]	[-1.76]	[-1.80]
Rollover	-0.357	-0.423	-0.329	-0.336	-0.307	1.227*	-1.170*
	[-0.69]	[-0.79]	[-0.64]	[-0.65]	[-0.60]	[1.65]	[-1.90]
Leverage	-0.132	-0.121	-0.166	-0.0789	-0.114	-0.578*	0.134
	[-0.61]	[-0.55]	[-0.77]	[-0.37]	[-0.52]	[-1.86]	[0.54]
Tangibility	-0.377*	-0.556***	-0.363*	-0.367*	-0.352*	-0.365	-0.399*
	[-1.93]	[-2.75]	[-1.85]	[-1.89]	[-1.81]	[-1.43]	[-1.86]

Table A6: Cox hazard regressions and acquisition activity – *Continued*

						Acquisition activity	
						Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tobin's Q	0.0287	0.0250	0.0288	0.0172	0.0173	0.0518	-0.00180
	[0.63]	[0.55]	[0.63]	[0.38]	[0.38]	[0.87]	[-0.03]
Profitability	1.149**	1.070**	1.150**	1.162**	1.161**	1.142*	1.085*
	[2.27]	[2.13]	[2.29]	[2.32]	[2.34]	[1.69]	[1.67]
ROA	-1.555***	-1.280***	-1.566***	-1.355***	-1.366***	-1.046**	-1.607***
	[-4.91]	[-4.06]	[-4.97]	[-4.22]	[-4.27]	[-2.00]	[-4.20]
Operating cash flow	-1.053**	-0.987**	-1.097**	-1.118**	-1.160***	-1.560***	-0.474
	[-2.30]	[-2.20]	[-2.41]	[-2.47]	[-2.58]	[-2.60]	[-0.80]
CAPEX/assets	2.980***	3.261***	3.042***	2.938***	2.989***	2.096***	3.590***
	[5.31]	[5.76]	[5.44]	[5.29]	[5.40]	[2.88]	[4.88]
PPE growth	-0.719***	-0.808***	-0.752***	-0.768***	-0.799***	-0.300**	-1.325***
	[-6.25]	[-7.25]	[-6.63]	[-6.72]	[-7.09]	[-2.33]	[-6.74]
Sales growth	-0.505***	-0.539***	-0.523***	-0.533***	-0.550***	-0.185	-0.782***
	[-4.15]	[-4.48]	[-4.30]	[-4.41]	[-4.56]	[-1.27]	[-4.56]
R&D/assets	0.110	0.0254	0.0689	-0.00919	-0.0446	-1.261	1.212
	[0.18]	[0.04]	[0.11]	[-0.02]	[-0.08]	[-1.44]	[1.64]
R&D missing (0,1)	-0.0427	-0.0424	-0.0428	-0.0461	-0.0461	-0.0113	-0.0643
	[-0.67]	[-0.65]	[-0.68]	[-0.73]	[-0.73]	[-0.14]	[-0.83]
Number of segments	0.109***	0.107***	0.109***	0.109***	0.109***	0.0844***	0.131***
	[6.70]	[6.23]	[6.68]	[6.70]	[6.69]	[4.19]	[6.03]
Ln(Assets)	0.311***	0.314***	0.317***	0.308***	0.312***	0.503***	0.219***
	[12.10]	[11.56]	[12.20]	[12.02]	[12.13]	[16.42]	[6.73]
SA index	0.200***	0.245***	0.202***	0.198***	0.199***	-0.172**	0.314***
	[2.96]	[3.56]	[2.97]	[2.91]	[2.91]	[-1.99]	[3.77]
Stock ownership	-0.0142	-0.0162*	-0.0140	-0.0142	-0.0140	-0.0143	-0.0158
	[-1.62]	[-1.83]	[-1.59]	[-1.62]	[-1.60]	[-1.13]	[-1.61]
Stock ownership missing (0,1)	-0.156***	-0.211***	-0.155***	-0.162***	-0.160***	0.0254	-0.303***
	[-2.82]	[-3.76]	[-2.79]	[-2.94]	[-2.92]	[0.32]	[-4.34]
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	584725	584725	584725	584725	584725	134609	450116
Pseudo R-squared	0.067	0.063	0.068	0.068	0.068	0.084	0.056
N_clust	6402	6402	6402	6402	6402	3304	6079